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How do Carbon Emissions Respond to Business-Cycle Shocks?

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Abstract

Carbon dioxide emissions are highly correlated with cyclical fluctuations in the U.S. economy; they increase during booms and fall during busts. We examine this relationship focusing on the sources of business cycles identified using structural vector autoregression methodologies. Using data for 1973–2012, we find that emissions fall after unanticipated technology and investment shocks, as well as anticipated technology shocks. Emissions, however, increase after an anticipated investment shock. Our findings have two implications for the emerging literature that examines the optimality of environmental policy using dynamic stochastic general equilibrium models with unanticipated technology shocks. First, the assumption that unanticipated technology shocks cause carbon emissions to move with the business cycle has little support in the data both at the aggregate and the state-level. Second, identifying the shocks that explain procyclical carbon emissions is an important first step for crafting effective environmental policy over the business cycle—an anticipated investment shock is a candidate.

JEL classification: E32, Q58, Q54

Keywords: structural shocks, business cycles, carbon emissions, environment

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1 Introduction

Carbon dioxide (CO_2) emissions are highly correlated with business-cycle fluctuations in the U.S. economy; they increase during booms and fall during busts (Figure 1). Using quarterly data for 1973Q1–2013Q4, the contemporaneous correlation between the cyclical components of GDP and emissions is 0.67.[1] These empirical facts raise two immediate questions. The first is whether such fluctuations in carbon emissions should be taken into account in improving environmental policy. The second is whether the source of business cycles prescribes the optimal type of environmental policy, such as intensity targets, caps, taxes, or even cyclical taxes targeted to specific economic sectors. Recent work in environmental economics introduces carbon emissions into dynamic stochastic general equilibrium (DSGE) models to answer these questions.[2] A common element in these environmental DSGE (E-DSGE) models is the assumption that unanticipated technology shocks drive business cycles. There is, however, little consensus in the macroeconomics literature on the type of shock(s) that drive business cycles. Thus, *a priori*, it is not clear which type of shock matters the most for the observed cyclical variation of carbon emissions. Surprisingly, there is no applied work that has determined the effects of empirically identified business cycle shocks on emissions. The primary objective of the paper is to fill this void.

A better understanding of carbon emissions' response to business-cycle shocks can help evaluate the relevance of the predictions in calibrated E-DSGE models regarding optimal environmental policy. If, for example, empirical evidence indicates that emissions decline after a positive technological improvement but the calibrated E-DSGE models point to a positive relationship, we should be cautious about the models' policy prescriptions over the business cycle. From this perspective, the empirical research on macroeconomic fluctuations becomes relevant for environmental economics. Using vector autoregression (VAR) methodologies, macroeconomists have identified several structural shocks, such as technology and investment, as potential sources of business cycles. We draw on this literature and focus exclusively on the response of carbon emissions to each type of identified shock.

We find that emissions *fall* significantly after a positive unanticipated technology shock identified using aggregate U.S. data and the methodology of Galí (1999). This is in sharp contrast with the predictions of calibrated E-DSGE models that emissions increase in response to a

[1] See Doda (2012) for cross-country evidence.

[2] See, for example, Chang, Chen, Shieh, and Lai (2009), Angelopoulos, Economides, and Philippopoulos (2010), Fischer and Springborn (2011), Heutel (2012), Dissou and Karnizova (2012), Lintunen and Vilmi (2013), Grodecka and Kuralbayeva (2014), and Annicchiarico and Dio (2015). Fischer and Heutel (2013) provides an overview.

positive unanticipated technology shock (e.g., Heutel (2012)). We also examine the relationship between state-level unanticipated technology shocks, as identified in Hauser (2014), and state-level emissions. The cross-sectional correlation is negative and fails to be statistically significant. These rather striking findings provide a motivation to consider alternative sources of business cycles that have been investigated in the recent macroeconomic literature. In particular, we consider anticipated technology shocks (Beaudry and Portier (2006)), unanticipated investment shocks (Fisher (2006)), and anticipated investment shocks (Ben Zeev and Khan (2015)), identified using standard structural VAR (SVAR) methodologies.[3] We find that carbon emissions increase after a positive anticipated investment shock.

There are two implications of our findings based on the structural shocks identified using SVARs. First, the welfare analysis of environmental policies based on existing E-DSGE models has pitfalls. We illustrate this point by constructing an E-DSGE model that features all four types of shocks. In the model, output and emissions rise after a positive shock of each type. However, only the response to an anticipated investment shock in the E-DSGE model is consistent with the estimated response. Because an anticipated investment shock generates empirically recognizable business cycles and procyclical emissions, this is a relevant shock to consider in E-DSGE models. Second, proper calculation of the welfare implications of alternative policies requires simulations conditional on a shock that drives the business cycle. If the model's prediction bears no empirical support, as is the case for unanticipated technology shocks, the relevance of any model-based calculations is called into question.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the types of structural shocks we consider along with the identification methodology. In Section 3, we discuss the data and the empirical results, and in Section 4 we present our E-DSGE model. Section 5 concludes. The tables and figures follow the main body of the text.

[3] For a recent example on the use of VARs to inform environmental policy, see the report to the California Air Resource Board by Borenstein, Bushnell, Wolak, and Zaragoza-Watkins (2014). Due to the nature of the data, the authors employ a VECM methodology to answer two questions related to the the price-collar (floor & ceiling) mechanism on allowance prices for the state's cap-and-trade market for GHG emissions. The first is assessing the probabilities that market prices will be near the floor or the ceiling. The second is the market participants' ability to affect allowance prices using strategic buying and withholding. An executive summary with findings and recommendations is available in pages 2–8 of their report.

2 Business Cycle Shocks

2.1 Overview

Given that our objective is to examine the response of carbon emissions to business-cycle shocks, a natural question is which shocks to consider. We draw on the literature that estimates shocks using identification restrictions within an SVAR framework, building on the early work of Shapiro and Watson (1988) and Blanchard and Quah (1989), focusing on the most empirically relevant ones. The set of shocks we consider are ubiquitous in DSGE models currently used to study business cycles.

i. Unanticipated Technology Shocks

In the real business-cycle literature, exogenous variation in current total factor productivity (TFP) is viewed as the main driver of business cycles. Although Galí (1999) suggests that an unanticipated technology shock accounts for only a small variation in output, the recent E-DSGE literature has widely adopted it in policy evaluation exercises (e.g., Heutel (2012)).

ii. Unanticipated Investment Shocks

Fluctuations in the price of investment goods relative to the price of consumption goods have also been shown to be important drivers of U.S. business cycles; see Greenwood, Hercowitz, and Huffman (2000), Fisher (2006), and Justiniano, Primiceri, and Tambalotti (2010). Exogenous movements in the current relative price of investment goods reflect investment-specific technology shocks. Although an unanticipated technology shock uniformly shifts the aggregate production possibilities frontier for consumption and investment goods, an unanticipated investment shock shifts the aggregate production possibilities frontier for investment goods relatively more.[4]

iii. Anticipated Technology Shocks

Following Beaudry and Portier (2006), recent work has shown that business cycles are driven by news about a future fundamental—see Jaimovich and Rebelo (2009), Barsky and Sims (2011)), Khan and Tsoukalas (2012), and Schmitt-Grohe and Uribe (2012).[5] One such fundamental is TFP and the notion of anticipated or technology "news" shocks applies to anticipated movements in future TFP that are uncorrelated with current TFP.

iv. Anticipated Investment Shocks

[4]These shocks are known as "neutral" and "investment-specific," respectively (Fisher (2006)).

