Technological Change and Innovation Diffusion Under Ambiguity and Climate Policy Risk

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Abstract

Climate finance studies overlook the effects that climate policy risk and ambiguity have on the required investments in new technology to transition to a green economy. We analyze the effects that climate policy risk and ambiguity have on firm-level private economic value of technological change and its diffusion through the stock market over the period 1994 to 2019. We find that climate policy risk has a positive impact on market valuations of patents for all firms and for green firms. However, climate policy risk does not appear to influence the market valuation of patents of brown firms. Confidence shocks about business conditions (one dimension of ambiguity), have a negative impact on market valuations of patents for all firms, including green and brown firms. Moreover, a highly connected productivity network with lower correlation uncertainty (another dimension of ambiguity) increases firms' investments in new technology, in particular by green firms. The results have important implications for a successful transition to a green economy, because ambiguity (unlike risk) has first-order welfare effects with the potential to generate inertia and inaction in the adoption of new green technologies.

Keywords: technological change, innovation diffusion, real options, ambiguity, climate policy risk

JEL Classification Codes: D81, G30, O31, O32, O33

1. Introduction

Following the Paris Agreement accord of 2015, an increasing number of nations across the world have been pursuing *concerted* actions to achieve net-zero emission targets by the year 2050. By 2023 as shown in Figure 1, six nations have self-declared to have reached the target, 27 are enforcing it by law, and 52 have included the target in a policy document. Only 47 out of 198 nations have no net-zero target. Yet, across regions, cities, and large corporations the situation is dire: three out of four have no net-zero targets planned. In the eight years since the Paris Agreement, a clear path to global climate goals has yet to materialize. Our research contemplates the paralysis that ambiguity can foster and the value implications.

The pioneering work of Nordhaus (1977, 1991, 1992) on climate change and the real economy, paved the way for what is now an influential literature on climate economics and finance. This literature studies the impact that carbon dioxide (CO2) and other greenhouse gas (GHG) emissions have on economic growth. An important aspect relates to the incentives and policies required to transition to a *green* (low carbon-emission) economy and achieve the net-zero target.[1]

[1] For critical reviews of this literature see Stern (2008, 2016); Balint, Lamperti, Mandel, Napoletano, Roventini and Sapio (2017); and Giglio, Kelly, and Stroebel (2021). Climate finance overlaps with the literature in finance on sustainable, environmental and social governance (ESG). For recent reviews of this literature see Friede, Busch, and Bassen (2015); and Atz, Van Holt, Liu, and Bruno (2023).

We investigate the impact of uncertainty on corporate investment associated with climate and transition risk. More specifically, we focus on technological change and innovation diffusion as key drivers of economic growth that underlie the structural change required to transition to a *green* economy. This transition involves governance challenges of an unprecedented scale due to its long-term horizon, global nature, and numerous uncertainties. Stern (2008) and Barnett, Brock, and Hansen (2020) argue the transition process is affected by uncertainty in the broadest sense, which includes both uncertainty regarding the outcome of events with known probabilities (risk) and uncertainty regarding the outcome of events with unknown probabilities (ambiguity). Yet to date, little attention has been given to the effects that uncertainty in the broadest sense may have on corporate investment strategies driving the shift from the old technological paradigm to the new *green* one.[2]

We attempt to close the existing gap in the climate finance literature by assessing the effects that climate policy risk and ambiguity may have on firm-level technological change and innovation diffusion. Specifically, we examine the market valuation of patents

[2] Knight (1921), Keynes (1921), and Shackle (1949), set the foundations for the influential literature in economics and finance on Knightian uncertainty or ambiguity, also referred as a preference for robustness. The relevance of ambiguity in decision making has been exposed by Ellsberg (1961) and related experiments (for a survey see Camerer and Weber, 1992), who demonstrate that when facing ambiguity, robust choices cannot be rationalized by any probability belief consistent with the Bayes-Savage paradigm. Ambiguity introduces a distinct behavioral response from risk. For a recent and extensive review of the literature with applications in macroeconomics and finance, see Ilut and Schneider (2022).

to measure the impact that climate policy risk and ambiguity have on the private economic value of technological change and its diffusion through the stock market across industries and across time in a sample of U.S. firms over the period 1994 to 2019.[3] Following the literature (Kogan, Papanikolau, Seru, and Stoffman, 2017), we view the stock market valuations of patents as a measure of firms' growth opportunities associated with technological change (see also Hirschey and Richardson, 2004; Hall, Thoma, and Torrisi, 2007; Glaeser, Michels, and Verrecchia, 2020; and Martens, 2021). Thus, we use the Kogan, Papanikolau, Seru, and Stoffman (2017) dataset of patents granted by the U.S. Patent and Trademark Office (USPTO).

Patents have been commonly modeled as *managerial real options*[4] in the classic literature on irreversible investment under risk. More recently, the theoretical literature on irreversible investment under ambiguity pioneered by Nishimura and Ozaki (2004, 2007), has shown that ambiguity has a distinct effect from risk on the value of a patent. Whereas an increase in risk increases the value of a patent as a real option, ambiguity reduces the value of a patent. Both risk and ambiguity increase the value of the option to wait, making waiting more likely, except during periods of extremely high ambiguity,

[3] We use 1994 as starting year of our dataset, because this is the first year that climate change started to appear in U.S. shareholder proposals at annual stockholder meetings.

[4] See the seminal work of Arrow (1968), Myers (1977), Brennan and Schwartz (1985), McDonald and Siegel (1986), Dixit and Pindyck (1994), and Trigeorgis (1997). For recent work on real options under risk, see Sarkar (2003), Lund (2003) Bloom, Bond and Van Reenen (2007), and Tsekrekos (2010).

where managers have no knowledge about the true distribution of future cash flows. In this case, ambiguity may erode completely the value of the option to wait (Miao and Wang, 2011).

Conceptually, we derive economic agents' valuations of technological change from a new Keynesian dynamic stochastic general equilibrium (DSGE) model under ambiguity, where managers' optimal behavior builds from the dynamic corporate finance literature on irreversible investment under ambiguity. Since Gilboa and Schmeidler (1989), it is common to incorporate ambiguity into economic agents' beliefs assuming multiple-priors preferences, which as shown by Epstein and Schneider (2003 pp. 16-17) are dynamically consistent. Robust economic agents hold some reference prior about the data-generating process (DGP) driving business conditions, but because of their lack of confidence, they also hold a statistically close set of multiple-priors around the reference prior.

Based on the theoretical literature, we conjecture that the market value of technological change should increase with climate policy risk and should decrease with an increase in the level of ambiguity in the economy. Furthermore, firms' innovations should increase with a more connected innovation network i.e., a more *resilient* network with lower correlation uncertainty. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), show that the transmission mechanism of technological change affecting current and future business conditions is conditional on the asymmetry and degree of connectedness of the productivity network of the economy. Lee and Viale (2023), show for the case of East Asia that a highly connected productivity network may signal a low level of correlation uncertainty. We test empirically these conjectures using a large longitudinal panel of firms in the U.S.

Our research resembles Coiculescu, Izhakian, and Ravid (2022), who also model patents or innovation investments as real options and look into the effects of risk and ambiguity on innovation. However, they focus on research and development (R&D) expenditures, while we examine the private economic value of patents. Furthermore, their interest lies in the Tech sector, while we consider all industries and separately investigate green and brown firms. Cohen, Gurun, and Nguyen (2022) investigate firms that produce green patents in the U.S. They reveal a *disconnect* between these firms and ESG-related investments. We have a different goal and we also differ conceptually and methodologically from these other related studies.

Empirically, we follow the dynamic corporate finance literature and implement a comprehensive panel data analysis. However, consistent with the ambiguity paradigm we complement standard econometric analyses with more robust and efficient statistical methods.[5] In particular, in the first step of the longitudinal analysis, alongside static fixed

[5] The foundational work on robust statistics can be traced back to Tukey (1960, 1962), Huber (1981), Rousseeuw and Yohai (1984), Hampel, Ronchetti, Rousseeuw, and Stahel (1986), Yohai (1987), and Staudte and Sheather (1990). For a comprehensive recent coverage of robust statistics methods see Maronna, Martin, Salibían-Barrera, and Yohai (2019).

effects panel data (PD) regressions, we run robust Prais-Winsten PD regressions with panel-corrected standard errors and robust PD regressions using the generalized LSM-estimator of Gervini and Yohai (2002). Subsequently, we run dynamic PD regressions using the continuous updating (CUE-GMM) feasible and efficient estimator of Hansen, Heaton, and Yaron (1996).[6] In the final analysis, we inspect the transmission mechanism of ambiguity and climate policy risk on investors' valuations by running a panel-VAR analysis complemented with a local projection impulse-response analysis.[7]

We find that climate policy risk has a significant positive impact on the market valuation of patents granted in the U.S. for the period 1994-2019, for all firms and for green firms. However, climate policy risk does not appear to influence the market valuation of patents of brown firms. Market volatility also has a significant positive impact on investors' valuations of firms' innovations, including brown firms.

We also find that confidence shocks on current and future business conditions (one dimension of ambiguity) have a significant negative impact on the market valuations of

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[6] The estimation of the system-GMM is implemented using Kripfganz (2019) **xtdpdgmm** package in STATA, which accounts for unobserved firm-specific heterogeneity and allows the inclusion of nonlinear moment conditions if required as suggested by Ahn and Schmidt (1995).

[7] We use the STATA command **locproj** developed by Ugarte-Ruiz (2023). The main advantages of this method are: 1) Impulse response functions (IRFs) can be computed without the estimation of a VAR, 2) IRFs can be estimated using simple regression analysis; 3) it is more robust to model misspecification; and 4) it can accommodate nonlinear flexible specifications. For a discussion of nonlinear impulse response functions see Potter (2000), Jordá (2005), Gonçalves, Herrera, Kilian and Pesavento (2021), and Gouriéroux and Lee (2023). For a recent survey see Jordá (2023).

patents. Also, a lower correlation uncertainty (another dimension of ambiguity) has a significant positive effect on green firms' investments in new technologies.

Further results from dynamic analyses reveal a complex transmission mechanism between risk, ambiguity, and investors' market valuations. Confidence shocks, contribute up to 38.92% of the variation of investors' patent valuations at the end of five years, and have a significant indirect effect by contributing up to 77.31% of the variation in correlation uncertainty, and up to 16.73% of the variation in climate policy risk after five years. For green firms, climate policy risk exerts an indirect effect on investors' patent valuations by contributing up to 35.80% of the variation in confidence shocks after five years. These shocks have a decaying value with a half life of 2 ½ years.

Furthermore, we find a positive association between patents' scientific value, investors' market valuations, and the number of patents granted, a result that is consistent with Kogan, Papanikolau, Seru, and Stoffman (2017). We also find an economically and statistically significant reaction of market valuations to the American Investors Protection Act (AIPA) of 2000. Also consistent with the literature, we do not find a strong and robust contemporaneous link between risk, ambiguity, and research and development (R&D) expenditures.

Finally, we do not find a significant market reaction to the result of the U.S. election of 2017 that signaled the official retirement of the U.S. from the Paris Accord. Ilhan, Sautner and Vilkov (2021) argue that President's Trump election was interpreted as a no-news event by investors because it did not change the climate policy status-quo of the U.S.

The rest of the article proceeds as follows. In section 2, we review the related literature. In section 3, we summarize the model that serves as a conceptual framework for the empirical analyses. In section 4, we describe the dataset. The empirical analyses with a discussion of results and their economic interpretation are included in section 5. We conclude in section 6.

2. Related Literature

Real options, such as the option to delay investment, switch technology, or expand (grow) the business, are common in corporate finance. Real option theory plays a significant role in dynamic corporate finance models of irreversible investment.[8] Real options like financial options, increase in value when the volatility of the underlying asset (risk) is higher. Additionally, since the pioneering work of Nishimura and Ozaki (2004, 2007), there is now a rich class of real option models under ambiguity that shows the distinct response of ambiguity from risk. Nishimura and Ozaki (2002), and Roubad et al. (2010), assume Choquet-based preferences following Schmeidler (1989). Nishimura and Ozaki

[8] For a survey, see Strebulaev and Whited (2012).

(2007), Riedel (2009), Thijssen (2011), Miao and Wang (2011), and Ferrari et al. (2022) adopt the multiple-priors preferences setting of Gilboa and Schmeidler (1989). Finally, Schröder (2011) builds his model from the α-MEU model of Marinacci (2002).[9]

Our article is also related to the endogenous growth literature that studies the link between technological change and economic growth at the firm level. More specifically, our article is related to the ambiguity literature on the real business cycle (RBC) and the medium-term cycle (between 8 and 50 years) (see Ilut and Schneider, 2022). According to this literature, negative confidence shocks about current and future business conditions may have a significant negative effect, distinct from risk, on technological change and consequently on economic growth and stock prices. Kogan et al. (2017) find that investors' valuations of technological innovation account for significant medium-term fluctuations in TFP and economic growth. Similar results can be found in Bloom and Van Reenen (2000), using the IFS-Leverhulme database that covers more than 200 major British firms. They find that patents have an economically and statistically

[9] The multiple-priors static model was introduced by Gilboa and Schmeidler (1989) and extended to a dynamic setting by Epstein and Wang (1994) and Epstein and Schneider (2003). One drawback of the multiple-priors approach is that it does not allow separation between ambiguity and ambiguity attitude. Alternative models that allow separation are the smooth ambiguity model of Klibanoff et al. (2005, 2009) and the α-MEU model of Marinacci (2002). As pointed out by Schröder (2020) and Beissner et al. (2020), α-maxmin preferences can be dynamically inconsistent. Furthermore, the α-MEU model can become intractable in discrete time (Beissner et al., 2020). Smooth ambiguity preferences imply smooth (not kinked) indifference curves, which as discussed by Lang (2017) cannot explain inertia and inaction in the markets (Illeditsch, 2011; 2021). Also, most of the applied work using this model has been solved numerically.

significant impact on firm-level productivity and market value. Their analysis, which is based on risk only and ignores ambiguity, focuses on patent citations, which is a proxy for scientific value rather than economic value. Bloom (2007) argues that firms are much less responsive to technological change during periods of high uncertainty (in the narrow sense of risk) as shown by firms' R&D expenditures.

Furthermore, Epstein and Halevy (2019) have recently pointed out another dimension of ambiguity: *correlation uncertainty*, also referred to as heterogeneity uncertainty or unmeasured heterogeneity, which is distinct from classic ambiguity about first and second moments of the DGP driving business conditions. Correlation uncertainty may arise from unobserved contemporaneous and dynamic complementarities across production functions (Bryant, 1983; Baxter and King, 1991; Durlauf, 1991; and Cooper and Johri, 1997). Lee and Viale (2023), using the Penn World dataset covering more than 12 East Asian economies from 1954 to 2019, show that although negative confidence shocks about future business conditions have a significant impact on technological change proxied by TFP, correlation uncertainty is low in the region.

Finally, we contribute to the literature that studies the transmission mechanism of climate-induced economic policies. Asano (2010), analyzes the effects that ambiguity may have on optimal environmental policies that seek to combat climate change. Millner et al. (2013) introduce scientific ambiguity into a dynamic integrated model of climate and the economy (DICE) model of the climate-economic system. Cai and Lontzek (2019), develop a dynamic stochastic model of the transmission mechanism of climate within the climate-economic system. Barnett et al. (2020), provide a comprehensive theoretical framework to assess the transmission mechanism under ambiguity of climate change-induced policies e.g., a carbon tax. We contribute, accordingly, by extending our understanding of climate ramifications and first order welfare effects due to the paralysis and indecision induced by ambiguity.

