Policy Uncertainty, Technological Competition, and Industry Dynamism

D. Daniel Keum
Management Division
Columbia Business School
610 Uris Hall, 3022 Broadway
New York, NY 10027
dk2721@columbia.edu

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Abstract

We examine how policy uncertainty affects firm innovation and industry dynamism. Drawing from research on R&D races, we propose that periods of high policy uncertainty provide a window for lagging firms to disrupt the status quo and overtake leaders. Using measures of uncertainty in economic policy from Baker et al. (2018), we find that policy uncertainty increases the rate of innovation by laggards relative to leaders, accelerates the pace of upward reversion in laggards' performance, and decreases industry concentration. The positive effect on laggards' investment is unique to innovation, absent for capital investment, and stronger in technologically deterministic, fast-changing, R&D intensive, and concentrated industries that better approximate the features of R&D races. Our findings characterize high policy uncertainty as a period of intensifying technological competition and demonstrate competitive interactions as a microeconomic channel through which uncertainty affects firm investment and industry dynamism beyond previous considerations of real and growth options.

Key words: Innovation, Uncertainty, Technological competition, Industry dynamism
JEL Classification: O31, G18, C73, D22

…in the spaciousness of uncertainty is room to act. When you recognize uncertainty, you recognize that you may be able to influence the outcomes…

– Rebecca Solnit, *Hope in the Dark*, 2004

1. Introduction

The seemingly self-reinforcing dominance of some firms (e.g., Amazon, Facebook, and Walmart) and declining competitive dynamism in the U.S. have raised significant concerns around their causes. In this vein, we examine how policy uncertainty affects technological competition and industry dynamism: do periods of high policy uncertainty provide a window for leading firms to increase their dominance or for lagging firms to catch up? Or, could policy uncertainty simply lead to a period of inaction and the status quo?

In contrast to the consensus on other investment variables, the effects of uncertainty on innovation remain subject to much dispute, reflecting its unique characteristics that generate multiple competing effects. On the negative side, firms try to avoid losses by delaying investment and waiting for uncertainties to resolve (Dixit and Pindyck, 1994; Bloom, 2009; Gulen and Ion, 2016; Bonaime et al., 2018). This can have a particularly negative effect on R&D activities that consist largely of specialized and irreversible investments, such as wages of R&D personnel. On the positive side, R&D activities and patents in particular can be viewed as investing in options for future growth opportunities that, similar to financial options, increase in value with volatility (Kogut, 1991; Kulatilaka and Perotti, 1998; Bloom and Van Reenen, 2002). Alternatively, short-term fluctuations in uncertainty may have little effect on innovation due to its long time-to-build and payoff (Bar-Ilan and Strange, 1996).

Extant empirical research draws on real options analysis and examines how uncertainty affects the *absolute* level of firm innovation. This study draws from research on competitive interactions and examines how policy uncertainty affects the *relative* rate of innovation between leading and lagging firms. Specifically, research on R&D races examines whether laggards invest more aggressively in innovation and overtake the leaders (i.e., decreasing dominance) or leaders increase their dominance over time (i.e., increasing dominance), as these dynamics have critical implications to the persistence of excess profits and industry concentration (e.g., Gilbert and Newbery, 1982; Reinganum, 1983; Doraszelski, 2003; Anderson and Cabral, 2007). While sharing the winner-takes-all assumption, this literature has generated "seemingly endless variations" (Gilbert, 2006:159) where a change to one specific assumption is sufficient to switch between increasing and decreasing dominance.[1] Across varied models, however, we point out that stochasticity (or uncertainty) in the innovation process serves as a critical contingency that separates models of increasing dominance from models of decreasing dominance.

If the innovation process is deterministic and firms that invest the most in innovation win the race with certainty, leaders can maintain their current leadership simply by matching laggards' investment. As a result, laggards stop innovating and drop out of the race knowing that it is impossible to overtake the leader. In contrast, if the innovation process is stochastic and subject to noise or luck, there is still some chance that laggards can overtake leaders. Even a slight chance is sufficient for laggards to continue to invest in innovation aggressively in a winner-takes-all competition where laggards have nothing to lose and everything to gain.[2]

Our main argument is that policy uncertainty shifts the dynamics of technological competition from a deterministic to a stochastic race where laggards invest more heavily in

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[1] Contingencies related to innovation include radical versus incremental, cost reduction versus new product, and sequential versus one-stage nature of innovation. Environment contingencies include the presence of spillover (that allows lagging firms to learn from the success of leading firms), the degree of patent protection, and the number of firms participating in the race.

[2] The results are most stark in a "winner-takes-all" setting, but the conclusions remain the same as long as the payoff function is convex ("winner-takes-most"). Budd, Harris and Vickers (1993), Cabral and Riordan (1994), and Athey and Schmutzler (2001) derive conditions for increasing dominance in dynamic competition. Refer to Doraszelski (2003) for a more detailed discussion on stochastic versus deterministic races across single stage and multi-stage races as well as races with and without knowledge accumulation.

innovation and decrease leaders' dominance. It is important to note that our prediction relates to the *relative* rate of innovation between leaders and laggards. In R&D races, it is the difference in the rate of innovation that determines the winner, and laggards can overtake leaders even as the absolute rate of innovation decreases. As a result, periods of high policy uncertainty and depressed investment provide a valuable yet fleeing window for laggards to challenge and overtake leaders.

Our argument accounts for three stylized facts that have been absent in prior discussions of uncertainty and (technological) competition: (i) industries have experienced both increases and decreases in competitive intensity and concentration over time within the general trend towards increasing concentration (Gutierrez and Philippon, 2017); (ii) there is a robust tendency for mean reversion in firm performance (McGahan and Porter, 1999; Wiggins and Ruefli, 2005) but (iii) also significant heterogeneity in the pace of upwards reversion in laggards' performance across industries and time periods. We link the industry and period differences in laggards' ability to overtake leaders to policy uncertainty and its effect on technological competition.

For our empirical analysis, we draw from Baker, Bloom, and Davis (2016) who conduct a textual analysis of newspapers to develop an economy-wide index of economic policy uncertainty (or more simply, EPU). The national index is unlikely to be driven by individual firms or industries and is uniquely suitable for our analysis that requires aggregate uncertainty shocks that apply to both leaders and laggards similarly. One key concern is that the index correlates highly with recession risks that also affect innovation investments (Ouyang, 2011; Fabrizio and Tsolmon, 2014). However, since a firm's position as a leader or laggard is measured *within* its primary industry and shifts over time, we can rigorously control for both macroeconomic and industry-specific conditions using industry-year fixed effects that are not available to prior studies that estimate the independent effect of uncertainty. To rule out alternative explanations, we also compare the effects of EPU on innovation to other investment variables that are not subject to the winner-takes-all dynamics of R&D races, including capital investment and employment growth.

We find robust support for our argument based on patent-based measures of firm innovation. One standard deviation increase in EPU is associated with a 1.7 percent increase in the number of patents and a 3.5 percent increase in citations accumulated by laggards. The magnitude is sufficient to swing the leader-laggard dynamics from increasing to decreasing dominance at high levels of EPU. The positive effect on laggards' investment is unique to innovation and absent for capital investment, mitigating concerns for an omitted variables bias. We also obtain consistent results using the partisan conflict index (Azzimonti, 2018) as an instrument for EPU.

Testing the dynamics of highly stylized models of R&D races creates important discrepancies from the data, and we next conduct a series of cross-sectional tests to verify that the shift towards more stochastic models of technological competition underpins the observed positive effect of EPU on laggards' innovation. We find that EPU decreases the productivity of past R&D investment and has the effect of "resetting" the playing field to the disadvantage of incumbent leaders. The positive effect on laggards' innovation is stronger in technologically deterministic, fast-changing, R&D intensive, and concentrated industries that closely approximate features of R&D races but absent in highly differentiated industries where the strategic interactions between competitors are less relevant. Finally, looking at more downstream consequences of closing the innovation gap, we find that EPU reduces the persistence of firm performance and increases industry dynamism, driven by faster upward reversion in laggards' performance. The acceleration is consistently stronger in industries where EPU has stronger effects on laggards' innovation. At the industry level, we find more tentative yet consistent evidence that EPU decreases industry concentration.

This study relates uncertainty, innovation, and competition and informs multiple strands of literature at their intersection. Most directly, beyond prior considerations of real and growth options, we identify competitive interactions as a microeconomic channel through which policy uncertainty operates and affects firm investment and industry dynamism. Minton and Schrand (1999), Goel and Ram (2001), and Czarnitzki and Toole (2011) find that uncertainty decreases innovation. Stein and Stone (2013), Atanassov, Julio, and Leng (2015), and Kraft, Schwartz, and Weiss (2018) obtain the opposite result. We reconcile these conflicting findings by showing that the effect of uncertainty on innovation depends on a firm's competitive position. Incorporating this simple insight explains why the uncertainty-innovation relation is more complex than a simple average effect in a way that can account for the substantial heterogeneity both across and within industries. The firm-level contingency complements prior research that focuses on the cross-industry differences, for example, based on investment reversibility (Kim and Kung, 2016), growth potential (Kogut, 1991; Kulatilaka and Perotti, 1998), competitive intensity (Grenadier, 2002; Weeds, 2002; Novy-Marx, 2007; Mason and Weeds, 2010), and the strength of patent protection (Czarnitzki and Toole, 2011).

The study also relates to research on competition and innovation, particularly those that explore strategic interactions between leading and lagging firms (e.g., Aghion et al. 2009; Varela, 2017). Our findings present rare empirical evidence to research on R&D races that has remained largely theoretical with conflicting predictions (cf. Lerner, 1997) and provide an uncertainty-based explanation to the significant differences in laggards' success in catching up to leaders across industries and time periods. They also confirm high policy uncertainty as a period of depressed investment and innovation but also characterize it as a period of intensifying technological competition that leads to a reshuffling in firms' competitive positions. One critical implication is that industry dynamism can intensify even as the overall level of innovation and investment declines, contrary to standard economic models.

Lastly, our findings uncover important yet overlooked positive aspects of uncertainty in economic policy. While a dominant share of academic and policy discussions takes a negative view of uncertainty, research on industry and product life cycles views (technological) uncertainty as encouraging innovation and entry (Abernathy and Utterback, 1978; Klepper, 1996). To the extent that the U.S. economy has a market power problem (Gutiérrez and Philippon, 2017; Crouzet and Eberly, 2018), policy uncertainty could have some long-term positive effects. This also suggests that there may be some unintended costs to improved policy formulation and the resulting "great moderation" in aggregate uncertainty (McConnell and Perez-Quiros, 2000; Stock and Watson, 2002).

2. Empirical Approach

2.1. Uncertainty in economic policy

Knight (1921), in his seminal work, distinguishes between risk and uncertainty based on measurability. Risk is defined as a measurable uncertainty with a known probability distribution while uncertainty is the unmeasurable risk for which the probability distribution of an event cannot be calculated.[3] Empirical research often takes a broad definition of uncertainty that mixes the two (Bloom, 2014) and uses the increase in the variance of expected outcome to stand in for uncertainty. The three most commonly used proxies of uncertainty are firm-level business uncertainty based on implied or realized volatility in cash flow or stock market returns (Minton and Schrand, 1999; Alfaro, Bloom, and Lin, 2019), regional uncertainty around elections and political events (Julio and Yook, 2012; Atanassov, Julio, and Leng, 2015; Jens, 2017), and more recently, national-level uncertainty in economic

[3] The distinction is sometimes criticized as lacking generalizability beyond highly controlled environments, such as casinos. Following Jurado et al. (2015:1177), we define uncertainty as "the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents."

policy. We use the updated news-based index of uncertainty in national economic policy by Baker, Bloom, and Davis (2016) (or BBD).