[5]Beaudry and Portier (2014) provide a detailed overview of this literature.

Ben Zeev and Khan (2015) have recently shown that news about future investment-specific technology is a significant force behind U.S. business cycles. They develop an identification scheme similar to Barsky and Sims (2011) but focus on the relative price of investment as the fundamental. The measure of investment-specific technical change is the inverse of the relative price of investment, denoted as IST. The identification scheme delivers anticipated movements in IST that are orthogonal to current IST and current TFP.

2.2 Identification

We briefly describe the identification methodology for each of the four shocks discussed in the previous section. Our focus is not on parsing the merits and drawbacks of the empirical approaches but rather take them as standard methods in the business-cycle literature.[6]

i. Unanticipated Technology Shocks

We follow the methodology in Galí (1999). The identification assumption is that only a technology shock affects labor productivity in the long run. The theoretical rationale for this assumption is that it holds in almost all commonly used business-cycle models. The empirical feasibility of this identification scheme requires a unit root to exist in labor productivity. This is the case for the U.S. and is well documented; see Galí (1999) and Francis and Ramey (2005). We consider the following bivariate VAR specification

$$\begin{bmatrix} \Delta LP_t \\ \Delta CO2_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^o \end{bmatrix} \equiv C(L)\varepsilon_t = \sum_{j=0}^{\infty} C_j \varepsilon_{t-j}. \tag{1}$$

In terms of notation, ΔLP_t and $\Delta CO2$ are the growth rates of labor productivity and CO_2 emissions per capita, respectively. In addition, ε_t^z is the the technology shock to be identified, and ε_t^o is the non-technology shock lacking a structural interpretation. Furthermore, $E[\varepsilon_t \varepsilon_t^{'}] = I$ and $E[\varepsilon_t \varepsilon_s^{'}] = 0$ for $t \neq s$. We use growth rates for carbon emissions because the Augmented-Dickey-Fuller test fails to reject the presence of a unit root in their levels. We can state the long-run identification assumption described above as follows

$$C^{12}(1) = \sum_{j=0}^{\infty} C_j^{12} = 0. \tag{2}$$

[6]We consider first-moment shocks as they have been extensively considered in the business-cycle literature. Recent work has explored the role of second-moment shocks as in Bloom (2009) and Christiano, Motto, and Rostagno (2014).

The reduced-form moving average (MA) representation associated with (1) is

$$\begin{bmatrix} \Delta LP_t \\ \Delta CO2_t \end{bmatrix} = \begin{bmatrix} A^{11}(L) & A^{12}(L) \\ A^{21}(L) & A^{22}(L) \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \equiv A(L)e_t = \sum_{j=0}^{\infty} A_j e_{t-j} \tag{3}$$

with $A_0 = I$, $E[e_t e_t^{'}] = \Omega$, $E[e_t e_s^{'}] = 0$ for $t \neq s$, and $\Omega = C_0 C_0'$. In addition, $e_t = C_0 \varepsilon_t$, and $C_j = A_j C_0$. The empirical implementation of (3) proceeds by estimating the following VAR

$$\begin{bmatrix} \Delta LP_t \\ \Delta CO2_t \end{bmatrix} = \begin{bmatrix} B^{11}(L) & B^{12}(L) \\ B^{21}(L) & B^{22}(L) \end{bmatrix} \begin{bmatrix} \Delta LP_{t-1} \\ \Delta CO2_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}, \tag{4}$$

where $B^{ij}(L)$ is a polynomial with four lags.

ii. Unanticipated Investment Shocks

We follow Fisher (2006) with the key identification assumption being that only an investment shock has a long-run effect on the relative price of investment

$$\begin{bmatrix} \Delta p_t \\ \Delta LP_t \\ \Delta CO2_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) & C^{13}(L) \\ C^{21}(L) & C^{22}(L) & C^{23}(L) \\ C^{31}(L) & C^{32}(L) & C^{33}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^{ist} \\ \varepsilon_t^{z} \\ \varepsilon_t^{o} \end{bmatrix} \equiv C(L)\varepsilon_t = \sum_{j=0}^{\infty} C_j \varepsilon_{t-j}, \tag{5}$$

where p_t is logarithm of the relative price of investment and ε_t^{ist} is the investment shock—the remaining shocks have the same interpretation as in (1). The empirical feasibility of this identification scheme requires a unit root in the relative price of investment. This is indeed the case for the U.S.—see Fisher (2006). There are two long-run identification assumptions used to estimate the shock. First, only an investment shock affects the relative price of investment. Second, both investment and technology shocks affect labor productivity. These identifying restrictions are implemented in (5) as follows

$$C^{12}(1) = C^{13}(1) = 0 \tag{6}$$

$$C^{23}(1) = 0. \tag{7}$$

iii. Anticipated Technology Shocks

We follow the methodology in Barsky and Sims (2011), which is based on the maximum forecast error variance (MFEV) over a medium-run horizon. This medium-run identification approach has certain advantages relative to long-run restrictions; see, for example, Uhlig (2002) and Francis, Owyang, Roush, and DiCecio (2013). The are two main identification assumptions regarding the anticipated technology shock. First, it maximizes TFP variation over a medium-run horizon of 10 years. Second, it is orthogonal to innovations in current TFP.

Let y_t be a 5×1 vector of observables with its elements being TFP (TFP_t), real non-durable consumption per capita (C_t), real output per capita (Y_t), CO_2 emissions per capita, and credit spread (CS_t). All variables except for the credit spread enter in logarithms. The MA representation of the VAR is

$$y_t \equiv \begin{bmatrix} TFP_t \\ C_t \\ Y_t \\ CO2_t \\ CS_t \end{bmatrix} = B(L)e_t, \tag{8}$$

where $B(L)$ is a matrix polynomial in the lag operator, and e_t is the vector of reduced-form innovations of appropriate dimension. Furthermore, we assume that there is a linear mapping between the reduced-form innovations e_t and the structural shocks ε_t given by

$$e_t = A\varepsilon_t. \tag{9}$$

Equation (8) and (9) imply a structural MA representation

$$y_t = C(L)\varepsilon_t, \tag{10}$$

where $C(L) \equiv B(L)A$ and $\varepsilon_t = A^{-1}e_t$. The impact matrix A is such that $AA' = \Sigma$, where Σ is the variance-covariance matrix of the reduced-form innovations. Note that there is an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, $\widetilde{A}$, the entire space of permissible impact matrices can be written as $\widetilde{A}D$, where D is a an orthonormal matrix.[7] The $h-$step ahead forecast error is

$$y_{t+h} - \widehat{y}_{t+h} = \sum_{\tau=0}^{h} B_\tau \widetilde{A} D \varepsilon_{t+h-\tau}, \tag{11}$$

where B_τ is the matrix of MA coefficients at horizon τ. The contribution of structural shock

[7] We use Choleski decomposition.

j to the forecast error variance of variable i is given by

$$\Omega_{i,j} = \sum_{\tau=0}^{h} B_{i,\tau} \widetilde{A} \gamma \gamma' \widetilde{A}' B'_{i,\tau}, \tag{12}$$

where γ is the jth column of D and $B_{i,\tau}$ represents the ith row of the matrix of MA coefficients at horizon τ. We place the current TFP shock in the first position of ε_t and index it as 1. We place the anticipated TFP shock in the second position and index it as 2.

