# Stalling the Green Transition: Investment under Climate Policy Uncertainty*

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**Abstract**

Combining newspaper-based measures of climate policy uncertainty with annual financial data among 8,000 publicly-listed firms in the US, we examine the impact of uncertainty on a firm's investment decisions. Importantly, we distinguish between investments on new and existing capital, as the former has implications on clean energy adoption. Our main result is that energy intensive firms respond to high environmental and climate policy uncertainty by reducing its net investment and increasing its replacement investment. These results hold when controlling for energy prices and are driven by manufacturing firms. Not only does energy intensity of the firm itself matter, but also its upstream and downstream exposure to energy-intensive sectors. Using a subsample of firms with reported CO2 emissions, we find that firms making new investment have lower emissions and energy use, suggesting a positive correlation between new investment and energy efficiency. These findings are consistent with implications of our putty-clay investment model that features a stochastic distribution of energy prices.

*JEL codes:* Q54, G10, D57, D22, D25
*Keywords:* Climate change, financial market, investment, network, policy uncertainty

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# 1 Introduction

Policy uncertainty in general and on specific policies, including the economy, trade, and the environment, can significantly influence economic stability and growth (Baker et al., 2016; Bloom, 2009; Handley and Limão, 2015; Gulen and Ion, 2015; Noailly et al., 2024). This uncertainty can permeate various aspects of the economy, but its impact on investment decisions is particularly profound. Investments, being inherently forward-looking, are sensitive to changes in the policy environment, making the study of policy uncertainty crucial. Moreover, the transmission of policy shocks through economic networks amplifies their impact, suggesting that a comprehensive understanding of these dynamics is essential.

In this paper, we focus on environmental and climate policy uncertainty and distinguish its impact between new and replacement investments at the firm level. Investments in new capital typically incorporates technological advancements, are more energy efficient and less polluting. Our analysis therefore provides critical insights on whether firms' responses to environmental and climate policy uncertainty have implications on a shift toward or away from cleaner technologies. Beyond individual firms, our paper also quantifies how firm-level shocks propagate through input-output linkages, providing a more granular view than industry-level analyses. This approach highlights the broader economic impact of climate policy uncertainty, as firm-level investment decisions can ripple through supply chains.

Using detailed financial and network data on publicly-listed US firms, our main reduced-form evidence is that climate policy uncertainty significantly reduces new investments. Leveraging firm-level network distances using data on customers and suppliers, we also show that the uncertainty impacts propagate through supply chains, with downstream firms being affected through their energy-intensive upstream suppliers. Firms adopting new investments also exhibit lower carbon intensity compared to those relying on replacements. Our results have critical implications for $CO_2$ emissions, as delayed adoption of greener technologies could reduce the efficiency of climate regulation.

To explain these findings, we present a putty-clay investment model in which firms make decisions on whether and how much to invest in new and replacement capital at every period.

Our model features a stochastic distribution of energy prices and two types of capital, new and replacement. These features allow the model to capture the difference in net and replacement investments we estimate between firms in more or less energy intensive industries in our sample. In the model, we show that in face of uncertainty regarding energy prices, firms delay new investment, driving substitution toward replacement capital. The model then has implications on how policy uncertainty can introduce variability into the distribution of energy prices, which in turn affect firm's investment decisions on asset allocation.

This theoretical framework departs from the literature on real options theory, contributing to our understanding of how uncertainty affects investment. A large body of work is grounded in the real options approach, which extends the financial options theory to capital investment, highlighting the value of waiting for more information before committing to irreversible decisions. McDonald and Siegel (1986), for example, demonstrate that under uncertainty, firms may delay investments even when the net present value is positive, as waiting provides strategic flexibility. Pindyck (1991) builds on this idea, arguing that uncertainty increases the value of waiting, making firms more reluctant to invest than to disinvest. Empirical evidence from Bloom (2009) supports these theoretical insights, showing that uncertainty shocks often lead to investment pauses, followed by sharp recoveries once uncertainty subsides. Kellogg (2014) also show that oil firms in Texas delay irreversible investments (drilling) in face of fluctuations in expected oil price volatility to preserve the option to invest later when conditions may be more favorable. However, few studies distinguish between investments in new and old capital, except for the recent study by Campello et al. (2024) that focuses on the shipping industry.

Our study also contributes to the understanding of how environmental policies influence firm productivity and emissions (Greenstone et al., 2012; Shapiro and Walker, 2018). Both studies use an interaction term between non-attainment status of US regions and an indicator variable for a plant being a heavy emitter in their specification. They find that stringent environmental regulations can negatively impact firm productivity. In our study, we adopt a similar approach by interacting climate policy uncertainty with an indicator variable for a firm that belongs to an industry with high energy intensity. We leverage firm-level data spanning multiple industries from the universe of publicly-listed US firms. Our results therefore have broad implications on how climate policy uncertainty can affect the real economy.

Third, we contribute to the literature on shock propagation through input-output linkages due to increasing production inter-dependencies. Earlier studies present theoretical models to show that sector-specific shocks can generate macroeconomic fluctuations (Long and Plosser, 1983). Acemoglu et al. (2012) further demonstrate that shocks to key upstream industries can disproportionately impact aggregate output, amplifying economic volatility. One of the first papers to quantify these effects empirically focus on productivity shocks induced by changes in government spending in the US (Acemoglu et al., 2016). Other studies leverage natural experiments to document the propagation of shocks, such as disasters (Barrot and Sauvagnat, 2016; Carvalho et al., 2020; Balboni et al., 2024). Our study is one of the first to quantify how climate policy uncertainty propagates through input-output linkages to affect firm-level investments. Our results highlight that even if a firm itself is not energy intensive, having energy intensive suppliers in face of climate policy uncertainty impacts its investment decisions in new and old capital.

The paper proceeds as follows: Section 2 describes the data sources; Section 3 presents the empirical strategy and provides empirical evidence on the negative effects of climate policy uncertainty on stock returns and capital investment; Section Section 4 presents a putty clay model to explain our reduced form results; and Section 6 concludes.

