Investment under Up- and Downstream Uncertainty ⋆

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Abstract

We empirically and theoretically show that uncertainty's impact on firms' investment decisions depends on its source in the supply-chain. A real-option model with time-to-build predicts that only upstream uncertainty suppresses firms' economic activity, since upstream uncertainty from suppliers affects firms in the shorter-run, while downstream uncertainty from customers affects the longer-run. Using production-network data, we provide micro-level evidence that upstream (downstream) uncertainty is negatively (positively) related to firm-level investment and valuations, as predicted theoretically. At the macro-level, these two uncertainties oppositely predict aggregate consumption, output, and investment growth. Lastly, COVID-19-induced uncertainty is predominantly downstream, which need not hinder economic recovery.

JEL classification: E32, D81, D50, L14, G11, G12

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The global economy experienced unprecedented uncertainty during the Great Recession and the COVID-19 pandemic. Accordingly, a growing literature in macroeconomics and finance documents that increased uncertainty is typically associated with lower investment, output, and stock prices.

By and large, the literature has taken a "top-down" approach to study the effects of uncertainty: either by constructing measures of aggregate uncertainty, or by assuming common examining uncertainty shocks in equilibrium models. In contrast, this paper takes a "bottom-up" approach and studies firms' investment decisions under micro-level uncertainties that originate from different locations in their supply-chain environments. What is the relation between a firm's upstream uncertainty (i.e., uncertainty originating from suppliers) and its investment or valuation? Is there a similar relation between a firm's downstream uncertainty (i.e., uncertainty originating from customers) and these variables? When aggregated, do both uncertainties suppress economic growth and financial markets, and rise in recessions? We address these questions both theoretically and empirically.

By combining two comprehensive datasets on dynamic supplier-customer relationships, we document a great deal of asymmetry between the impact of firms' upstream and downstream uncertainty. We theoretically predict, and then empirically show, that higher upstream uncertainty strictly decreases firm-level investment, sales, and valuation ratios, whereas higher downstream uncertainty either has no effect or a positive effect on these variables. The fact that downstream uncertainty can spur micro-level real and financial outcomes is novel, and contrasts the commonly documented negative interaction between economic growth and other facets of uncertainty.

We also show that this asymmetry holds at the aggregate level. Using a measure of upstreamness (i.e., distance to final consumers) based on the Bureau of Economic Analysis Input-Output tables, we classify industries as upstream or downstream, and compute the macro-level uncertainty of each group. We then show that macro-level upstream and downstream uncertainty induce *polar* opposite and significant impacts on aggregate variables, such as consumption, output, investment, and the market's valuation, in line with the micro-level evidence. Moreover, we show that the marginal utility of investors rises (falls) with more upstream (downstream) uncertainty. This stark difference between the two uncertainties, and the positive effects of downstream uncertainty in particular, may explain why the causality or the magnitude of the relation between uncertainty and the economy is sometimes called into question.

Our results bear implications for policymaking. First, knowledge of whether increased macro-level uncertainty is driven by upstream or downstream firms can assist policymakers to project whether a contractionary shock will be amplified by uncertainty fluctuations. For example, we find that the increase in uncertainty during the COVID-19 crisis was mostly driven by downstream firms, and may not hinder the economic recovery. Second, we show that the impact of downstream uncertainty on investment turns positive for longer-duration investment projects. Thus, regulation that prolongs the incubation period of projects may attenuate the adverse effect of uncertainty on the economy.