Formally, this identification strategy requires solving the following optimization problem

$$\begin{aligned} \gamma^* = \text{argmax} \sum_{h=0}^{H} \Omega_{1,2}(h) &= \sum_{h=0}^{H} \sum_{\tau=0}^{h} B_{1,\tau} \widetilde{A} \gamma \gamma' \widetilde{A}' B'_{1,\tau} && (13) \\ \text{subject to } \ \widetilde{A}(1,j) &= 0 \ \ \forall j > 1 && (14) \\ \gamma(1,1) &= 0 && (15) \\ \gamma' \gamma &= 1. && (16) \end{aligned}$$

The constraints in (14) and (15) ensure that the anticipated technology shock has no contemporaneous effect on TFP. The constraint in (16) is a unit-variance restriction on the identified technology shock.

iv. Anticipated Investment Shocks

Following Ben Zeev and Khan (2015), we order TFP and the IST as the first and the second variables in a VAR system. We now write (8) as follows

$$y_t \equiv \begin{bmatrix} TFP_t \\ IST_t \\ Y_t \\ CO2_t \\ CS_t \end{bmatrix} = B(L) e_t, \tag{17}$$

where $IST_t = -\Delta p_t$. We place the current TFP and IST shocks in the first and second positions in the ε_t vector and index them as 1 and 2, respectively. We place the anticipated IST shock in the third position and index it as 3. The identification assumptions are that an anticipated IST shock maximizes the variation in future IST over a medium-term horizon of 10 years and is orthogonal to the innovation in current TFP and current IST. Formally, this identification strategy requires solving the following optimization problem

$$\gamma^* = \operatorname{argmax} \sum_{h=0}^{H} \Omega_{2,3}(h) = \operatorname{argmax} \sum_{h=0}^{H} \sum_{\tau=0}^{h} B_{2,\tau} \widetilde{A} \gamma \gamma' \widetilde{A}' B'_{2,\tau} \tag{18}$$

$$\text{subject to } \widetilde{A}(1,j) = 0 \ \forall j > 1 \tag{19}$$

$$\widetilde{A}(2,j) = 0 \ \forall j > 2 \tag{20}$$

$$\gamma(1,1) = 0 \tag{21}$$

$$\gamma(2,1) = 0 \tag{22}$$

$$\gamma'\gamma = 1. \tag{23}$$

The first four constraints ensure that the identified anticipated shock has no contemporaneous effect on TFP and IST. Constraint (23) is equivalent to (16).

3 Empirical Analysis

3.1 Data

The U.S. aggregate data span the period 1973Q1–2012Q1. We calculated quarterly CO_2 emissions as follows. First, we obtained monthly total energy CO_2 emissions (million metric tons of carbon dioxide) from Table 12.1 in the EIA December 2013 Monthly Energy Review. Second, we adjusted these monthly emissions for seasonality using the X-12-ARIMA filter. Finally, we aggregated them to quarterly frequency.[8] We calculate CO_2 emissions per capita using quarterly data on civilian non-institutional population.[9]

The output series is real GDP (billions of chained 2009 dollars) per capita.[10] The labor productivity series is the ratio of real GDP to hours of all persons in the non-farm business sector.[11] The consumption series is real non-durable consumption (billions of chained 2009 dollars) per capita.[12] The quarterly utilization-adjusted TFP series is the difference between the business-sector TFP and the utilization of capital and labor from Fernald (2014),

[8] http://www.eia.gov/totalenergy/data/monthly/#environment.

[9] This is the quarterly series CNP16OV from the Federal Reserve Economic Data (FRED) of the St. Louis Fed.

[10] We construct a quarterly series of real per capita GDP using the quarterly FRED series GDPC96, and CNP16OV.

[11] We use the quarterly FRED series GDPC96 and HOANBS, respectively.

[12] We use the quarterly average of the FRED series PCEND and DNDGRG3M086SBEA to obtain real consumption.

which are available from the Federal Reserve Bank of San Francisco.[13] The relative price of investment is the ratio of the implicit price deflator for nondurable consumption goods to the quality adjusted investment prices for business equipment & software and consumer durables.[14] Finally, the credit spread is the quarterly average of the difference between the monthly BAA and AAA corporate bond yields, which are available from FRED.

The state-level data are annual for 1976–2006. The CO_2 emissions from fossil-fuel burning are available from the Carbon Dioxide Information Analysis Center (CDIAC).[15] The employment data (Total Employment) are from the Personal Income and Employment by Major Component (SA4) data of the Bureau of Economic Analysis (BEA).[16] The real GDP data (All Industry Total) are from the BEA Regional Economic Accounts.[17] Finally, the unanticipated technology shocks are from Hauser (2014).

3.2 Results with Aggregate Data

Figure 2 shows the impulse responses of carbon emissions to a positive unanticipated technology shock. Panel (a) shows that carbon emissions fall after an unanticipated technology shock. Emissions slowly increase back to the steady-state level within a year.[18] Panel (b) shows the response of emission to the same type of shock in Heutel (2012)—note that emissions rise after a positive unanticipated technology shock. Annicchiarico and Dio (2015) also find that emissions rise after a positive unanticipated technology shock in a New Keynesian model with nominal and real frictions.[19]

As discussed in Heutel (2012), emissions rise after a positive unanticipated technology shock

[13] See also `http://www.frbsf.org/economic-research/total-factor-productivity-tfp/`. We use their `dtfp_util` series, which we transform from percent changes at an annual rate to levels.

[14] We use the quarterly average of the FRED series `DNDGRG3M086SBEA`. Patrick Higgins from the Atlanta Fed generously provided the quarterly series of the quality adjusted investment prices.

[15] `http://cdiac.ornl.gov/CO2_Emission/timeseries/usa`.

[16] `http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=4#`.

[17] `http://www.bea.gov/regional/downloadzip.cfm`.

[18] Chang and Hong (2006) suggest using total factor productivity instead of labor productivity when using long-run identification of unanticipated technology shocks. Therefore, we considered an alternative specification of (1) replacing ΔLP_t with ΔTFP_t. Emissions fall on impact in this case as well, similar to Figure 2.

[19] We also examined the relationship between per-capita carbon emissions and the oil price shocks in Kilian (2009). Using an SVAR methodology, Kilian identifies supply shocks, shocks to global demand for all industrial commodities, and demand shocks that are specific to the global crude oil market interpreted as "precautionary" shocks. We repeated the regression analysis in his Section III this time to examine the response of emissions to each of the three identified shocks. According to our findings, unanticipated oil supply disruptions have no effect on emissions on impact. Positive aggregate and precautionary demand shocks, however, do have a positive, albeit moderate, effect on emissions. The results are available upon request.

because in his model the price effect dominates the income effect under plausible calibration. An increase in wealth due to the productivity shocks leads to higher demand for a clean environment with lower emissions (income effect). At the same time, the opportunity cost of investing on abatement instead of capital is higher and abatement becomes more expensive leading to lower demand for abatement and higher emissions (price effect). Although it is theoretically possible in the model to generate a negative response of emissions on impact as estimated in panel (a), one can do so only under implausible calibration. The negative response of emissions on impact in panel (a) also means that the strong procyclicality of emissions shown in Figure 1 is not driven by an unanticipated technology shock.