3. The Model

In this section, we discuss the new Keynesian DSGE model of the economy that builds from the DSGE model under ambiguity of Ilut and Schneider (2014). New Keynesian DSGE models are standard in modern macroeconomics (see Smets and Wouters, 2007). The object of interest in our conceptual analysis is the individual firm.

3.1. Technological Change and Production

We start with the standard assumption of a *Lucas-type* production economy (Lucas, 1988) indexed discretely by time $t \in [0, T]$ and a (finite) state-space Ω that represents the set of all $\{\omega\}_{\theta=1}^{\Theta}$ plausible events in the economy with probability $\mathbb{P}\colon \mathcal{F} \longrightarrow [0{,}1] \equiv \sum_{\omega_t \in \Theta} p_{t,\omega}$. A compact metric space with Borel σ-algebra $\mathcal{B}(\Omega)$ completed by $\mathbb{P}$-null sets and information structure $\{\mathcal{F}_t\}_{t=0}^{T}$ defined by the history of realizations that defines the state-space of the economy $\omega_t \in \Omega$, where $\mathcal{F}_0 = \{\emptyset, \Omega\}$ and $\mathcal{F}_T = 2^{\Omega}$. Let $u = \theta + 1$ be the up state, and $d = \theta - 1$ the down state. One way to visualize this technical setup is as an event tree with time-state nodes (t, ω) and up and down branches.

Final aggregate output is assumed to be produced by a continuum (with measure one) of competitive one-shot type of firms. Technology is represented by a stock of $j \in (0, \cdots, J)$ patents, investment projects, or production units that supply intermediate goods (*the fruit*) to the economy operated by $n \in [0, N]$ price-setting monopolistically competitive firms (*the trees*), owned by infinitely-lived investors. Aggregate output Y_t (the numeraire) equals:

$$Y_t = \left[\int_0^1 Y_{n,t}^{\frac{\lambda-1}{\lambda}} \mathrm{d}n\right]^{\frac{\lambda}{\lambda-1}}, \tag{1}$$

where $Y_{n,t} = \sum_j Y_{j,n,t}$ is the intermediate output from firm n; and λ determines the elasticity of substitution across goods. Intermediate output from the jth production unit in firm n is generated via homogeneous production functions of the form:

$$Y_{j,n,t} = Max\{Z_{j,n,t} K_{j,n,t}^{\alpha} (\gamma^t L_{j,n,t})^{1-\alpha} - \Phi\gamma^t, 0\}, \tag{2}$$

where $K_{j,n,t}$ denotes the stock of physical capital used in production unit j; $\alpha \in (0{,}1)$ is the share of capital; $L_{j,n,t}$ denotes the use of specialized labor services supplied by competitive employment agencies that demand specialized labor from households who experience disutility from working; the time trend γ^t denotes the growth rate of human capital that augments technical progress (Uzawa, 1965; Lucas, 2015); Φ represents fixed operating costs[10] to run the production unit, measured in numeraire; and $Z_{n,t}$ represents technological change or total factor productivity (TFP), with DGP possibly driven by endogenous and exogenous shocks, including economic agents' confidence shocks about current and future business conditions (one dimension of ambiguity), and the degree of connectedness of the network of n firms (another dimension of ambiguity).

3.2. Productivity Shocks, Free Cash Flow in Operations and Managers' Ambiguity

Let $p_{t,\omega} \in (\Omega, \mathcal{F}_{t+1}, \mathbb{P})$ denote the (t, ω)-one-step-ahead conditional probability i.e., the prior about the next step of the economy in the tree at $t+1$, which depends only on information available up to time t.[11] Managers' beliefs are assumed to conform to some model about the true (hidden) evolution of the state process $\{\omega_t\}$, some time-homogeneous Markov chain $X_t(\omega_t = \theta)$ adapted to $\mathcal{F}_t$. Technological change in each production unit j follows the law of motion:

$$ln\, Z_{j,n,t} = \mu_{j,n,z}(X_t) + \sigma_{j,n}^2 u_{j,n,t-1}, \tag{3}$$

[10] Overhead costs unrelated to the scale of the production unit and independent from technological shocks. For example, legal and labor costs that arise from the restructuration and/or reorganization of the business because of a merger or spinoff, a new regulation, and/or lawsuits (Bianchi et al., 2017).

[11] To achieve dynamic consistency it is critical to consider one-step-ahead conditional probabilities (Epstein and Schneider, 2013).

where $\mu_{j,n,z}$ is long-run productivity growth of production unit j in firm n, which depends on the latent state of the economy $X_t(\omega_\theta)$; $\sigma_{j,n}$ denotes the constant diffusion parameter; and $u_{j,n,t-1}$ is an *i.i.d.* normal zero-mean shock.

Under ambiguity, managers' beliefs instead of being represented by a single probability measure $p_{t,\omega}$, are represented by a set $P_{t,\omega} \subset (\Omega, \mathcal{F}_{t+1}, \mathbb{P})$ of multiple probability measures. Intuitively, managers' lack of confidence about the latent state of the economy makes them entertain several models about the DGP driving technological change. Formally, they hold some common reference prior $\hat{p}_{t,\omega} \in P_{t,\omega}$ about next period's state of the economy, but because of their lack of confidence, they entertain other plausible *close distorted* priors $p_{t,\omega} \in P_{t,\omega}$. We restrict the set $P_{t,\omega}$ to conform to the space of *structured* or statistically close parameterized models around the reference model. Moreover, to obtain well-behaved learning dynamics, we adopt the solution in Heyen (2014) and do not exclude the reference prior from the multiple-priors set at all times t. These technical conditions guarantee that the expected log-likelihood ratio between reference and distorted priors converges to the unconditional value of one-period relative entropy or Kullback-Leibler (KL) discrepancy $D(p\|\hat{p}) = -E\left[ln\left(\frac{p}{\hat{p}}\right)\right]$ satisfying the bound:

$$D_t(p_{t,\omega}\|\hat{p}_{t,\omega}) \leq \eta_t, \tag{4}$$

where $D_t(p_{t,\omega}\|\hat{p}_{t,\omega})$ is a pseudo-metric as it is not symmetric and does not satisfy the triangular inequality; and η_t is a parameter related to the level of confidence that the manager has on the reference model. We note that the use of relative entropy follows from information theory where managers' decision problem is viewed as a strategic game against *Nature*, which always picks the worst-case scenario from the set of all plausible states of the world, with probability $p^*_{t,\omega} \in P_{t,\omega}$.[12]

For each production unit j in firm n, average productivity growth $\mu_{j,n,z}$ is perceived as ambiguous lying in the interval $\left[\underline{\mu}_{j,n,z}, \overline{\mu}_{j,n,z}\right] = [\hat{\mu}_n - z_{j,n,t}, \hat{\mu}_n + z_{j,n,t}]$, where $\hat{\mu}_n$ can be interpreted as the benchmark productivity growth rate under some reference prior $\hat{p}_{t,\omega}$, and $z_{j,n,t}$ is the loss or gain in productivity as a consequence of managers' lack of confidence. If managers are confident about their reference models, then $z_{j,n,t} = 0$ and the interval collapses to the singleton $\hat{\mu}_n$, with $\eta_t = 0$ and (4) collapsing to an equality. Otherwise, $z_{n,t} > 0$, $\eta_t > 0$ and the size of the interval denotes the level of ambiguity in the production process of unit j as well as managers' lack of confidence or ambiguity about the economy.

Let's consider the *N*-dimensional covariance-stationary DGP driving the joint dynamics of the productivity network of the n firms. A variance decomposition network analysis of contemporaneous and dynamic complementarities (productivity spillovers) will reveal the degree of connectedness of the network, which proxies for correlation uncertainty i.e., another dimension of ambiguity, which is especially relevant in firm level

[12] The worst-case scenario is the one with lowest productivity growth and lower aggregate output.

studies of economic growth. A persistent and highly connected network, in principle, should imply a low level of correlation uncertainty. On the other hand, an intermittent and disconnected network warrants a high level of correlation uncertainty.

At each date t, a patent with obsolescence date T becomes available to firm n. Using the patent to run the production unit requires an immediate irreversible (sunk) investment $I_{j,n,t} > 0$, and capital accumulation evolves by:[13]

$$K_{j,n,t+1} = (1-\delta_n)K_{j,n,t} + [1 - \tfrac{1}{2}\kappa_n(\gamma - I_{j,n,t}/I_{j,n,t-1})^2]I_{j,n,t}, \tag{5}$$

where δ_n is the rate of capital depreciation; $\kappa_n > 0$ is the internal rate of return; and the rest of the variables are defined as before. Let $\boldsymbol{q}$ denote a vector of prices. The demand function for the nth firm is equal to $q_{n,t}^{Y_n} = \left[\frac{Y_{n,t}(X_t)}{Y_t(X_t)}\right]^{-\frac{1}{\lambda}}$, where the price of the final output (the numeraire) is set to $q_t^Y = 1$. Total revenues for the nth firm is equal to $q_{n,t}^{Y_n} Y_{n,t}(X_t) = Y_t^{\frac{1}{\lambda}} Y_{n,t}^{1-\frac{1}{\lambda}}$. Then, the production unit j stream of cash flows from operations (FCFO) is:

$$\Pi_{j,n,t}(X_t) = q_{n,t}^{Y_n} Y_{j,n,t}(X_t) - I_{j,n,t} - \tau_{n,k}\left[q_{n,t}^{Y_n} Y_{j,n,t}(X_t) - \delta q_{t-1}^{k} K_{j,n,t-1} - I_{j,n,t}\right], \tag{6}$$

where $\tau_{n,k}$ is the corporate tax rate of firm n; and the rest of the variables are defined as before. Under ambiguity, managers are not confident about TFP, output/revenues, and the FCFO $[\Pi_{j,n,s}(X_t)]_{s \geq t}$. We now discuss managers' optimal behavior under ambiguity.

[13] Capital accumulation is subject to adjustment costs that increase with the scale of the business

3.3. Managers' Optimal Investment Behavior under Ambiguity

At each date t, the value of the patent used with obsolescence date T and free cash flow in operations $\mathit{\Pi}_{j,n,t}$ is:

$$V^{*}_{j,n,t}[\mathit{\Pi}_{j,n,s\geq t}(X_t)] = \min_{p^{*}\in P}\left\{E^{p^{*}}\left[\sum\nolimits_{s=t+1}^{T}(\mathit{\Pi}_{j,n,s}M_s)\middle|X_s\right]\right\}, \tag{7}$$

where $E^{p^{*}}$ denotes expectation under the worst-case probability measure $p^{*}_{t,\omega}$; $M_{s>t} \in (0,1)$ with $M_{s=t} = 1$ is the pricing kernel or stochastic discount factor pricing all assets in the economy, which we are going to discuss in the next subsection; and the rest of the variables are defined as before.

Let's consider a project in firm n to build production unit j to obtain patented products $Y_{j,n}$ with cost $I_{j,n}$ and future stream of cash flows $[\mathit{\Pi}_{j,n,s}(X_t)]_{s\geq t}$, such that $\mathit{\Pi}_{j,n,d} < I_{j,n} < \mathit{\Pi}_{j,n,u}$. As we show in equation (2), managers' decisions to use the patent are analogous to the decision of exercising an American financial call option with maturity T (Nishimura and Ozaki, 2007; Miao and Wang, 2011). At each date t, the manager now faces an investment opportunity with the problem of choosing the $(\mathcal{F}_t)$-stopping time $t' \in [t, T]$ that maximizes the value of the investment opportunity after the investment is made:

$$V^{*}_{j,n,t}[\mathit{\Pi}_{j,n,s\geq t}(X_s)] = \max_{t'\geq t}\left\{\min_{p^{*}\in P}\left(E^{p^{*}}\left[\left(\sum\nolimits_{s=t'+1}^{T}(\mathit{\Pi}_{j,n,s}M_s) - I_{j,n}M_{t'}\right)\middle|X_t\right]\right)\right\}. \tag{8}$$

The value of the nth firm W_n is the sum of the values of all active production units in the firm (*the assets in place*) and those waiting (*the growth options*). Following the corporate finance literature, at each date t robust corporate managers run their firms with the goal to maximize shareholders' value $W^*_{n,t}$ discounting the worst-case scenario. To this purpose they solve the following Hamilton-Jacobi-Bellman (HJB) backward dynamic functional equation (Nishimura and Ozaki, 2007; Miao and Wang, 2011):[14]

$$W^*_{n,t} = \max\left\{V^*_{n,t} - I_n, \min_{p^* \in P}\left(E^{p^*}_t[p^*_{t,u} W_{n,s}(V^u_{n,s}) + (1 - p^*_{t,u}) W_{n,s}(V^d_{n,s})]\right)\right\}, \qquad (9)$$

The economic interpretation of managers' dynamic **maxmin** optimization problem is as follows. The first term in the right-hand side is the value of all the projects that result from exercising the option to *invest now* (the sum of all active projects at time t or assets in place) and the second term *to wait* (the sum of all projects waiting or growth options). At each date t, robust managers solve first the inner constrained minimization problem in order to identify the worst-case scenario with probability measure $p^*_{t,\omega}$, and then solve the stopping time problem. This allows the manager to calculate the certainty equivalent of the continuation value function $W_{n,s}$ under the worst-case scenario probability measure $p^*_{t,\omega}$.

If we assume managers to be ambiguous about the future stream of cash flows only, that is, they are confident about the termination values of their projects, then the threshold value that makes them indifferent between investing and waiting is $V^*_{j,n} = I_{j,n}$.

[14] In general, it will be difficult to derive an analytic solution to the HJB equation. It can be simplifed if one assumes *i.i.d.* ambiguity and an infinite planning horizon (see Nikimura and Ozaki, 2007, section 3.5).

In any case, the option value to invest now and the option value of waiting, both decrease with ambiguity. The former effect dominates the latter and consequently the manager delays the investment. However, if managers have zero confidence on current and future business conditions, then ambiguity may erode away the option value from waiting and managers will choose to invest now. In this case, robust managers end up adopting a *myopic NPV* investment rule, always discounting the worst-case scenario without regret, and the value of the firm is simply the present value of all future cash flows from projects with positive *NPV*s (Miao and Wang, 2011).

Note that even if one assumes risk neutral managers, risk enters into the model as a mean-preserving spread over the reference prior $\hat{p}_{t,\omega} \in P_{t,\omega}$, affecting positively the option value to wait. The trascendental insight from standard investment theory under only risk, is that an increase in risk will allow managers to capture the upside gains and minimize the downside loss of waiting.

3.4. Robust Asset Prices and Innovation Market Diffusion

On the investor side, we follow García-Feijóo and Viale (2022) and assume robust investors with endowment comprised of $n \in [1, N]$ *trees* or assets with supply normalized to one plus government transfers equal to $\tau_l \gamma^t$. Gross returns are defined as $\frac{V_{j,n,t}}{V_{j,n,t-1}} \equiv R_{j,n,t} = \exp\left(\sum_{\tau=1}^{t} r_{j,n,\tau}\right) R_{n,0}$, with $R_{n,0}$ given, and following the law of motion

$r_{n,t} \equiv lnR_{n,t} = m_n^e(X_t) + \sigma_n v_{n,t}$, where m_n^e is the expected long-run mean return, which depends on the latent state of the economy $X_t(\omega_s)$; σ_n denotes the constant diffusion parameter or standard deviation of asset *n*; and $v_{n,t}$ is an *i.i.d.* normal zero-mean shock. There is also a risk-free asset in zero net supply that pays a constant gross return $R_f = \exp(r_f)$. Then, the gross return of the representative shareholder or investor's wealth at time t is equal to $R_t^W = R_f + \sum_{n=1}^{N} \xi_{n,t-1} R_{n,t}$, where $\boldsymbol{\xi}$ is a column vector of portfolio shares invested in the $n+1$ assets.