## 2 Data and Empirical evidence

### 2.1 Data

The analysis utilizes three primary data sources. Investment and firm-level information are obtained from the Compustat unbalanced panel, which provides annual data for approximately 8,000 US public firms from 1990 to 2021. Climate and environmental policy uncertainty is measured using a monthly index derived from the work of Baker et al. (2016) and Noailly et al. (2024), covering the period from 1990 to 2019. Additionally, firm-level customer-supplier relationships are captured through production network data from Capital IQ. Together, these sources offer a robust foundation for exploring the relationships between investment behavior, policy uncertainty, and production networks.

***Climate policy uncertainty index*** The seminal work by Baker et al. (2016) is one of the first studies to use newspaper coverage frequency and keyword searches to measure economic policy uncertainty. Building on this approach, Engle et al. (2020) examine how investors perceive climate risks by analyzing climate change news in The Wall Street Journal. More recently, Noailly et al. (2024) constructed a comprehensive index of environmental and climate policy (EnvP) spanning 1981 to 2019, using content from 10 major U.S. newspapers. The index proxies for media attention on the topic by counting articles that include keywords related to "climate change and the environment" as well as "policy and regulations". In their earlier work, the authors also develop an uncertainty index (EnvPU), which is the monthly share of environmental policy uncertainty articles relative to all environmental and climate policy coverage (Noailly et al., 2022).

We also developed our own newspaper-based index measuring uncertainty following the methodology in Baker et al. (2016). To the best of our knowledge, we are one of the first studies to construct a monthly uncertainty index that reflects the frequency of newspaper articles with one or more terms about "economics," "policy," "uncertainty," and "climate change" in 11 U.S. newspapers.[1] We normalize the index to 100 from 1985 to 2018, with values above 100 reflecting higher-than-average uncertainty. Newspaper-based measures of uncertainty are forward-looking in that they reflect the real-time uncertainty perceived and expressed by journalists. We validate our index with well-known events on climate change discussions such as the Kyoto Protocol, the Paris summit, and IPCC assessment reports.[2]

***Firm level fundamentals*** Our sample consists of firms in the Compustat North America annual files from 1990 to 2022. We follow the steps outlined in Livdan and Nezlobin (2021) to arrive at an analysis sample consisting of about 8,000 firms. We also construct three measures of investment at the firm-level using the Compustat data based on accounting relationships out-

[1]The 10 US newspapers we pull data from are the Boston Globe, Chicago Tribune, Dallas Morning news, Houston Chronicles, LA Times, Miami Herald, San Francisco Chronicles, USA Today, Washington Post, The New York Times and Wall Street Journal.

[2]A recent study by Palikhe et al. (2024) complements our work by building a similar index. Unlike our focus on 11 major US newspapers, these authors utilize newspaper counts from over 15,000 local US newspapers.

lined in the same study. First, we compute total investment as the sum of pre-tax write-downs (*WDP* in Compustat), depreciation expenses (*DPC*), and the yearly change in net book value of property, plant, and equipment (*PPENT*). This measure captures variations in net capital stock while accounting for asset write-downs and depreciation. Second, we compute net investment by calculating the annual change in gross property, plant, and equipment (*PPGNT*), reflecting the firm's additions to capital before accounting for depreciation and impairments. Our third measure is replacement investment, which is the simple difference between total investment and net investment. A simple interpretation of replacement investment is that it accounts for capital expenditures necessary to maintain the existing asset base. In our empirical analysis, we scale all the investment measures by a firm's level of capital stock, measured by gross PP&E in the data, to compute the investment rates. This exercise ensures comparability of investment across firms and time periods.

***Input-output linkages*** To measure input-output linkages at the firm level, we use the lists of customers and suppliers for each firm on Capital IQ. We then link these firms to the firm-level financial data from the Annual Compustat Files from 1990 to 2022. We then follow the methodology outlined in Carvalho (2014) to compute both upstream and downstream links for each firm, extending up to four degrees of network distance.

***Other data*** Data on energy prices are from the EIA's Annual Electric Power Industry Report (Form EIA_861), which collects data from distribution utilities and power marketers of electricity at the state level. Data on firm level emissions come from S&P Global's Trucost Environmental dataset, which includes data on annual emissions at the firm level from 2000.

### 2.2 Descriptive Statistics

Figure 1 plots the three-year moving averages of the net and replacement investment rates of firms in our analysis sample (left axis) from 1990 to 2020 against the environmental and climate policy uncertainty index (right axis). Before 2012, net investment is more than 10% of a firm's capital stock, much higher than replacement investment, which is around 3% to 9% in the same period. Net investment (blue line) appears to co-move with the uncertainty index (grey dotted line) between 1990 to 1999 and after 2017. Besides a peak at almost 25% in 1996, however, net investment trends down over time and is between 10% and 15% from 1999 to 2017. Meanwhile, net replacement is gradually increasing over time, eventually catching up to the net investment in 2013, even surpassing it from 2014 to 2017.

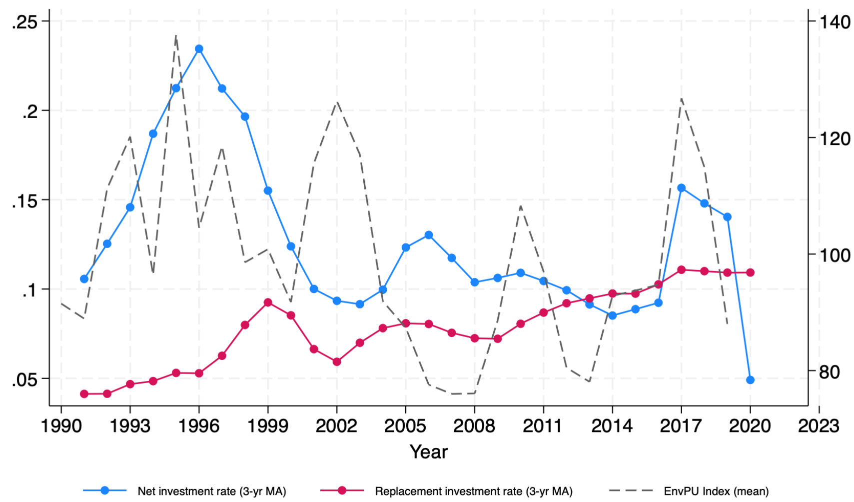


Figure 1: Net and Replacement Investment 1990 to 2020

**Note**: The figure plots the three-year moving averages of annual net and replacement investment rates of publicly-listed US firms from the period 1990 to 2022. The grey line in the background represents the environmental and climate policy uncertainty (EnvPU) index developed by Noailly et al. (2024).