There are two immediate implications of these findings for the existing E-DSGE models. First, the welfare analysis of environmental policies for calibrated E-DSGE models driven by unanticipated technology shocks is problematic because the emissions' response has the opposite sign of what we see in the data. This calls into question the relevance of compensating-variation calculations for alternative environmental policies that require simulations conditional on this particular type of shock. Second, the procylicality of emission observed in the data may arise from other types of shocks and propagation channels that have not yet been considered in the E-DSGE literature. Hence, one needs to consider alternative shocks that are capable of delivering the procyclicality observed in the data, in order to investigate the optimality of alternative environmental policies over the business cycle. Aside from the unanticipated technology shock, the existing E-DSGE literature has not examined the emissions' response to alternative types of shocks discussed in Section 2.

Panels (b) through (d) of Figure 3 document the emissions' response to positive unanticipated investment shocks, anticipated technology shocks, and anticipated investment shocks, respectively. Panel (a) replicates its analog from 2. Table 1 provides a summary of effect on impact for the various types of shocks considered in this section on emissions. In more detail, emissions fall after a positive unanticipated investment shock in panel (b). Panel (c) shows that emissions fall on impact after a positive anticipated technology shock. The response becomes positive after the second quarter but is not statistically significant. Panel (d) shows that a positive anticipated investment shock triggers a hump-shaped response over a two-year horizon. The increase that characterizes the first year is statistically significant.[20] Therefore, anticipated investment shocks are more likely to generate the procyclical pattern of emissions we see in the data than an unanticipated technology shock as suggested in the

[20]We also considered the investment deflator in Beaudry, Moura, and Portier (2015) to construct the relative price of investment. Carbon emissions rise in a statistically significant manner even on impact using this deflator. The results are available upon request. We thank Alban Moura for sharing the data from their paper.

existing E-DSGE literature. We introduce anticipated technology and investment shocks in the E-DSGE model discussed in Section 4.

3.3 Results with State-Level Data

Figure 4 shows a scatter plot of the cyclical component of carbon emissions against the cyclical components of GDP and employment extracted using the H-P filter on a logarithmic transformation of annual data between 1976 and 2006 for the 48 contiguous states. The correlation between emissions and GDP is rather notable with a value of 0.22. The correlation between emissions and employment is also positive and relatively larger with a value of 0.32. A simple OLS regression with the data in Panel (a) delivers a slope coefficient for GDP that is significant at 1% and an R-squared value of 0.05. The same regression with the data in Panel (b) delivers a slope coefficient for employment that is also significant at 1% and an R-squared of 0.10.[21]

Due to state-level data limitations, only the identification of the unanticipated technology shocks is possible. Figure 5 is a scatter plot of the cyclical component of emissions against the estimated unanticipated technology shocks in Hauser (2014). The correlation between the two variables is essentially zero and the same holds for the slope coefficient of a simple OLS regression delivering an R-squared of less than 0.01. Hence, as in our analysis with aggregate data, emissions do not appear to increase after a positive technology shock.

4 An E-DSGE Model

In this section, we present an E-DSGE model to determine the responses of carbon emissions to a variety of shocks, building on Heutel (2012). First, we introduce capital utilization and investment adjustment costs to generate positive business-cycle comovement with respect to anticipated technology shocks (Jaimovich and Rebelo (2009)). Second, we incorporate investment and anticipated technology shocks.[22]

Following Heutel (2012), the current stock of carbon emissions, X_t, is assumed to have a

[21] In all three regressions discussed in this section, we use heteroskedasticity robust standard errors.

[22] We note some differences relative to Annicchiarico and Dio (2015), who develop a new Keynesian model E-DSGE model. Their model includes capital adjustment costs and sticky nominal prices. By contrast, we consider flexible prices with investment adjustment costs and capital utilization. Their set of shocks includes technology, monetary, and government spending shocks. We include technology, investment, and anticipated shocks.

negative effect on output that is captured by a damage function $D(X_t)$ with $0 < D(X_t) < 1$, $D'(X_t) > 0$, and $D''(X_t) > 0$. The stock decays at rate η. Domestic emissions (M_t), as well as emissions from the rest of the world (M_t^{row}), contribute to the current pollution stock. Domestic emissions are positively related to output via $H(Y_t)$ and negatively related to the abatement rate $0 < \mu_t < 1$. The abatement rate μ_t is determined by the share of abatement expenditures in output given by $G(\mu_t) = Z_t/Y_t$, after setting the price of abatement to one.

The social planner chooses $\{C_{t+s}, U_{t+s}^K, K_{t+1+s}, I_{t+s}, X_{t+1+s}, \mu_{t+s}\}$, $s = 0, 1, ..., \infty$ to maximize the expected discounted lifetime utility of the representative agent

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s U(C_{t+s}) \tag{24}$$

$$\begin{aligned}
Y_t &= (1 - D(X_t))A_{1,t}F(U_t^K K_t) && (25)\\
X_{t+1} &= \eta X_t + M_t + M_t^{row} && (26)\\
Z_t &= G(\mu_t)Y_t && (27)\\
Y_t &= C_t + I_t + Z_t && (28)\\
K_{t+1} &= (1 - \delta(U_t^K))K_t + A_{2,t}\left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right) I_t && (29)\\
M_t &= (1 - \mu_t)Y_t^{1-\gamma} && (30)\\
\ln A_{1,t} &= \rho_1 \ln A_{1,t-1} + \varepsilon_{1,t} + \varepsilon_{2,t-4}^4 && (31)\\
\ln A_{2,t} &= \rho_2 \ln A_{2,t-1} + \varepsilon_{2,t} + \varepsilon_{2,t-4}^4. && (32)
\end{aligned}$$

The innovations $\varepsilon_{j,t}$ and $\varepsilon_{j,t-4}^4$ are independent normal with variances σ_j^2, $\sigma_{j,4}^2$ for $j = 1, 2$. The innovations $\varepsilon_{1,t-4}^4$ and $\varepsilon_{2,t-4}^4$ denote 4-period ahead news about technology and investment received by the social planner at period $t - 4$.