Like robust managers, under ambiguity robust investors with multiple-priors preferences are not confident about current and future business conditions and solve at each date t a **maxmin** optimization problem in the same spirit of (9) satisfying bound (4). But investors seek to maximize the long-run mean growth rate of wealth assessing period by period each candidate portfolio under the worst-case scenario.[15] Under ambiguity, the optimal portfolio allocation $\boldsymbol{\xi}^* = \boldsymbol{\Sigma}^{-1}\boldsymbol{m}^*$ is the one that maximizes the reward to risk ratio or Sharpe's ratio under the worst-case return distribution with mean return $\boldsymbol{m}^*$ and variance $\boldsymbol{\Sigma}$.

In the general dynamic case for $t = \{0,1,..,T-1\}$, the size of the multiple-priors set changes over time with the arrival of new information, and robust investors optimize

[15] The worst-case scenario for a long position in the asset is the distribution with lowest mean return. On the other hand, the worst-case scenario for a short position in the asset is the distribution that has the highest mean return.

solving the following recursive Hamilton-Jacobi-Bellman (HJB) functional equation (see e.g., Viale et al., 2014):

$$J_{W,t} = \max_{C_{t,\{\boldsymbol{\xi}_t\}}} \left\{ U(C_t) + \min_{p^* \in P} E_t^{p^*} \left[p_{t,u}^* J_{W_{t+1}^u, t+1} + (1 - p_{t,u}^*) J_{W_{t+1}^d, t+1} \right] \right\}, \qquad (10)$$

$$s.\ t.\ C_t + \boldsymbol{q_t^{\xi'}} \boldsymbol{\xi_t^*} = (1-\alpha)Y_t + R_{t-1}^W - \tau_i[(1-\alpha)Y_t + R_{t-1}^W] - \tau_c C_t, \qquad (11)$$

where without loss of generality J_W denotes marginal indirect utility of wealth; $U(C_t)$ is utility on consumption C_t, which is assumed to be increasing and concave; (11) is the budget constraint; $\boldsymbol{q_t^{\xi'}}$ is the transposed vector of asset prices; τ_i and τ_c represent the tax bill on labor income and consumption, respectively; and the rest of the variables are defined as before.

Under some technical conditions (see Epstein and Wang 1994, Lemma 1, Theorems 2, 3, and 4), the optimal **maxmin** solution of the HJB equation (10) leads to the fundamental asset pricing equation:

$$E_t^{p^*}[R_{t+1} M_{t,t+1}^* | X_t] = 1, \qquad (12)$$

Where **1** denotes a vector of ones; R_{t+1} is a vector of test assets gross returns that includes the set of primitive assets (including the safe asset) plus the set of all plausible $\mathcal{F}_t$-adapted portfolio strategies;[16] $M_{t,t+1}^* \equiv \frac{J_W(W_{t+1},t+1)}{J_W(W_t,t)}$ is the robust admissible stochastic

[16] Test asset returns are assumed to belong to the linear space $L^2(\Omega, \mathcal{F}_{t+1}, \mathbb{P})$ of random variables with finite second moments adapted to the information set $\mathcal{F}_t$.

discount factor (SDF) or *pricing kernel* that prices all assets in the economy under the worst-case scenario probability measure $p^*_{t,\omega}. \in P$.[17]

3.5. The Government and Climate Policy Risk

We close the section with the following warning. We do not seek to model formally the goverment. Like Bianchi et al. (2017), we just assume that the government is an agency that collects taxes and transfers lump sums to balance its budget. However, because of our research goal, we acknowledge the potential role of the government to induce the structural economic change required to transition to a green economy by introducing necessary incentives to managers and investors alike, probably changing the tax bill and transfers across different economic sectors, as shown in equations (6) and (11). As we explain next, we use a climate policy risk index based on textual analysis on news as proxy of shifts in climate policies. In any case, the government should always satisfy the usual market clearing condition in the goods markets: $C_t + I_t + \left[\tau_k \left(q_t^Y \; Y_t - \delta q_{t-1}^k K_{t-1} - I_t\right) + \tau_i[(1-\alpha)Y_t + R_{t-1}^W] + \tau_c C_t - \tau_l \gamma^t\right] = Y_t$.

[17] Some random variable satisfying $M^*_{t,t+1} \in L^2(\Omega, \mathcal{F}_{t+1}, \mathbb{P})$ given the absence of arbitrage opportunities at all dates t. Moreover (12) guarantees that assets are priced in the economy to clear the capital markets.

4. Data

4.1. Firm Level Data

The sample includes annual data from the fiscal years 1994 through 2019. The firm level data used in the empirical analysis is drawn from the patent dataset constructed by Kogan et al. (2017)[18] and the CRSP/COMPUSTAT merged database. The KPSS patent database includes 1,801,879 patents granted in the U.S. by the U.S. Patent and Trademark Office (USPTO), collected from the entire history of U.S. patent documents in Google Patents (7.8 million patents) and complemented with the hand-collected reference data of Nicholas (2008). The final dataset was obtained by matching it with the NBER and CRSP databases to eliminate duplications. For a detailed explanation of the construction process of the patent dataset, please see Kogan et al. (2017). From this dataset, we use the patents private economic value; the number of patents granted; and number of citations. In Figure 2 we plot the log change of patent valuations, number of patents granted and their citations.

Firm level data from the CRSP/COMPUSTAT merged database includes annual total revenues in USD billions; leverage, calculated as the ratio of the sum of long-term debt and debt in current liabilities to the total value of stockholders equity; end of year

[18] https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

market capitalization in USD billions; Tobin's Q, calculated as the ratio of total assets plus the book value of equity minus common ordinary equity to total assets; and Total R&D expenditures, normalized by the amount of total assets both in USD billions.

For comparative purposes, we group firms into two groups: 1) *Green* firms with patents related to climate change mitigation technologies in any kind of industrial processing or production activity (USPTO subclass CPC Y02, excluding brown firms), and 2) *brown* firms from the energy, utility, petrol production and extraction industries.

4.2. Ambiguity and Risk Factors

In the financial economics literature, ambiguity has been measured using different proxies, such as disagreement in survey forecasts; implicit market volatility (VIX); the variance risk premium (VRP); macroeconomic and financial uncertainty indexes; and the Kullback-Leibler divergence measure between transition probabilities.

Jurado et al. (2015) point out that disagreement in survey forecasts is likely to be a weak proxy for ambiguity, because forecasts will be affected by heterogeneity in characteristics and not necessarily by confidence shocks. Similarly, VIX is a volatility index rather than an ambiguity index. Aït-Sahalia et al. (2021) and García-Feijóo and Viale (2023) show that there is a time-varying disconnection between VIX and ambiguity in the stock market. On the other hand, VRP is driven by shifts in stochastic risk aversion and hence may not be a clean proxy for investors' ambiguity aversion (Bekaert et al., 2013, 2020). We note that most of the financial and macroeconomic uncertainty indexes in the literature are based on the intuition that the source of uncertainty resides in the lack of precision of agents' forecasts.

We use the ambiguity index *KUNC* of Viale et al. (2014) as a forward looking proxy of ambiguity about current and future business conditions. Given that is based on the Kullback-Leibler divergence, unlike the other ambiguity measures, this proxy is consistent with the ambiguity literature in economics and finance and displays properties desirable in an empirical measure of ambiguity. The empirical construction of *KUNC* is based on Good (1965), who argues that robust Bayesian statisticians should use a set of priors rather than a single prior in solving complex inference problems.

Correlation uncertainty is proxied by the degree of connectedness of total factor productivity (TFP). To this purpose, we follow Diebold and Yilmaz (2014) and calculate the connectedness index between the TFP of a group of 19 leading innovating economies across East Asia, Europe, the Middle East and America.[19] Intuitively, the estimation procedure seeks to assess the share of forecast error variation in the sample of returns due to unobservable shocks. We measure the degree of connectedness using the package

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[19] The dataset is drawn from the Penn World Table (PWT) version 10.0 constructed by Feenstra et al. (2015). Our sample includes TFP series for the U.S., Denmark, Finland, Germany, Israel, the Netherlands, Sweden, Switzerland, Mainland China, Hong Kong SAR (China), India, Indonesia, Japan, Republic of Korea, Malaysia, Philippines, Singapore, Thailand, and Taiwan (Taipei, China).

in R v.0.2.1 developed by Baruník and Křehlík (2018), with a forecasting window for the VAR of 36 months and 60 months.

We plot the time series of *KUNC* and TFP connectedness in Figure 3. Ambiguity is highest during the 2001 and 2008 economic recessions. It has been low since 2009, probably because of the unprecedented accommodative monetary policy of the Federal Reserve. On the other hand, correlation uncertainty has been decreasing consistently, given that the degree of connectedness of the productivity network has been increasing, at an accelerating pace since 2014.

As our proxy of climate risk, we use the climate policy uncertainty index of Gavriilidis (2021). This index is constructed using textual analysis from news in eight major U.S. newspapers that capture important events related only to climate policy. According to the author, this index has a strong and negative effect on carbon emissions, both at the aggregate and sector level. Engle et al. (2020), also apply textual analysis to construct a climate change news index, but the news come from articles only in the Wall Street Journal (WSJ) and includes other news related to climate change like e.g. natural disasters. In robustness check analyses, we use the CBOE market implicit volatility index VIX (not seasonally adjusted) as a proxy for market risk.

In Figure 4, we plot the climate policy risk index and VIX. Market volatility has been decreasing persistently since the end of the financial crisis of 2008. On the other hand, climate policy risk has been increasing since 2006, accelerating its pace since 2017, probably as a result of news from the U.S. about leaving the Paris accord.

We provide a description of the variables and their corresponding sources in Table 1. Summary statistics of firm level variables are provided in Table 2. In Table 3, Panel A, we provide summary statistics of the proxies used for risk and ambiguity. In Panel B, we report their correlation matrix.

Note that the *typical* green firm has a patent with an average market valuation that is 2.5 times the average value across all firms, and 1.73 times higher than the value of the patent from a *typical* brown firm. Moreover, the average number of patents granted and citations are both significantly higher for green firms than the rest of the firms. From Table 2, one can characterize the typical green firm with size and leverage similar to the typical brown firm, but both larger and less leveraged than the rest of the firms in the sample.

5. Quantitative Implications

5.1. Comparative Static Longitudinal Analyses: Green versus Brown Firms

A well-known fact of multiple-priors preferences models that restrict ambiguity to conditional means only, is that they can be solved and estimated using simple first order approximations.

Our first step in the empirical analysis, is to inspect if, consistent with theory, private economic valuations of patents, *Pat_value*, are contemporaneously related to i) climate policy risk *Crisk*, ii) investors' ambiguity about current and future business conditions *Kunc*, iii) correlation uncertainty *Tfpcon*, and iv) patents' scientific values *Pat_cites*. We control for firm-level variables such as *sales*, *leverage*, *size*, and Tobin's Q *tq*, which the corporate finance literature finds to be related with innovation. We also include two time dummies for the year 2000 and 2017. The year 2000 dummy controls for the American Inventors Protection Act (AIPA) coming into effect; and the year 2017 dummy controls for the impact (if any) of the election of President Trump.

We run the following within-industry groups and pair-wise differenced fixed effects PD regression in natural logs, so that we can interpret estimated coefficients β as (market valued) *productivity elasticities*:[20]

$$ln\_pat\_value_t^n = \alpha + \beta_{crisk} ln\_crisk_t^n + \beta_{kunc} ln\_kunc_t^n + \beta_{tfpcon} ln\_tfpcon_t^n + \beta_{pat\_cites} ln\_pat\_cites_t^n + \beta_{sales} ln\_sales_t^n + \beta_{leverage} ln\_leverage_t^n + \beta_{size} ln\_size_t^n + \beta_{tq} ln\_tq_t^n + \lambda_{s=2000} + \lambda_{s=2017} + \psi_n + s_t + \varepsilon_{n,t}, \tag{13}$$

where α is a constant; the variables included in the regression are defined in Table 1; ψ_n is a firm specific dummy for unobserved fixed effects; s_t is a time specific dummy for unobserved fixed effects; and $\varepsilon_{n,t}$ is the error term.

[20] Results from the ubiquitous Hausman test, not provided to save space, lead us to reject the null hypothesis in favor of fixed effects panel data models.

In the first column of results in Table 4, we report PD fixed effects (Fe) econometric estimates across all industries with robust standard errors adjusted by industry (SIC) clusters. In Table 5, we report estimates for green firms, and in Table 6, for brown firms. The high value of residual correlations across panels (from 0.42 to 0.82) suggests the presence of cross-sectional dependence across SIC clusters. Thus, we assess the potential model misspecification running more robust PD regressions.

First, we run regression (13) using a robust Prais-Winsten estimator with panel-corrected standard errors (Prais and Winsten, 1954). Robust econometric Prais-Winsten estimates (P-W) are reported in the second column of results in Tables 4, 5 and 6. For the full sample in Table 4, estimated coefficients are significantly different from zero at the 1% level for climate policy risk (*ln crisk*), investors' ambiguity about current and future business conditions (*ln kunc*), correlation uncertainty (*ln tfpcon*), and patents' scientific value. The firm specific variables and the year 2000 dummy are also statistically significant but the year 2017 dummy is not. Moreover, all variables have the correct sign as hypothesized by theory. That is, investors' real option valuations increase with climate policy risk, a more connected productivity network, patents' scientific values, firm's sales, size, and Tobin's Q. On the other hand, investors' real option valuations decrease with ambiguity about current and future business conditions and firm leverage.

Next, we run PD regression (13) using the robust MM estimator of Gervini and Yohai (2002) with 85% efficiency and robust standard errors adjusted by industry clusters. A comparison of results reported in column (P-W) and column (MM), shows that except for correlation uncertainty and Tobin's Q, the rest of the variables are economically significant and robust to model misspecification. As shown in Table 4, investors' valuations increase by 0.3286% for a 1% shock in climate policy risk; by 0.1180% for a 1% increase in the patent's scientific value; by 0.2771% for a 1% increase in the firm sales; and by 0.2934% for a 1% increase in the firm size. On the other hand, valuations decrease by 0.1669% for a 1% increase in ambiguity about business conditions; and decrease by 0.1296% for a 1% increase in leverage.

We report results for green firms in Table 5. Robust (MM) estimates are statistically significant for *ln crisk*, *ln kunc*, *ln pat cites*, *ln tq*, and the year 2000 dummy. Economically, investors' valuations increase by 0.2532% for a 1% increase in climate policy risk; by 0.0820% for a 1% increase in patent's scientific value; by 0.7916% for a 1% increase in Tobin's Q; and they decrease by 0.1913% for a 1% increase in investors' ambiguity.

By contrast, in Table 6, for brown firms, only *ln kunc* and the year 2000 dummy are statistically significant. Climate policy risk does not seem to impact investors' valuations, but a 1% increase in investors' ambiguity decreases investors' valuations by

0.2603%, relatively more than valuations of patents from green firms in Table 5. This finding is consistent with Ilhan et al. (2021) who find that the cost of option protection against downside (left) tail risk is larger for firms with more carbon-intense business models.