Figure 2 presents the three-year moving averages of firms' net investment rates (top panel) and replacement investment rates (bottom panel) by industry-level energy intensity over the same period. The net investment rate is consistently higher for non-energy-intensive firms, with both firm types exhibiting similar trends over time. Notably, from 2016, the net investment rate among non-energy-intensive firms surges before experiencing a sharp decline in 2020. In contrast, the replacement investment rate follows a different pattern. Non-energy-intensive firms maintain higher replacement investment levels throughout the period, rising from below 2% of a firm's capital stock in 1990 to over 5% in 2020. Meanwhile, for energy-intensive firms, the replacement investment rate remains relatively stable, hovering just under 1%. These divergent trends in net and replacement investment rates by energy intensity suggest that firms' fundamental characteristics and investment decision-making processes may vary depending on the industry's energy intensity.

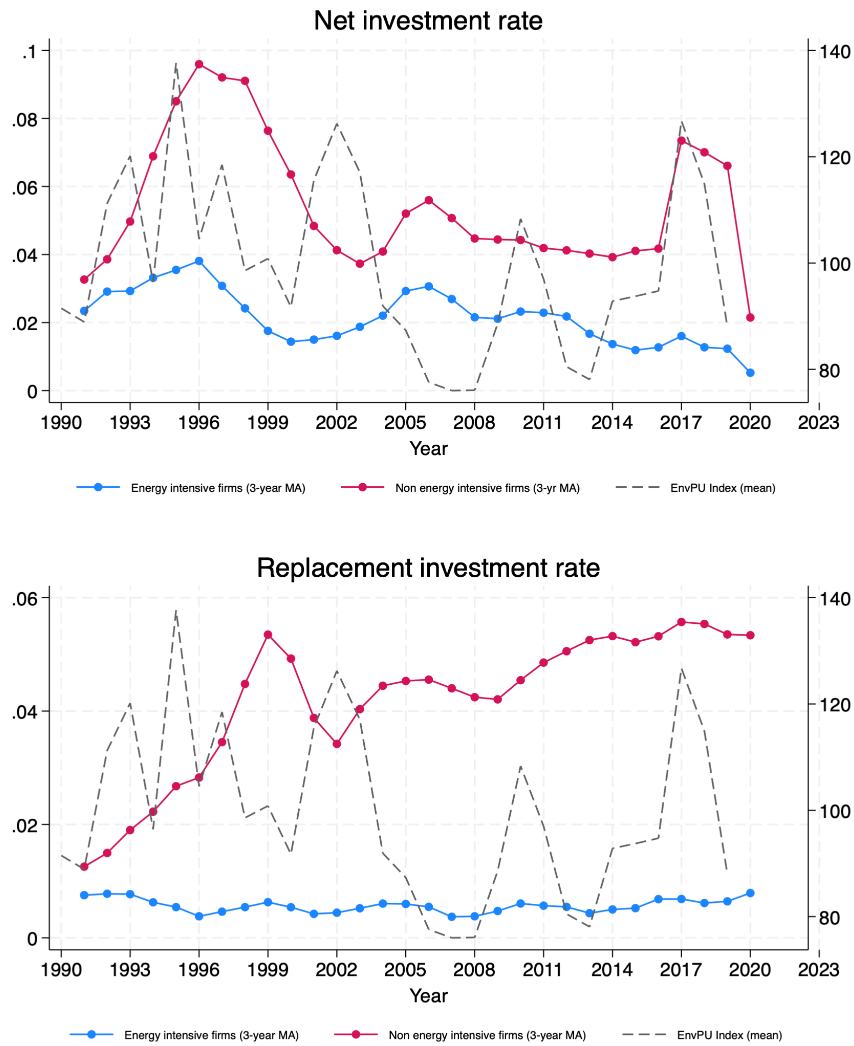


Figure 2: Net and Replacement Investment by Firm Energy Intensity

**Note**: The figure plots the three-year moving averages of annual net and replacement investment rates of publicly-listed US firms by energy intensity of industry. The grey line in the background represents the environmental and climate policy uncertainty (EnvPU) index developed by Noailly et al. (2024).

Table 1 presents summary statistics for the key variables used in our empirical analysis. All investment rates are winsorized at the 0.1% level. We divide the sample into three sectors — Manufacturing, Trade, and Energy. Investment levels are relatively similar across sectors, with the average total investment rate ranging from 18% to 20%. Net investment follows a similar trend, with Energy firms having the highest rates (16%) and Manufacturing firms having the lowest rate (11%), on average. In contrast, replacement investment is the lowest in the Energy sector (2%) compared to the other two sectors (7% in manufacturing and 6% in trade).

Table 1: Descriptive Statistics

| | Manufacturing | | Trade | | Energy | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd |
| *Investment* | | | | | | |
| Total investment | 0.18 | 0.26 | 0.19 | 0.29 | 0.20 | 0.36 |
| Net investment | 0.11 | 0.25 | 0.13 | 0.27 | 0.16 | 0.34 |
| Replacement investment | 0.07 | 0.11 | 0.06 | 0.10 | 0.02 | 0.12 |
| *Firm characteristics* | | | | | | |
| Energy intensity | 0.12 | 0.57 | 0.03 | 0.02 | 0.13 | 0.07 |
| Firm size (employees) | 12.22 | 34.01 | 25.08 | 102.69 | 4.43 | 13.28 |
| Sales | 4,961.04 | 19,849.19 | 6,499.79 | 25,059.94 | 2,097.35 | 8,240.22 |
| Capital | 3,795.39 | 20,496.58 | 3,388.88 | 13,077.85 | 5,091.55 | 14,911.51 |
| *Networks (max EI)* | | | | | | |
| DS1 firms | 0.16 | 0.72 | 0.46 | 1.26 | 1.35 | 1.87 |
| DS2 firms | 0.75 | 1.50 | 0.82 | 1.59 | 2.57 | 1.94 |
| DS3 firms | 1.98 | 1.99 | 1.49 | 1.94 | 2.82 | 1.86 |
| **Number of firms** | 3,596 | | 1,134 | | 683 | |

*Notes*: The table presents descriptive statistics for the main variables used in our empirical analyses over the 1990–2022 period. Dependent variables are the three measures of investment.