Using equations (25), (27), and (30), we can write the Lagrangian as follows

$$\begin{aligned}
\mathcal{L} = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \Big(U(C_{t+s}) + \lambda_{1,t+s}\big[(1-G(\mu_{t+s}))(1-D(X_{t+s}))A_{1,t+s}(U_{t+s}^K K_{t+s})^{\alpha} - C_{t+s} - I_{t+s}\big] + \\
\lambda_{2,t+s}\big[(1 - \delta(U_{t+s}^K))K_{t+s} + A_{2,t+s}\Big(1 - S\Big(\frac{I_{t+s}}{I_{t-1+s}}\Big)\Big) I_{t+s} - K_{t+1+s}\big] + \\
\lambda_{3,t+s}\big[\eta X_{t+s} + (1 - \mu_{t+s})\Big(\big(1 - D(X_{t+s})\big)A_{1,t+s}(U_{t+s}^K K_{t+s})^{\alpha}\Big)^{1-\gamma} + M_t^{row} - X_{t+1+s}\big]\Big).
\end{aligned} \tag{33}$$

Following Heutel (2012), we assume an isoelastic utility function of the form $U(C_t) = C_t^{1-\theta_c}/(1 - \theta_c)$. The specification for endogenous capital depreciation $\delta(U_t^K) \equiv \delta\big(U_t^K\big)^{\phi}$

follows Burnside and Eichenbaum (1996). The function for the investment adjustment costs is $S(I_t/I_{t-1}) = \psi(I_t/I_{t-1}-1)^2$ as in Christiano, Eichenbaum, and Evans (2005). The specifications for the abatement rate, $G(\mu_t) = \theta_1\mu_t^{\theta_2}$, and the damage function, $D(X_t) = d_2X_t^2 + d_1X_t + d_0$, are identical to those in Heutel (2012).

The first order conditions with respect to C_t, U_t^K, μ_t, I_t, K_{t+1}, X_{t+1}, $\lambda_{1,t}$, $\lambda_{2,t}$, and $\lambda_{3,t}$ are given by

$$C_t^{-\theta_c} = \lambda_{1,t} \tag{34}$$

$$Q_tK_t\delta'(U_t^K) = A_{1,t}\alpha(U_t^K)^{\alpha-1}K_t^{\alpha} + \bar{Q}_t\alpha(1-\gamma)(1-\mu_t)\frac{Y_t^{1-\gamma}}{U_t^K}, \tag{35}$$

where

$$Y_t = (1-D(X_t))A_{1,t}(U_t^KK_t)^{\alpha} \tag{36}$$

$$G'(\mu_t)Y_t = -\bar{Q}_tY_t^{1-\gamma} \tag{37}$$

$$1 = Q_tA_{2,t}\Big(1 - S\Big(\frac{I_t}{I_{t-1}}\Big) - S'\Big(\frac{I_t}{I_{t-1}}\Big)\frac{I_t}{I_{t-1}}\Big)\mathbb{E}_t\Big\{Q_{t+1}\Big(\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\Big)\beta A_{2,t+1}S'\Big(\frac{I_{t+1}}{I_t}\Big)\Big(\frac{I_{t+1}}{I_t}\Big)^2\Big\} \tag{38}$$

$$\begin{aligned} Q_t = \mathbb{E}_t\Big\{\beta\Big(\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\Big)\Big\{\big(1-G(\mu_{t+1})\big)\alpha\frac{Y_{t+1}}{K_{t+1}} - Q_{t+1}\delta(U_{t+1}^K) + \\ \bar{Q}_{t+1}(1-\mu_{t+1})(1-\gamma)\alpha\frac{Y_{t+1}^{1-\gamma}}{K_{t+1}}\Big\}\Big\} \end{aligned} \tag{39}$$

$$\begin{aligned} \bar{Q}_t = \mathbb{E}_t\Big\{\beta\Big(\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\Big)A_{1,t+1}\big(U_{t+1}^KK_{t+1}\big)^{\alpha}D'(X_{t+1})\Big\{\bar{Q}_{t+1}\Big(\eta - (1-\mu_{t+1})(1-\gamma)Y_{t+1}^{-\gamma}\Big) \\ -(1-G(\mu_{t+1}))\Big\}\Big\} \end{aligned} \tag{40}$$

$$(1-G(\mu_t))(1-D(X_t))A_{1,t}(U_t^KK_t)^{\alpha} = C_t + I_t \tag{41}$$

$$(1-\delta(U_t^K))K_t + A_{2,t}\Big(1 - S\Big(\frac{I_t}{I_{t-1}}\Big)\Big)I_t = K_{t+1} \tag{42}$$

$$\eta X_t + (1-\mu_t)\big(1-D(X_t)\big)\big)A_{1,t}(U_t^KK_t)^{\alpha}\big)^{1-\gamma} + M_t^{row} = X_{t+1} \tag{43}$$

$$Q_t \equiv \lambda_{2,t}/\lambda_{1,t} \tag{44}$$

$$\bar{Q}_t \equiv \lambda_{3,t}/\lambda_{1,t}. \tag{45}$$

4.1 Impulse Responses

Figures 6 through 9 display the impulse responses of output and CO_2 emissions to unanticipated technology shocks, unanticipated investment shocks, anticipated technology, and anticipated investment shocks. There are two key points to note. First, the optimal levels of output and emissions in the E-DSGE model increase after each of the four types of shocks. Thus, in the model, carbon emissions increase during a boom. This positive relationship between output and emissions is consistent with that observed in the data in Figure 1. The mechanism that generates such a relationship resembles that in Heutel (2012).

There are two offsetting effects that the social planner balances. On one hand, a positive shock produces a wealth effect that implies a higher demand for clean environment and, hence, less pollution. This effect tends to decrease emissions. On the other hand, a positive shock raises the marginal productivity of capital, which in our E-DSGE model is also aided by an optimal increase in capital utilization. This increase in the marginal productivity of capital lowers the opportunity cost of output-enhancing capital investment making abatement less desirable compared to the model considered by Heutel. For plausible calibration parameters provided in Table 2, the price effect dominates the wealth effect leading to an increase in the optimal level of emissions.

Second, the response of emissions in the E-DSGE model is in sharp contrast to the empirical responses *conditional* on the unanticipated business-cycle shocks, as shown in Figures 2 and 3. The movement of emissions conditional on three of the four identified sources of business cycles sharply is the opposite to that produced in a plausibly calibrated E-DSGE model.

Overall, our findings imply that welfare analysis of environmental policies based on E-DSGE models has pitfalls. Welfare calculations to assess alternative policies require simulations conditional on a shock that drives the business cycle and generates procyclical emissions. We find that unanticipated shocks utilized in the current E-DSGE literature bear no empirical support. This result calls into question the relevance of such calculations.

5 Conclusions

Carbon emissions are highly procyclical suggesting that they are linked with the shocks that drive fluctuations in the economy. In this paper, we investigate how emissions respond to various types of business-cycle shocks. The analysis draws on a rich empirical macroeconomic literature that seeks to identify and quantify the relative importance of a variety of shocks to technology and investment. Our findings are relevant for the emerging literature on environmental dynamic stochastic general equilibrium (E-DSGE) models studying the optimality of environmental policies over the business cycles and has thus far considered only unanticipated technology shocks as a potential source of fluctuations.

Using U.S. data for 1973–2012, we find that emissions fall after an unanticipated positive estimated technology shock, which is in sharp contrast with the result in calibrated E-DSGE models, where emissions rise after such a shock under plausible calibration. Turning to other types of estimated shocks, we find that emissions typically fall after unanticipated investment and anticipated technology shocks, respectively. Anticipated investment shocks, however, lead to an increase in carbon emissions. This finding suggests that the strong procyclicality of emissions might be driven by these types of business-cycle shocks. A natural first step to assess alternative environmental policies over the business cycle is to consider shocks that generate both empirically recognizable fluctuations and procyclical emissions—the anticipated investment shock discussed in this paper satisfies this criteria.