5.2. Transitional Dynamics: The Impact of Temporary Shocks

We now proceed to examine the impact that temporary shocks to climate policy risk, investors' confidence on current and future business conditions (i.e., the first dimension of ambiguity), correlation uncertainty (i.e., the second dimension of ambiguity), and patents' scientific values may have on the dynamic behavior of investors' private valuations of patents. The empirical specification of the dynamic model is as follows:

$$ln\_pat\_value_t^n = \alpha + \sum_{k=1}^{K} \rho_k \, ln\_pat\_value_{(t-k)}^n + \beta_{crisk} ln\_crisk_t^n + \sum_{k=1}^{K} \beta_{crisk} \quad ln\_crisk_{(t-k)}^n + \beta_{kunc} ln\_kunc_t^n + \sum_{k=1}^{K} \beta_{kun} \quad ln\_kunc_{(t-k)}^n + \beta_{tfpcon} ln\_tfpcon_t^n + \sum_{k=1}^{K} \beta_{tfpcon,k} \, ln\_tfpcon_{(t-k)}^n + \beta_{pat\_cite} \; ln\_pat\_cites_t^n + \sum_{k=1}^{K} \beta_{pat\_cites,} \quad ln\_pat\_cites_{(t-k)}^n + \beta_{sales} ln\_sales_t^n + \beta_{leverage} ln\_leverage_t^n + \beta_{size} ln\_size_t^n + \lambda_{s=2000} + \lambda_{s=2017} + \psi_n + s_t + \varepsilon_{n,t}, \qquad \text{for } t = q+1, \cdots, T, \tag{14}$$

where variables' definitions are provided in Table 1; k is the lag order of the DGP; q=k is the maximum lag order, without any loss of generality we assume an AR(1) process; ψ_n is a firm specific dummy for unobserved fixed effects; s_t is a time specific dummy for unobserved fixed effects; and $\varepsilon_{n,t}$ is the error term. Note that we drop Tobin's Q from the control variables because of its poor results in static PD regressions. As pointed out by Woeppel (2022), the weak explanatory power of standard proxies for Q most likely is the result of substantial measurement error.

In Table 7, we report econometric estimates of the system-GMM dynamic panel data model (14) across all industries. In Table 8, we report estimates across green firms and in Table 9, across brown firms. In all cases, we use the continuous updating GMM (CUE-GMM) estimator of Hansen, Heaton, and Yaron (1996) implementing Kripfganz (2019) **xtdpdgmm** package in STATA. The implementation incorporates linear and nonlinear moment conditions as suggested by Ahn and Schmidt (1995). Robust standard errors are adjusted by industry clusters.

We summarize the main econometric results as follows. There is a dynamic impact of climate policy risk, which is positive and statistically significant at a 1% level, for all industries and for green firms, but not for brown firms. The dynamic impact of ambiguity is negative and statistically significant at a 1% level across all industries, and more significant for brown companies than for the rest of firms. With respect to correlation uncertainy, lagged shocks are statistically and economically significant at a 5% level for all industries and for green firms but not for brown firms.

5.3. The Transmission Mechanism of Climate Policy Risk, Ambiguity, and Innovation

In this section, we analyze long run (permanent) transitional dynamics, which will allow us to understand the transmission mechanism for the impact of climate policy risk and of both dimensions of ambiguity on investors' market valuations of firms' growth opportunities. At the same time, we investigate any possible dynamic interaction between climate risk, investors' ambiguity about business conditions, and correlation uncertainty.

We analyze the long run (10 years) transitional dynamics through the estimation of a first-order non-structural panel vector-autoregression (VAR) across all firms, following the econometric approach developed by Holtz-Eakin et al. (1998). In Table 10, we report econometric estimates of a panel VAR that includes $ln\_pat\_value_t^n$, $ln\_crisk_t^n$, $ln\_kunc_t^n$, $ln\_tfpcon_t^n$, and $ln\_pat\_cites_t^n$, including results from Granger's non-causality (Granger 1969) and stability tests. In Table 11 we report results from the variance decomposition analysis and plot orthogonalized impulse-response functions in Figures 5 and 8. Results for green firms are reported in Table 12 (panel VAR estimates) and Table 13 (variance decomposition analysis, up to 5 years only).

The 5 years dynamic behavior of the transmission mechanism is assessed through impulse response functions obtained from local projections obtained from previous PD regression estimates, with the addition of a dummy for the year 2008 as control for the economic recession. IRFs from local projections constitute a robustness check on possible model misspecification in the estimation of non structural VARs. Comparative results (not shown to save space) confirm that this is the case for green firms as a result of its relatively small sample. In Figures 6 and 7 we plot the IRFs for all firms and green firms, respectively.

We highlight the following results. Climate policy risk and both dimensions of ambiguity (Granger causes)[21] the market valuations of firms' growth opportunities. Furthermore, investors' confidence shocks have a persistent negative impact on innovation valuations contributing up to 38.92% of the variation of investors' valuations at the end of five years. Moreover, investors' confidence shocks also have a persistent and significant contribution of 77.31% to, and increasing, correlation uncertainty adding an indirect effect on market valuations of firms' innovations (Figure 8). Moreover, there is a short lived, indirect effect that works through climate policy risk (with a one period lag) contributing up to 16.73% of the variation in climate policy risk (decreasing it) as shown in Figures 7 and 8.

Climate policy risk and correlation uncertainty contributions are less significant, equal to 1.34% and 3.68%, respectively (Figures 8 and 9). However, for green firms there is a significant impact from (lower/higher) climate policy risk (decreasing/increasing)

[21] One well-known caveat with the Granger non-causality test, is that it does not confirm true causality given the effect of some confounding unobserved variable driving variables. For a complete discussion, see Clive Granger's revised Noble Prize lecture (Granger, 2004)

economic agents' confidence, adding up to 35.80% of the variation of investors' ambiguity after five years (Table 13). Consistent with our results, Ilhan et al. (2021) find that climate policy uncertainty has some effect on VRP, a proxy for ambiguity. We also observe that permanent shocks are decaying through time with a half life of 2 ½ years for all firms, including green firms.

5.4. Robustness Checks

We close the empirical analyses with the following robustness checks. First, we look into the effect of climate policy risk and both dimensions of ambiguity on firms' R&D expenditures. In Tables 14, 15, and 16 we provide results from static PD regressions for all firms, green firms, and brown firms, respectively. Our results are consistent with those in the existing literature. Bloom (2007) finds that R&D expenditures are relatively more persistent than sales/revenues and earnings and have a time-varying relation with risk. Moreover, R&D expenditures are considered in the literature a proxy of innovation input rather than output of innovative activities within the firm (Hall et al., 2007).

In Tables 17, 18, and 19 we provide results from running count regressions on the number of patents granted using a Poisson GEE population-averaged estimator. Except for correlation uncertainty, the results are similar to those obtained using patents' valuations. A highly connected productivity network entails lower correlation uncertainty propping up firms' investments in innovations and aggregate economic growth.

Finally in Tables 20, 21, and 22 we provide estimates of PD static regressions using VIX instead of climate risk. Like climate risk, VIX has a statistically and economically significant positive impact on investors' patent valuations as expected from the dynamic corporate finance literature on irreversible investment.

6. Concluding Remarks

Consistent with real option theory under ambiguity, we show that climate policy risk has a significant positive impact on the market valuations of firms' growth opportunities and firms' innovations, except for brown firms. Confidence shocks about current and future business conditions have a significant negative effect on valuations of firms' growth opportunities and firms' innovations for all firms, with a significantly higher impact for brown firms. A highly connected productivity network with lower correlation uncertainty also has a positive effect on firms' innovations, in particular for green firms.

The empirical study reveals a distinct market reaction for green and brown firms. We find that climate policy risk has little effect on the market valuations of patents from brown firms, but a significant impact for green firms. This is somewhat surprising, because Cohen et al. (2023) show that energy firms' patents are mostly dedicated to *green research*. However, we also find that the market valuation of patents from brown firms react significantly more to confidence shocks than those from green firms and consequently exhibit valuations well below those of green firms. In this regard, the results suggest that there is a disconnect between brown innovators and ESG-driven investments, probably as a result of current governmental policies, as argued by Cohen et al. (2023). One relevant question we explore in a separate asset pricing paper, is if this *disconnect* is priced in the cross-section of stocks returns.

Our results have important implications for a successful transition to a sustainable, environmentally, and socially responsible green economy, because ambiguity unlike risk has first-order welfare (permanent) effects with the potential to generate inertia and inaction in the adoption of new green technologies.

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Table 1. Variable Definitions

This table provides the description and source of the variables used in empirical analyses.

Dependent Variables	**Description**	**Source**
pat_value	Patents private economic value	Kogan, Papanikolaou, Seru & Stoffman (2017)
pat_count	Number of patents granted	Kogan, Papanikolaou, Seru & Stoffman (2017)
rnd_assets	R&D expenditures/total assets in billions of USD	CRSP/COMPUSTAT merged database
Explanatory Variables		
pat_cites	Number of citations on patents i.e., proxy for patents scientific value	Kogan, Papanikolaou, Seru & Stoffman (2017)
crisk	Climate policy risk index	Gavriilidis (2021)
Kunc	Investors' ambiguity or Knightian uncertainty index	Viale, García-Feijóo & Giannetti (2014)
tfpcon	*TFP* Connectedness/correlation uncertainty index	Penn World Table from Feenstra et al. (2015)
VIX	CBOE volatility index	FRED database
sales	Total revenues in Billions of USD	CRSP/COMPUSTAT merged database.
leverage	(Debt in current liabilities + Long term debt) / Total equity	CRSP/COMPUSTAT merged database
Size (ME)	Market value in billions of USD	CRSP/COMPUSTAT merged database
tq	Tobin's q (Total assets + Book value of Equity – Common equity) / Total assets	CRSP/COMPUSTAT merged database
year2000	American inventors Protection Act (AIPA) November 2000	
year2017	U.S. election results	

Table 2. Summary Statistics – Firm Specific Variables

This table provides the description and source of the variables used in empirical analyses.

Variables	**# Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total Firms					
pat_value	10497	35.50	144.04	0.00	4357.90
pat_count	10497	2.84	8.41	0.00	127
pat_cites	10497	85.42	410.96	0.00	13679
rnd_assets	10497	0.01	0.03	0.00	1.06
sales	10497	54681.23	175017.80	-1366.74	3600928
leverage	10497	2.62	145.13	-12595.61	6241.89
size	10497	61672.29	197912.70	0.00	4102966
tq	10497	2.14	37.24	0.35	3780.73
Green firms					
pat_value	933	90.31	211.28	0.00	3524.36
pat_count	933	9.36	18.17	1.00	114
pat_cites	933	252.35	642.31	0.00	5255
rnd_assets	933	0.033	0.03	0.00	0.21
sales	933	104989.50	184138.40	87.80	1625715
leverage	933	2.23	4.20	-7.99	89.18
size	933	160262.60	345177.90	49.25	4102966
tq	933	1.81	0.75	0.72	7.28
Brown firms					
pat_value	650	51.85	124.48	0.00	1243.21
pat_count	650	1.89	2.65	0.00	14
pat_cites	650	36.94	82.89	0.00	686
rnd_assets	650	0.00	0.01	0.00	0.07
sales	650	161249.60	451327.70	0.00	3600928
leverage	650	2.01	1.51	-4.40	16.30
size	650	159464.70	364407.20	3.16	2922882
tq	650	1.40	0.64	0.71	12.21

Table 3. Summary Statistics – Risk and Ambiguity Factors

This table provides summary statistics and correlation matrix between risk and ambiguity factors used in empirical analyses for the sample period 1994-2019, *t*-stats in black denote significance at 95% level.

Panel A – Summary Statistics

Variables	**# Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
crisk	26	104.26	48.62	47.86	242.88
kunc	26	0.18	0.24	0.08	0.99
tfpcon	26	0.79	0.03	0.74	0.84
VIX	26	19.43	5.91	11.09	32.70

Panel B – Correlation Matrix

	ln tfpcon	*ln kunc*	*ln crisk*
ln tfpcon		-0.07	-0.02
ln kunc			0.23
ln crisk			

t-values – 95% signifcance level (*t*-critical: 2.07)

	ln tfpcon	*ln kunc*	*ln crisk*
ln tfpcon		0.33	0.10
ln kunc			1.10
ln crisk			

Table 4. Robust Static Model - Private Economic Value of Technology (All Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for all firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 4,869 / MM = 4,832			**# SIC Groups: Fe&P-W = 367 / MM = 330**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln crisk	0.3350	0.2838	0.3286	7.88/11.45	0.00***/0.00***
	(0.0426)	(0.0360)	(0.0287)		
ln kunc	-0.1700	-0.1536	-0.1669	-11.70/-15.75	0.00***/0.00***
	(0.0134)	(0.0131)	(0.0106)		
ln tfpcon	1.6305	4.126	0.6691	7.40/1.69	0.00***/0.09*
	(0.5565)	(0.5578)	(0.3958)		
ln pat_cites	0.1410	0.1843	0.1180	16.98/8.83	0.00***/0.00***
	(0.0164)	(0.0108)	(0.0134)		
ln sales	0.2085	0.3150	0.2771	5.86/2.69	0.00***/0.01***
	(0.1692)	(0.0538)	(0.1031)		
ln leverage	-0.1063	-0.1299	-0.1296	-3.94/-3.20	0.00***/0.00***
	(0.0484)	(0.0330)	(0.0405)		
ln size	0.4120	0.3649	0.2934	7.42/3.06	0.00***/0.00***
	(0.1421)	(0.0492)	(0.0958)		
ln tq	0.1083	0.2427	0.2869	2.65/1.93	0.01***/0.06*
	(0.2180)	(0.0916)	(0.1490)		
year 2000	1.0210	0.9714	1.050	12.91/17.66	0.00***/0.00***
	(0.0727)	(0.0753)	(0.0595)		
year 2017	0.0579	0.0666	0.0960	1.03/1.82	0.30/0.07*
	(0.0838)	(0.0648)	(0.0527)		
α	-3.6286	-3.9272			0.00***/0.00***
	(0.7034)	(0.1969)			
Statistics					
R^2	0.5600	0.5471	Wald-$\chi^2(10)$ =	501.87	
$F(10,366)$	38.46		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	1.24		M-estimator =	3.44	
σ_ε	0.85		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	0.19		Scale =	0.89	
ρ =	0.68	[0,0.82]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	25.21				
p-value	(0.0050)				