In terms of firm characteristics, firm size, measured by the number of employees, is the largest in Trade (mean = 25.08) but highly variable (sd = 102.69), while Manufacturing firms are smaller on average (12.22 employees), with energy firms being the smallest in size (4.43 employees on average). Trade firms have the highest average sales while energy firms have the highest average value of capital stock. Energy intensity is the highest in the Energy sector (13%) and the lowest in Trade (3%). The average manufacturing firms is as energy intensive as a typical firm in Energy, with 12% energy intensity.

We follow the steps outlined in Carvalho (2014) to compute both upstream and downstream links for each firm, extending up to four degrees of network distance. To measure how energy intensive a firm's input-output linkages are, we use the highest energy intensity level among a firm's suppliers for each degree of network distance. We see that while manufacturing and energy firms have a similar level of energy intensity, energy firms are connected to more energy intensive firms in their upstream networks, with average energy intensities at least double those in the network of manufacturing firms.

### 2.3 Empirical Strategy

We adopt two strategies to quantify the effects of a climate policy uncertainty shock on the real economy. First, we refine our in-house climate policy uncertainty index to a daily scale to study its impact on stock returns. Specifically, we regress the daily index on returns of most stocks traded in the United States with a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model (Savickas, 2003). Since price spikes induce volatility and are often serially correlated, using a GARCH model for estimation on financial data allows for a varying conditional variance to account for serial heteroscedasticity.

Our key finding is that daily climate policy uncertainty negatively impacts daily stock market returns, with energy-intensive firms and their connected industries experiencing more pronounced effects. Moreover, firms that are generally viewed as clean by heavily relying on intermediate goods from energy-intensive firms are also affected.

Next, we estimate the effect of environmental and climate policy uncertainty on investment in a standard two-way fixed effects model:

$$\Delta \ln Y_{i,t+1} = \gamma_t + \beta EI_{i,2012} \times EnvPU_t + X'_{it}\delta + \alpha_i + \sigma_t + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t+1}$ is firm $i$'s investment, for example, total, net and replacement investment in the next period; $EI_{i,2012}$ is the energy intensity of $i$'s industry in 2012; $EnvPU_{t-1}$ is the annual uncertainty index on climate and environmental policy outlined in Noailly et al. (2024). Identification relies on comparing the effect of uncertainty on investment between energy-intensive firms with non-energy-intensive firms. $\alpha_i$ denotes firm fixed effects and $\sigma_t$ represents fiscal year fixed effects. Standard errors are clustered at 3 digit NAICS level.

## 3 Reduced-form Results

Our analysis uses the environmental and climate policy indices (first and second moments) developed by Noailly et al. (2024) as the main measure of uncertainty. In their work, the authors find that higher environmental and climate policy uncertainty (EnvPU) is associated with a greater likelihood of clean-tech startups receiving venture capital funding, while high-emission firms, which are more exposed to environmental regulations, experience reduced stock returns. Our paper extends these insights by demonstrating that environmental policy uncertainty also significantly influences firms' own investment decisions in their production technologies, with implications on asset allocation.

We begin with exploring the relationship between environmental and climate policy uncertainty and total investment. Table 2 shows that a shock in environmental and climate policy uncertainty discourages investment. In our specifications, we first standardize the uncertainty indices and investment rates, and then interact the uncertainty indices with an indicator variable that equals one if a firm belongs to a high energy intensity industry (more than 50% of output). We find that a one s.d. increase in uncertainty is associated with an approximately 0.03 s.d. decrease in total investment for firms in energy intensive industries. The result holds when controlling for the average policy uncertainty (column 2) and state-level energy prices (column 3).

Table 2: Environmental and Climate Policy Uncertainty and Total Investment

| | Total Investment Rate$_{t+1}$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| High EI x Env. Policy Uncertainty (mean) | -0.0319$^{***}$ | -0.0322$^{***}$ | -0.0350$^{***}$ |
| | (0.00734) | (0.0108) | (0.0125) |
| High EI x Env. Policy (mean) | | -0.00191 | -0.00342 |
| | | (0.0472) | (0.0532) |
| Energy Prices | | | -0.0130$^{*}$ |
| | | | (0.00747) |
| Mean of dep. var. | -.00116 | -.00116 | .0138 |
| Observations | 91,601 | 91,601 | 72,833 |
| R-squared | 0.366 | 0.366 | 0.364 |

Notes: Standardized beta coefficients are reported. Standard errors are clustered at the 3-digit NAICS level.*** p<0.01, ** p<0.05, * p<0.1.

Next, we decompose total investment into the net and replacement components following Livdan and Nezlobin (2021) to investigate the source of the reduction in total investment. Table 3 reports our finding that energy intensive firms respond negatively to high environmental and climate policy uncertainty by reducing its net investment, while we see some evidence for increasing replacement investment. Specifically, we find that a one s.d. increase in uncertainty is associated with an approximately 0.05 s.d. decrease in net investment for firms in energy intensive industries (columns 1 to 3); while replacement investment increases by about 0.02 s.d. (columns 4 to 6). The decomposition exercise suggests that firms in high energy intensive industries tend to delay net investments (investments into new capital) in face of high climate poliy uncertainty. Meanwhile, we show evidence that these firms increase their investment into existing capital, perhaps by repairs or buying replacement parts.