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Tables and Figures

Table 1: Effects of alternative types of estimated shocks on CO_2 emissions on impact

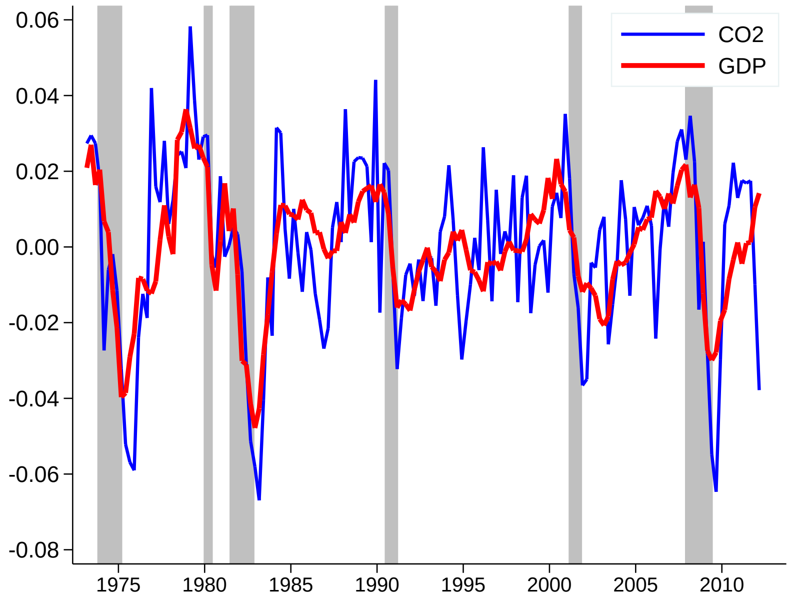
Shock	Effect
Unanticipated Technology	$-$
Unanticipated Investment	$-$
Anticipated Technology	$-$
Anticipated Investment	$+$

Table 2: Calibration parameters for the E-DSGE Model

Parameter	**Value**	**Description**
a	0.36	Curvature of production function
β	0.98267	Quarterly discount rate
δ	0.069833	Capital depreciation
ρ_{A_1}	0.95	Persistence of TFP shock
ρ_{A_2}	0.95	Persistence of investment shock
ϕ	1.5	Curvature of depreciation function
ψ	5	Investment adjustment costs
η	0.9979	Pollution depreciation
θ_1	0.05607	Abatement cost function:
θ_2	2.245	$G(\mu) = \theta_1 \mu^{\theta_2}$
d_2	5.2096E-10	Pollution damages function:
d_1	-1.2583E-06	$D(X) = d_2 X^2 + d_1 X + d_0$
d_0	1.3950E-03	
γ	1-0.696;	1 - elasticity of emissions with respect to output
ϕ_c	2	CRRA for consumption
M^{row}	5.289	Rest-of-the-world emissions

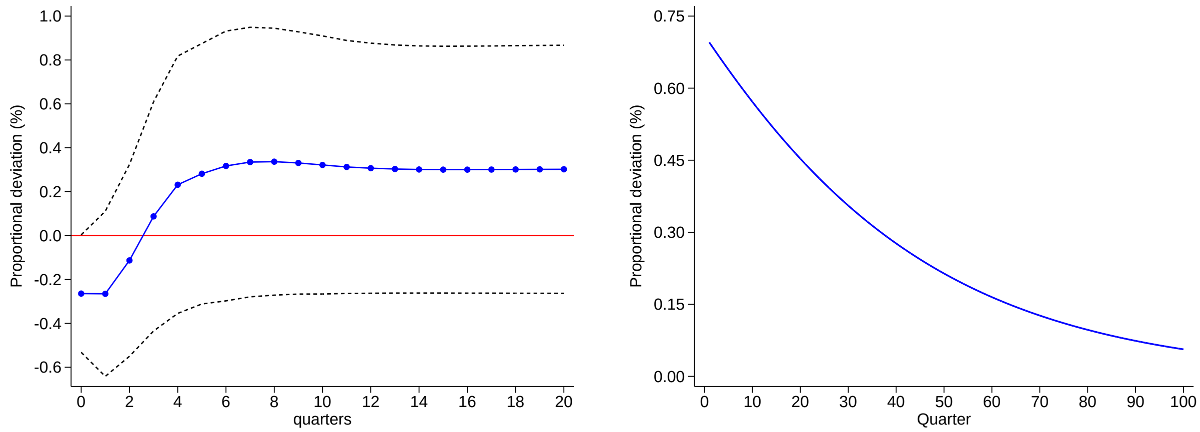
Note: The parameter values excluding ρ_{A_2}, δ, ϕ, and ψ are from Heutel (2012). We calculate δ using $U = [(1-a)Y/(\phi\delta K)]^{1/\phi}$, which is identical to equation (16) in Burnside and Eichenbaum (1996). We use $K = 27.9101$, $Y = 3.3055$, $a = 0.36$, $\phi = 1.5$, and $U = 0.806$. The values for K and Y are the steady-state ones from Heutel. The value of ϕ is comparable to the value of 1.56 reported in Burnside and Eichenbaum. The value of U is the average of the monthly capacity utilization (total industry) from FRED for 1967Q1–2015Q3. The value of ψ falls between the 5th and 95th percentiles of the posterior distribution in Table 1A of Smets and Wouters (2007). Following Heutel, we assume that the U.S. is responsible for about one-fourth of global anthropogenic carbon emissions. As a result, M^{row} equals 3 times the the steady state value of U.S. emissions M. For additional discussion, including assumptions and functional forms, see Section 4.

Figure 1: CO_2 emissions and business cycles



Note: We provide a time series plot of the cyclical components of per capita U.S. carbon emissions and real GDP extracted using the H-P filter for 1973Q1–2013Q4 with a smoothing parameter of 1,600. The grey shaded areas correspond to the NBER recessions dates.

Figure 2: Impulse responses of CO_2 emissions to unanticipated technology shocks

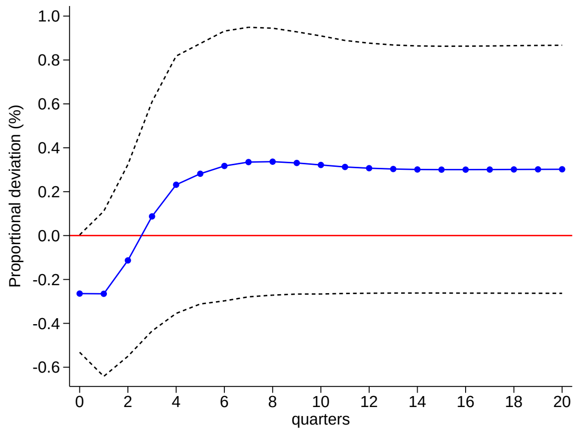


(a) Unanticipated technology shock, estimated

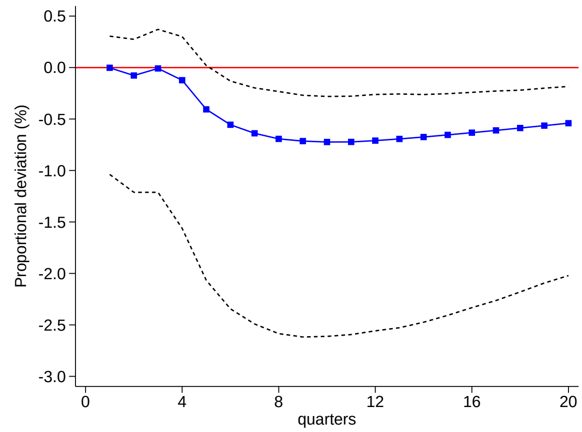
(b) Unanticipated technology shock, calibrated

Note: In Panel (a), we plot impulse responses using aggregate U.S. data for 1973Q3–2013Q3 following the VAR methodology described in Section 2. The dashed lines represent one standard-error bootstrapped confidence bands. In Panel (b), we replicate figure (4) in the calibrated E-DSGE model of Heutel (2012) using only the emissions' response.