Table 5. Robust Static Model - Private Economic Value of Technology (*Green* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for green firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that all coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 815 / MM = 791			**# SIC Groups: Fe&P-W = 121 / MM = 98**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln crisk	0.2451	0.1924	0.2532	1.91/3.66	$0.06^{*}/0.00^{***}$
	(0.0939)	(0.1005)	(0.0692)		
ln kunc	-0.1716	-0.1708	-0.1913	-4.63/-6.81	$0.00^{***}/0.00^{***}$
	(0.0435)	(0.0369)	(0.0281)		
ln tfpcon	0.4518	1.6076	0.2244	1.37/0.23	0.17/0.82
	(1.0034)	(1.1702)	(0.3958)		
ln pat_cites	0.1094	0.1499	0.0820	5.88/2.54	$0.00^{***}/0.01^{***}$
	(0.0327)	(0.0255)	(0.0322)		
ln sales	0.2000	0.4989	0.2230	2.55/0.89	$0.01^{***}/0.38$
	(0.2284)	(0.1957)	(0.2502)		
ln leverage	-0.1480	-0.0223	-0.1926	-0.24/-1.91	0.81/0.06
	(0.1227)	(0.0936)	(0.1007)		
ln size	0.2217	0.0763	0.1255	0.41/0.65	0.68/0.51
	(0.1813)	(0.1841)	(0.1917)		
ln tq	0.6522	1.2485	0.7916	3.74/2.68	$0.00^{***}/0.01^{***}$
	(0.3071)	(0.3339)	(0.2952)		
year 2000	1.1706	1.0407	1.1882	4.78/6.54	$0.00^{***}/0.00^{***}$
	(0.1856)	(0.2178)	(0.1817)		
year 2017	-0.1141	-0.2073	-0.0936	-1.63/-0.85	$0.10^{*}/0.40$
	(0.1072)	(0.1268)	(0.1103)		
α	-2.3981	-4.0479			$0.00^{***}/0.00^{***}$
	(1.5503)	(0.3395)			
Statistics					
R^2	0.4213	0.7105	Wald-$\chi^2(10)$ =	109.93	
F(10,120)	10.94		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	1.45		M-estimator =	3.44	
σ_ε	0.69		S-estimator =	1.55	
$\rho_{\eta_i, Xb}$ =	0.22		Scale =	0.81	
ρ =	0.82	[0,0.82]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	10.30				
p-value	(0.4147)				

Table 6. Robust Static Model - Private Economic Value of Technology (*Brown* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for brown firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002)that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that all coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 316 / MM = 314			**# SIC Groups: Fe&P-W = 21 / MM = 19**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln crisk	0.1840	0.1497	0.2689	0.86/1.81	0.40/0.09*
	(0.2718)	(0.1737)	(0.1484)		
ln kunc	-0.2815	-0.2302	-0.2603	-3.42/-4.88	0.00***/0.00***
	(0.0567)	(0.0673)	(0.0533)		
ln tfpcon	5.3556	3.1804	2.7724	1.22/1.16	0.22/0.26
	(3.1509)	(2.6150)	(3.3984)		
ln pat_cites	0.1969	0.2384	0.1150	4.28/1.72	0.00***/0.10*
	(0.0961)	(0.0557)	(0.0669)		
ln sales	-0.0993	0.3187	-0.1893	1.48/-0.90	0.14/0.38
	(0.3566)	(0.2148)	(0.2105)		
ln leverage	0.4441	-0.4681	-0.0984	-2.10/-0.34	0.04**/0.74
	(0.5763)	(0.2231)	(0.2888)		
ln size	0.6411	0.3647	0.5664	1.69/1.88	0.09*/0.08*
	(0.4841)	(0.2156)	(0.3017)		
ln tq	-0.2470	-0.3187	0.0278	-0.78/0.05	0.43/0.96
	(0.7110)	(0.3339)	(0.5668)		
year 2000	0.9702	0.9017	1.2384	2.54/5.70	0.01***/0.00***
	(0.3153)	(0.3556)	(0.2172)		
year 2017	0.0868	-0.0870	-0.0421	-0.27/-0.26	0.78/0.80
	(0.2745)	(0.3190)	(0.1602)		
α	-2.2955	-4.1401			0.00***/0.00***
	(4.2585)	(0.7204)			
Statistics					
R^2	0.6063	0.5715	Wald-$\chi^2(10)$ =	379.33	
$F(10,120)$	9.83		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	0.92		M-estimator =	3.44	
σ_ε	1.08		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	0.41		Scale =	1.00	
ρ =	0.42	[0,1]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	19.57				
p-value	(0.0336)				

Table 7. GMM Dynamic Model - Private Economic Value of Technology (All Firms) Sample (1994-2019)

This table provides regression estimates of the system-GMM dynamic panel data model of *ln pat_value* for all firms using the continuous updating GMM (CUE-GMM) estimator of Hansen, Heaton, and Yaron (1996) implementing Kripfganz (2019) **xtdpdgmm** package in STATA. The implementation incorporates (21) linear and (1) nonlinear moment conditions as suggested by Ahn and Schmidt (1995) under homoskedasticity and absence of serial correlation. The instruments for the forward orthogonal deviations equation are the endogenous variable *ln pat_value* with lags (2/4) and the pre-determined variables *ln crisk*, *ln kunc*, *ln tfpcon* and *ln pat_cites* with lags (1/3). The instruments for the equation in levels are *ln pat_value* lagged one period and the control variables *ln sales*, *ln leverage*, and *ln size*. GMM-type instruments are curtailed and collapsed to standard instruments in order to reduce the number of instruments. Robust standard errors are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance.

Instruments = 22	# Obs. = 4,080		# SIC groups	= 300
ln pat_value	**Coefficient**	**Std. Error**	***t*-stat**	***p*-value**
$\ln pat_{value t-1}$	0.2455	0.0462	5.32	0.0000***
$ln\ crisk_t$	0.5814	0.1314	4.42	0.0000***
$ln\ crisk_{t-1}$	0.2234	0.0788	2.84	0.0050***
$ln\ kunc_t$	-0.2674	0.0410	-6.52	0.0000***
$ln\ kunc_{t-1}$	-0.0610	0.0233	-2.62	0.0090***
$ln\ tfpcon_t$	1.8268	1.4539	1.26	0.2100
$ln\ tfpcon_{t-1}$	4.8559	2.2045	2.20	0.0280**
$\ln pat_{citest}$	0.3787	0.0816	4.64	0.0000***
$\ln pat_{citest-1}$	-0.1002	0.0443	-2.26	0.0250**
ln sales	0.4890	0.1648	2.97	0.0030***
ln leverage	-0.2454	0.0760	-3.23	0.0010***
ln size	0.0800	0.0640	1.25	0.2120
year2000	1.0510	0.1968	5.34	0.0000***
year2017	0.2811	0.1809	1.505	0.1210
α	-2.8449	1.3220	-2.15	0.0320**
Arellano-Bond AR first diff. test				
AR(1) = -6.78 (0.0000)				
AR(2) = 1.28 (0.2006)				
AR(3) = -0.23 (0.8177)				
Sargan-Hansen test for overid. restr. (χ^2_7) = 9.55 (0.2155)				

Table 8. GMM Dynamic Model - Private Value of Technology (*Green* Firms)

Sample (1994-2019)

This table provides regression estimates of the System GMM dynamic panel data model of *ln pat_value* for green firms using the continuous updating GMM (CUE-GMM) estimator of Hansen, Heaton, and Yaron (1996) implementing Kripfganz (2019) xtdpdgmm package in STATA. The implementation incorporates (22) linear and (1) nonlinear moment conditions as suggested by Ahn and Schmidt (1995) under homoskedasticity and absence of serial correlation. The instruments for the forward orthogonal deviations equation are the endogenous variable *ln pat_value* with lags (2/4) and the pre-determined variables *ln crisk*, *ln kunc*, *ln tfpcon* and *ln pat_cites* with lags (1/3). The instruments for the equation in levels are *ln pat_value* lagged one period and the control variables *ln sales*, *ln leverage*, and *ln size*. GMM-type instruments are curtailed and collapsed to standard instruments in order to reduce the number of instruments. Robust standard errors are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance.

Instruments = 22	# Obs. = 771		# SIC groups	= 115
ln pat_value	**Coefficient**	**Std. Error**	***t*-stat**	***p*-value**
$\ln pat_{value\,t-1}$	0.2751	0.0710	3.87	0.0000***
$ln\ crisk_t$	0.7336	0.2518	2.91	0.0040***
$ln\ crisk_{t-1}$	0.4407	0.1660	2.65	0.0090***
$ln\ kunc_t$	-0.3019	0.0618	-4.88	0.0000***
$ln\ kunc_{t-1}$	-0.0629	0.0419	-1.50	0.1360
$ln\ tfpcon_t$	0.5298	3.2657	0.16	0.8710
$ln\ tfpcon_{t-1}$	5.0208	2.4719	2.03	0.0450**
$\ln pat_{cites\,t}$	0.2665	0.1081	2.47	0.0150**
$\ln pat_{cites\,t-1}$	0.0400	0.0658	0.61	0.5460
ln sales	0.0592	0.1808	0.33	0.7440
ln leverage	-0.2999	0.1465	-2.05	0.0430**
ln size	0.3776	0.1189	3.18	0.0020***
year2000	0.9420	0.3068	3.07	0.0030***
year2017	0.1623	0.2633	0.62	0.5390
α	-2.1132	1.3630	-1.55	0.1240
Arellano-Bond AR first diff. test				
AR(1) = -2.97 (0.0030)				
AR(2) = -1.62 (0.1042)				
AR(3) = 1.82 (0.0689)				
Sargan-Hansen test for overid. restr. (χ^2_7) = 9.84 (0.1975)				

Table 9. GMM Dynamic Model - Private Value of Technology (*Brown* Firms)

Sample (1994-2019)

This table provides regression estimates of the System GMM dynamic panel data model of *ln pat_value* for brown firms using the continuous updating GMM (CUE-GMM) estimator of Hansen, Heaton, and Yaron (1996) implementing Kripfganz (2019) xtdpdgmm package in STATA. The implementation incorporates (16) linear and (1) nonlinear moment conditions as suggested by Ahn and Schmidt (1995) under homoskedasticity and absence of serial correlation. The instruments for the forward orthogonal deviations equation are the endogenous variable *ln pat_value* with lags (3/4) and the pre-determined variables *ln crisk*, *ln kunc*, *ln tfpcon* and *ln pat_cites* with lags (1/2). The instruments for the equation in levels are *ln pat_value* lagged one, two and three periods and the control variables *ln sales*, *ln leverage*, and *ln size*. GMM-type instruments are curtailed and collapsed to standard instruments in order to reduce the number of instruments. Robust standard errors are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance.

Instruments = 17	# Obs. = 302		# SIC groups	= 19
ln pat_value	**Coefficient**	**Std. Error**	***t*-stat**	***p*-value**
$\ln pat_{value\,t-1}$	0.2121	0.0865	2.45	0.0250**
$ln\ crisk_t$	-0.8651	0.4514	-1.92	0.0710*
$ln\ crisk_{t-1}$	-0.2139	0.1774	-1.21	0.2430
$ln\ kunc_t$	-0.4787	0.2012	-2.30	0.0290**
$ln\ kunc_{t-1}$	-0.0353	0.1181	-0.30	0.7680
$ln\ tfpcon_t$	18.2052	13.4472	1.35	0.1930
$ln\ tfpcon_{t-1}$	-14.3338	11.7448	-1.22	0.2380
ln sales	-1.1419	0.6610	-1.73	0.1010
ln leverage	-0.3469	0.7611	-0.46	0.6540
ln size	1.1211	0.5073	2.21	0.0400**
year2000	0.8630	0.9280	0.93	0.3650
year2017	-0.7208	0.5502	-1.31	0.2070
α	3.8805	4.0017	0.97	0.3450
Arellano-Bond AR first diff. test				
AR(1) = -2.91 (0.0036)				
AR(2) = -1.58 (0.1149)				
AR(3) = 1.86 (0.0636)				
Sargan-Hansen test for overid. restr. (χ^2_4) = 0.67 (0.9551)				

Table 10. Non-Structural Panel Data VAR Model - (All Firms) - Sample (1994-2019)

This table provides estimates of the panel data VAR estimated using iterated GMM and forward orthogonal deviations (Helmert transformation), following Holtz-Eakin, Newey, and Rosen (1998). Robust standard errors are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. The Granger non-causality test has null hypothesis that the excluded variable does not Granger-cause the dependent variable. The panel VAR eigenvalue-stability test is calculated based on the modulus of each eigenvalue of the fitted model. The VAR model is stable if all moduli of the companion matrix is inside the unit circle.

# Obs. = 3,569		# SIC groups = 269		
ln pat_value	**Coefficient**	**Std.Error**	***z*-stat**	***p*-value**
$\ln pat_{valuet-1}$	0.6722	0.1260	5.33	0.0000^{***}
$ln\ crisk_{t-1}$	0.3801	0.1129	3.37	0.0001^{***}
$ln\ kunc_{t-1}$	-0.1231	0.0464	-2.65	0.0008^{***}
$ln\ tfpcon_{t-1}$	4.4986	1.0890	4.13	0.0000^{***}
$\ln pat_{citest}$	0.1290	0.0276	4.67	0.0000^{***}
ln tfpcon				
$\ln pat_{valuet-1}$	0.0496	0.0024	1.91	0.0560^{*}
$ln\ crisk_{t-1}$	-0.0025	0.0018	-1.37	0.1710
$ln\ kunc_{t-1}$	-0.0165	0.0007	-22.33	0.0000^{***}
$ln\ tfpcon_{t-1}$	0.8022	0.0321	24.99	0.0000^{***}
$\ln pat_{citest}$	-0.0040	0.0007	-5.47	0.0000^{***}
ln crisk				
$\ln pat_{valuet-1}$	-0.1204	0.0367	-3.28	0.0010^{***}
$ln\ crisk_{t-1}$	-0.4244	0.0290	-14.61	0.0000^{***}
$ln\ kunc_{t-1}$	-0.0999	0.0105	-9.51	0.0000^{***}
$ln\ tfpcon_{t-1}$	-0.0457	0.4537	-0.10	0.9200
$\ln pat_{citest}$	-0.0186	0.0099	-1.88	0.0600^{*}
ln kunc				
$\ln pat_{valuet-1}$	0.0496	0.0900	0.55	0.5820
$ln\ crisk_{t-1}$	1.0180	0.0851	11.96	0.0000^{***}
$ln\ kunc_{t-1}$	0.5059	0.0235	21.50	0.0000^{***}
$ln\ tfpcon_{t-1}$	1.3408	1.0742	1.25	0.2120
$\ln pat_{citest}$	0.0056	0.0264	0.21	0.831

Granger non-causality Wald test

ln pat_value	$\chi^2(1)$	***p*-value**	**ln tfpcon**	$\chi^2(1)$	***p*-value**
$ln\ crisk_{t-1}$	11.33	0.0010^{***}	$ln\ pat\ value_{t-1}$	3.64	0.0560^{*}
$ln\ kunc_{t-1}$	7.05	0.0080^{***}	$\ln crisk_{t-1}$	1.87	0.1710
$ln\ tfpcon_{t-1}$	17.06	0.0000^{***}	$ln\ kunc_{t-1}$	498.77	0.0000^{***}
All(df=3)	33.83	0.0000^{***}	All(df=3)	1419.62	0.0000^{***}
ln crisk	$\chi^2(1)$	***p*-value**	**ln kunc**	$\chi^2(1)$	***p*-value**
$ln\ pat\ value_{t-1}$	10.73	0.0010^{***}	$ln\ pat\ value_{t-1}$	0.30	0.5820
$ln\ kunc_{t-1}$	90.34	0.0000^{***}	$\ln crisk_{t-1}$	143.00	0.0000^{***}
$ln\ tfpcon_{t-1}$	0.01	0.9200	$ln\ tfpcon_{t-1}$	1.56	0.2120
All(df=3)	449.76	0.0000^{***}	All(df=3)	230.39	0.0000^{***}

eigenvalue-stability test

Modulus 0.8740/0.4604/0.4604/0.2291 - (All roots are inside the unit circle)

Table 11

Forecast-error variance decomposition (FEVD) analysis (All Firms)

Sample (1994-2019)

In this table we report the results of the implied FEVD analysis using the Cholesky causal ordering implied by the non-structural panel VAR(1) that includes *ln pat_value*, *ln_crisk*, *ln_kunc*, and *ln_tfpcon*. Confidence intervals were computed using 1,000 Monte Carlo simulations using estimates reported in Table 10.