Table 3: Environmental and Climate Policy Uncertainty Discourages Net Investment

| | Net Investment Rate$_{t+1}$ | | | Replacement Investment Rate$_{t+1}$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| High EI x Env. Policy Unc. | -0.0533*** | -0.0519*** | -0.0551*** | 0.0250** | 0.0233* | 0.0223* |
| | (0.00941) | (0.0154) | (0.0174) | (0.0101) | (0.0118) | (0.0118) |
| High EI x Env. Policy | | 0.00732 | 0.00779 | | -0.00984 | -0.0124 |
| | | (0.0520) | (0.0594) | | (0.0161) | (0.0215) |
| Energy Prices | | | -0.00727 | | | -0.0109** |
| | | | (0.00781) | | | (0.00523) |
| Firm FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Mean of dep. var. | -.000332 | -.000332 | .00773 | -.000955 | -.000955 | .019 |
| Observations | 91,242 | 91,242 | 72,567 | 90,991 | 90,991 | 72,354 |
| R-squared | 0.272 | 0.272 | 0.270 | 0.484 | 0.484 | 0.480 |

Notes: Standardized beta coefficients are reported. Standard errors are clustered at the 3-digit NAICS level.*** p<0.01, ** p<0.05, * p<0.1.

These patterns of asset allocation have broad policy implications if different types of investments have systematically different consequences on emissions. To validate this hypothesis, we use firm-level data from Trucost that include their self-reported emissions and link this subsample of firms to the Compustat dataset. Table 4 shows that when we correlate net and replacement investments with various measures of greenness, including Scope 1 to Scope 3 emissions and energy use, we find that higher net investments, on average, are correlated with lower Scopes 1 and 2 emissions (columns 1 and 2) and energy use (column 4), suggesting that new capital is more energy efficient. In contrast, we find that replacement investments correlate negatively with Scope 3 emissions, which are, be definition, indirect greenhouse gas emissions from in a firm's supply chain, such as purchasing of inputs and transportation costs.

Table 4: Correlation of Investments and Greenness of Firm

| | Scope 1 $CO_2$ | Scope 2 $CO_2$ | Scope 3 $CO_2$ | Energy Use |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Net Investment$_{t+1}$ | -0.008$^{*}$ | -0.012$^{*}$ | -0.011 | -0.018$^{**}$ |
| | (0.0702) | (0.0723) | (0.229) | (0.0898) |
| Replacement Investment$_{t+1}$ | -0.002 | 0.010 | -0.041$^{**}$ | -0.005 |
| | (0.168) | (0.223) | (0.509) | (0.300) |
| Firm FE | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes |
| Mean of dep. var. | 11.9 | 12.2 | 12.8 | 6.43 |
| Observations | 3411 | 3331 | 1861 | 2991 |
| R-squared | 0.974 | 0.955 | 0.815 | 0.889 |

Notes: Dependent variables are two-period leads. Standardized beta coefficients are reported. Standard errors are clustered at the 3-digit NAICS level.*** p<0.01, ** p<0.05, * p<0.1.

The evidence so far is consistent with the literature showing that firms delay new investments in the face of uncertainty (Campello et al., 2024). The novelty in our results lies in the finding that uncertainty's effect on investment is more prominent for firms in more energy intensive industries. To check whether this relationship between climate policy uncertainty and asset allocation differs across industries after controlling for energy intensity, we repeat the estimation of equation 1 by looking at manufacturing firms and trade and services firms separately. Table 5 reports the results. We find that for a one s.d. increase in environmental and climate policy uncertainty, manufacturing firms in more energy intensive industries reduce its net investment by about 0.02 s.d. (column 1) and increase its replacement investment by 0.01 s.d. (column 2), we do not document any response in asset allocation for trade firms (columns 3 and 4).

As outsourcing becomes more important in firms' organization, studies have documented that productivity shocks can ripple through the supplier and customer networks of firms and industries, affecting entities far removed from the initial point of impact (Carvalho et al., 2020). Likewise, the interconnected nature of modern economies means that a policy shift that generates uncertainty shocks in one sector can have unforeseen consequences in others, such as through supply chain and business network relationships. To quantify the propagation of policy uncertainty shocks through input-output linkages in our data, we re-estimate the baseline equation with additional interaction terms using the average energy intensities of a firm's immediate suppliers (*DS1*).

Table 5: Heterogeneity by Industry: Uncertainty and Investment

| | Manufacturing | | Trade | |
|---|---|---|---|---|
| | $NI_{t+1}$ | $RI_{t+1}$ | $NI_{t+1}$ | $RI_{t+1}$ |
| | (1) | (2) | (3) | (4) |
| High EI x Env. Policy Uncertainty | -0.0237** | 0.0125** | -0.0203 | 0.00646 |
| | (0.00972) | (0.00525) | (0.0257) | (0.00939) |
| High EI x Env. Policy | 0.0410 | -0.0378** | 0.0901** | -0.0168 |
| | (0.0312) | (0.0154) | (0.0343) | (0.0185) |
| Constant | -0.0760*** | -0.0803*** | 0.0126*** | -0.140*** |
| | (0.000459) | (0.000197) | (0.000496) | (0.000297) |
| Mean of dep. var. | -.0768 | -.0797 | .0108 | -.140 |
| Observations | 43,846 | 43,836 | 13,970 | 13,954 |
| R-squared | 0.256 | 0.383 | 0.260 | 0.416 |

Notes: Standardized beta coefficients are reported. Standard errors are clustered at the 3-digit NAICS level.*** p<0.01, ** p<0.05, * p<0.1.

Consistent with our evidence so far, Table 6 shows that firms that are connected to more energy intensive suppliers exhibit a higher reduction in net investment in face of climate policy uncertainty (columns 1 to 3). This result is true for manufacturing and trade firms. However, the decision to increase replacement investment is driven by manufacturing firms that are themselves more energy intensive (columns 4 and 5). Being connected to suppliers in more energy intensive industries is not correlated with the replacement investment decision. Overall, the key insight is that for energy intensive trade firms, even if environmental and climate policy uncertainty does not affect its own investment decision (see Table 5), there is a negative effect on net investment if the firm is connected to energy intensive suppliers.