To motivate the empirical analysis, we consider an intuitive distinction between the horizons at which upstream and downstream uncertainty impact firms. A typical investment project is comprised of three steps: purchasing inputs from suppliers, using these inputs to assemble an output product, and then finally selling this product to customers. In reality, the middle stage takes considerable time and is often referred to as "time-to-build." This includes the time required to process the inputs, perform R&D, clear regulatory bars, and construct any necessary equipment. Consequently, upstream uncertainty that is associated with uncertainty about input prices from suppliers typically affects firms in the short-run, while downstream uncertainty that is associated with uncertainty about the selling price to customers typically affects firms in the longer-run.[1] We check whether this intrinsic horizon-based asymmetry between the two uncertainties yields different implications for firms' investment.[2]

We construct a real-option model of investment under these supply-chain uncertainties to address the former point. To build intuition, we start with a discrete-time

[1]The economic fundamentals of a firm's suppliers (e.g., their technology or markup shocks) affect the firm's input price by shifting the supply of inputs (assuming supply and demand curves are not perfectly elastic). Thus, upstream economic uncertainty is related to input-price uncertainty. Likewise, uncertainty about customers' fundamentals is related to uncertainty regarding the firm's selling price, as this downstream uncertainty affects the variability of future demand shocks.

[2]Of course, there could be exceptions to this horizon-based asymmetry. In some cases, investments involve pre-paid orders. In other cases, futures contracts that hedge output price variation (e.g., for certain commodity producers) may exist. Nonetheless, to the extent that actual production entails an exchange of goods with suppliers *before* an exchange of goods with customers, this horizon-based asymmetry is largely descriptive of the typical investment project. In our empirical analysis we find evidence that supports this assumption of horizon asymmetry, through the lens of our model.

model in which uncertainty lasts one period, and then generalize the results to a continuous-time model. The firm is endowed with a growth option. Upon exercising the option, the firm buys an input from its supplier, builds a production line, and then sells a stream of output to its customer. Notably, the second stage of the investment project involves time-to-build: if the real option is exercised at time t, then the firm can only sell its first product at $t + \tau$, for $\tau \geq 1$. The project is partially reversible due to an abandonment option. Given this setting, the firm solves an optimal stopping problem and chooses between investing now and waiting.

Importantly, the underlying economic fundamentals of the supplier and the customer vary over time. This shifts the input supply and the output demand, and results in input and output price fluctuations, respectively. Consequently, economic uncertainty over fundamental shocks that originate upstream (downstream) drives uncertainty over both the future input (output) price and the supplier's (customer's) valuation. We employ these interactions in the empirical analysis.

Because input and output prices fluctuate regardless of whether the firm invests today, there is value in waiting for new information to arrive before committing to the partially irreversible project. This benefit of waiting applies to learning about either input or output prices: higher upstream or downstream uncertainty increases the likelihood of extreme outcomes, and enhances the option value of waiting.

However, there are also two opportunity costs of waiting to invest. First, if the future input price rises by more than the output price, then the project can become uneconomical despite having a positive NPV today. Thus, the firm can lose a positive revenue stream by not investing today. This opportunity cost does not depend on the amount of upstream uncertainty, but increases with downstream uncertainty since the lost revenues become larger as output prices rise. Second, by not investing today, the firm forgoes any profits during the waiting period. This forgone revenue becomes stochastic with time-to-build, as the missed revenue depends on the *future* output price that is realized when the time-to-build period ends. The option to abandon the project caps these forgone revenues from below, and makes this opportunity cost a convex function of the future output price. Consequently, this cost of waiting increases with downstream uncertainty, but is unaffected by upstream uncertainty.

The fact that the opportunity cost of waiting rises with downstream uncertainty, but is unrelated to upstream uncertainty, creates asymmetry between the two uncertainties. If the time-to-build period is sufficiently large, then higher downstream uncertainty can cause the opportunity cost of waiting to dominate the benefit, and hasten investment. In all, we hypothesize that: (i) the relation between upstream uncertainty and investment is unambiguously negative, and (ii) the association between downstream uncertainty and investment is weaker in absolute value, but can even be positive. As investment and stock prices comove in general-equilibrium models, the same conjectures apply to valuations.