Response variable and forecast horizon	*ln pat_value*	*ln_crisk*	*ln_kunc*	*ln_tfpcon*
ln pat_value				
0	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	0.0000
2	0.9026	0.0236	0.0630	0.0107
3	0.7493	0.0187	0.2086	0.0234
4	0.6366	0.0155	0.3162	0.0318
5	0.5607	0.0132	0.3892	0.0368
ln tfpcon				
0	0.0000	0.0000	0.0000	0.0000
1	0.0186	0.0038	0.3066	0.6710
2	0.0366	0.0073	0.6176	0.3384
3	0.0416	0.0041	0.7210	0.2333
4	0.0482	0.0030	0.7572	0.1916
5	0.0539	0.0025	0.7731	0.1704
ln crisk				
0	0.0000	0.0000	0.0000	0.0000
1	0.0082	0.9918	0.0000	0.0000
2	0.0626	0.7894	0.1480	0.0000
3	0.0679	0.7808	0.1496	0.0018
4	0.0724	0.7686	0.1553	0.0035
5	0.0740	0.7536	0.1673	0.0050
ln kunc				
0	0.0000	0.0000	0.0000	0.0000
1	0.0090	0.0189	0.9721	0.0000
2	0.0072	0.0326	0.9599	0.0003
3	0.0080	0.0323	0.9586	0.0010
4	0.0082	0.0324	0.9580	0.0014
5	0.0082	0.0324	0.9577	0.0016

Table 12. Non-Structural Panel Data VAR Model - (*Green* Firms) - Sample (1994-2019)

This table provides estimates of the panel data VAR estimated using iterated GMM and forward orthogonal deviations (Helmert transformation), following Holtz-Eakin, Newey, and Rosen (1998). Robust standard errors are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. The Granger causality test has null hypothesis that the excluded variable odes not Granger-cause the dependent variable. The panel VAR eigenvalue-stability test is calculated based on the modulus of each eigenvalue of the fitted model. The VAR model is stable if all moduli of the companion matrix is inside the unit circle.

# Obs. = 630		# SIC groups = 89		
ln pat_value	**Coefficient**	**Std.Error**	***z*-stat**	***p*-value**
$\ln pat_{valuet-1}$	-0.2213	0.0667	-3.32	0.0010^{***}
$ln\ crisk_{t-1}$	0.2321	0.0761	3.05	0.0020^{***}
$ln\ kunc_{t-1}$	-0.1654	0.0257	-6.44	0.0000^{***}
$ln\ tfpcon_{t-1}$	3.4184	1.1486	2.98	0.0030^{***}
$\ln pat_{citest}$	0.1028	0.0618	1.66	0.0960^{*}
ln tfpcon				
$\ln pat_{valuet-1}$	-0.0066	0.0031	-2.14	0.0330^{**}
$ln\ crisk_{t-1}$	0.0148	0.0029	5.07	0.0000^{***}
$ln\ kunc_{t-1}$	-0.0094	0.0007	-13.31	0.0000^{***}
$ln\ tfpcon_{t-1}$	-0.1223	0.0370	-3.31	0.0010^{***}
$\ln pat_{citest}$	-0.0126	0.0015	-8.18	0.0000^{***}
ln crisk				
$\ln pat_{valuet-1}$	-0.1592	0.0266	-0.60	0.5500
$ln\ crisk_{t-1}$	-1.0090	0.0296	-34.06	0.0000^{***}
$ln\ kunc_{t-1}$	0.0741	0.0090	8.25	0.0565^{*}
$ln\ tfpcon_{t-1}$	-3.9700	0.4952	-8.02	0.0000^{***}
$\ln pat_{citest}$	-0.1830	0.0148	-12.39	0.0000^{***}
ln kunc				
$\ln pat_{valuet-1}$	-0.3985	0.0847	-4.70	0.0000^{***}
$ln\ crisk_{t-1}$	-0.9235	0.0588	-15.95	0.0000^{***}
$ln\ kunc_{t-1}$	-0.0830	0.0199	-4.18	0.0000^{***}
$ln\ tfpcon_{t-1}$	-3.9162	0.9534	-4.11	0.0000^{***}
$\ln pat_{citest}$	-0.1146	0.0336	-3.41	0.0010^{***}

Granger non-causality Wald test

ln pat_value	$\chi^2(1)$	***p*-value**	**ln tfpcon**	$\chi^2(1)$	***p*-value**
$ln\ crisk_{t-1}$	9.31	0.0020^{***}	$ln\ pat\ value_{t-1}$	4.57	0.0330^{**}
$ln\ kunc_{t-1}$	41.47	0.0000^{***}	$\ln crisk_{t-1}$	25.71	0.0000^{***}
$ln\ tfpcon_{t-1}$	8.86	0.0030^{***}	$ln\ kunc_{t-1}$	177.06	0.0000^{***}
All(df=3)	52.36	0.0000^{***}	All(df=3)	180.06	0.0000^{***}
ln crisk	$\chi^2(1)$	***p*-value**	**ln kunc**	$\chi^2(1)$	***p*-value**
$ln\ pat\ value_{t-1}$	0.36	0.5500	$ln\ pat\ value_{t-1}$	22.13	0.0000^{***}
$ln\ kunc_{t-1}$	68.12	0.0000^{***}	$\ln crisk_{t-1}$	254.54	0.0000^{***}
$ln\ tfpcon_{t-1}$	64.27	0.0000^{***}	$ln\ tfpcon_{t-1}$	16.87	0.0000^{***}
All(df=3)	170.95	0.0000^{***}	All(df=3)	341.29	0.0000^{***}

eigenvalue-stability test

Modulus -0.9030/-0.3137/-0.3137/0.0951 - (All roots are inside the unit circle)

Table 13

Forecast-error variance decomposition (FEVD) analysis (*Green* Firms)

Sample (1994-2019)

In this table we report the results of the implied FEVD analysis using the Cholesky causal ordering implied by the non-structural panel VAR(1) that includes *ln pat_value*, *ln_crisk*, *ln_kunc*, and *ln_tfpcon*. Confidence intervals were computed using 1,000 Monte Carlo simulations using estimates reported in Table 10.

Response variable and forecast horizon	*ln pat_value*	*ln_crisk*	*ln_kunc*	*ln_tfpcon*
ln pat_value				
0	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	0.0000
2	0.9278	0.0012	0.0508	0.0202
3	0.9218	0.0018	0.0529	0.0234
4	0.9206	0.0022	0.0531	0.0242
5	0.9201	0.0024	0.0531	0.0243
ln tfpcon				
0	0.0000	0.0000	0.0000	0.0000
1	0.0457	0.0051	0.0443	0.9050
2	0.0544	0.0061	0.0890	0.8504
3	0.0678	0.0087	0.0989	0.8249
4	0.0708	0.0112	0.1003	0.8177
5	0.0711	0.0132	0.1004	0.8153
ln crisk				
0	0.0000	0.0000	0.0000	0.0000
1	0.0002	1.0000	0.0000	0.0000
2	0.0009	0.9011	0.0351	0.0628
3	0.0014	0.8715	0.0361	0.0910
4	0.0012	0.8593	0.0346	0.1049
5	0.0010	0.8536	0.0331	0.1123
ln kunc				
0	0.0000	0.0000	0.0000	0.0000
1	0.0000	0.1451	0.8543	0.0000
2	0.0576	0.2304	0.6985	0.0134
3	0.0592	0.2884	0.6326	0.0198
4	0.0560	0.3290	0.5881	0.0269
5	0.0530	0.3580	0.5560	0.0332

Table 14. Robustness Check – Robust Static Model – Research & Development (All Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln rnd_assets* for all firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 6,705 / MM = 6,696			**# SIC Groups: Fe&P-W = 377 / MM = 368**		
ln rnd_assets	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln crisk	0.0760	0.0656	0.0168	2.99/1.07	$0.00^{***}/0.29$
	(0.0394)	(0.0220)	(0.0157)		
ln kunc	-0.0409	-0.0444	-0.0146	-5.34/-3.13	$0.00^{***}/0.00^{***}$
	(0.0127)	(0.0083)	(0.0047)		
ln tfpcon	0.7723	1.2195	0.4523	2.71/1.64	$0.01^{***}/0.10^{*}$
	(0.7374)	(0.4505)	(0.2762)		
ln sales	0.1115	-0.0495	0.2334	-0.91/3.52	$0.36/0.00^{***}$
	(0.1458)	(0.0544)	(0.0664)		
ln leverage	-0.1181	-0.0897	-0.1318	-3.86/-5.42	$0.00^{***}/0.00^{***}$
	(0.0436)	(0.0232)	(0.0243)		
ln size	-0.3405	-0.1457	-0.4070	-3.24/-8.18	$0.00^{***}/0.00^{***}$
	(0.1048)	(0.0450)	(0.0498)		
ln tq	0.7653	0.5023	0.7838	6.51/9.89	$0.00^{***}/0.00^{***}$
	(0.1657)	(0.0772)	(0.0792)		
year 2000	0.3392	0.2668	0.0610	5.18/2.07	$0.00^{***}/0.04^{**}$
	(0.0784)	(0.0515)	(0.0293)		
year 2017	0.0780	0.0155	0.0122	0.46/0.47	0.64/0.64
	(0.0673)	(0.0335)	(0.0260)		
α	-3.4933	-4.2194			$0.00^{***}/0.00^{***}$
	(0.8339)	(0.2802)			
Statistics					
R^2	0.0243	0.7040	Wald-$\chi^2(9)$ =	183.42	
F(9,376)	7.57		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	2.50		M-estimator =	3.44	
σ_ε	0.93		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	-0.06		Scale =	0.54	
ρ =	0.88	[0.90,1]	Efficiency =	85%	
Hausman-$\chi^2(9)$ =	14.06				
p-value	(0.1202)				

Table 15. Robustness Check – Robust Static Model – Research & Development (*Green* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln rnd_assets* for green firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 836 / MM = 812			**# SIC Groups: Fe&P-W = 118 / MM = 94**		
ln rnd_assets	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln crisk	-0.0169	-0.0027	-0.0140	-0.04/-0.60	0.97/0.55
	(0.0337)	(0.0690)	(0.0232)		
ln kunc	-0.0020	-0.0691	-0.0055	-2.62/-0.61	0.00***/0.54
	(0.0114)	(0.0264)	(0.0089)		
ln tfpcon	0.2500	6.4456	-0.3599	3.32/-0.80	0.00***/0.42
	(0.5307)	(1.9391)	(0.4494)		
ln sales	0.4724	0.0309	0.4659	0.66/3.01	0.51/0.00***
	(0.1572)	(0.4652)	(0.1549)		
ln leverage	-0.1346	-0.2036	-0.1583	-1.55/-3.08	0.12/0.00***
	(0.0488)	(0.1310)	(0.0514)		
ln size	-0.5935	-0.3076	-0.5377	-0.72/-3.82	0.47/0.00***
	(0.1166)	(0.4285)	(0.1407)		
ln tq	0.9505	1.2686	0.9097	1.65/4.90	0.10*/0.00***
	(0.1638)	(0.7689)	(0.1855)		
year 2000	0.0501	0.2049	0.0423	1.01/0.75	0.31/0.45
	(0.0628)	(0.2030)	(0.0560)		
year 2017	0.0299	-0.3249	0.0059	-1.58/0.16	0.12/0.87
	(0.0498)	(0.2059)	(0.0361)		
α	-3.001	-3.5590			0.00***/0.00***
	(0.7589)	(0.2802)			
Statistics					
R^2	0.0029	0.8311	Wald-$\chi^2(9)$ =	47.91	
F(9,117)	7.11		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	2.08		M-estimator =	3.44	
σ_ε	0.26		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	-0.17		Scale =	0.25	
ρ =	0.98	[0,1]	Efficiency =	85%	
Hausman-$\chi^2(9)$ =	8.08				
p-value	(0.5264)				

Table 16. Robustness Check – Robust Static Model – Research & Development (*Brown* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for brown firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 412 / MM = 412			**# SIC Groups: Fe&P-W = 19 / MM = 19**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat*/*t*-stat**	***p-value***
ln crisk	-0.0818	0.1740	-0.1184	1.38/-1.62	0.17/0.12
	(0.1763)	(0.1258)	(0.0287)		
ln kunc	-0.0344	-0.0492	0.0112	-1.01/0.55	0.31/0.55
	(0.0474)	(0.0487)	(0.0205)		
ln tfpcon	-2.5091	0.7023	-1.2242	0.32/-1.42	0.75/0.17
	(2.3019)	(2.2240)	(0.8628)		
ln sales	-0.1128	1.3323	0.0843	6.51/0.50	0.00***/0.62
	(0.2993)	(0.2045)	(0.1672)		
ln leverage	-0.0973	-1.1205	-0.3894	-5.46/-4.33	0.00***/0.00***
	(0.2594)	(0.2053)	(0.0899)		
ln size	-0.2973	-1.5213	-0.4142	-7.53/-3.28	0.00***/0.00***
	(0.2335)	(0.2019)	(0.1262)		
ln tq	0.2841	2.7618	0.4891	7.22/1.95	0.00***/0.07*
	(0.3352)	(0.3823)	(0.2509)		
year 2000	0.2285	0.2514	-0.056	0.90/-0.47	0.37/0.64
	(0.3512)	(0.2786)	(0.1170)		
year 2017	0.0964	0.2467	-0.1626	1.43/-1.13	0.15/0.27
	(0.3113)	(0.1725)	(0.1437)		
α	-3.4607	-5.1107			0.00***/0.00***
	(1.0364)	(0.7375)			
Statistics					
R^2 (*within*)	0.0663	0.7172	Wald-$\chi^2(9)$ =	93.87	
$F(9,18)$	12.26		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	2.39		M-estimator =	3.44	
σ_ε	0.87		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	-0.11		Scale =	0.60	
ρ =	0.88	[0.46,0.93]	Efficiency =	85%	
Hausman-$\chi^2(9)$ =	5.04				
p-value	(0.8309)				

Table 17. Robustness Check - Static Model – Number of Patents Granted (All Firms)
Sample period: 1994-2019

This table provides estimates of the model for *pat_count* for all firms using a Poisson GEE population-averaged estimator assuming independent correlations. Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs. = 4,869			**# SIC Groups = 367**	
pat_count	**Coefficient**	**Std.Error**	***z*-stat**	***p-value***
ln crisk	0.2671	0.0325	8.22	0.0000***
ln kunc	-0.0691	0.0081	-8.54	0.0000***
ln tfpcon	5.4514	0.6116	8.91	0.0000***
ln pat_cites	0.4114	0.0191	21.55	0.0000***
ln sales	-0.2502	0.1426	-1.75	0.0800*
ln leverage	-0.2421	0.0810	-2.99	0.0003***
ln size	0.4765	0.1420	3.36	0.0010***
ln tq	-0.2243	0.1668	-1.34	0.1790
year 2000	0.1844	0.0466	3.95	0.0000***
year 2017	0.6149	0.0644	9.55	0.0000***
α	-1.0518			0.0050***
Statistics				
Wald-$\chi^2(10)$	1010.65			
p-value	(0.0000)			
Deviance	10408.33			
Dispersion	2.14			
Pearson-$\chi^2(4869)$	11968.12			
Dispersion (Pearson)	2.46			
Scale	1			