In constructing an index of economic policy uncertainty, BBD searches ten leading U.S. newspapers and counts the articles that contain a trio of the following terms: "economic," "uncertainty," "policy," and their close variations. The raw counts of qualifying articles are then divided by the total number of articles in the same newspaper for a given month. They normalize the time series from each newspaper to unit standard deviation and then normalize the sum of the ten newspapers to a mean of 100 from 1985 to 2010. This provides a monthly index of economic policy uncertainty. By disaggregating policy terms into specific components, they also construct eleven sub-indexes of policy uncertainty: (1) monetary policy, (2) fiscal policy, (3) taxes, (4) government spending, (5) healthcare, (6) national security, (7) entitlement programs, (8) regulation, (9) financial regulation, (10) trade policy, and (11) sovereign debt. For example, to measure policy uncertainty related to regulation, BBD further requires the article to include specific terms, such as "competition policy," "merger policy," "antitrust," "monopoly," "patent," and "at-will employment." Prior studies take the average of the monthly index to match the frequency of the dependent variables at quarterly (e.g., CAPEX, acquisitions) or annual (e.g., employment) frequency. Given that our main proxy for innovation (i.e., the number of patent applications) is reported with significant noise and lags, we use mean values of the index for each calendar year.[4]

The BBD index offers several distinct advantages for testing the leader-laggard interaction. First, the aggregate nature of the index provides a measure of uncertainty shocks that apply to all U.S. firms and industries and helps to attribute differential effects across

[4] Some studies use a composite index from BBD that additionally takes into account potential tax code expirations and forecast disagreement in monetary and fiscal policy (e.g., Gulen and Ion, 2016; Bonaime et al., 2018). We use the news-based index in part because we find a null effect to laggards' innovation in response to uncertainty in the tax code change and because news-based uncertainty provides category-specific indexes that permit a more granular cross-sectional analysis. Our findings are robust to using the composite index.

firms and industries to some theoretically specified characteristics (e.g., investment irreversibility). Firm-specific uncertainty shocks, for example based on differential exposures to exchange rate fluctuations (Alfaro, Bloom, and Lin, 2019) or political risks (Hassan et al., 2019), do not suit our analysis that requires similar changes in the level of uncertainty for both leaders and laggards.

Second, innovation, uncertainty, and firm performance and their persistence are subject to a similar set of difficult-to-observe factors, such as industry life cycle, exposure to new (foreign) competitors, deteriorating investment opportunities, and innovation by rival firms. More problematically, low firm performance tends to increase uncertainty in future firm performance, as firms increase restructuring activities whose effects on future cash flows are more difficult to predict, such as layoffs and divestiture. However, fluctuations in national levels of EPU are plausibly exogenous to individual firms and industries, some of which are driven by political and international events, such as partisan gridlocks, the Gulf War in 1990, and the Russian Crisis in 1998. This ensures that uncertainty drives innovation and not the other way around. Third, the index has been used by several recent studies. While limiting data-related contributions, it allows us to demonstrate the uniqueness of R&D investment as a strategic variable by comparing our results to employment growth, capital investment (Baker et al., 2016; Gulen and Ion, 2016), and acquisitions (Bonaime et al., 2018). If the proposed positive effect of uncertainty on laggards' innovation is indeed driven by shifting the dynamics of technological competition, we expect it to be absent for other investment variables.

2.2. Innovation and other dependent variables

We use the count of patent applications for each calendar year and citations received as the main proxies of a firm's innovation activity. Kogan et al. (2017) provide estimated market values of patents based on 3-day abnormal returns in response to news of its grant by the US

Patent Office. The market value of a patent is arguably a better proxy for firm innovation performance, but problematic because uncertainty likely affects the valuation of innovation by the capital market. The 3-day market returns overestimate the long-term effects of EPU if a patent recovers its value with the resolution of uncertainty in the mid- to long-term. We test the robustness of our findings to all three proxies: patent counts, citations, and market value.

Because of the competing effects discussed earlier, whether innovation should be more or less sensitive to EPU relative to capital investment is theoretically ambiguous. Some studies find larger swings in R&D investments compared to non-R&D investments in response to uncertainty shocks (Minton and Schrand, 1999; Goel and Ram, 2001), but innovation research emphasizes persistence in firm innovation activities due to high adjustments costs (e.g., Klette and Kortum, 2004; Raymond et al., 2010; Peter and Taylor, 2017). For comparison, we estimate the effects of EPU on capital investment intensity (capital investment normalized by total assets with a one-year lag), employment growth (calculated as a year-to-year percentage change in the total number of employees), and the number of acquisitions. Variable definitions and data sources are described in greater detail in Appendix A.

2.3. A firm's competitive position

Prior research relies on two metrics to assess a firm's position as a leader or laggard: financial and technological performance (Lerner, 1997; Aghion et al., 2005). We use industry-adjusted ROA as the primary measure of a firm's relative competitive position. While firms compete to be the first to discover and patent a single technology in theoretical models, firms comprise of multiple products and products of multiple technologies. As a result, technological performance is a noisy proxy for a firm's competitive position. For evaluating firm and managerial performance, ROA serves as a highly salient metric that has been used in previous research that explores the effects of industry concentration and policy changes (e.g., Giroud and Mueller, 2010; Grullon, Larkin, and Michaely, 2019). Our findings are robust to using TFP as an alternative measure of a firm's relative performance, detailed in Appendix B.

In our baseline specification, we use a simple binary variable $Laggard_{it}$ that equals one if annual firm performance (P_{it}) is below the average competitor proxied by the industry performance benchmark (IB_{it}). IB_{it} is defined as the median ROA at a four-digit SIC level for each year. The binary measure is intuitive but does not distinguish between laggards with performance moderately and significantly below leaders who may benefit from a more aggressive increase in innovation. As a secondary measure, we form a linear spline of firm performance relative to the industry benchmark. $Overperformance_{it}$ takes the value of $P_{it} - IB_{it}$ if firm performance is above the benchmark and zero otherwise, and $Underperformance_{it}$ takes the value of $P_{it} - IB_{it}$ if firm performance is below the benchmark and zero otherwise. $Underperformance_{it}$ takes a negative value by construction, and we take its absolute value for the ease of interpretation.

2.3. Empirical specification

BBD and subsequent empirical studies on uncertainty and investment provide well-established precedence for our empirical strategy. We first start with the following standard OLS regression:

$$Innovation_{it+n} = \alpha_i + \beta_1 EPU_t + X_{it} + \varepsilon_{it} \quad (1)$$

where i and t denotes a firm and year. Firm fixed effects are captured as α_i respectively. n is the number of years after the current time period t. A shock on firm incentives to innovate should affect patents with some lags, typically ranging between two to four years (Aghion et al., 2013; Acharya et al., 2014; Cerqueiro et al., 2016). Uncertainty affects other investment variables, such as capital investments or acquisitions, more immediately. We use a three-year lag (n=3) for patent-based variables and a one-year lag for other investment variables.

We augment equation (1) by including a firm's competitive position, its interaction with EPU, and year fixed effects (α_t):

$$Innovation_{it+n} = \alpha_i + \alpha_t + \beta_1 EPU_t + \beta_2 Laggard_{it} + \beta_3 EPU_t \times Laggard_{it} + X_{it} + \varepsilon_{it} \quad (2).$$

β_2 captures the extent to which a firm increases or decreases innovation when a firm becomes a laggard with below-industry performance. A negative coefficient is consistent with the increasing gap in innovation whereby leaders pull further ahead and increase their dominance, and an insignificant or positive coefficient indicates decreasing dominance whereby laggards continue to invest in innovation and challenge leaders despite falling behind. The interaction between $Laggard_{it}$ and EPU_t allows the effect of being a laggard to vary based on the level of economic policy uncertainty, and we predict its coefficient to be positive.

Because EPU is measured at the national level for each period, the independent effect of EPU cannot be estimated with time fixed effects. Prior studies instead include an extensive set of controls for industry time-trends, such as the risk of recession, elections, industry lifecycle, and changes in consumer demand that could result in a spurious relation. In our analysis, the within-industry, within-firm shifts in a firm's position as a leader or laggard over time permit including year fixed effects and also year and 3-digit SIC code interacted fixed effects (Year×SIC3), which flexibly and robustly control for any industry-year trends unrelated to EPU and a firm's competitive position. An alternative explanation would have to meet the industry-level requirements of (i) coinciding with fluctuations in economy-wide uncertainty and (ii) having stronger effects in industries that better approximate features of R&D races, and the firm-level requirements of (iii) positively moderating the effects of EPU only on innovation and not other investments by laggards and (iv) showing effects on patents with lags while affecting other investments more immediately. In particular, requirement (iii) effectively rules out credit constraints and mismeasurement of investment opportunity, and we have been hard-pressed to find an alternative explanation that meets all four requirements.

All standard errors are two-way clustered at the firm and year level to address serial and cross-sectional correlation in the independent variables: *Laggard* and *EPU* (Peterson, 2009).

2.4. Control variables

We control for factors related to a firm's innovation performance and investment opportunities, including Tobin's Q, industry revenue growth rates, and firm size (log of sales). Prior research emphasizes liquidity constraint as a critical impediment to innovation, especially during recessions or periods of high uncertainty (Ouyang, 2011; Alfaro, Bloom, and Lin, 2019). We include four different measures of a firm's financial resources: distance from bankruptcy based on Altman's Z-score (1983), financial leverage based on its debt ratio, and financial slack measured with the current ratio (current assets divided by current liabilities) and working capital to sales ratio. To control for industry concentration, we include the Herfindahl-Hirschman Index (HHI) and its square term based on the revenue of Compustat firms. All industry-level controls are constructed at the 4-digit SIC code level, in line with our measure of a firm's competitive position.

We also verify robustness to controlling for a firm's total factor productivity but do not include it in our main specification as its computation results in significant sample attrition. The results are robust to including other firm and industry-level measures of economic uncertainty, including the CBOE Volatility Index (VXO) that captures investors' expectations for short-term (30-day) volatility in the stock market, the standard deviation of a firm's stock returns (Alfaro, Bloom, and Lin, 2019), and firm-level political risk (Hassan et al., 2019).

2.5. Sample

We start with the universe of U.S. public firms recorded in the Compustat database between 1985 and 2006. The time window is determined by the joint availability of the EPU index (1985-2018) and the patent data from Kogan et al. (2017) (1926-2010). We limit the window to 2006 because there is a discontinuous drop in patent coverage after 2006. This also helps to minimize truncation bias for analyses using citations and inventor mobility. Firms on average apply for 10.5 patents per year.[5] To address the concern that the results may be driven by outlier firms with extremely high and low performance, we start with firm-year observations with ROA less than 100 percent and greater than -100 percent and winsorize ROA at the 99^{th} and 1^{st} percentile. All of the results are unaffected by their inclusion. Our baseline sample consists of 72,338 firm-year observations. Lastly, we divide the EPU index by 100 for the ease of interpreting results. The EPU index has a mean of 1.01, a standard deviation of 0.25, and minimum and maximum values of 0.59 and 1.38. Figure 1 plots the annual mean of the EPU index for each calendar year.

--------------------------------------- Insert Table 1 Here ---------------------------------------

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3. Baseline results: Does EPU decrease the innovation gap?

In Table 2, we sequentially introduce economic policy uncertainty (*EPU*), a firm's competitive position (*Laggard*), and their interaction (*EPU*$\times$*Laggard*). The dependent variable is logged, and the coefficient is interpreted as a percentage change in firm innovation associated with changes in *EPU*. In column 1, EPU has a negative but insignificant effect (p=0.118). In column 2, there is a 1.4 percent decrease (p<0.01) in the number of patent applications when firms are in a laggard position relative to when they are in a leader position, indicating the dynamics of decreasing dominance that is more consistent with deterministic races. Including *EPU* and *Laggard* simultaneously in column 3 makes little difference to their coefficients. However, with the inclusion of their interaction in column 4, there is a drastic increase in their economic and statistical significance: one standard

5 This is higher than the mean value of 6.55 reported in Acharya et al. (2014). The difference stems from using a different time window and patent data from Kogan et al. (2017) that provide improved matching to Hall et al. (2001) used in Acharya et al. (2014).

deviation increase in policy uncertainty is associated with a 2.4 percent (p=0.041) decrease in firm innovation, and firms slow their rate of innovation by 8.5 percent in response to falling behind (p=0.024). This pattern indicates that a firm's competitive position is a critical context under which policy uncertainty shapes the incentives to engage in technological competition.