Motivated by these hypotheses, we collect data on supplier-customer relationships from two sources: Compustat Segments and Factset Revere. The former source is available for a longer time period, whereas the latter is more novel, contains significantly more relationships, but is only available for a shorter time period. We combine these sources to obtain the most complete dynamic data on each firm's customers and suppliers available. Notably, input and output prices are not directly observed in the data.[3] Yet, as previously noted, a firm's input (output) price uncertainty is positively related to uncertainty over the valuations of its suppliers (customers) in equilibrium.[4] We verify this relation using the NBER-CES manufacturing database. Consequently, we measure the upstream (downstream) uncertainty of each firm using the realized volatility of its suppliers' (customers') stock returns. While we acknowledge that return volatility is backwards looking, robustness tests show that using a forward-looking proxy based on option-implied volatility yields similar results.

We then estimate panel regressions in which the dependent variable is a firm's investment rate, price-to-earnings ratio, sales growth, or inventory growth, and the independent variables include the firm's upstream and downstream uncertainties, the firm's own uncertainty, and a host of controls. We show that upstream uncertainty is associated with a significant reduction in all variables of interest, consistent with hypothesis (i). In contrast, higher downstream uncertainty either has no effect or a positive impact on these outcomes, in line with hypothesis (ii). We also find that the effect of a firm's *own* uncertainty on these variables becomes muted when controlling

[3]Similarly, economic fundamentals such as real variables are not available at a sufficiently high frequency to construct a reliable volatility measure.

[4]This result is used widely in the literature. For example, in the context of investment-specific technology shocks, the return of investment firms net of consumption can proxy for the relative price of investment goods (see, e.g., Kogan and Papanikolaou (2014)).

for the supply-chain uncertainties.

Importantly, the validity of the empirical evidence does not depend on the assumptions of our economic model, including the horizon-based asymmetry. As such, we do not rule out that the findings may arise for reasons outside of our framework. Nonetheless, we test our proposed economic mechanism in two ways. First, we split firms into groups based on their sectors as a proxy for time-to-build. This is motivated by the notion that the construction of perishable goods is quicker than that of durable or capital goods (e.g., the time required to produce a bottle of water versus a water desalination machine). The "short" time-to-build group only includes the producers of non-durable consumption goods and services, whereas the "long" time-to-build group includes durable goods producers and the investment sector. We find that the relation between downstream uncertainty and investment is significantly higher (more positive) for the "long" time-to-build group, consistent with the theory. Second, we show that the positive (negative) effect of downstream (upstream) uncertainty is amplified (attenuated) for firms whose abandonment option is less costly, as proxied by the degree of capital redeployability.

While our theory pertains to firm-level outcomes, we also examine whether the asymmetry between upstream and downstream uncertainty holds at the aggregate level. To this end, we use the BEA's Input-Output tables to construct "upstreamness" scores that capture each industry's weighted distance from final consumption good production (see Antràs and Chor (2018) and Gofman, Segal, and Wu (2020)). We dynamically classify each industry as upstream (downstream) if its upstreamness score is in the top (bottom) of the cross-sectional distribution of these scores. To parallel the firm-level analysis, we use the realized stock return volatilities of these two portfolios as our proxies for the macro-level upstream and downstream uncertainties.

We then compute impulse responses from each type of macro-level uncertainty to output, consumption, and investment growth, the market's price-to-dividend ratio, and the risk-free rate, using the smooth local projection (SLP) method of Barnichon and Brownlees (2019). Controlling for both uncertainties, the impulse responses from upstream (downstream) macro-level uncertainty shocks to the variables of interest are negative (positive), in line with the micro-level evidence. In absolute terms, the negative impact of macro-level upstream uncertainty is stronger than the positive impact of macro-level downstream uncertainty. Lastly, we estimate the prices of risk of the predictable components of the two macro-level uncertainties using a GMM procedure. In line with the impulse responses to consumption, we find that macro-level upstream (downstream) uncertainty has a negative (positive) price of risk. That is, upstream (downstream) macro uncertainty increases (decreases) investors' marginal utility.