Table 18. Robustness Check - Static Model – Number of Patents Granted (*Green* Firms)
Sample period: 1994-2019

This table provides estimates of the model for *pat_count* for green firms using a Poisson GEE population-averaged estimator assuming independent correlations. Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs. = 815			**# SIC Groups = 121**	
pat_count	**Coefficient**	**Std.Error**	***z*-stat**	***p-value***
ln crisk	0.3416	0.0543	6.29	0.0000***
ln kunc	-0.0595	0.0229	-2.60	0.0090***
ln tfpcon	8.6720	1.4300	6.06	0.0000***
ln pat_cites	0.3967	0.0339	11.71	0.0000***
ln sales	-0.1747	0.1650	-1.06	0.2900
ln leverage	-0.4821	0.2053	-2.35	0.0190**
ln size	0.3357	0.1681	2.000	0.0460**
ln tq	-0.1396	0.3330	-0.42	0.6750
year 2000	0.3127	0.1022	3.06	0.0020***
year 2017	0.4776	0.1121	4.26	0.0000***
Statistics				
Wald-$\chi^2(10)$	1309.32			
p-value	(0.0000)			
Deviance	1311.16			
Dispersion	1.61			
Pearson-$\chi^2(815)$	1573.32			
Dispersion (Pearson)	1.93			
Scale	1			

Table 19. Robustness Check - Static Model – Number of Patents Granted (*Brown* Firms)
Sample period: 1994-2019

This table provides estimates of the model for *pat_count* for brown firms using a Poisson GEE population-averaged estimator assuming independent correlations. Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs. = 55			**# SIC Groups = 9**	
pat_count	**Coefficient**	**Std.Error**	***z*-stat**	***p-value***
ln crisk	0.2471	0.1278	1.93	0.0530*
ln kunc	-0.0943	0.0200	-4.70	0.0000***
ln tfpcon	4.2310	2.0133	2.10	0.0360**
ln pat_cites	0.1548	0.0848	1.83	0.0680*
ln sales	0.4150	0.2421	1.71	0.0860*
ln leverage	0.0029	0.2474	0.01	0.9910
ln size	-0.2660	0.2548	-1.04	0.2970
ln tq	0.4835	0.4697	1.03	0.3030
year 2000	0.3841	0.1660	2.31	0.0210**
year 2017	0.4826	0.0981	4.92	0.0000***
Statistics				
Wald-$\chi^2(8)$	3070.61			
p-value	(0.0000)			
Deviance	33.78			
Dispersion	0.61			
Pearson-$\chi^2(55)$	33.62			
Dispersion (Pearson)	0.61			
Scale	1			

Table 20. Robustness Check – Robust Static Model – with VIX (All Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for all firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 4,869 / MM = 4,832			**# SIC Groups: Fe&P-W = 367 / MM = 330**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln VIX	0.5015	0.3236	0.5373	4.69/10.52	$0.00^{***}/0.00^{***}$
	(0.0606)	(0.0690)	(0.0511)		
ln kunc	-0.0737	-0.0838	-0.0709	-7.08/-7.38	$0.00^{***}/0.00^{***}$
	(0.0123)	(0.0118)	(0.0096)		
ln tfpcon	-0.3176	2.2511	-1.5251	3.95/-3.34	$0.00^{***}/0.00^{***}$
	(0.6134)	(0.5702)	(0.4568)		
ln pat_cites	0.0952	0.1635	0.0683	14.60/5.48	$0.00^{***}/0.00^{***}$
	(0.0163)	(0.0112)	(0.0125)		
ln sales	0.2136	0.3113	0.2639	5.70/2.41	$0.00^{***}/0.02^{**}$
	(0.1705)	(0.0546)	(0.1094)		
ln leverage	-0.0952	-0.1459	-0.1151	-4.28/-2.78	$0.00^{***}/0.01^{***}$
	(0.0496)	(0.0341)	(0.0414)		
ln size	0.4888	0.3941	0.3992	7.94/3.94	$0.00^{***}/0.00^{***}$
	(0.1440)	(0.0496)	(0.1014)		
ln tq	0.1091	0.2573	0.2857	2.77/1.90	$0.01^{**}/0.06^{*}$
	(0.2173)	(0.0929)	(0.1502)		
year 2000	0.6235	0.6230	0.6594	9.88/11.61	$0.00^{***}/0.00^{***}$
	(0.0745)	(0.0630)	(0.0568)		
year 2017	0.0737	0.0155	0.1129	0.23/2.38	$0.82/0.02^{**}$
	(0.0805)	(0.0668)	(0.0474)		
α	-6.2183	-5.5014			$0.00^{***}/0.00^{***}$
	(0.7661)	(0.3239)			
Statistics					
R^2	0.5479	0.5379	Wald-$\chi^2(10)$ =	428.22	
$F(10,366)$	34.42		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	1.25		M-estimator =	3.44	
σ_ε	0.85		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	0.08		Scale =	0.87	
ρ =	0.68	[0,1]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	27.70				
p-value	(0.0020)				

Table 21. Robustness Check – Robust Static Model – with VIX (*Green* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for green firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 815 / MM = 791			**# SIC Groups: Fe&P-W = 121 / MM = 98**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat*/*t*-stat**	***p-value***
ln VIX	0.4557	0.4190	0.5044	2.85/4.86	0.00***/0.00***
	(0.1158)	(0.1469)	(0.1038)		
ln kunc	-0.0932	-0.1119	-0.1125	-3.23/-4.97	0.00***/0.00***
	(0.0384)	(0.0347)	(0.0277)		
ln tfpcon	-1.4914	0.3873	-1.8741	0.32/-1.81	0.75/0.07*
	(1.1697)	(1.1991)	(1.0342)		
ln pat_cites	0.0675	0.1144	0.0364	4.24/1.31	0.00***/0.19
	(0.0324)	(0.0270)	(0.0279)		
ln sales	0.2035	0.4729	0.2104	2.32/0.89	0.02**/0.38
	(0.2158)	(0.2035)	(0.2359)		
ln leverage	-0.1331	-0.0433	-0.1812	-0.46/-1.87	0.64/0.06*
	(0.1181)	(0.0935)	(0.0969)		
ln size	0.3375	0.1269	0.2790	0.66/1.55	0.51/0.12
	(0.1747)	(0.1912)	(0.1799)		
ln tq	0.6124	1.2123	0.7188	3.54/2.65	0.00***/0.01***
	(0.2833)	(0.3429)	(0.2716)		
year 2000	0.8290	0.7857	0.8243	4.06/4.86	0.00***/0.00***
	(0.1673)	(0.1936)	(0.1696)		
year 2017	-0.0789	-0.1374	-0.0600	-1.07/-0.62	0.29/0.54
	(0.0936)	(0.1290)	(0.0973)		
α	-5.2874	-5.6838			0.00***/0.00***
	(1.6415)	(0.5745)			
Statistics					
R^2	0.4107	0.7120	Wald-$\chi^2(10)$ =	104.94	
$F(10,120)$	11.59		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	1.42		M-estimator =	3.44	
σ_ε	0.68		S-estimator =	1.55	
$\rho_{\eta_i,Xb}$ =	0.09		Scale =	0.80	
ρ =	0.81	[0,0.79]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	7.65				
p-value	(0.6633)				

Table 22. Robustness Check – Robust Static Model – with VIX (*Brown* Firms)
Sample period: 1994-2019

This table provides estimates of the static model for *ln pat_value* for brown firms using: 1) a (within-industry) pair-wise differenced fixed effects panel data regression estimator (Fe); 2) a Prais-Winsten panel data regression with heteroskedastic panel-corrected standard errors (PCSEs) and autocorrelations computed using panel-specific autocorrelations by panel sizes with the assumption that residuals follow an AR(1) stochastic process; and 3) the robust MM estimator of Gervini and Yohai (2002) that combines an initial high breakdown S estimator with a subsequent redescending M estimator a là Huber (1973). Robust standard errors in parenthesis are adjusted by industry clusters and calculated using the sandwich estimator. The Hausman test between models at the bottom of the table has null hypothesis that coefficients are not different. Statistical significance is reported as follows: *** = 1 % statistical significance, ** = 5% statistical significance, and * = 10% statistical significance. Variable definitions are provided in Table 1.

# Obs.: Fe&P-W = 316 / MM = 314			**# SIC Groups: Fe&P-W = 21 / MM = 19**		
ln pat_value	**(Fe)**	**(P-W)**	**(MM)**	***z-stat/t*-stat**	***p-value***
ln VIX	0.3890	0.8060	0.4132	2.66/2.29	$0.01^{***}/0.03^{**}$
	(0.2434)	(0.3025)	(0.1804)		
ln kunc	-0.2207	-0.1432	-0.1951	-2.26/-3.76	$0.02^{**}/0.00^{***}$
	(0.0646)	(0.0634)	(0.0519)		
ln tfpcon	4.0322	1.2360	0.8430	0.47/0.38	0.64/0.70
	(3.0298)	(2.6526)	(2.1952)		
ln pat_cites	0.1695	0.1938	0.0761	3.42/1.15	$0.00^{***}/0.27$
	(0.0994)	(0.0566)	(0.0664)		
ln sales	-0.1072	0.3476	-0.2201	1.54/-1.29	0.12/0.21
	(0.3438)	(0.2260)	(0.1709)		
ln leverage	0.4387	-0.5272	-0.1498	-2.25/-0.49	$0.02^{**}/0.63$
	(0.5740)	(0.2344)	(0.3032)		
ln size	0.7202	0.3619	0.6541	1.61/2.38	$0.11/0.03^{**}$
	(0.4676)	(0.2247)	(0.2746)		
ln tq	-0.3124	-0.2119	-0.0373	-0.51/-0.07	0.61/0.94
	(0.7060)	(0.4188)	(0.5077)		
year 2000	0.7180	0.5535	0.9328	1.80/4.66	$0.07^{*}/0.00^{***}$
	(0.3064)	(0.3077)	(0.2003)		
year 2017	0.1623	0.1760	-0.0128	0.53/-0.07	0.60/094
	(0.2720)	(0.3318)	(0.1838)		
α	-4.4323	-7.1384			$0.00^{***}/0.54$
	(3.8377)	(1.3413)			
Statistics					
R^2	0.6096	0.5471	Wald-$\chi^2(10)$ =	497.08	
$F(10,20)$	12.08		*p-value* =	(0.0000)	
p-value	(0.0000)		Break point =	50	
σ_η	0.91		M-estimator =	3.44	
σ_ε	1.08		S-estimator =	1.55	
$\rho_{\eta_i, Xb}$ =	0.28		Scale =	0.98	
ρ =	0.42	[0,0.82]	Efficiency =	85%	
Hausman-$\chi^2(10)$ =	25.82				
p-value	(0.0040)				

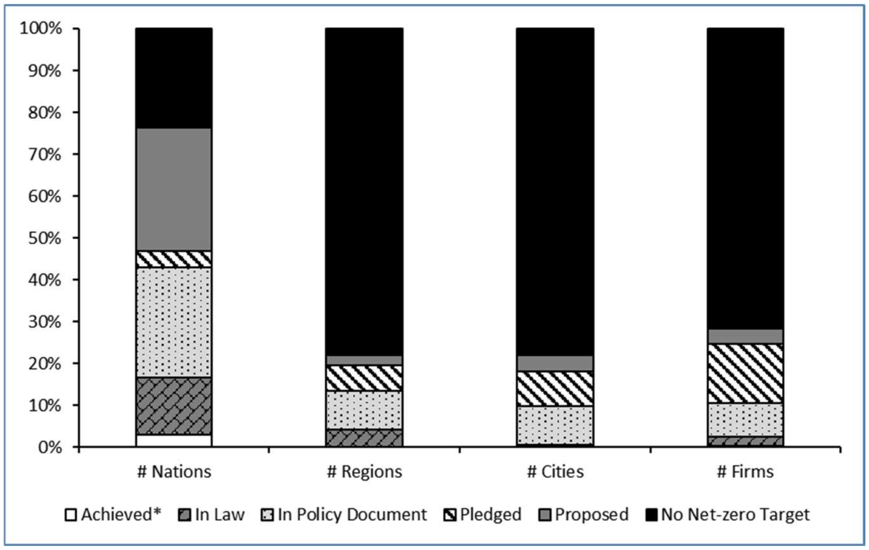

Figure 1. This chart plots net-zero commitments updated to the year 2023 of: 1) all UNFCCC (UN Climate Change Paris Agreement) member states; 2) regions in the top 25-emiting countries; 3) cities with population above 500,000 inhabitants; and the world's largest publicly traded firms included in the Forbes 2000 list. The data is collected from publicly available sources such as international commitments, laws, governmental policies, entities' websites, corporate annual reports, sustainability reports and press releases. It is collected and updated on a rolling basis by Black et al. (2023) in the following institutions: Net Zero Tracker, Energy and Climate Intelligence Unit, Data-Driven EnviroLab, and NewClimate Institute. The data is updated on a rolling basis up to 2023.

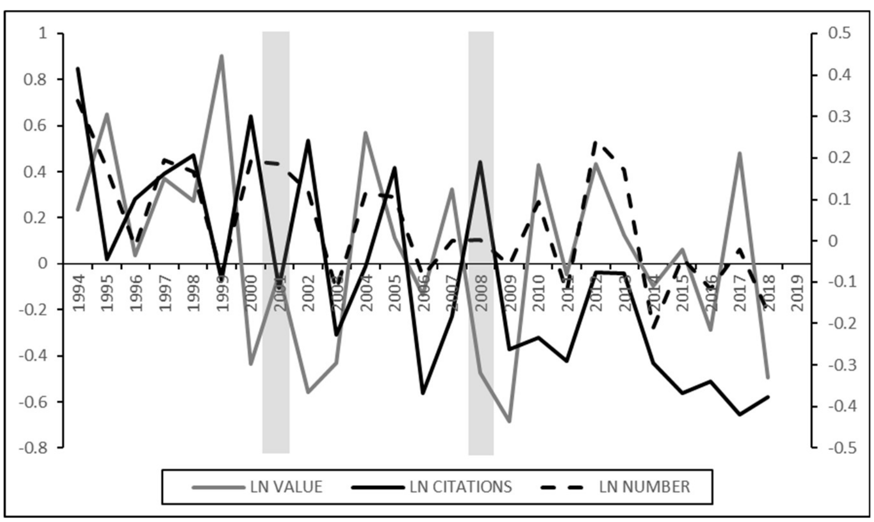

Figure 2. In this chart we show the natural log of the number of patents granted, the number of patent citations and the natural log of the private economic value of patents granted in the U.S. from 1994 to 2019. Grey bars indicate indicate NBER dated economic recessions.