The coefficient on the interaction term *EPU*×*Laggard* is positive and significant (p=0.01) and sufficient in magnitude to almost fully moderate the decrease in laggards' innovation at the average level of EPU. With EPU ranging between 0.56 and 1.38, *EPU*×*Laggard* can swing the dynamics of technological competition from increasing to decreasing dominance where laggards innovate at the same or faster rate relative to leaders. Column 5 includes industry-year fixed effects, and EPU is subsumed and dropped from the estimation. Coefficients for both *Laggard* and *EPU*×*Laggard* remain largely unaffected. In Appendix C, we use the recent update to Kogan et al. (2017) by Stoffman, Woeppel, and Yavuz (2019) and expand the sample period to 2014; the overall results remain the same.

Taken together, we find that increasing policy uncertainty closes the gap in the rate of innovation between leaders and laggards and renders the technological competition to be more neck-and-neck. Our results also indicate that omitting a firm's competitive position poses a significant risk of under-specification and likely underpins some of the conflicting findings on the uncertainty-innovation relation in prior empirical studies.

Panel B repeats the analysis with capital investment (I/K) as the dependent variable.[6] As expected, firms reduce capital investment in response to high policy uncertainty and below-competitor performance. However, adding *EPU*×*Laggard* generates little difference to the coefficients of *EPU* and *Laggard*, and *EPU*×*Laggard* lacks both statistical and economic significance in column 4. The contrast to the pattern observed in Panel A indicates that

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[6] We find similar results using as the dependent value nominal values of capital investment (log) without the normalization by total asset. The coefficient of *EPU*×*Laggard* is positive and significant but moderates *Laggard* by less than 15%.

uncertainty affects innovation and capital investment differently and supports the argument that the positive effect of policy uncertainty on laggards' innovation stems from shifting the dynamics of technological competition, not mismeasurement of uncertainty or investment opportunities. Table 3 repeats the analysis in a specification that simultaneously includes four lags of *EPU, Laggard*, and $EPU \times Laggard$ between *t*-1 and *t*-4. Policy uncertainty affects laggards' innovation with a lag of three years, mitigating concerns of reverse causality.

------------------------------------ Insert Table 2 and 3 Here ------------------------------------

3.1. Alternative proxies of firm innovation and investment activities

Table 4 repeats the baseline analysis with alternative proxies of firm innovation and investment activities. We find a consistent pattern with respect to the number of citations received in columns 1 and 2 and the market value of patents in columns 3 and 4. Columns 5 and 6 examine the number of new inventor hires using the disambiguated inventor database by Li et al. (2014).[7] Firms reduce the hiring of new inventors in response to increasing policy uncertainty and below-competitor performance, but the interaction term $EPU \times Laggard$ again almost fully moderates the decrease in laggards' hiring. Columns 7 and 8 examine employment growth. Firms decrease employment by 0.68 percent (p=0.01) in response to one standard deviation increase in EPU and by 1.8 percent in response to below-competitor performance (p<0.01). The coefficient on the interaction term $EPU \times Laggard$ is positive and significant, but the moderation of 26.3 percent is significantly smaller compared to innovation-related variables that range between 71.2 percent (patent counts) and 84.8 percent (market values). Lastly, in columns 9-10, we examine marketing spend (log) as an alternative investment in a firm's intangible resources that are not subject to the dynamics of technological competition. EPU and below-competitor performance decreases marketing

[7] Data Appendix provides a more detailed description of how new inventors are identified as well as limitations of the approach.

spend significantly, but their interaction lacks economic and statistical significance.

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We next examine in Table 5 whether incorporating competitive interaction can inform the analysis of non-innovation variables, specifically acquisition activities that resemble innovation in terms of low investment reversibility and albeit more weakly, winner-takes-all dynamics.[8] In columns 1 through 3, EPU and below-competitor performance are associated with a substantive decrease in the number of acquisitions. The interaction term $EPU \times Laggard$ is positive and significant, moderating *Laggard* by 54.1 percent. The magnitude is greater than capital investment and employment growth but smaller than innovation-related variables. Columns 6-7 and 8-9 divide acquisitions into majority and minority acquisitions based on acquiring more or less than 50 percent of target firm equity. The overall effect on acquisitions is driven by majority acquisitions that take on strong winner-takes-all dynamics.

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3.2. Does EPU decrease leaders' innovation?

Models of decreasing dominance propose two distinct yet related dynamics of how laggards close the innovation gap and decrease leaders' dominance: increasing innovation by laggards (Reinganum, 1983) and decreasing innovation by leaders (Doraszelski, 2003). If the innovation process is stochastic, it can be optimal for leaders to 'rest on their laurels' and minimize replacing their own past innovations (Arrow, 1962), knowing that laggards cannot overtake them with certainty and that it is possible to reclaim their position even when laggards get lucky and pull ahead (Doraszelski, 2003).

Table 6 replaces the binary *Laggard* with a linear spline of a firm's competitive

[8] While only the successful bidder gets to acquire the target firm, unlike patents, it does not preclude rivals from acquiring other firms in the same industry and continuing with the competition.

position relative to the industry benchmark: *Overperformance* and *Underperformance*. This allows us to identify whether the negative effect of *Laggard* arises from decreasing innovation by leaders or increasing innovation by laggards and whether the positive interaction term *EPU*×*Laggard* arises from disincentivizing leaders or incentivizing laggards. Across columns 1 to 4, we find both dynamics to be present with respect to patent citations, patent market value, and new inventor hires: the coefficient of *Overperformance* is positive and *Underperformance* is negative, and both are moderated by interactions with EPU.

-- Insert Table 6 Here --

3.3. Does all categories of policy uncertainty matter equally?

In Table 7, we repeat the baseline analysis from column 4 of Table 2 but use the eleven category-specific measures of policy uncertainty from BBD. With respect to patent counts in Panel A, uncertainty in fiscal policy, regulation, national security, monetary policy, financial regulation, and government spending have the largest effects (in descending order) while uncertainty in sovereign debt, taxes, health care, and entitlement program has little to no effect. The pattern is consistent with the intuition that uncertainty in policies that affect returns to investing in innovation more materially should have larger effects. There is high correspondence in the effect sizes of negative *Uncertainty* and its positive moderation by *Uncertainty*×*Laggard*. Uncertainty in monetary policy is a notable exception with a large negative effect but insignificant moderation by its interaction with *Laggard*. While our argument assumes an uncertainty shock that affects leaders and laggards similarly, uncertainty in monetary policy asymmetrically penalizes lagging firms, especially in their ability to fund risky projects ('flight-to-quality') (Ouyang, 2011; Aghion et al., 2012; Alfaro, Bloom, and Lin, 2019). With respect to capital investment in Panel B, the coefficient for the interaction term *Uncertainty*×*Laggard* lacks significance in nine out of eleven categories except for a small negative effect for trade policy and health care.

These results indicate that not all types of uncertainty matter equally. In particular, the U.S. government wields an outsized influence on the dynamics of technological competition by influencing uncertainty in government spending, fiscal policy, and regulation (Pastor and Veronesi, 2012). The results also address the concern that the BBD index captures the effect of general economic uncertainty, rather than the effect of policy uncertainty. However, we expect our results to generalize to any uncertainty shock as long as it increases uncertainty in the outcomes of technological competition.

--------------------------------------- Insert Table 7 Here ---------------------------------------

3.4. Partisan conflict as an instrument for EPU

To further address potential omitted variable bias, we next use partisan polarization as an instrument for EPU. Partisan polarization leads to legislative gridlocks (McCarty, Poole, and Rosenthal, 2016) and, in turn, uncertainty in economic policy. We use the partisan-conflict index from the Federal Reserve Bank of Philadelphia (Azzimonti, 2018). Similar to BBD, this index is based on the frequency of newspaper articles reporting lawmakers' disagreement about policy. We expect it to satisfy the exclusion restriction, as "it is not immediately apparent how the level of disagreement between politicians on the liberal-conservative dimension should drive firm investment in a way other than through its effect on political uncertainty (Gulen and Ion, 2016:558)."

Both EPU and partisan conflicts are measured at the national level at a monthly frequency with the same values for all firms, and the usual two-stage least squares approach that estimates the first stage for each firm-year likely overestimates the instrument's relevance. We instead regress each subcomponent of the BBD index on the partisan-conflict index at a monthly frequency and take the average of fitted values for each calendar year. The partisan-conflict index is a strong instrument for eight of the eleven sub-components of EPU with the exception of sovereign, financial regulation, and trade uncertainty (the first-stage results are reported in Appendix D). While being a strong instrument for several subcategories individually, the partisan index is a weak instrument for overall EPU because it negatively predicts security uncertainty ('rally around the flag' effect) and monetary uncertainty while positively predicting other components. In Table 8, we focus on fiscal policy, government spending, and financial regulation uncertainty that show the largest effect in Table 7. Because we are using estimated regressors, standard errors are bootstrapped with two-way clustering at the firm and year level using the algorithm from Gow, Ormazabal, and Taylor (2010).[9] While policy uncertainty is no longer independently significant, we arrive at essentially the same conclusion with similar marginal effects: high levels of uncertainty significantly moderates a decline in laggards' innovation.

--------------------------------------- Insert Table 8 Here ---------------------------------------

3.5. Mechanisms: erosion of knowledge stock

In Table 9, we test whether EPU erodes firms' existing knowledge stock to the effect of resetting the playing field. Knowledge accumulation (or "learning") serves as a critical barrier to laggards' catching up; it advantages currently successful firms by increasing the productivity of their R&D investment and permits them to retain technological leadership even while investing less (Harris and Vickers, 1985; Doraszelski, 2003; Klette and Kortum, 2004).

We proxy for a firm's knowledge stock ($\textit{Past R\&D Investment}_{it}$) as the average R&D investment (log) in the past three years (t+0, t-1, and t-2) with an annual discount rate of 15 percent.[10] We then estimate how $\textit{Past R\&D Investment}_{it}$ affects future innovation performance in a specification analogous to equation (2). Because incorporating knowledge accumulation (or any other forms of path dependence) greatly complicates deriving closed-

[9] Available at http://acct.wharton.upenn.edu/~dtayl/code.htm
[10] Other feasible lags and discount rates provide consistent results.

form results, most models of R&D races are ‘memoryless’ and assumes the coefficient on *Past R&D Investment*$_{it}$ to be zero. We find that a ten percent increase in *Past R&D Investment*$_{it}$ is associated with 1.28 percent higher patent counts and 2.28 percent higher patent value at *t*+3 even after controlling for firm and industry-year fixed effects. The coefficient on *EPU*×*Past R&D Investment*$_{it}$ is negative and moderates the positive effect of *Past R&D Investment*$_{it}$ on patent counts by 39.8 percent and on patent values by 50.4 percent. We do not observe any effects on citations received.

--------------------------------------- Insert Table 9 Here --

3.6. Mechanisms: increasing stochasticity in innovation

In Table 10, we divide our sample into industries that approximate stochastic *versus* deterministic races. If EPU’s positive effect on laggards’ innovation is indeed driven by the shift in dynamics of technological competition from a deterministic to a stochastic race, then models of R&D races provide three cross-sectional predictions. First, the coefficient of *Laggard* should be more negative in deterministic industries. Deterministic races are characterized by a period of intense competition when firms compete neck-and-neck, but once a firm pulls ahead, laggards stop innovating knowing that it is impossible to overtake the leader (i.e., ‘ε-preemption’). Second, the independent negative effect of policy uncertainty should be weaker in stochastic industries where firms already deal with high levels of uncertainty. Third, the positive coefficient on *EPU*×*Laggard* should be larger in deterministic industries relative to stochastic industries where there is little innovation gap between leaders and laggards in the first place.