Finally, we show that the component of downstream uncertainty that is *orthogonal* from upstream uncertainty is procyclical, and typically drops in recessions. However, while the recent COVID-19 crisis was accompanied by increased uncertainty, we find that this rise in uncertainty was predominantly due to higher downstream uncertainty. Through the lens of our results, this suggests that the COVID-19 recession may not be deepened by higher economic uncertainty. In fact, so long as downstream uncertainty remains more dominant, recovery could be relatively swift.

In all, our evidence highlights that not all types of uncertainty cause or are associated with recessions: downstream uncertainty may induce the opposite effect.

1 Related literature

The empirical literature in macroeconomics and finance typically documents a negative relation between uncertainty and economic activity. On the macro side, the negative association between growth and uncertainty is shown in Ramey and Ramey (1995), Martin and Rogers (2000), Engel and Rangel (2008), Bloom (2009), and Baker and Bloom (2013), among many others. Recently, Nakamura, Sergeyev, and Steinsson (2017) estimate growth and volatility shocks for a panel of countries, and report a negative relation between the two.[5] Likewise, most asset-pricing studies suggest that higher aggregate uncertainty lowers valuations. Bansal, Khatchatrian, and Yaron (2005) show that consumption volatility is negatively related to price-dividend ratios. Boguth and Kuehn (2013) and Bansal, Kiku, Shaliastovich, and Yaron (2014) show that consumption uncertainty has a negative price of risk, whereas Drechsler and Yaron (2011) report that higher macroeconomic uncertainty positively predicts risk premia. The negative effect of uncertainty on asset prices also holds for other types of uncertainty, such as fiscal or monetary policy uncertainty (Pastor and Veronesi, 2012; Croce, Nguyen, and Schmid, 2012; Baker, Bloom, and Davis, 2016; Bretscher,

[5]Refer to Bloom (2014) for a comprehensive survey of uncertainty and macroeconomic growth.

Hsu, and Tamoni, 2020; Husted, Rogers, and Sun, 2020) and the common component of idiosyncratic volatility (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2016).[6]

A small set of papers finds evidence that uncertainty's impact on growth and prices can be positive, at least for certain outcome variables or particular types of uncertainty. For example, Stein and Stone (2013) find that uncertainty depresses investment and hiring, but encourages R&D. In contrast, we show that the positive effects of downstream uncertainty are not confined to R&D, but extend to a wide range of outcomes, including capital investment, consumption, and stock prices. Other papers find ambivalent links between different facets of uncertainty and prices. Segal, Shaliastovich, and Yaron (2015) distinguish between the negative and the positive semivariances of industrial production and show that the latter semivariance can increase stock prices.[7] We focus on total variation, and show that total variance has different implications depending on where it originates in the supply chain. While Segal (2019) considers cross-sectoral heterogeneity in uncertainty, and finds the TFP volatility of final consumption (investment) good producers has a negative (positive) impact on prices, our baseline decomposition of uncertainty into its upstream and downstream components is firm-specific, and is not based on a firm's sector. In most cases, the firm, its customers, and its suppliers operate *within* the same sector.

In line with the former studies, we demonstrate that not all facets of uncertainty are negatively correlated with the real and financial economy. Yet our evidence is granular: we start with micro-level analysis, and show that the same conclusions hold at the macro-level. The findings also demonstrate that the effect of uncertainty shocks can propagate both upstream and downstream, yet with different implications

[6] Some studies also argue that in contrast to the former papers, the negative relation between uncertainty and growth or prices is either weak or non-causal. Dew-Becker, Giglio, Le, and Rodriguez (2017) find that only short-run (realized) volatility is priced by investors. Ludvigson, Ma, and Ng (2020) use a structural vector autoregression approach to show that macroeconomic uncertainty shocks do not cause a decline in industrial production, but the converse is true – a drop in output predicts higher macro uncertainty. Our paper can perhaps reconcile the mixed evidence regarding the strength or the causal impact of aggregate uncertainty on the real and the financial economy. We show that aggregate uncertainty has a component (namely, the downstream part) that often exhibits a positive correlation with growth and prices. Due to the offsetting effects of upstream and downstream uncertainty, the association between total macro-level uncertainty and economic growth may become less pronounced or ambiguous.