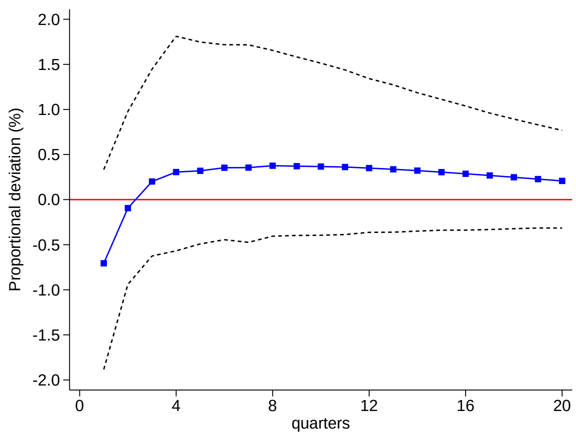
Figure 3: Impulse responses of CO_2 emissions to estimated business-cycle shocks



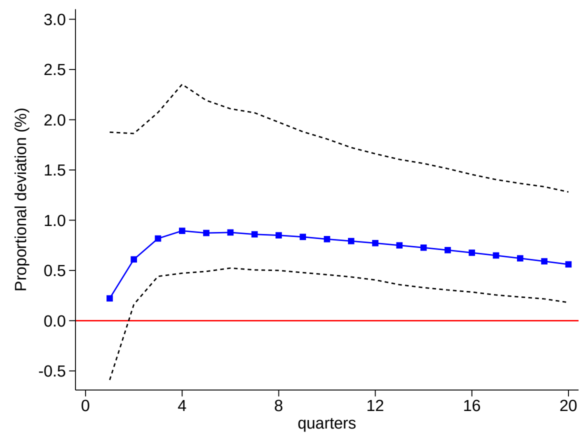
(a) Unanticipated technology shock



(b) Unanticipated investment shock



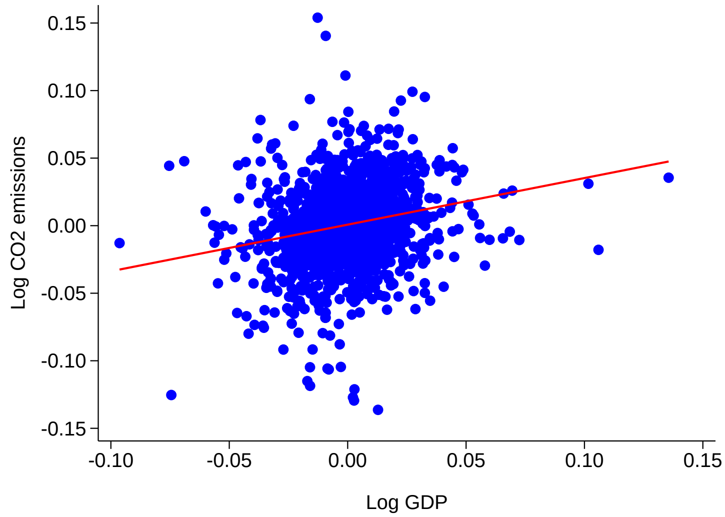
(c) Anticipated technology shock



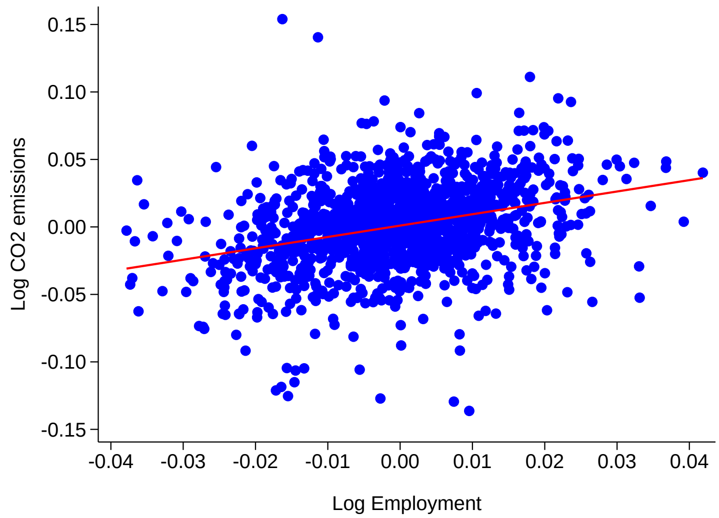
(d) Anticipated investment shock

Note: We plot impulse responses using aggregate U.S. data for 1973Q1–2012Q4 following the VAR methodology described in Section 2. The dashed lines correspond to the 1st and 99th percentile confidence bands generated from a residual based bootstrap procedure as in Hall (1992).

Figure 4: State-level CO_2 emissions and economic activity



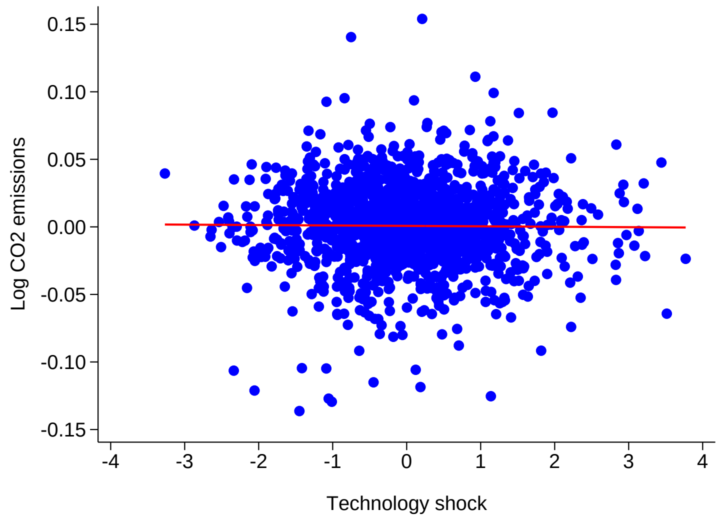
(a) GDP



(b) Employment

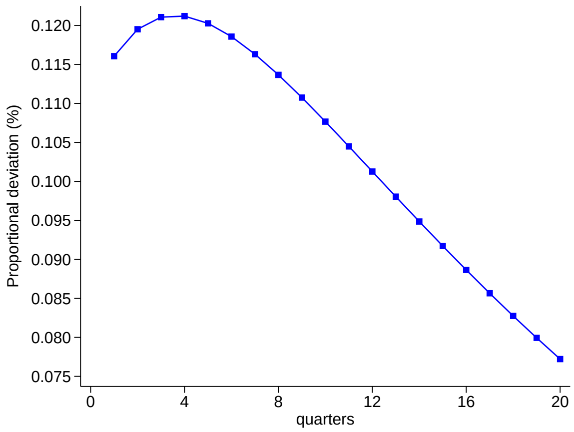
Note: In panel (a), we provide a scatter plot of the cyclical components of the logarithm of emissions and the logarithm of GDP. In panel (b), we provide a scatter plot of the cyclical components of the logarithm of emissions and the logarithm of employment. In both panels, we extract the cyclical component of the variables of interest using the H-P filter with annual data for the 48 contiguous states between 1976 and 2006. The red line corresponds to an OLS fit.