We first estimate the stochasticity in the R&D process for each 2-digit SIC code using the following regression:

$$\textit{Market value of patents}_{it} = \alpha_i + \beta_1 \textit{Past R\&D Investment}_{it} + \varepsilon_{it} \quad (3)$$

High β_1 indicates that R&D investment produces valuable innovation with high certainty in a deterministic process while low β_1 indicates a stochastic process. Columns 1 and 2 divide our sample into high and low uncertainty industries based on the median value of β_1.[11] Columns 3 and 4 and 5 and 6 divide each 2-digit SIC code based on the persistence in R&D spending and firm performance estimated from regressing R&D spending and industry adjusted ROA at time t+1 on t+0.

$$R\&D\ spending_{it+1} = \alpha_i + \beta_1\ R\&D\ spending_{it} + \varepsilon_{it} \tag{4}$$

$$Industry\ adjusted\ ROA_{it+1} = \alpha_i + \beta_1\ Industry\ adjusted\ ROA_{it} + \varepsilon_{it} \tag{5}$$

Stochastic races are characterized by frequent churns in a firm's competitive position as a leader or laggard (i.e., decreasing dominance), and firms actively adjust their R&D investment based on their competitive position as a leader or laggard (Reinganum, 1983). This reduces persistence in R&D spending and performance, resulting in low β_1. Deterministic races where leaders continue to innovate and win is characterized by high persistence in R&D and performance, resulting in high β_1.

Across all three subsamples, coefficients on *Laggard*, *EPU*, and *EPU*×*Laggard* are substantially larger in deterministic industries (columns 1, 3, and 5). In contrast, with respect to capital investment in Panel B, the differences in the statistical and economic significance of *EPU* and *Laggard* are negligible, and *EPU*×*Laggard* again lacks significance. These results provide highly nuanced evidence that EPU closes the innovation gap by making technological competition more stochastic.

-- Insert Table 10 Here --

3.7. Mechanisms: R&D races

We examine in Table 11 whether EPU's positive effect on laggards' innovation is stronger in industries that more closely approximate the features of R&D races. In columns 1 and 2, we

[11] Industries with high values of β_1 include Oils and Gas Extraction, Heavy Construction, and Paper Products. Industries with low values of β_1 include Chemicals and Allied Products, Electronic and other Electrical Equipment, and Business Services including software companies.

test the intuition that the dynamics of technological competition modeled in R&D races better characterize R&D intensive industries and divide each 3-digit SIC code based on the median value of average industry R&D intensity. Columns 3 and 4 divide each 3-digit SIC code into technologically fast or slow-moving industries based on the mean speed at which patents accumulate citations (Fabrizio and Tsolmon, 2014). We expect fast-moving industries to better approximate R&D races where firms compete to be the first to discover and patent valuable technology. The coefficients for *Laggard* and $EPU \times Laggard$ show higher economic and statistical significance in columns 1 and 3.[12] The negative independent effect of EPU is also larger in columns 1 and 3, consistent with policy uncertainty taking a larger toll in industries with higher R&D intensity and shorter payoff periods (Bar-Ilan and Strange, 1996).

Columns 5 and 6 divide each 3-digit SIC code based on the median value of industry differentiation based on Hoberg and Phillips (2016) that estimate the degree of a firm's product-level similarity with its competitors. The racing models assume that firms compete against each other head-to-head instead of avoiding direct competition through differentiation. The coefficients for *Laggard* and $EPU \times Laggard$ are larger in low differentiation industries.

Columns 7 and 8 divide each 3-digit SIC code based on its growth potential proxied by the median value of industry Tobin's Q. EPU has a significant negative effect only in industries with low growth potential, consistent with the presence of the positive growth-option effect that offsets the negative effect of uncertainty. In contrast, there is little difference in the coefficients of *Laggard* and $EPU \times Laggard$, which suggests that EPU's effect on the leader-laggard interaction operates through a separate channel.

With respect to capital investment in Panel B, the coefficient on $EPU \times Laggard$

[12] There is concern that the lag structure may be different for fast versus slow changing industries. The pattern holds across various lags of *Laggard* and $EPU \times Laggard$.

uniformly lacks economic and statistical significance, and there is little difference in the coefficients of EPU in columns 3 through 8. These results provide consistent support for our argument and show that the effect of uncertainty on innovation can vary significantly based on a firm's competitive position and industry-level characteristics such as R&D intensity, the pace of technological change, and growth potential.

------------------------------------ Insert Table 11 Here ------------------------------------

3.8. Mechanisms: industry-level competitive intensity

In Table 12, we divide each 3-digit SIC code into high, medium, and low concentration industries based on the Herfindahl-Hirschman Index estimated by Hoberg and Phillips (2010) and examine how industry-level competitive intensity affects (i) the independent effect of EPU on uncertainty and (ii) its positive effect on laggards' innovation.

Whether industry concentration positively or negatively moderates the negative effect of EPU on innovation remains an empirical question due to two competing effects. On the one hand, competition increases the risk of being preempted and the cost of waiting for uncertainty to resolve, decreasing the negative effect of policy uncertainty on firm investment (Grenadier, 2002; Weeds, 2002; Novy-Marx, 2007; Mason and Weeds, 2010). With respect to innovation, however, the intense competition also reduces the duration of Schumpeterian rent and the value of innovation as options for future growth, decreasing the potential positive effect of uncertainty (Aghion et al., 2005). We first start by replicating in Panel B the result from Bonaime et al. (2018) who find that competition moderates the negative effect of EPU on acquisitions.[13] EPU has a significantly larger negative effect in high concentration industries relative to low concentration industries with a higher risk of competitive preemption. We observe the opposite pattern with respect to innovation in Panel A; the

[13] Their analysis is at the quarterly frequency. We keep our analysis at the yearly level to compare effect sizes against other dependent variables measured at yearly frequency.

negative coefficient of *EPU* is larger and significant only in low concentration industries, indicating that the Schumpeterian and growth option effects are substantial (as observed in columns 7 and 8 of Table 11) and outweigh the risk of preemption.

With respect to the leader-laggard interaction, R&D racing models assume an imperfect, duopolistic or oligopolistic competition where firms act and react to a tractable number of rivals, and we expect EPU's positive effect on laggards' innovation to be attenuated in highly competitive markets with a large number of firms (Cabral and Riordan, 1994; Athey and Schmutzler, 2001). The coefficients of *Laggard* and $EPU \times Laggard$ are larger in more concentrated industries for both innovation in Panel A and acquisitions in Panel B.

These results verify existing considerations of industry-level competitive intensity based on preemption risks but also establish the firm-level, leader-laggard interaction as a distinct channel through which uncertainty affects innovation and firm investment.

------------------------------------- Insert Table 12 Here -------------------------------------

3.9. Mechanisms: real options *versus* competitive interactions

In Table 13, we divide our sample based on investment reversibility and explicate the real options effect from competitive interactions. Investment reversibility reduces the cost of making mistakes and, in turn, the benefits of delaying investment for the uncertainty to resolve (Kim and Kung, 2016). For the same reason, reversibility may reinforce laggards' response to falling behind; it reduces the cost of risk-taking and experimentation necessary to increase innovation. This leads to a stronger, rather than weaker, positive effect of EPU on laggards' innovation in high reversibility industries.

Lacking a measure of reversibility specific to R&D investment, we divide each 3-digit SIC code based on four industry-level proxies of reversibility in capital investment (Gulen and Ion, 2016; Bonaime et al., 2018). We first estimate the share of sunk costs by dividing firms' rent expense, depreciation expense, and past sale of PP&E by lagged net PP&E (Kessides, 1990; Farinas and Ruano, 2005). The costs of investing in physical assets that are rented, depreciate faster, or have an active secondary market can be more readily recouped in the case of an unexpected adverse shock. Second, we estimate the specificity of investments by looking at how widely the input resources are used across different industries (Kim and Kung, 2016). Active secondary markets facilitate access to new resources and also reduce the cost of liquidating past investments. We use the 1997 BEA capital flows table from the Bureau of Economic Analysis (BEA), which contains capital expenditures data for 123 industries across 180 asset categories. Asset specificity is calculated as the share of industries that use a given asset category, weighted by the percentage share to the industry's total expenditure. Third, we use the industry capital intensity ratio, calculated as the mean value of net PP&E divided by the total value of assets. The assumption is that firms in capital-intensive industries tend to use more firm-specific and illiquid physical equipment. Fourth, we estimate the liquidation values based on the cyclicality of firm sales (Almeida and Campello, 2007). Firms in highly cyclical industries are more likely to sell their assets at the same time and be forced to provide deeper discounts. We estimate cyclicality by regressing each firm's quarterly sales on GNP for each 3-digit SIC code and take their coefficients (Gulen and Ion, 2016).

We first show in Panel B that our proxies of investment reversibility behave as expected. EPU has stronger negative effects on capital investment in low reversibility industries in columns 1, 3, 5, and 7 relative to high reversibility industries in columns 2, 4, 6, and 8. Laggards also make a larger reduction in capital investment in low reversibility industries, consistent with the higher risk of accessing new resources that constrain an aggressive response. The coefficient of $EPU \times Laggard$ is insignificant across both conditions with the exception of a small negative effect in column 7.

We find the opposite pattern with respect to innovation in Panel A. The positive coefficient of *EPU*×*Laggard* is consistently larger in high reversibility industries and lacks statistical significance in low reversibility industries with the exception of column 5. We also find that the coefficients of *Laggard* and *EPU* are larger in high reversibility industries. This is driven in significant part by the overlap in investment reversibility and other industry characteristics that amplify the effects of EPU on innovation examined in Table 10 and Table 11; capital-intensive industries are not only lower in investment reversibility but also persistence in firm performance (Villalonga, 2004; Peter and Taylor, 2017) and R&D spending relative to knowledge-intensive industries. In our sample, the correlation of capital intensity to persistence in firm performance and R&D spending (β_1 from equations 4 and 5) is -0.53 and -0.44. The overall pattern demonstrates the leader-laggard interaction as a distinct channel that differs from real options considerations based on investment reversibility.

--------------------------------------- Insert Table 13 Here ---------------------------------------

4. EPU and Persistence of Under-Performance

It is unclear whether EPU's effect on laggards' innovation should have more downstream consequences on firm performance and industry dynamism. Closing the innovation gap should increase industry dynamism. However, EPU also decreases the *absolute* level of firm innovation and investments, which should reinforce the status quo.

Table 14 examines whether EPU affects the persistence of firm performance, specifically the pace at which laggards' performance reverts upward to the industry mean. In a specification similar to equation 5, we regress a firm's ROA at year *t*+1 on its positive and negative performance relative to the industry performance benchmark at year *t*+0. Given the autoregressive model that includes linear splines of the lagged dependent variable, we estimate a random-effects model and exclude firm fixed effects to address Nickell's bias (1981) (Villalonga, 2004; Bennett and Gartenberg, 2016). A coefficient of one for

Underperformance and *Overperformance* indicates that 100 percent of the current performance carries over to the next year whereas a coefficient of zero indicates a random walk.

We find significant persistence in both positive and negative performance in column 1. In looking at how EPU affects the persistence of firm performance in column 2, the coefficient of *EPU*×*Underperformance* is positive and reduces the persistence of negative performance by 24.2 percent (p<0.01), consistent with accelerated catch up by laggards. In contrast, *EPU*×*Overperformance* lacks both statistical and economic significance. Adding industry-year fixed effects in column 3 makes little difference to the overall findings. We expand the sample period to 2014 in columns 4 through 6 as there is no requirement for patent-related data and find a consistent pattern.

--------------------------------------- Insert Table 14 Here ---------------------------------------

Table 15 repeats the analysis from column 3 of Table 14 but divides the sample into deterministic and stochastic industries as in Table 10. EPU has a stronger effect of accelerating the upward reversion in deterministic industries characterized by high technological certainty (column 1 *versus* 2), high persistence in R&D spending (column 3 *versus* 4), and high persistence in firm performance (column 5 *versus* 6). The results are well-aligned with the earlier results on innovation and support the closing innovation gap as driving the accelerated catch-up.

Table 16 uses a more blunt binary measure *Lead* as the dependent variable that equals one if firm performance beats the industry benchmark. We estimate a linear probability model that simultaneously includes four lags (t-1 to t-4) of *EPU*, *Laggard*, and *EPU*×*Laggard*. Consistent with the persistence of negative performance and the mean reversion in firm performance over time, a firm's status as a laggard negatively predicts the likelihood of becoming a leader, but its importance declines over time from 32.7 percent at t-

1 to 8.2 percent at t-4. The coefficient on $EPU_{t-n} \times Laggard_{t-n}$ becomes positive in three years and becomes statistically significant in four years. The accelerated catch-up observed in Table 15 accumulates and contributes to beating the industry benchmark over four years, around the timing of increased innovation by laggards. Industry-year fixed effects make little difference in column 2. Refer to Appendix E for results with longer lags.