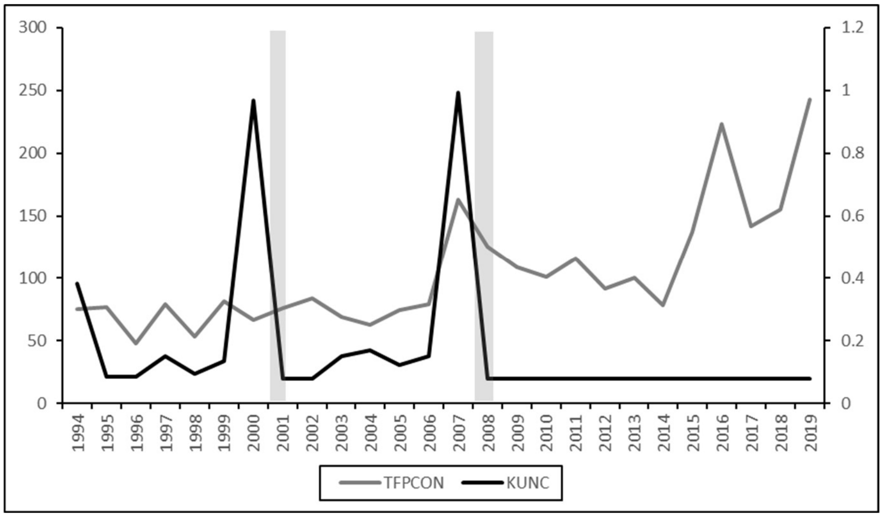

Figure 3. In this chart we show the time-series behavior of the two ambiguity factors *KUNC* and *TFP* connectedness. Grey bars correspond to NBER-dated U.S. economic recessions.

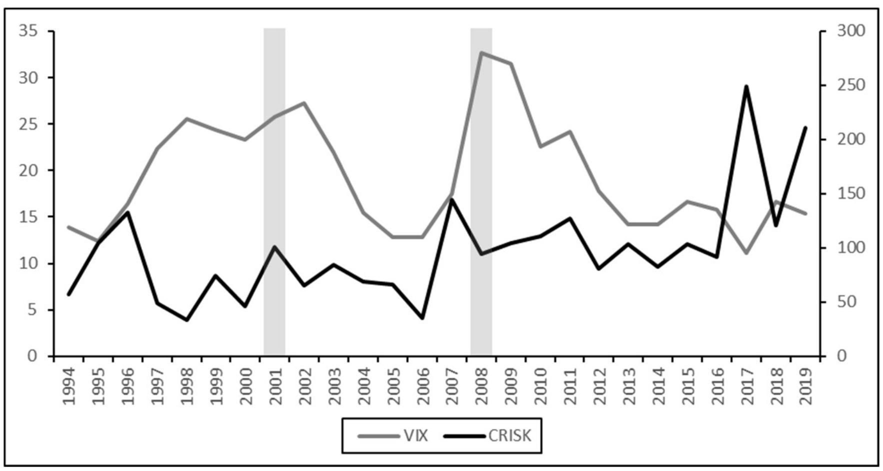

Figure 4. In this chart we show the time-series behavior of the two risk factors *CRISK* and *VIX*. Grey bars correspond to NBER-dated U.S. economic recessions.

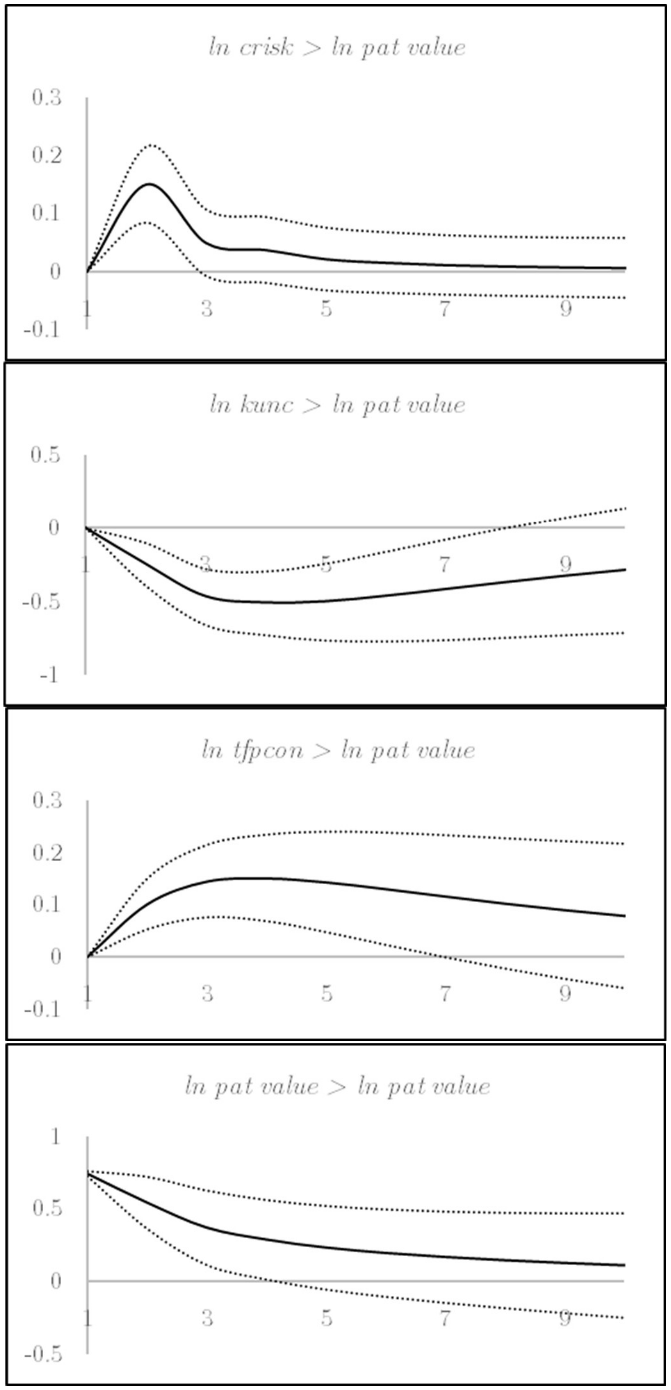

Figure 5. In this chart we plot orthogonalized impulse-response functions using 1,000 Monte Carlo simulations and the nonstructural panel VAR(1) estimates across all firms reported in Tables 10 and 11, for a period of 10 years using Choleski decomposition.

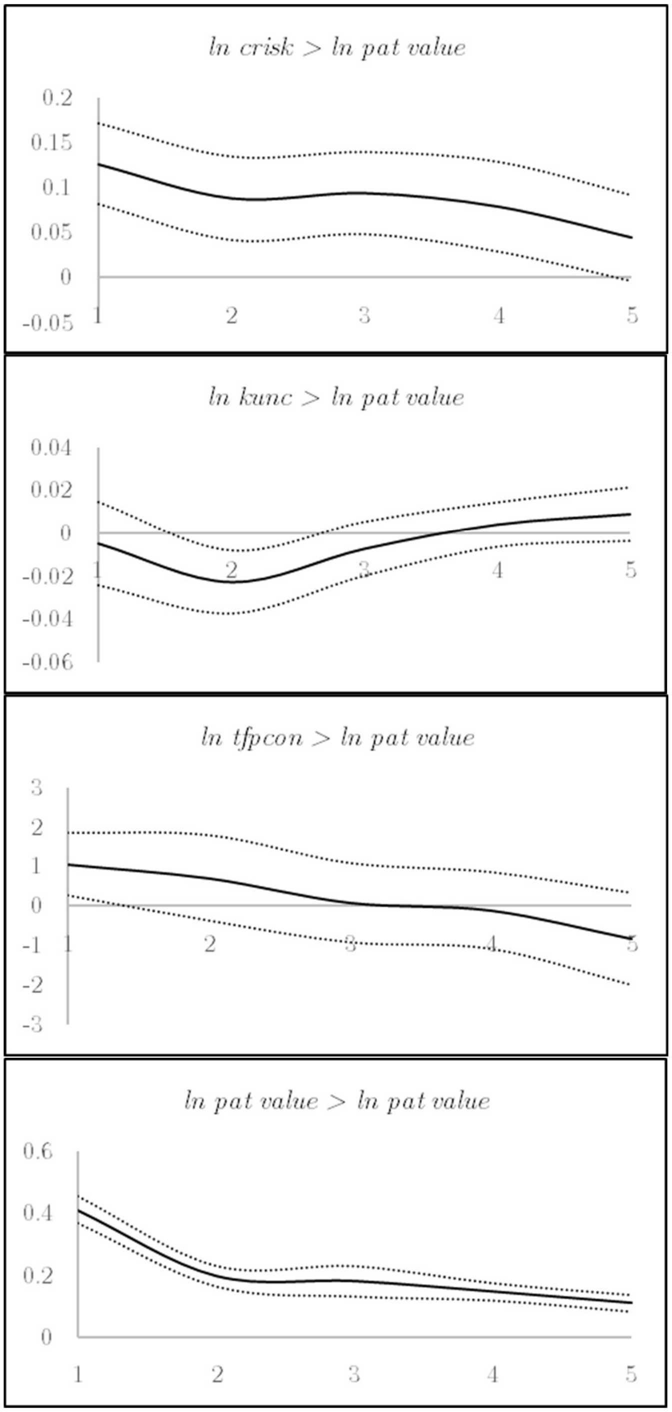

Figure 6. In this chart we plot impulse-response functions from local projections using the fixed effects(Fe) PD regression in Table 4, adding as control the recession of 2008, for all firms for a period of 5 years.

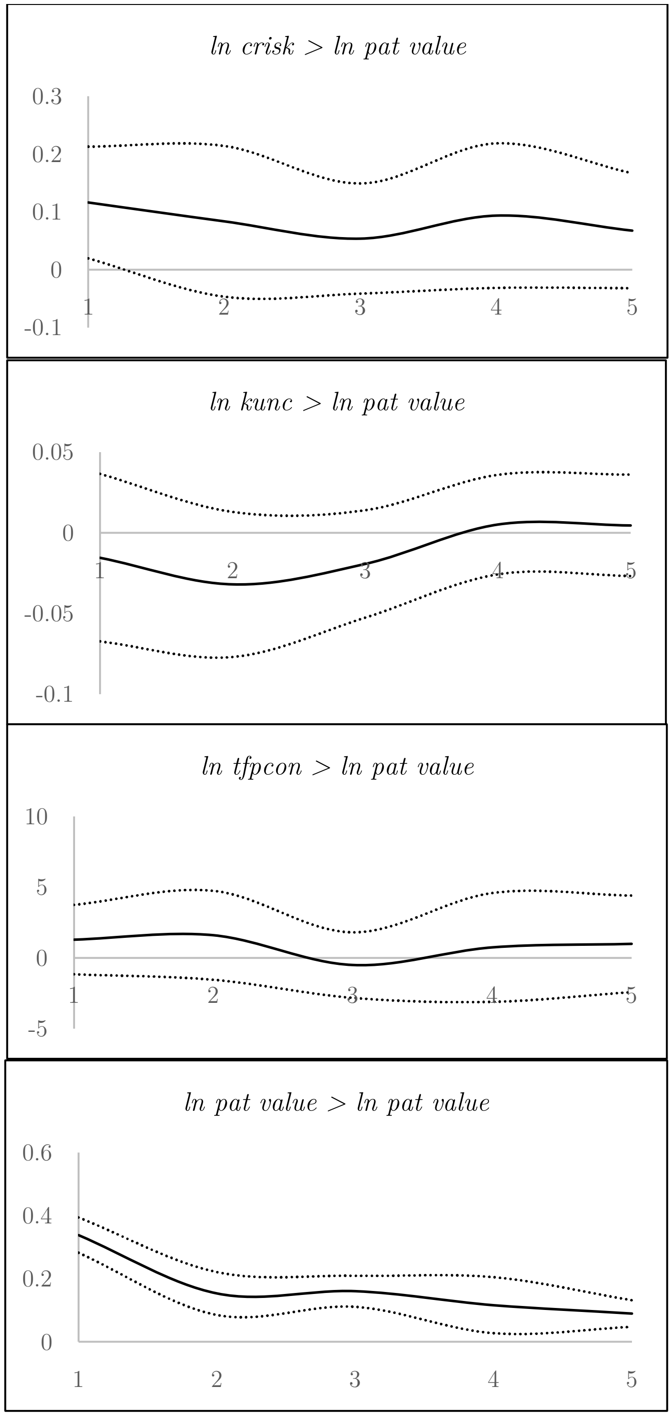

Figure 7. In this chart we plot impulse-response functions from local projections using the fixed effects(Fe) PD regression in Table 5, adding as control the recession of 2008, for green firms for a period of 5 years.

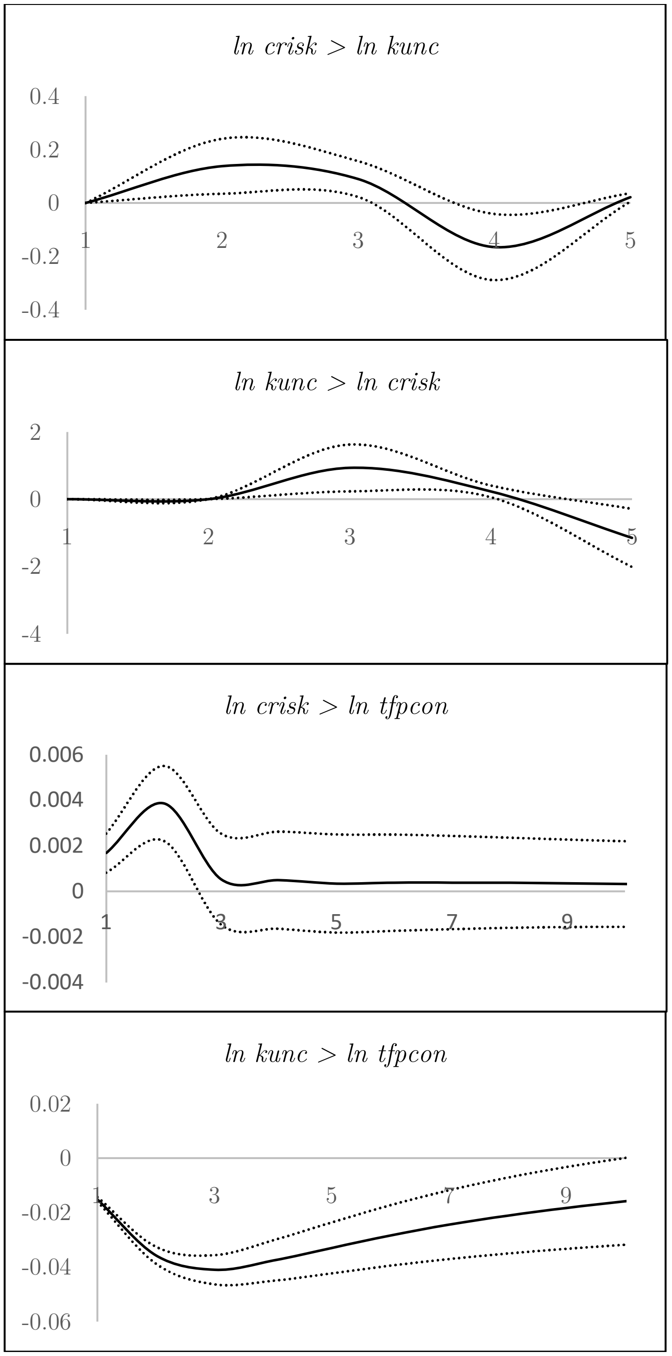

Figure 8. In the two top charts we plot impulse-response functions from local projections using the fixed effects(Fe) PD regression in Table 4 for the interaction between *ln crisk* and *ln kunc*, for all firms for a period of 5 years. In the two bottom charts we plot orthogonalized impulse-response functions for the interaction between *ln crisk*, *ln kunc*, and *ln tfpcon* using the nonstructural panel VAR(1) estimates across all firms reported in Tables 10 and 11, for a period of 10 years using Choleski decomposition.