Figure 5: CO_2 Emissions and state-level estimated unanticipated technology shocks

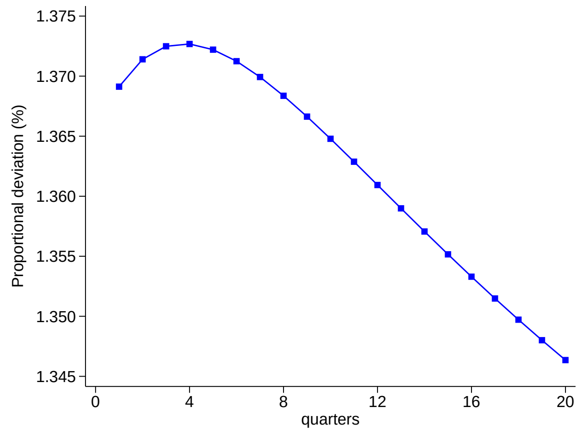


Note: We provide a scatter plot of the cyclical component of the logarithm of emissions extracted using the H-P filter and the estimated unanticipated technology shocks from Hauser (2014) for the 48 contiguous states using annual data between 1976 and 2006. The red line corresponds to an OLS fit.

Figure 6: EDSGE model: impulse responses to an unanticipated technology shock

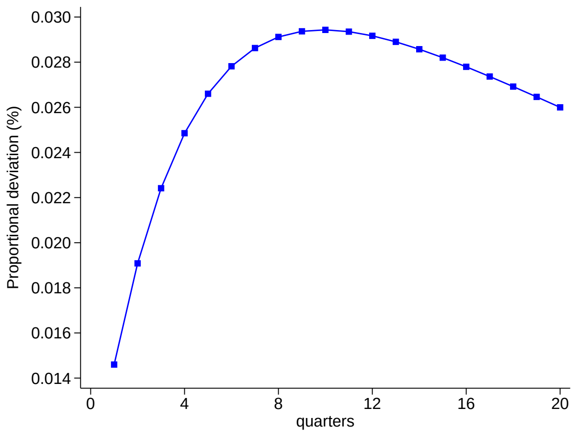


(a) Output

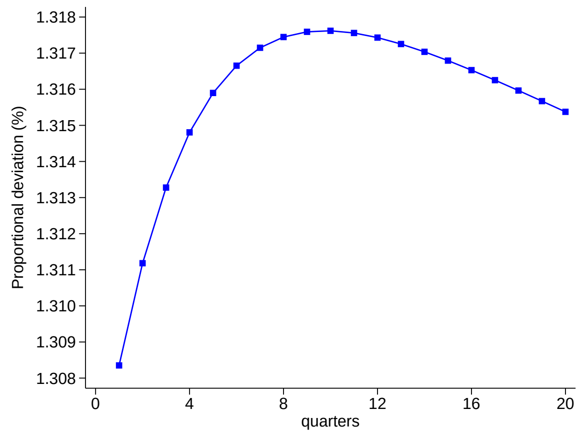


(b) Emissions

Figure 7: EDSGE model: impulse responses to an unanticipated investment shock

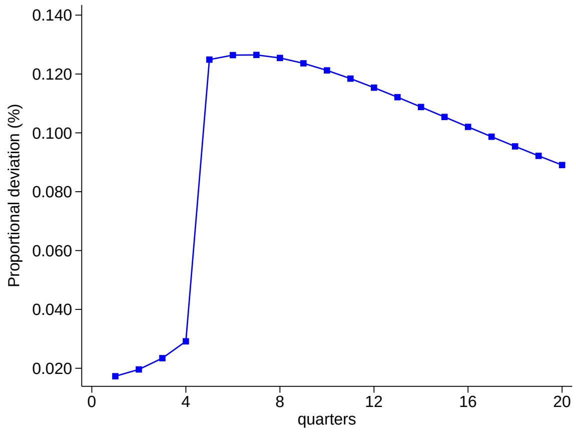


(a) Output

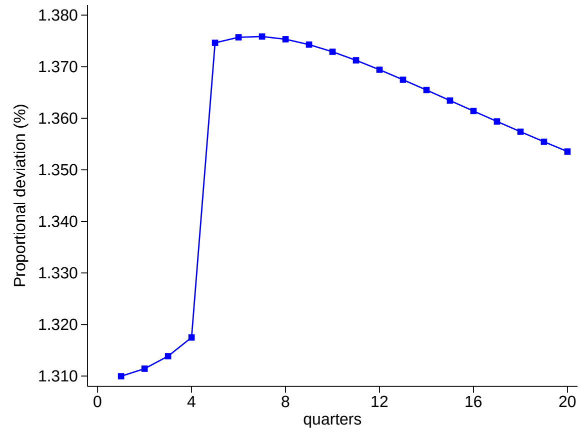


(b) Emissions

Figure 8: EDSGE model: impulse responses to an anticipated technology shock

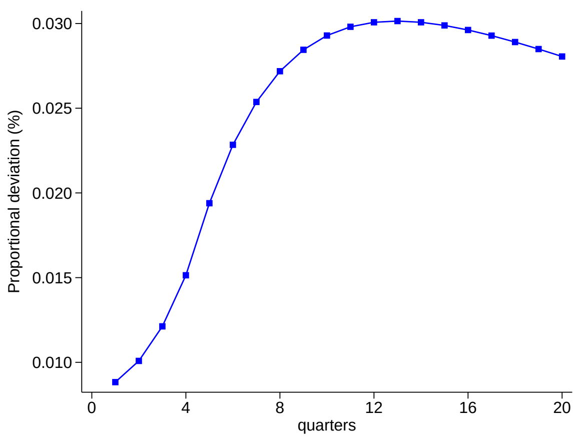


(a) Output

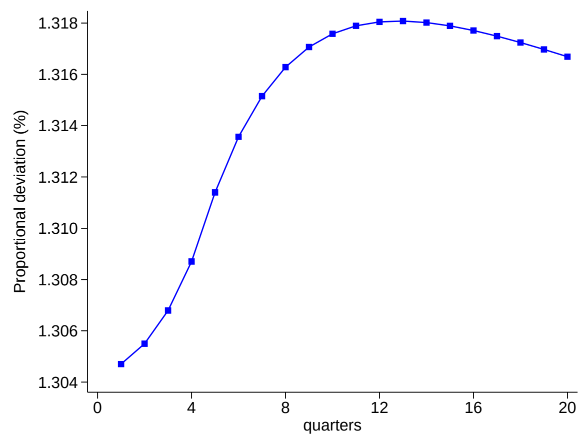


(b) Emissions

Figure 9: EDSGE model: impulse responses to an anticipated investment shock



(a) Output



(b) Emissions