---------------------------------- Insert Table 15 and 16 Here ----------------------------------

4.1. EPU and industry concentration

Lastly, in an auxiliary analysis, we shift the unit of analysis from firm-year to industry-year and examine how EPU affects industry concentration. An influential body of research within economics and finance relates uncertainty and business cycles (e.g., Bernanke, 1983; Hubbard, 1994; Dixit and Pindyck, 1994; Klette and Kortum, 2004), but how uncertainty affects industry concentration remains scarcely examined. As its empirical proxy, we obtain HHI from Hoberg and Phillips (2010) that combines Compustat data with Census Bureau data to estimate revenue-based HHI that covers both public and private firms for each SIC3-year. EPU likely affects entry and firm formation, and the inclusion of private firms is critical to assessing the accurate effect of uncertainty on industry concentration.

In column 1 of Table 17, we first examine how EPU from year t-1 to t-4 affects industry concentration at year t+0. EPU has a deconcentrating effect with a lag of four years. The substantive lag is consistent with the lagged effect on innovation and overtaking leaders (Table 16) but confounds attributing decreasing concentration to the closing innovation gap, especially as EPU affects acquisitions and other firm investments. Columns 2 through 9 divide the sample into deterministic and stochastic industries as in Table 10. The deconcentrating effect of EPU is stronger in industries with low technological uncertainty and high persistence in firm R&D activities in columns 2 and 4, consistent with earlier findings on innovation and accelerated upward reversion. However, EPU has a significant but smaller effect in industries with high persistence in firm performance in column 7.

These results are robust to the first-difference specification as well as controlling for a wide range of macroeconomic control variables, such as the consumer confidence index from the University of Michigan, expected GDP growth from the biannual Livingstone Survey, and other industry-level measures of uncertainty. Using the instrumented values of EPU yields consistent results (reported in Appendix F).

--------------------------------------- Insert Table 17 Here ----------------------------------

5. Conclusion

The causes of declining industry dynamism have been at the center of academic and policy debates in recent years. We examine the effect of uncertainty on technological competition and industry dynamism. Using a news-based index of economic policy uncertainty in the U.S. from Baker, Bloom, and Davis (2016), we find highly robust and nuanced support for the argument that policy uncertainty closes the gap in the rate of innovation between leaders and laggards and increases industry dynamism. Our findings indicate that uncertainty affects firm investment and innovation through at least three distinct channels: (i) real options effect based on investment irreversibility reflected in the negative independent effect of EPU on innovation, capital investment, employment, and acquisitions (ii) growth options effect reflected in the moderation of the negative effect of EPU in high growth industries and competitive industries, and (iii) the competitive interaction between leaders and laggards captured in the significant interaction between EPU and a firm's position as a laggard. As a result, the effects of EPU vary significantly both *within* industries based on a firm's competitive position and *across* industries based industry-level characteristics, such as uncertainty in the innovation process, persistence in performance, R&D intensity, the pace of technological change, competitive intensity, and growth potential.

These results have important, counterintuitive policy implications. There are growing calls to reduce policy uncertainty, for example, by increasing transparency to the Fed's interest rate-setting process, reducing legislative gridlocks and government shutdowns, and streamlining the patent approval process. These measures should increase the overall level of innovation and firm investment but can also take away uncertainties in innovation and competitive processes that create opportunities for laggards to challenge and overtake leaders. To the extent that increasing industry concentration generates inefficiencies, our study shows that even policy uncertainty, even those that arise from partisan conflicts and legislative gridlocks, has a silver lining.

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Table 1. Sample statistics

Variables	N	Mean	SD	Min	Max	Data Source
1. Economic policy uncertainty$_t$ (EPU)	72,338	1.02	0.25	0.59	1.38	Baker, Bloom, and Davis (2016)
2. Patent counts$_{t+3}$	72,338	10.50	96.84	0.00	4,422	Kogan et al. (2017)
3. Patent counts$_{t+3}$ (log)	72,338	0.55	1.15	0.00	8.39	Kogan et al. (2017)
4. Patent citations$_{t+3}$ (log)	72,338	0.91	1.90	0.00	11.47	Kogan et al. (2017)
5. Patent market value$_{t+3}$ (log)	72,338	0.71	1.71	0.00	11.56	Kogan et al. (2017)
6. Capital investment intensity$_{t+1}$	82,345	0.08	0.10	0.00	0.87	Compustat
7. Employee growth$_{t+1}$	83,688	0.02	0.11	-0.33	0.45	Compustat
8. Acquisition$_{t+1}$ (log)	88,159	0.27	0.51	0.00	4.34	SDC platinum
9. Laggard$_t$ (=1)	72,338	0.44	0.50	0.00	1.00	Compustat
10. Industry adjusted performance$_t$	72,338	-0.03	0.19	-1.07	1.27	Compustat
11. Overperformance$_t$	72,338	0.04	0.07	0.00	1.27	Compustat
12. Underperformance$_t$	72,338	0.07	0.16	0.00	1.07	Compustat
13. Total asset$_t$ (log)	72,338	4.80	2.22	0.02	12.51	Compustat
14. Debt ratio$_t$	72,338	0.24	0.26	0.00	12.60	Compustat
15. Current ratio$_t$	72,338	3.19	9.50	-0.03	1456	Compustat
16. Working capital to sales ratio$_t$	72,338	2.58	88.06	-2,692	13,450	Compustat
17. Distance to bankcruptcy$_t$	72,338	5.91	25.82	-1,959	2,566	Compustat
18. Industry concentration$_t$	72,338	0.24	0.18	0.02	1.00	Compustat
19. Industry concentration$_t$	63,254	0.06	0.02	0.03	0.25	Hoberg and Phillips (2010)

This table presents summary statistics for the main variables used in the study. The baseline sample includes all Compustat firms between 1985 and 2003 and their patent portfolio between 1988 and 2006, which is measured with a lead period of three years. *Patent counts*, *Patent citations*, and *Patent market value* are from Kogan et al. (2017). For patent-related variables, we transform them by taking the natural log of one plus their nominal values. The measure of news-based economic policy uncertainty (*EPU*) comes from Baker, Bloom, and Davis (2016). *Laggard* is a binary variable that takes the value of one if firm performance (ROA) exceeds the industry performance benchmark and zero otherwise for each firm-year. *Industry adjusted performance* is the difference between the nominal firm ROA and the industry median ROA at the 4-digit SIC code level. *Overperformance* and *Underperformance* capture the positive and negative components of *Industry adjusted performance* in a linear spline. Refer to Appendix A for a detailed description of how each variable is constructed.

Table 2. Economic policy uncertainty and innovation by laggards

	(1)	(2)	(3)	(4)	(5)
Panel A	DV: Patent count$_{t+3}$ (log)				
EPU$_t$	-0.064		-0.064	-0.094**	
	[0.039]		[0.039]	[0.041]	
Laggard$_t$		-0.014***	-0.014***	-0.085***	-0.085***
		[0.005]	[0.005]	[0.024]	[0.025]
EPU$_t$ × Laggard$_t$				0.069**	0.065**
				[0.025]	[0.025]
Adj. R-squared	0.88	0.88	0.88	0.88	0.89
Obs.	72,338	72,338	72,338	72,338	72,338
Panel B	DV: Capital investment (I/K)$_{t+1}$				
EPU$_t$	-0.017***		-0.017***	-0.016***	
	[0.005]		[0.005]	[0.005]	
Laggard$_t$		-0.018***	-0.018***	-0.016***	-0.016***
		[0.001]	[0.001]	[0.004]	[0.004]
EPU$_t$ × Laggard$_t$				-0.002	-0.002
				[0.004]	[0.004]
Adj. R-squared	0.52	0.52	0.52	0.52	0.57
Obs.	82,345	82,345	82,345	82,345	82,345
Controls	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*yes*
Obs.	79,555	79,555	79,555	79,555	79,555

This table reports OLS estimations of equation (1). We regress patent counts (Panel A) and capital investment intensity (Panel B) on economic policy uncertainty (*EPU*), a binary variable for a firm's competitive position (*Laggard*), and their interaction. Patent counts and capital investment intensity have a lead period of three years and one year, respectively. All specifications include as controls Tobin's Q, industry growth rate, firm size, industry concentration based on HHI and its square term, four proxies of financial constraint, and firm fixed effects. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Lagged effects of EPU on innovation

DV:	Patent count$_t$ (log)							
	(1)				(2)			
	Run simultaneously				Run simultaneously			
	n = 1	*n* = 2	*n* = 3	*n* = 4	*n* = 1	*n* = 2	*n* = 3	*n* = 4
EPU$_{t-n}$	-0.021	-0.032*	-0.015	0.004				
	[0.026]	[0.016]	[0.024]	[0.020]				
Laggard$_{t-n}$	-0.025	-0.026	).064***	-0.041*	-0.022	-0.026	-0.055**	-0.041*
	[0.021]	[0.021]	[0.021]	[0.021]	[0.022]	[0.022]	[0.022]	[0.021]
EPU$_{t-n}$ × Laggard$_{t-n}$	0.023	0.028	0.063**	0.037*	0.020	0.028	0.053**	0.034
	[0.023]	[0.022]	[0.023]	[0.020]	[0.022]	[0.022]	[0.022]	[0.020]
Controls	*yes*				*yes*			
Firm FE	*yes*				*yes*			
Year × SIC3 FE	*no*				*yes*			
Adj. *R*-squared	0.89				0.90			
Obs.	54,270				54,270			

This table repeats the OLS estimation from Table 2 in a specification that simultaneously includes four lags of the main independent variables. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Alternative proxies of firm innovation and investment activities

DV:	Citations$_{t+3}$		Patent value$_{t+3}$		Inventor hire$_{t+3}$		Emp. growth$_{t+1}$		Marketing$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPU$_t$	-0.099		-0.171**		-0.174***		-0.027**		-0.093***	
	[0.148]		[0.075]		[0.047]		[0.009]		[0.028]	
Laggard$_t$	-0.163***	-0.185***	-0.165***	-0.166***	-0.099***	-0.101***	-0.038***	-0.037***	-0.036*	-0.042*
	[0.045]	[0.038]	[0.040]	[0.039]	[0.020]	[0.019]	[0.005]	[0.005]	[0.020]	[0.022]
EPU$_t$ × Laggard	0.135***	0.141***	0.140***	0.134***	0.088***	0.087***	0.010**	0.009*	0.013	0.014
	[0.039]	[0.032]	[0.039]	[0.037]	[0.017]	[0.017]	[0.005]	[0.005]	[0.019]	[0.020]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*
Adj. R-squared	0.78	0.81	0.87	0.88	0.67	0.71	0.27	0.34	0.97	0.98
Obs.	72,338	72,338	72,338	72,338	72,338	72,338	83,688	83,688	28,655	28,655

This table repeats the baseline analysis from Table 2 using alternative proxies of firm innovation and investment activities. Dependent variables are *ln(1+number of citations received)* in column 1, *ln(1+market value of patents)* in column 2, *ln(1+number of new inventors)* in column 3, the year-to-year percentage change in the number of employees in column 4, and *ln(1+the number of announced acquisitions)* in column 5. Acquisitions are divided into majority and minority share acquisitions in columns 6 and 7 based on whether the deal involves more than 50% of a target company's shares. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. EPU and acquisitions

DV:	Acquisition$_{t+1}$ (log)								
	All					Majority		Minority	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPU$_t$	-0.135***		-0.135***	-0.168***		-0.112***		-0.023***	
	[0.032]		[0.032]	[0.037]		[0.022]		[0.007]	
Laggard$_t$		-0.061***	-0.061***	-0.135***	-0.136***	-0.096***	-0.099***	-0.014***	-0.014***
		[0.006]	[0.006]	[0.020]	[0.020]	[0.016]	[0.017]	[0.005]	[0.005]
EPU$_t$ × Laggard$_t$				0.073***	0.069***	0.050***	0.049***	0.010*	0.009*
				[0.020]	[0.019]	[0.016]	[0.016]	[0.005]	[0.005]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*yes*	*no*	*yes*	*no*	*yes*
Adj. R-squared	0.52	0.52	0.52	0.52	0.56	0.46	0.51	0.35	0.40
Obs.	88,159	88,159	88,159	88,159	88,159	88,159	88,159	88,159	88,159

This table repeats the baseline analysis from Table 2 with the *number of acquisitions (log)* as the dependent variable. Acquisitions are divided into majority and minority share acquisitions based on whether the deal involves more than 50% of a target company's shares. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Does EPU slow down leaders' innovation?