[7] Other papers that depart from Gaussianity or feature an ambivalent relation between uncertainty and prices include Okou, Jahan-Parvar, Feunou, et al. (2018); Dou (2017); Bekaert and Engstrom (2017); Bianchi, Kung, and Tirskikh (2019).

and magnitudes.[8]

The theoretical literature that treats uncertainty shocks as exogenous typically shows that uncertainty leads to depressed investment, consumption and output. Higher uncertainty can induce higher markups (see, e.g., Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2015; Basu and Bundick, 2017), or higher credit spreads and cost of capital (see, e.g., Christiano, Motto, and Rostagno, 2010; Gilchrist, Sim, and Zakrajšek, 2014; Arellano, Bai, and Kehoe, 2019), which lowers investment. Real-option studies (see, e.g., Dixit (1992), Pindyck (1993), Bloom (2009) and Alfaro, Bloom, and Lin (2019)) show that uncertainty can inhibit investment due to a "bad news principle" (Bernanke, 1983). Uncertainty implies that future bad states are more severe. With investment irreversibility, there is a greater benefit of waiting for new information to avoid the potential loss incurred by investing just before a bad state is realized,[9] as the opportunity cost of waiting (namely, the forgone profits during the waiting period) is typically deterministic.

Nonetheless, related studies suggest that real-option models can be enriched to introduce a countervailing force. With certain assumptions, uncertainty can raise the opportunity cost of waiting and/or expected profits (i.e., the "growth option" value). In these theories, a mean-preserving spread leads to an unbounded upside but a capped downside, suggesting an increase in expected profits by convexity (see, e.g., Oi, 1961; Hartman, 1972; Abel, 1983). One assumption that yields an increase in the growth option value, and the opportunity cost of waiting, is time-to-build (see, e.g., Majd and Pindyck (1987) and Bar-Ilan and Strange (1996)).

Our contribution vis-à-vis these studies is threefold. First, we cast the notion of time-to-build into a (reduced-form) supply-chain environment, and study a model that features two types of uncertainty. We show that the time-to-build mechanism applies to downstream (customer-level) uncertainty but to for upstream (supplier-level) uncertainty. Second, our empirical findings provide strong support for the prediction of these "growth option" theories and, in particular, the time-to-build channel. Em-

[8] While our paper considers the propagation of second-moment shocks, ample existing studies consider the propagation of first-moment shocks, along the supply chain (see, e.g., Atalay, Hortaçsu, and Syverson, 2014; Acemoglu, Akcigit, and Kerr, 2016; Baqaee, 2018; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021, among others).

[9] Also see, for example, Abel, Eberly, et al. (1994) for a detailed exposition of investment under uncertainty in a model featuring adjustment costs and irreversibiltiy.

pirical evidence in favor of this channel hinges on our decoupling of uncertainty into its upstream and downstream parts. Third, we show that the interaction between upstream and downstream uncertainty can lead to a separate channel through which downstream uncertainty hastens investment, even in the absence of time-to-build.[10]

2 Theoretical evidence

We present theoretical evidence showing the differential effects of upstream and downstream uncertainty on firm-level investment. To build intuition, Section 2.1 presents a discrete-time model in which uncertainty only lasts a single period. Section 2.2 then generalizes this model to a dynamic and continuous-time setting.

2.1 Building intuition: uncertainty lasting one period

Consider a firm deciding whether to invest in a capital input (e.g., a machine or a stock of inventory) that is purchased from its supplier (denoted by s) to produce a flow of output products to sell to its customer (denoted by c). Time is discrete, and the firm can either invest in the project today (time 0) or wait until next period (time 1). We assume the investment option expires at time 1 for ease of exposition.