Table 6: Transmission of Uncertainty Through Networks

| | Net Investment$_{t+1}$ | | | Replacement Investment$_{t+1}$ | | |
|---|---|---|---|---|---|---|
| Firms | All | Manu. | Trade | All | Manu. | Trade |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Env. Unc. x EI | -0.0134*** | -0.00837** | -0.0124* | 0.00341** | 0.00275*** | 0.00132 |
| | (0.00244) | (0.00326) | (0.00645) | (0.00137) | (0.000705) | (0.00118) |
| Env. Unc. x EI DS1 | -0.00121*** | -0.000542* | -0.00226*** | 0.0000325 | -0.0000108 | 0.0000158 |
| | (0.000280) | (0.000297) | (0.000566) | (0.0000837) | (0.000119) | (0.000172) |
| Mean of dep. var. | .131 | .11 | .134 | .0771 | .0662 | .0579 |
| Observations | 91,242 | 43,846 | 13,970 | 90,991 | 43,836 | 13,954 |
| R-squared | 0.272 | 0.256 | 0.261 | 0.484 | 0.383 | 0.416 |

Notes: Standardized beta coefficients are reported. Standard errors are clustered at the 3-digit NAICS level.*** p<0.01, ** p<0.05, * p<0.1.

# 4 A Model of New and Replacement Investment

To understand the implications of reduced investment in new, greener technology and the substitution between new and replacement investments on welfare and carbon emissions, we develop a putty-clay investment model, based on Gilchrist and Williams (2000) and Wei (2003). In this class of models, firms decide on the characteristics of capital (e.g., energy intensity) at the time of investment. However, once capital is installed, its characteristics remain fixed throughout its useful life. Deviating from this class of model, we consider the possibility of a replacement investment, as a marginal change of the number of machines for older vintage, as well as uncertainty on energy price $P$, to proxy for the policy uncertainty that our empirical analysis section showed.

We first consider a simple model with two periods and establish a standard result from the investment under uncertainty literature applicable to our model. Then, we will extend our model by considering two types of machine in the second period, where one type of machine is inherited, and the decision maker can only decide on the scale but not the characteristics of the machines, mimicking our replacement investment in our empirical specification.

## 4.1 Setting and Timing of the Model

We consider a simple two-period model, a partial equilibrium environment, in which firms invest in the first period and profits are realized in the second period. This is equivalent to a generic model when the vintage of each machine is one in Gilchrist and Williams (2000).

The following is an overview of the timing of the model, where we provide additional details below:

1. In period 1, the firm decides on the number of machines $Q$ to invest in, as well as the property of each machine: capital-energy ratio $k$ and energy-labor ratio $e$. Each machine is subject to an idiosyncratic productivity shock $\theta$ and is operated by one worker only.
2. In period 2, the following occur in the stated order:
   (a) The energy price $P$ is obtained from a known distribution $H$.
   (b) The productivity shock $\theta$ is realized for each machine installed.
   (c) The firm decides which machine to operate and profits are realized.

The output for each machine $i$ follows a standard Cobb-Douglas formulation:

$$Y_i = \theta_i k_i^{\lambda\alpha} e_i^{\alpha} L_i \equiv \theta_i X L_i \tag{2}$$

where in the last equality we define $X$ to be the average productivity for each machine, and the firm will optimally choose the same value of $k$ and $e$ for all machines before $\theta$ is realized.

We follow the literature and assume the idiosyncratic productivity term follow the following lognormal distribution:

$$\log \theta_i \sim N(-\frac{1}{2}\sigma^2, \sigma^2) \tag{3}$$

and we assume that $\theta$ is independently and identically distributed.

With this in mind, we begin to solve the firm's problem sequentially. In step 2c, the firm observes the energy price $P$ and the cost of labor $W$, with the latter assumed to be fixed.[3]

[3] In this partial equilibrium setting, we ignore the general equilibrium effect of changing the distribution of $P$ on $W$.

Therefore, the firm will operate a machine if $\theta_i X \geq P \cdot e + W$. Following the distributional assumption, the standard result in the literature suggests that we can express the proportion of machines operated as

$$\Pr[X > P \cdot e + W | W, P] = 1 - \Phi(z) \tag{4}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal random variable and

$$z = \frac{1}{\sigma}\left[\log(Pe + W) - \log(X) + \frac{1}{2}\sigma^2\right] \tag{5}$$

The total profits, before $\theta$ is realized (and after $P$ is realized) can be expressed as

$$\Pi(Q, e, k, P) = (1 - \Phi(z(e, k, P) - \sigma))QX(e, k) - (1 - \Phi(z(e, k, P)))Q(Pe + W) \tag{6}$$

where $\Phi(z - \sigma)$ is the ratio of output produced to the level of output at full capacity.[4]

We can now express the investment problem for the firm as follows:

$$\Omega(P) = \max_{Q,e,k} \{\mathbb{E}(\Pi(Q, e, k, P)) - c(Qek)\} \tag{7}$$

The cost function $c(\cdot)$ is assumed to be increasing and convex, which takes into account non-linear adjustment cost of capital. The expectation sign $\mathbb{E}$ takes into account the stochastic distribution $H$ for energy price $P$, which is unknown at the time of the investment but known at the point of the machine utilization decision (i.e., equation (6)).

Before showing how the investment choice is affected by the distribution $H$, it is helpful to state the following assumption and two lemmas.

**Assumption 1.** $\sigma > \frac{\phi(z)}{1-\Phi(z)}$ *for all values of* $z$.

The energy price here has two effects on the total cost facing a firm. While the energy price raises the cost of running a given machine, the energy price also decreases the probability of running a machine, hence it may decrease the total costs through the scale effect. Assumption 1 is a sufficient condition that requires the dispersion of productivity to be more important than

[4] See Gilchrist and Williams (2000) for details and proof.

the dispersion of machines shutting down, hence ensuring the second effect is bounded and that it cannot dominate the first effect.

**Lemma 1.** *Suppose Assumption 1 is satisfied. Then, $\Pi(\cdot)$ is strictly decreasing in $P$ when $P$ is sufficiently large.*

*Proof.* Notice that $z$ is an increasing function of $P$. Therefore, as $P$ goes to infinity, $\Phi(z-\sigma)$ (and $\Phi(z)$) will converge to one, which imply $(1-\Phi(\cdot))$ converges to zero. While this means that the revenue term (the first term in $\Pi(\cdot)$) converges to zero, assumption 1 implies that cost increases in $P$, hence $\Pi(\cdot)$ is decreasing in $P$. $\square$

With the lemma stated, we summarize the standard investment under uncertainty result below:

**Proposition 1.** *Suppose Assumption 1 is satisfied and let $F$ and $G$ be two cumulative distribution functions on $\mathbb{R}_+$. In addition, suppose that $G$ is a mean-preserving spread of $F$. Define the optimal solution $(Q,e)$ to the problem in (7) if $P$ follows a generic distribution $H$ as $(Q_H^*, e_H^*)$. Then,*

$$Q_G^* \leq Q_F^* \qquad e_G^* \leq e_F^*$$

Proposition 1 states that, if the decision maker faces an increase in uncertainty in the distribution of energy price $P$, then the firm will choose to lower the energy intensity and the quantity of the investment. This is analogous to the results in the investment under uncertainty literature (Dixit and Pindyck, 1994).