DV:	Patent count$_{t+3}$	Patent citation$_{t+3}$	Patent value$_{t+3}$	Inventor hire$_{t+3}$
	(1)	(2)	(3)	(4)
Overperformance$_t$	0.521***	0.785**	0.934***	0.424**
	[0.173]	[0.294]	[0.272]	[0.155]
Underperformance$_t$	-0.101	-0.422***	-0.203**	-0.226***
	[0.069]	[0.135]	[0.086]	[0.060]
EPU$_t$ × Overperformance$_t$	-0.416**	-0.734**	-0.728***	-0.389**
	[0.162]	[0.264]	[0.249]	[0.137]
EPU$_t$ × Underperformance$_t$	0.104	0.310**	0.226**	0.213***
	[0.071]	[0.119]	[0.090]	[0.056]
Controls	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*
Adj. R-squared	0.89	0.81	0.88	0.71
Obs.	72,338	72,338	72,338	72,338

This table replaces the binary *Laggard* with a linear spline of firm performance. *Overperformance* (*Underperformance*) takes the nominal value of industry adjusted firm performance (ROA) if firm performance is positive (negative), and zero otherwise. *Underperformance* takes a negative value by construction, and we take its negative value for the ease of interpretation. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Policy uncertainty by subcategories

Category:	Monetary policy (1)	Fiscal policy (2)	Taxes (3)	Gov. spending (4)	Health care (5)	National security (6)	Entitlemt. program (7)	Regulation (8)	Financial regulation (9)	Trade policy (10)	Sovereign debt (11)
Panel A	DV: Patent count$_{t+3}$ (log)										
Uncertainty$_t$	-0.066**	-0.085**	-0.001**	-0.060**	0.000	-0.067***	0.000	-0.083**	-0.062***	0.021*	0.013***
	[0.026]	[0.034]	[0.000]	[0.022]	[0.023]	[0.018]	[0.000]	[0.034]	[0.017]	[0.012]	[0.004]
Laggard$_t$	-0.046	-0.057***	-0.044**	-0.061***	0.002	-0.037***	0.023	-0.067***	-0.041***	-0.012	-0.014**
	[0.028]	[0.016]	[0.017]	[0.011]	[0.012]	[0.011]	[0.018]	[0.023]	[0.008]	[0.009]	[0.006]
Uncertainty$_t$ × Laggard$_t$	0.030	0.043**	0.031	0.043***	-0.018	0.021*	-0.036*	0.055**	0.031***	-0.003	-0.001
	[0.028]	[0.017]	[0.019]	[0.009]	[0.013]	[0.011]	[0.018]	[0.024]	[0.009]	[0.005]	[0.002]
Adj. R-squared	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Obs.	72,338	72,338	72,338	72,338	72,338	72,338	72,338	72,338	72,338	72,338	72,338
Panel B	DV: Capital investment$_{t+1}$										
Uncertainty$_t$	-0.015***	-0.009**	-0.000**	-0.004	-0.002	-0.010***	0.000	-0.017**	-0.010***	0.003**	0.001
	[0.003]	[0.004]	[0.000]	[0.003]	[0.004]	[0.002]	[0.000]	[0.006]	[0.002]	[0.001]	[0.001]
Laggard$_t$	-0.019***	-0.018***	-0.019***	-0.017***	-0.015***	-0.018***	-0.020***	-0.014***	-0.018***	-0.015***	-0.018***
	[0.004]	[0.003]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]	[0.004]	[0.002]	[0.001]	[0.001]
Uncertainty$_t$ × Laggard$_t$	0.001	0.000	0.000	-0.001	-0.003*	0.000	0.002	-0.005	0.000	-0.003***	0.000
	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.004]	[0.002]	[0.001]	[0.000]
Adj. R-squared	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52
Obs.	82,345	82,345	82,345	82,345	82,345	82,345	82,345	82,345	82,345	82,345	82,345
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*

This table replaces the aggregate measure of EPU with its eleven category-specific components. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Instrumental variable estimation using partisan conflict index

DV:	Patent count$_{t+3}$					
Category:	Fiscal policy		Gov. spending		Regulation	
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty$_t$	0.114		0.091		0.127	
	[0.237]		[0.191]		[0.261]	
Laggard$_t$	-0.387***	-0.384***	-0.303***	-0.302***	-0.438***	-0.434***
	[0.145]	[0.148]	[0.112]	[0.110]	[0.160]	[0.169]
Uncertainty$_t$ × Laggard$_t$	0.383**	0.377**	0.304**	0.300**	0.426**	0.419**
	[0.151]	[0.154]	[0.112]	[0.118]	[0.163]	[0.172]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*yes*	*no*	*yes*	*no*	*yes*
Adj. R-squared	0.88	0.89	0.88	0.89	0.88	0.89
Obs.	72,338	72,338	72,338	72,338	72,338	72,338

This table replicates the OLS estimation from Table 6 in a two-stage least-squares analysis. The three subcategories of policy uncertainty – fiscal policy, government spending, and regulation – are predicted with the partisan conflict index from Azzimonti (2018) as the instrument. Standard errors are bootstrapped with two-way clustering at the firm and year level as in Gow, Ormazabal, and Taylor (2010) with one thousand repetitions, and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Does policy uncertainty erode knowledge stock?

DV:	Patent count$_{t+3}$		Patent citation$_{t+3}$		Patent value$_{t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Past R&D Investment$_t$	0.128***	0.211***	-0.088*	-0.033	0.114**	0.228***
	[0.027]	[0.037]	[0.043]	[0.100]	[0.048]	[0.075]
EPU$_t$ × Past R&D Investment$_t$		-0.084***		-0.056		-0.115**
		[0.025]		[0.110]		[0.053]
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R-squared	0.89	0.89	0.82	0.82	0.89	0.89
Obs.	70,754	70,754	70,754	70,754	70,754	70,754

This table reports OLS estimations on the effect of past R&D investment on future patent counts. *Past R&D Investment$_t$* is defined as the average firm R&D investment (log) in the past three years with an annual discount rate of 15%. Columns 3 and 4 divides each 2-digit SIC code into technologically high and low uncertainty industries based on whether R&D investment translates to valuable patents with high certainty, estimated using equation (3). Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Deterministic *versus* stochastic industries

	Tech. certainty		Perf. persistence		R&D persistence	
	High	Low	High	Low	High	Low
Panel A	DV: Patent count$_{t+3}$					
EPU$_t$	-0.122**	-0.064	-0.138**	-0.034	-0.129**	-0.046*
	[0.052]	[0.038]	[0.063]	[0.020]	[0.060]	[0.024]
Laggard$_t$	-0.117***	-0.060**	-0.112***	-0.046*	-0.099***	-0.059**
	[0.039]	[0.026]	[0.031]	[0.024]	[0.030]	[0.028]
EPU$_t$ × Laggard$_t$	0.090**	0.054*	0.100***	0.027	0.084**	0.045
	[0.039]	[0.026]	[0.031]	[0.024]	[0.029]	[0.028]
Adj. R-squared	0.88	0.87	0.88	0.86	0.88	0.84
Obs.	32,007	35,758	37,267	34,211	39,074	30,743
Panel B	DV: Capital investment (I/K)$_{t+1}$					
EPU$_t$	-0.022***	-0.011*	-0.010*	-0.022***	-0.017***	-0.015***
	[0.005]	[0.006]	[0.005]	[0.006]	[0.005]	[0.005]
Laggard$_t$	-0.014**	-0.013**	-0.016***	-0.013**	-0.018***	-0.010**
	[0.006]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]
EPU$_t$ × Laggard$_t$	-0.001	-0.006	-0.002	-0.004	-0.003	-0.003
	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]
Adj. R-squared	0.53	0.52	0.43	0.55	0.52	0.54
Obs.	36,344	40,790	41,895	39,460	44,064	35,439
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*no*	*no*

This table estimates whether policy uncertainty (*EPU*) has stronger effects in industries characterized by low levels of uncertainty. Each 2-digit SIC code is divided into high versus low uncertainty based on the uncertainty in returns to R&D investments estimated in equation (3) in columns 1 and 2; the persistence in R&D spending estimated in equation (4) in columns 3 and 4; and the persistence in industry-adjusted ROA estimated in equation (5) in columns 5 and 6. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Proximity to models of R&D races

	R&D intensity		Pace of tech. change		Differentiation		Growth potential	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	DV: Patent count$_{t+3}$							
EPU$_t$	-0.154**	-0.045*	-0.151**	-0.048	-0.066*	-0.137**	-0.038	-0.139**
	[0.062]	[0.024]	[0.058]	[0.032]	[0.032]	[0.057]	[0.029]	[0.052]
Laggard$_t$	-0.107**	-0.058**	-0.122***	-0.048**	-0.059**	-0.109***	-0.078***	-0.087**
	[0.037]	[0.022]	[0.039]	[0.023]	[0.021]	[0.034]	[0.023]	[0.033]
EPU$_t$ × Laggard$_t$	0.097**	0.042**	0.105**	0.036	0.048**	0.092**	0.062***	0.075**
	[0.036]	[0.020]	[0.039]	[0.024]	[0.022]	[0.034]	[0.021]	[0.034]
Adj. R-squared	0.88	0.85	0.88	0.87	0.88	0.88	0.90	0.89
Obs.	35,781	35,585	35,682	35,508	35,594	36,725	31,861	40,477
Panel B	DV: Capital investment (I/K)$_{t+1}$							
EPU$_t$	-0.013**	-0.022***	-0.014**	-0.018***	-0.014**	-0.015**	-0.017***	-0.014**
	[0.006]	[0.007]	[0.005]	[0.006]	[0.006]	[0.006]	[0.004]	[0.006]
Laggard$_t$	-0.009	-0.021***	-0.011**	-0.019***	-0.015***	-0.017***	-0.020***	-0.011**
	[0.005]	[0.005]	[0.005]	[0.006]	[0.005]	[0.004]	[0.004]	[0.005]
EPU$_t$ × Laggard$_t$	-0.007	0.002	-0.006	0.000	-0.006	0.002	0.004	-0.006
	[0.005]	[0.005]	[0.005]	[0.006]	[0.005]	[0.003]	[0.004]	[0.005]
Adj. R-squared	0.48	0.55	0.52	0.52	0.53	0.50	0.57	0.58
Obs.	39,183	38,433	40,722	40,251	41,676	40,644	35,805	46,540
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*

This table estimates whether policy uncertainty (*EPU*) has stronger effects in industries that more closely approximate the modeling assumptions of R&D races. Columns 1 and 2 divide each 2-digit SIC code based on the industry median values of average firm R&D intensity. Columns 3 and 4 divide each 4-digit SIC code based on the median pace at which patents accumulate citations. Columns 5 and 6 divide each 3-digit SIC code into high *versus* low differentiation industries based on the median value of industry-level product similarity from Hoberg and Phillips (2016). Columns 7 and 8 divide each 3-digit SIC code into high and low growth potential industries based on the median value of industry Tobin's Q. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12. Industry competitive intensity and leader-laggard interaction