Both the customer firm and the supplier firm have economic fundamentals denoted by z_c and z_s, respectively, that can fluctuate over the first period. These fundamentals can capture technology, markup, or utilization shocks.[11] Whenever the fundamental z_c (z_s) changes, the output demand (input supply) shifts, changing the input (output) price. For example, a positive (negative) productivity shock to z_c increases the demand for the firm's output, and increases (decreases) the sale price. Likewise, a positive (negative) productivity shock to z_s increases the supply of the firm's inputs, and decreases (increases) the input price. While first-moment shocks to z_c or z_s can each affect relative prices with opposite signs, second-moment shocks to these fundamentals always increase the variability of relative prices, regardless of the underlying

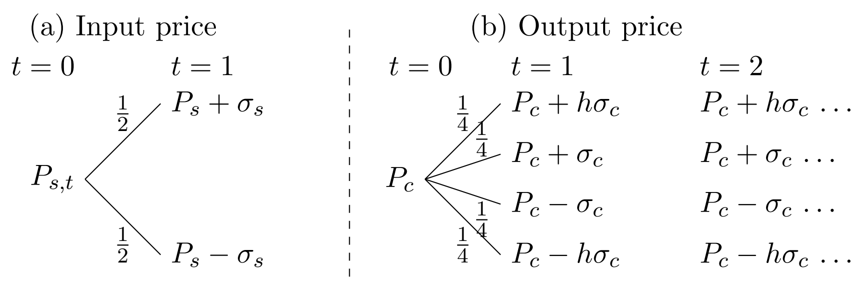
[10] Upstream uncertainty implies that the future input price could increase sharply, while the output price could simultaneously rise, but only moderately. In this case, the investment's project NPV can turn negative, even if the current NPV is positive. Thus, a firm delaying investment in the presence of upstream uncertainty may suffer a potential loss of the future revenue stream (which positively depends on the output price). Therefore, the opportunity cost of waiting increases with downstream uncertainty, creating an asymmetry to upstream uncertainty. See more details in Section 2.1.

[11] In principle, the customer (c) could represent a household. In this case, the economic fundamental z_c may represent a taste shock, which shifts the demand for the firm's output.

nature of z_c or z_s. Consequently, upstream uncertainty, $Var_t[z_{s,t+1}]$, is positively related to input price uncertainty, whereas downstream uncertainty, $Var_t[z_{c,t+1}]$, relates to output price uncertainty. In equilibrium, the valuations of the supplier and the customer also reflect z_s and z_c, respectively. We use this observation to examine the model's implications in the data.

Accordingly, both the input price, paid to the supplier s, and the output price, received from the customer c, can change between time 0 and time 1. The input price at time 0 is $P_{s,0} = P_s$, but the price at time 1 ($P_{s,1}$) will increase to $P_s + \sigma_s$ or decrease to $P_s - \sigma_s$, with equal probabilities. Thus, $P_{s,1}$ is a mean-preserving spread of $P_{s,0}$, and $E[P_{s,1}] = P_{s,0}$ and $Var[P_{s,1}] = \sigma_s^2$. This suggests that σ_s is associated with upstream uncertainty. Likewise, the current output price is $P_{c,0} = P_c$. Letting h represent a constant greater than one, the output price at time 1 ($P_{c,1}$) will (1) increase to $P_c + h\sigma_c$ ("very good" news); (2) increase to $P_c + \sigma_s$ ("good" news); (3) decrease to $P_c - \sigma_c$ ("bad" news); or (4) decrease to $P_c - h\sigma_c$ ("very bad" news), with equal probabilities. Thus, $P_{c,1}$ is a mean-preserving spread of $P_{c,0}$, and $\partial Var[P_{c,1}]/\partial\sigma_c > 0$. Therefore, σ_c is associated with downstream uncertainty. For simplicity, we assume that output price uncertainty only lasts between time 0 and time 1, and consequently $P_{c,t} = P_{c,1}$ $\forall t > 1$. These price dynamics are outlined in Figure 1.