We present a sketch of the proof below by contradiction. Suppose $Q_F^* \leq Q_G^*$. If $G$ is a mean-preserving spread of $F$, then according to Rothschild and Stiglitz (1970), for any function $\psi(P)$,

$$\int_{-\infty}^{a} \psi(P)dG(P) \leq \int_{-\infty}^{a} \psi(P)dF(P) \quad \forall a \in \mathbb{R} \tag{8}$$

Equation (8) implies that, for a given $(Q,e,k)$, the objective function evaluating at distribution $F$ will have a higher expectation than the one evaluating at distribution $G$, implying that $\mathbb{E}_F(\Pi(Q_F^*)) \geq \mathbb{E}_G(\Pi(Q_F^*))$. By the definition of $Q_G^*$, we also have $\mathbb{E}_G(\Pi(Q_G^*)) \geq \mathbb{E}_G(\Pi(Q_F^*))$.

Lemma 1 implies that there is an $\epsilon > 0$ such that $\mathbb{E}_F\left[\Pi(Q_F^*, e_F^*, k_F^*)\right] - \mathbb{E}_G\left[\Pi(Q_F^*, e_F^*, k_F^*)\right] \geq \epsilon > 0$. In other words, large $Q_F^*$ exposes the firm to substantially worse outcomes in the high-$P$ tail under $G$ than under $F$. We now pick a slightly smaller $(\widetilde{Q}, \widetilde{e})$ with $\widetilde{Q} < Q_F^*$. Under $F$, scaling down reduces payoff *only a little* (since $F$ puts less mass in high-$P$ states). On the other hand, under $G$, that reduction in scale substantially mitigates the high-price tail penalty, or $\mathbb{E}_G\left[\Pi(\widetilde{Q}, \widetilde{e}, k_F^*)\right] > \mathbb{E}_G\left[\Pi(Q_F^*, e_F^*, k_F^*)\right] + \frac{1}{2}\epsilon$. Combining these implies $\mathbb{E}_G\left[\Pi(\widetilde{Q}, \widetilde{e}, k_F^*)\right] > \mathbb{E}_G\left[\Pi(Q_F^*, e_F^*, k_F^*)\right]$. But since $Q_G^* \geq Q_F^*$ by hypothesis, and $\mathbb{E}_G\left[\Pi(Q_G^*, e_G^*, k_G^*)\right] \geq \mathbb{E}_G\left[\Pi(Q_F^*, e_F^*, k_F^*)\right]$, this contradicts the supposed optimality of $(Q_G^*, e_G^*)$ under $G$, hence $Q_G^* < Q_F^*$.

### 4.2 With Replacement Investment

After establishing the standard uncertainty (of energy price) that discourages investment result in our framework, we now extend our model by considering the two types of capital: old-vintage capital (denoted capital 1) and new-vintage capital (denoted capital 2). The two types of capital are produced according to the exact same Cobb-Douglas formulation in (2). The timing of the game remains identical, except that the decision maker cannot choose the characteristics of capital 1 but only the level of capital 1, while we maintain the setting in which the decision maker can decide both on the characteristics and level of capital 2.

In other words, denoting the type of capital using subscripts 1 or 2, the decision maker decides on the investment in both capitals, holding the property of the old capital $e_1, k_1$ fixed. This mimics a vintage-based setting in Gilchrist and Williams (2000) where the capital-labor ratio is held fixed during the entire vintage of the capital. In the standard putty-clay model, the number of machines $Q$ is also decided at the beginning of the lifetime and it is subject to depreciation. Here we extend their framework by considering replacement investment where the number of machines can be ex-post adjusted.[5]

[5] Our setting is thus equivalent to a case where the number of machines depreciates fully in one period when the lifetime of the machine is two. Qualitatively, the main finding of our paper does not change whether we consider a marginal adjustment to $Q_1$ or assume $Q_1$ to be a decision variable in period 1.

In the second period, the profit of the firm is now

$$\Pi(Q_1, Q_2, e_2, k_2, P) = (1 - \Phi(z(e_1, k_1, P) - \sigma))Q_1 X(e_1, k_1) - (1 - \Phi(z(e_1, k_1, P)))Q_1(Pe_1 + W) + (1 - \Phi(z(e_2, k_2, P) - \sigma))Q_2 X(e_2, k_2) - (1 - \Phi(z(e_2, k_2, P)))Q_2(Pe_2 + W) \quad (9)$$

where $e_1, k_1$ are fixed parameters from the perspective of the decision maker in period 1.

With this setting, we can now establish the following proposition:

**Proposition 2.** *The new capital $Q_2$ is more exposed to large values of $P$ and therefore is more risky than the old capital $Q_1$. Furthermore, greater uncertainty in $P$ discourages investment, particularly in new capital.*

We provide several intuitions on the proposition below. Similarly to what was shown in Proposition 1, uncertainty discourages investment, including both types of new and replacement investment. However, a new investment has an additional value of waiting, while firms can invest in replacement capital as an outside option. At the tail of high energy prices, we can show that the variance of profits is higher for new capital, thus the new capital's return is more at risk with energy price fluctuations. This is also analogous to standard results in portfolio theory, where investors shift towards safer assets, in this case, old vintage capital, as uncertainty grows.

## 5 Quantitative model of investment under uncertainty

In this section, we present a full model that features the vintage structure.