	Industry concentration					
	High		Mid		Low	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	DV: Patent count$_{t+3}$					
EPU$_t$	-0.022	-0.063	-0.002	-0.038	-0.141**	-0.143**
	[0.038]	[0.044]	[0.041]	[0.045]	[0.050]	[0.051]
Laggard$_t$		-0.126***		-0.099***		-0.022
		[0.033]		[0.034]		[0.029]
EPU$_t$ × Laggard$_t$		0.102***		0.084**		0.004
		[0.031]		[0.032]		[0.030]
Adj. R-squared	0.90	0.90	0.90	0.90	0.87	0.87
Obs.	19,699	19,699	20,541	20,541	22,855	22,855
Panel B	DV: Acquisition$_{t+1}$					
EPU$_t$	-0.173***	-0.206***	-0.126***	-0.163***	-0.092***	-0.111**
	[0.043]	[0.048]	[0.033]	[0.039]	[0.030]	[0.040]
Laggard$_t$		-0.155***		-0.135***		-0.109***
		[0.027]		[0.045]		[0.034]
EPU$_t$ × Laggard$_t$		0.080***		0.083*		0.044
		[0.027]		[0.041]		[0.032]
Adj. R-squared	0.56	0.57	0.56	0.56	0.55	0.56
Obs.	22,569	22,569	23,748	23,748	27,099	27,099
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*no*	*no*

This table examines how industry concentration affects EPU's effect on innovation and acquisitions. Each 3-digit SIC code is divided into high, medium, and low concentration industries based on the Herfindahl-Hirschman index (HHI) from Hoberg and Phillips (2010). Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13. Investment reversibility and leader-laggard interaction

	Sunk cost		Asset specificity		Capital intensity		Cyclicality	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	DV: Patent count$_{t+3}$							
EPU$_t$	-0.052	-0.136**	-0.076**	-0.131*	-0.052	-0.131**	-0.054*	-0.113**
	[0.035]	[0.053]	[0.036]	[0.064]	[0.030]	[0.056]	[0.027]	[0.053]
Laggard$_t$	-0.059**	-0.104***	-0.061*	-0.119***	-0.078***	-0.082**	-0.061**	-0.099***
	[0.026]	[0.035]	[0.030]	[0.037]	[0.022]	[0.035]	[0.024]	[0.031]
EPU$_t$ × Laggard$_t$	0.041	0.093**	0.048	0.107***	0.056**	0.074**	0.041	0.088**
	[0.026]	[0.035]	[0.029]	[0.036]	[0.023]	[0.035]	[0.024]	[0.031]
Adj. R-squared	0.89	0.87	0.87	0.88	0.89	0.87	0.88	0.87
Obs.	34,628	34,377	30,831	29,747	32,958	36,047	32,948	36,212
Panel B	DV: Capital investment (I/K)$_{t+1}$							
EPU$_t$	-0.024***	-0.010*	-0.024***	-0.005	-0.027***	-0.008*	-0.026***	-0.006
	[0.006]	[0.005]	[0.005]	[0.006]	[0.007]	[0.004]	[0.007]	[0.005]
Laggard$_t$	-0.021***	-0.009*	-0.018***	-0.014**	-0.024***	-0.006*	-0.020***	-0.012**
	[0.006]	[0.005]	[0.006]	[0.006]	[0.006]	[0.003]	[0.006]	[0.004]
EPU$_t$ × Laggard$_t$	0.004	-0.009	0.001	-0.006	0.003	-0.007**	0.000	-0.004
	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]	[0.003]	[0.005]	[0.004]
Adj. R-squared	0.52	0.54	0.52	0.53	0.52	0.47	0.55	0.46
Obs.	38,747	39,801	34,951	33,991	37,078	41,470	37,646	41,093
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*no*	*no*	*no*	*no*

This table examines how investment reversibility affects the effects of uncertainty on laggards for innovation in Panel A and capital investment in Panel B. Each 2-digit SIC code is divided into high versus low reversibility industries based on the share of sunk costs in columns 1 and 2, asset specificity in columns 3 and 4, industry median value of capital investment intensity in columns 5 and 6, and sales cyclicality in columns 7 and 8. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14. EPU and the persistence of firm performance

DV:	ROA_{t+1}					
Sample period:	1985-2003			1985-2014		
	(1)	(2)	(3)	(4)	(5)	(6)
EPU_t		0.013			0.008	
		[0.016]			[0.013]	
$Overperformance_t$	0.366***	0.266**	0.599***	0.326***	0.282***	0.616***
	[0.028]	[0.097]	[0.066]	[0.018]	[0.055]	[0.048]
$Underperformance_t$	-0.526***	-0.694***	-0.595***	-0.555***	-0.716***	-0.611***
	[0.019]	[0.054]	[0.047]	[0.018]	[0.047]	[0.043]
$EPU_t \times Overperformance_t$		0.100	-0.022		0.044	-0.072
		[0.104]	[0.068]		[0.056]	[0.051]
$EPU_t \times Underperformance_t$		0.168***	0.133***		0.161***	0.126***
		[0.051]	[0.044]		[0.048]	[0.045]
Adj. R-squared	0.275	0.277	0.372	0.292	0.293	0.393
Obs.	81,335	81,335	81,335	117,568	117,568	117,568
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*no*	*no*	*no*	*no*	*no*	*no*
Year × SIC3 FE	*no*	*no*	*yes*	*no*	*no*	*yes*

This table estimates how EPU affects the pace of downward and upward reversion in firm performance by regressing firm performance (ROA) at year *t*+1 on over- and under-performance relative to the industry performance benchmark at year *t*. Columns 1 through 3 cover the period of 1985-2006, and columns 4 and 6 cover the period of 1985-2014. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15. EPU and heterogeneous effects on the persistence of firm performance

DV:	ROA_{t+1}					
	Tech. certainty		R&D persistence		Perf. persistence	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$Overperformance_t$	0.545***	0.719***	0.559***	0.780***	0.603***	0.708***
	[0.100]	[0.119]	[0.090]	[0.110]	[0.093]	[0.071]
$Underperformance_t$	-0.699***	-0.509***	-0.675***	-0.489***	-0.667***	-0.515***
	[0.061]	[0.053]	[0.058]	[0.079]	[0.048]	[0.051]
$EPU_t \times Overperformance_t$	0.026	-0.071	0.084	-0.220*	0.070	-0.170**
	[0.096]	[0.117]	[0.086]	[0.111]	[0.092]	[0.076]
$EPU_t \times Underperformance_t$	0.244***	0.056	0.200***	0.064	0.174***	0.105**
	[0.057]	[0.054]	[0.055]	[0.073]	[0.048]	[0.050]
Adj. R-squared	0.30	0.34	0.33	0.32	0.36	0.28
Obs.	36,002	40,082	39,790	40,202	41,434	38,913
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*no*	*no*	*no*	*no*	*no*	*no*
Year × SIC3 FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*

This table repeats the analysis from Table 12 but divides the sample based on industry characteristics explored in Table 9: deterministic *versus* stochastic industries. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 16. EPU and competitive dynamism

DV:	Lead(=1)$_t$							
	(1)				(2)			
	Run simultaneously				Run simultaneously			
	n = 1	n = 2	n = 3	n = 4	n = 1	n = 2	n = 3	n = 4
EPU$_{t-n}$	-0.015	-0.013	-0.003	0.000				
	[0.010]	[0.016]	[0.015]	[0.012]				
Laggard$_{t-n}$	-0.327***	-0.110***	-0.079***	-0.082***	-0.320***	-0.109***	-0.077***	-0.086***
	[0.015]	[0.021]	[0.017]	[0.016]	[0.015]	[0.021]	[0.018]	[0.015]
EPU$_{t-n}$ × Laggard$_{t-n}$	-0.006	-0.006	0.020	0.026*	-0.007	-0.003	0.019	0.031**
	[0.014]	[0.016]	[0.017]	[0.014]	[0.015]	[0.017]	[0.018]	[0.014]
Controls	*yes*				*yes*			
Firm FE	*yes*				*yes*			
Year × SIC3 FE	*no*				*yes*			
Adj. R-squared	0.27				0.30			
Obs.	53,463				53,463			

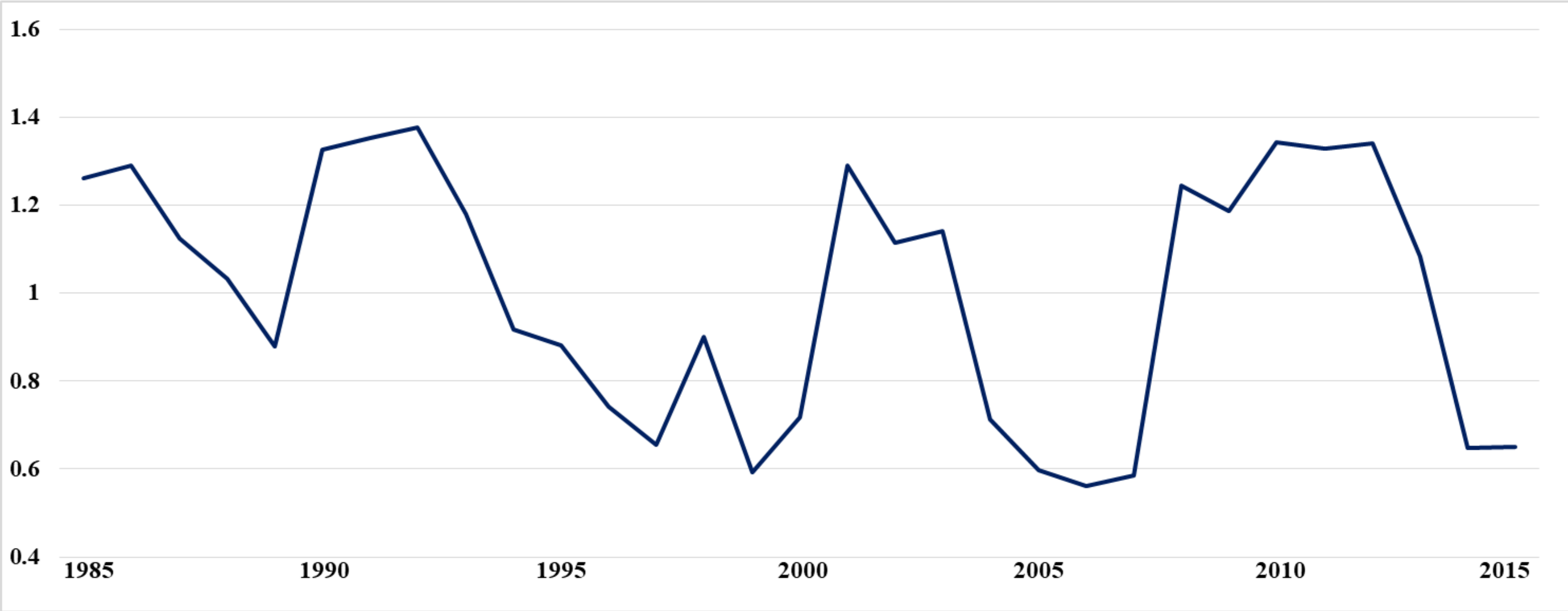
This table estimates a linear probability model with the dependent variable *Leader* that equals one if a firm's performance is above the industry performance benchmark and zero otherwise. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 17. EPU and industry concentration

DV:	Industry concentration: HHI_t						
	All	Tech. Certainty		R&D persistence		Perf. persistence	
		High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EPU_{t-1}	-0.036	0.103	0.369*	0.037	0.326**	0.243	0.075
	[0.275]	[0.216]	[0.197]	[0.258]	[0.150]	[0.227]	[0.190]
EPU_{t-2}	0.011	-0.228*	-0.016	-0.269*	0.005	-0.035	-0.233*
	[0.190]	[0.112]	[0.061]	[0.146]	[0.069]	[0.115]	[0.123]
EPU_{t-3}	-0.320	-0.477**	-0.312	-0.786**	-0.115	-0.387*	-0.591**
	[0.229]	[0.192]	[0.181]	[0.303]	[0.137]	[0.209]	[0.204]
EPU_{t-4}	-0.513*	-0.447**	-0.175	-0.681**	-0.095	-0.402	-0.428**
	[0.282]	[0.198]	[0.250]	[0.315]	[0.160]	[0.300]	[0.191]
Industry FE	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adj. R-squared	0.824	0.777	0.862	0.822	0.811	0.852	0.779
Obs.	2,936	1,131	1,190	1,146	1,298	1,284	1,280

This table estimates EPU's effect on industry concentration with the Herfindahl-Hirschman index (HHI) from Hoberg and Phillips (2010) as the dependent variable. Columns 2 to 7 divide the sample based on industry characteristics explored in Table 9: deterministic *versus* stochastic industries. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1. Economic policy uncertainty index



This figure plots the annual calendar mean of the monthly Baker et al. (2016) index of news-based policy uncertainty.