Figure 1: Input- and output-price dynamics under the discrete-time model
The figure illustrates the dynamics of the input price from suppliers (Panel A) and output price to customers (Panel B) in the discrete time model of Section 2.1. P_s (P_c) denotes the unconditional price of the input (output). σ_S (σ_C) positively relate to upstream (downstream) uncertainty.



To start the investment project at time t, the firm first needs to acquire the capital input for price $P_{s,t}$. Acquiring the capital input allows the firm to build up its production line, and then produce one unit of output per period. No additional capital is required beyond the capital input purchased at t. The marginal labor cost for each unit of product is constant over time, and is given by $\omega > 0$. Therefore, the cash inflow during every period $\tau \geq t$ in which production takes place is $P_{c,\tau} - \omega$. For the purpose of illustration, we assume that $\sigma_c > P_{c,0} - \omega > 0$. This suggests that the cash inflow is positive under the "good" or "very good" news case for $P_{c,1}$, but negative under the "bad" or "very bad" news case for $P_{c,1}$.

The time discount factor of the firm's owner is β. Given β, the project's NPV at time 0 is positive (i.e., the real option is in the money). To make the dynamics non trivial, we assume that the effect of input price uncertainty (σ_s) on the viability of the project depend on the future output price. If the input price $P_{s,1}$ increases to $P_s + \sigma_s$, but the output price also increases by a large amount (i.e., the "very good" news case for $P_{c,1}$), then the project is still viable at time 1. However, if the input price increases, but the output price rises by a smaller amount (i.e., the "good" news case for $P_{c,1}$), then project has a negative NPV at time 1.

The investment is partially reversible. When production starts, the firm can abandon the project for a cost of $a > 0$. The firm will not abandon the project under a "very good" or a "good" realization of $P_{c,1}$. We assume that $0 > P_c - \sigma_c - \omega + a(1-\beta) > (h-1)\sigma_c$, meaning that the project is only abandoned in the "very bad" news case.

Lastly, we consider two separate assumption for the production process.

Model 1: No time-to-build. Once the decision to invest is made, and input is purchased from the supplier, the firm can immediately produce and sell output to the customer. This instantaneous time-to-build assumption is standard in the real option literature (e.g., Dixit (1992) and Pindyck (1993)).

Model 2: Time-to-build. There is a one period interval between investing and receiving the project's first revenue. This captures the time required to convert the input into an output stream (e.g., construction) before entering the product market.

2.1.1 Analysis of Model 1

We start by analyzing how an increase in upstream uncertainty (σ_s) and downstream uncertainty (σ_c) each affect a firm's decision to invest under Model 1. Below, $P_c(VG)$, $P_c(G)$, $P_c(B)$, $P_c(VB)$ denote the future output prices if "very good," "good," "bad," and "very bad" news materializes, respectively, and the subscripts of each NPV denote the project's NPV given a realization of the future output price.

If the firm decides to invest at time 0, then the firm will operate the project indefinitely, unless "very bad" news arrive at time 1 and the project is abandoned.

Alternatively, if the firm decides to wait, it will only exercise the option at time 1 if (1) $P_c(G)$ materializes and the input price has decreased; (2) $P_c(VG)$ materializes and the input price has decreased; or (3) $P_c(VG)$ materializes and the input price has increased. Each of these three cases occurs with probability $\frac{1}{8}$.