**Timing.**

**Production.**

We can write down the value function of a representative firm in sector $s$ at time t as follows:

$$V_{s,t}(Q,e,k,P) = \max_{e_t,k_t,q_t} \Bigg\{ \sum_{j=1}^{M} \Big[ \Big( (1-\Phi(z_{s,t-j}-\sigma_s)) P_{s,t} \Xi_{s,t-j}$$
$$- (1-\Phi(z_{s,t-j}))(W_t + P_t^E e_{s,t-j} + \sum_{s'} P_{s',t} x_{ss'} k_{s,t-j} e_{s,t-j}) \Big) Q_{s,t,t-j} \Big]$$
$$- \sum_{j=0}^{M-1} c(k_{s,t-j} e_{s,t-j} q_{s,t,t-j}) + \mathbb{E}_t m_{t,t+1} V_{s,t+1}(Q',e',k',P') \Bigg\} \quad (10)$$

where

$$z_{s,t-j} = \frac{1}{\sigma_s} \left[ \log(W_t + P_t^E e_{s,t-j} + \sum_{s'} P_{s',t} x_{ss'} k_{s,t-j} e_{s,t-j}) - \log(P_{s,t} \Xi_{s,t-j}) + \frac{1}{2}\sigma_s^2 \right] \quad (11)$$

and

$$\Xi_{s,t-j} = \left( \prod_{s'} x_{ss'}^{\gamma_{s's}} \right)^{\Gamma_s} k_{s,t-j}^{\Gamma_s + \lambda_s \alpha_s (1-\Gamma_s)} e_{s,t-j}^{\Gamma_s + \alpha_s (1-\Gamma_s)} \quad (12)$$

The first order conditions are:

$$-c'(k_{s,t} e_{s,t} q_{s,t,t}) k_{s,t} q_{s,t,t} + \mathbb{E}_t m_{t,t+1} \frac{\partial V_{s,t+1}}{\partial e_{s,t}} = 0 \quad (13a)$$

$$-c'(k_{s,t} e_{s,t} q_{s,t,t}) e_{s,t} q_{s,t,t} + \mathbb{E}_t m_{t,t+1} \frac{\partial V_{s,t+1}}{\partial k_{s,t}} = 0 \quad (13b)$$

$$-c'(k_{s,t-j} e_{s,t-j} q_{s,t,t-j}) k_{s,t-j} e_{s,t-j} + \mathbb{E}_t m_{t,t+1} \frac{\partial V_{s,t+1}}{\partial Q_{s,t+1,t-j}} = 0 \quad \forall j = 0, ..., M-1 \quad (13c)$$

The first partial of the value function is given by, for all $s$, $t$ and $j$:

$$
\begin{aligned}
\frac{\partial V_{s,t+1}}{\partial e_{s,t-j}} = \Bigg[ & (1-\Phi(z_{s,t-j}-\sigma_s))P_{s,t}\frac{\partial \Xi_{s,t-j}}{\partial e_{s,t-j}} - \phi(z_{s,t-j}-\sigma_s)\frac{\partial z_{s,t-j}}{\partial e_{s,t-j}} P_{s,t}\Xi_{s,t-j} \\
& - \phi(z_{s,t-j})\frac{\partial z_{s,t-j}}{\partial e_{s,t-j}}(W_t + P_t^E e_{s,t-j} + \sum_{s'} P_{s',t} x_{ss'} k_{s,t-j} e_{s,t-j}) \\
& -(1-\Phi(z_{s,t-j})(P_t^E + \sum_{s'} P_{s',t} x_{ss'} k_{s,t-j})\Bigg] Q_{s,t,t-j} + \mathbb{E}_t m_{t,t+1}\frac{\partial V_{s,t+1}}{\partial e_{s,t-j}} \qquad \text{(14a)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial V_{s,t+1}}{\partial k_{s,t-j}} = \Bigg[ & (1-\Phi(z_{s,t-j}-\sigma_s))P_{s,t}\frac{\partial \Xi_{s,t-j}}{\partial k_{s,t-j}} - \phi(z_{s,t-j}-\sigma_s)\frac{\partial z_{s,t-j}}{\partial k_{k,t-j}} P_{s,t}\Xi_{s,t-j} \\
& - \phi(z_{s,t-j})\frac{\partial z_{s,t-j}}{\partial k_{s,t-j}}(W_t + P_t^E e_{s,t-j} + \sum_{s'} P_{s',t} x_{ss'} k_{s,t-j} e_{s,t-j}) \\
& -(1-\Phi(z_{s,t-j})(\sum_{s'} P_{s',t} x_{ss'} e_{s,t-j})\Bigg] Q_{s,t,t-j} + \mathbb{E}_t m_{t,t+1}\frac{\partial V_{s,t+1}}{\partial k_{s,t-j}} \qquad \text{(14b)}
\end{aligned}
$$

(14c)

**Consumers.**

**Equilibrium conditions.**

### 5.1 Calibration and simulation

We calibrate the model using U.S. macroeconomic data, including equilibrium capital-energy ratios, carbon emissions from energy use, and variations in wholesale and retail energy prices. We simulate the economy's response to a one standard deviation increase in energy price uncertainty. Preliminary results suggest that

## 6 Conclusions

Climate policy uncertainty is a significant concern for investors, especially in the context of industrial decarbonization and sustainable development. The urgency and complexity of climate change demand robust and predictable policy frameworks to guide investment in green technologies and practices. However, the fluctuating nature of climate policies creates a layer of uncertainty that can hinder these critical investments. In this study, we empirically investigate the specific impact of climate policy uncertainty on investment decisions among firms, using relevant indices to measure this uncertainty. We focus on how such shocks disproportionately affect energy-intensive firms directly and other firms indirectly via supply chain linkages.

Our result that more energy intensive firms delay potentially more energy effiicent new investment in face of climate policy uncertainty have important policy implications. As global warming becomes a critical issue, many countries have implemented new climate change regulations (e.g., China) or strengthened existing policies (e.g., EU). However, backlash against such measures, such as Canada's federal carbon tax, has created uncertainty about their future. Economic literature highlights that policy uncertainty can significantly affect firms' returns and investments, with broader impacts on national and global welfare. Our results and theoretical model illustrate how uncertainty shocks from climate policies influence firm-level returns, investment decisions, and their transmission through supply chains.

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