Appendix A. Variable Definitions and Data Sources

A.1. Patent related variables

They are from Kogan et al. (2017), accessible at https://kelley.iu.edu/nstoffma/. We transform them by taking the natural log of one plus their nominal values.

1. Patent counts: number of patent applications for each calendar year
2. Patent citations: total number of citations received for each calendar year
3. Patent market value: total market value of patents filed for each calendar year
4. Inventor hire: refer to Data Appendix

A.2. Other dependent variables

1. Capital investment intensity (K/I): capital investment (*capx*) divided by total assets with one year lag (*at*), winsorized at the top and bottom one percent
2. Employment growth: year-to-year change in the number of employees (*emp*), calculated as a log difference
3. Acquisitions (log): the total number of announced acquisitions documented in SDC platinum database each calendar year
4. Return on assets (ROA): net income (*ni*) divided by total assets (*at*).
5. Herfindahl-Hirschman Index: from Hoberg and Phillips (2010), accessible at http://hobergphillips.tuck.dartmouth.edu/

A.3. Independent variables

1. Updated news-based economic policy uncertainty: from Baker, Bloom, and Davis, 2016, accessible at https://www.policyuncertainty.com/categorical_epu.html
2. Laggard: binary variable that equals one if firm performance (P_{it}) is lower than the industry benchmark (IB_{it}). IB_{it} is defined as the median ROA at a four-digit SIC level for each year
3. Overperformance and Underperformance: $Overperformance_{it}$ takes the value of $P_{it} - IB_{it}$ if firm performance is above the benchmark and zero otherwise, and $Underperformance_{it}$ takes the value of $P_{it} - IB_{it}$ if firm performance is below the benchmark and zero otherwise. $Underperformance_{it}$ takes a negative value by construction, and we take its absolute value for the ease of interpretation
4. Partisan conflict index: from Azzimonti (2018), accessible at https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index

A.4. Control variables

1. Tobin's Q: [market value of equity (*mve*) + total assets (*at*) - book value of equity (*ceq*) – deferred taxes (*txdb*)] / total assets (*at*)
2. Firm size: natural logarithm of total assets (*at*)
3. Industry growth: industry mean value of ln(revenue ($revt_t$)) – ln(lagged sales ($revt_{t-1}$)) at the 4-digit SIC level
4. Book leverage: long-term debt (*dlc*) plus debt in current liabilities (*dltt*) divided by

total assets (*at*)

5. Altman's Z: 1.2 × working capital (*wcap*) / total assets (*at*) +1.4×retained earnings (*re*) / total assets (*at*) + 3.3 × operating income before depreciation (*ebit*) / total assets (*at*) + 0.6 × (market value of equity (*mve*) / total liabilities (*lt*)) + 1.0 × (revenue (*revt*) / total assets (*at*))
6. Total factor productivity (TFP): from İmrohoroğlu and Tüzel (2014), accessible at https://sites.google.com/usc.edu/selale-tuzel/home?authuser=2
7. Working capital ratio: working capital (*wcap*) divided by revenue (*revt*)
8. Current ratio: current total assets (*act*) divided by current total liabilities (*lct*)
9. Herfindahl-Hirschman Index (HHI): calculated at the 4-digit SIC code level based on the revenue of Compustat firms

Appendix B. Laggard based on TFP

	(1)	(2)	(3)	(4)	(5)
Panel A	**DV: Patent count$_{t+3}$ (log)**				
EPU$_t$	-0.066		-0.066	-0.103*	
	[0.044]		[0.044]	[0.052]	
Laggard (TFP)$_t$		-0.001	-0.002	-0.084**	-0.081**
		[0.010]	[0.010]	[0.033]	[0.032]
EPU$_t$ × Laggard (TFP)$_t$				0.080**	0.079**
				[0.029]	[0.031]
Adj. R-squared	0.90	0.90	0.90	0.90	0.91
Obs.	40,493	40,493	40,493	40,493	40,493
Panel B	**DV: Capital investment (I/K)$_{t+1}$**				
EPU$_t$	-0.018***		-0.019***	-0.019***	
	[0.004]		[0.004]	[0.004]	
Laggard (TFP)$_t$		-0.014***	-0.015***	-0.015***	-0.013***
		[0.001]	[0.001]	[0.003]	[0.003]
EPU$_t$ × Laggard (TFP)$_t$				0.000	-0.001
				[0.003]	[0.003]
Adj. R-squared	0.58	0.58	0.59	0.59	0.64
Obs.	46,443	46,443	46,443	46,443	46,443
Controls	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*yes*

This table replicates Table 2 but identifies laggards based on firm-level total factor productivity (TFP) from İmrohoroğlu and Tüzel (2014). The smaller sample size is due to the data requirement for computing TFP. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix C. Expanded sample window: 1985-2014

	(1)	(2)	(3)	(4)	(5)
Panel A	**DV: Patent count$_{t+3}$ (log)**				
EPU$_t$	-0.020		-0.020	-0.044	
	[0.047]		[0.047]	[0.050]	
Laggard$_t$		-0.023***	-0.023***	-0.080***	-0.082***
		[0.006]	[0.006]	[0.025]	[0.024]
EPU$_t$ × Laggard$_t$				0.057**	0.061**
				[0.024]	[0.023]
Adj. R-squared	0.84	0.84	0.84	0.84	0.86
Obs.	98,359	98,359	98,359	98,359	98,359
Panel B	**DV: Capital investment (I/K)$_{t+1}$**				
EPU$_t$	-0.016***		-0.016***	-0.014***	
	[0.004]		[0.004]	[0.004]	
Laggard$_t$		-0.017***	-0.017***	-0.013***	-0.013***
		[0.001]	[0.001]	[0.003]	[0.003]
EPU$_t$ × Laggard$_t$				-0.004	-0.004
				[0.003]	[0.003]
Adj. R-squared	0.52	0.52	0.52	0.52	0.57
Obs.	112,398	112,398	112,398	112,398	112,398
Controls	*yes*	*yes*	*yes*	*yes*	*yes*
Firm FE	*yes*	*yes*	*yes*	*yes*	*yes*
Year × SIC3 FE	*no*	*no*	*no*	*no*	*yes*

This table replicates Table 2 but expands the sample period from 1985-2006 to 1985-2014 using updates to the patent database from Kogan et al. (2017) by Stoffman, Woeppel, and Yavuz (2019). Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix D. Partisan conflict as an instrument for EPU – first stage results

	DV: EPU_{month}											
	All	Monetary policy	Fiscal policy	Taxes	Gov. spending	Health care	National security	Entitlemt. program	Regulation	Financial regulation	Trade policy	Sovereign debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Partisan $conflict_{month}$	0.108*	-0.296***	0.436***	0.413***	0.548***	1.070***	-0.233**	0.577***	0.391***	0.109	0.261	0.248
	[0.058]	[0.082]	[0.087]	[0.087]	[0.136]	[0.115]	[0.110]	[0.113]	[0.073]	[0.163]	[0.164]	[0.273]
Adj. R-squared	0.008	0.03	0.06	0.05	0.04	0.17	0.01	0.06	0.07	0.00	0.01	0.00
F-statistic	3.5	13.0	25.0	22.7	16.2	87.1	4.5	25.9	28.4	0.4	2.5	0.8
Obs.	414	414	414	414	414	414	414	414	414	414	414	414

This table reports the first stage results for the 2SLS regression used in Table 7. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The analysis is at the monthly frequency and covers the period of Jan. 1985 to Jun. 2019.

Appendix E. Lagged effects of uncertainty on innovation

	DV: Lead(=1)$_t$					
	Run simultaneously					
	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6
Laggard$_{t-n}$	-0.324***	-0.098***	-0.075***	-0.070***	-0.026	-0.015
	[0.018]	[0.025]	[0.020]	[0.018]	[0.019]	[0.032]
EPU$_{t-n}$ × Laggard$_{t-n}$	0.005	-0.011	0.021	0.030*	0.001	-0.015
	[0.017]	[0.019]	[0.019]	[0.017]	[0.017]	[0.032]
Controls			*yes*			
Firm FE			*yes*			
Year × SIC3 FE			*yes*			
Adj. R-squared			0.31			
Obs.			39,198			

This table expands the analysis in Table 3 by examining additional lags of Laggard and *EPU* ×*Laggard*. Standard errors are clustered at the firm and year level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix F. Instrumental variable estimation for Table 15.

	DV: HHI		
	Fiscal policy	**Gov. spending**	**Regulatory**
	(1)	(2)	(3)
Panel A	**DV: HHI**		
EPU$_{t\text{-}1}$	-0.025	-0.020	-0.028
	[0.016]	[0.013]	[0.017]
EPU$_{t\text{-}2}$	-0.019	-0.015	-0.021
	[0.014]	[0.011]	[0.001]
EPU$_{t\text{-}3}$	-0.038***	-0.030***	-0.042***
	[0.013]	[0.010]	[0.015]
EPU$_{t\text{-}4}$	0.006	0.005	0.007
	[0.010]	[0.007]	[0.010]
Industry FE	*yes*	*yes*	*yes*
Adj. R-squared	0.826	0.826	0.826
Obs.	2,936	2,936	2,936

This table repeats the analysis in Table 15 but, instead of the aggregate EPU, it uses the predicted values of uncertainty in fiscal policy, government spending, and regulation with the partisan conflict index from Azzimonti (2018) as the instrument. Standard errors are bootstrapped with two-way clustering at the firm and year level as in Gow, Ormazabal, and Taylor (2010), and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Data Appendix: Inventor mobility

We start with the database by Li et al. (2014) that disambiguates the names of inventors contained in all of the USPTO patents and assigns a unique identification to each inventor. We first merge this DB with the latest NBER patent DB (Hall, Jaffe, and Trajtenberg, 2001) to identify i) the assignee firm for each patent and ii) GVKEY. Some inventors file multiple patents in a given year, and we take the assignee firm associated with the last patent filed in a given year as the employer of the inventor. We record firm A (based on GVKEY) to have hired a new external inventor if the inventor has worked for a different company previously or produced patents as an independent inventor between year t-3 and t-1. There are two notable exceptions. First, in the case of firm A (Year 1) – "missing" (Year 2) - firm A (Year 3), we replace missing (Year 2) with firm A. "Missing" (Year 2) is likely from an assignment issue and is not considered as a new inventor hire. Second, we exclude cases where an inventor is considered a new hire because of transitioning from missing GVKEY to non-missing GVKEY despite sharing the same PDPASS (a company identifier assigned by Hall et al., 2001) across the transitioning years.

While providing complete coverage of all inventors that file for patents, the precise date of an inventor's move from firm A to firm B cannot be identified based on the NBER dataset. An inventor's employer is revealed only when the inventor files for a patent (as assignees), and unless an inventor files for patents consecutively without a gap year, the precise year of the movement cannot be identified. For example, it is unclear which year (2001 vs. 2002 vs. 2003) inventor A moved to firm Y from firm X in the following case.

Inventor A – Patent 1 – Year 2000 – Firm X
Inventor A – Patent 2 – Year 2003 – Firm Y

We record the year of application for the new patent (2003) as the year of movement. Note that this is an upper bound for the year of the movement. Some inventors have significant gaps in between patents, and we restrict the sample to inventors with less than four-year gaps to reduce the noise. All of the results are robust to using a mid-point year (2002, rounded up), but this affects the number of lags after which the implied contract exception becomes significant.

Lastly, there is a significant number of spelling errors and mistakes in reported assignee names (e.g., KELLY COMPANY INC vs. KELLEY COMPANY INC) that result in false classification. As long as these errors do not systemically correlate with firm performance and the EPU index, any inferences remain valid.