For the purpose of brevity, we relegate the complete expressions for the NPV of investing now, denoted $NPV_0^{\text{Model 1}}$, and the expected NPV of waiting, denoted $E_0[NPV_1^{\text{Model 1}}]$, to Section OA.1 of the Online Appendix. Below, we present the net benefit of waiting under Model 1, $E_0[NPV_1^{\text{Model 1}}] - NPV_0^{\text{Model 1}}$:

$$\text{NetBenefit(Wait, Model 1)} = \underbrace{\left(-\frac{1}{4}NPV_{0[P_c(B)]} - \frac{1}{4}NPV_{0[P_c(VB)]}\right)}_{\text{(I)}} + \underbrace{(\frac{1}{2} - \frac{3}{8}\beta)P_s + \frac{1}{8}\beta\sigma_s}_{\text{(II)}}$$
$$\underbrace{-\frac{1}{2}(P_c - \omega)}_{\text{(III)}} \underbrace{-\frac{1}{8}\frac{\beta}{1-\beta}(P_c + \sigma_c - \omega)}_{\text{(IV)}}. \qquad (1)$$

Terms (I) and (II) capture the benefits of waiting, while terms (III) and (IV) capture the opportunity costs of waiting. We outline the intuition underlying each term below.

Term (I) is the benefit of waiting to avoid bad news about P_c following the "bad news principle" (Bernanke, 1983). If the output price P_c increases at time 1, the firm will exercise the option (provided P_s does not rise in the $P_c(G)$ case) and earn the same revenue had it exercised the option at time 0. In these cases, there is no benefit from waiting. However, if P_c falls under the $P_c(VB)$ and $P_c(B)$ cases, then the option will not be exercised at time 1. By waiting, the firm avoids the net loss of investing in an ex-post uneconomical project. Higher σ_c increases the potential loss from investing in the project immediately, as $NPV_{0[P_c(B)]}$ falls with σ_c. This implies that the benefit of waiting, captured by this term, increases in downstream uncertainty σ_c.

Similar to downstream uncertainty, upstream (input price) uncertainty creates a benefit of waiting for new information. Mechanically, term (II) is the difference between the input cost under the three positive NPV cases at time 1, and the input cost under the two ex-post positive NPV cases at time 0 (i.e., if $P_c(G)$ or $P_c(VG)$ materializes). Economically, this term captures the benefit of waiting to learn that the input price has fallen in the cases in which "good" news about the output price is realized and the project is still viable at time 1.[12] This is a "good news principle," associated with upstream uncertainty, as the benefit of waiting increases in σ_s.

Term (III) is the main opportunity cost of waiting, and captures the forgone revenue during the inaction period if $P_c(G)$ or $P_c(VG)$ arise and the project is viable ex post. Without time-to-build the firm can both invest and enter the product market at time 0, so the forgone profit from inaction is the time-0 revenue. Thus, this opportunity cost of waiting is not stochastic, and is independent of both σ_c and σ_s.

Finally, term (IV) is another cost of waiting that arises due to input price (upstream) uncertainty. This term captures the potential loss of the future revenue stream in the case that the input price increases at time 1, but the output price increases by a smaller amount in the $P_c(G)$ case. By assumption, σ_s is sufficiently large so that the project has negative NPV if $P_{s,1}$ is equal to $P_s + \sigma_s$, and $P_{c,1}$ is equal to $P_c + \sigma_c$. In this scenario, a waiting firm forgoes the positive profits it could have earned had it invested at time 0 (before P_s increased), and learned the "good" news regarding the output price. This term is independent of σ_s, but increases in σ_c. Importantly, without the input price uncertainty, this term would not exist.

Overall, upstream uncertainty has an unambiguous effect on investment: High σ_s delays investment at time 0 because the benefit of waiting increases in σ_s (term (II)), while the opportunity cost is independent of σ_s (terms (III) and (IV)). In contrast, downstream uncertainty has a more subtle effect on investment in the presence of upstream uncertainty. This is because the benefit of waiting increases in σ_c (term (I)), but the opportunity cost of waiting also depends on σ_c, provided σ_s is sufficiently large (term (IV)). This creates some asymmetry between the effects of upstream and downstream uncertainty. However, without time-to-build, more downstream uncertainty also suppresses investment. To see this, we collect the coefficients of σ_c in terms (I) and (IV) and obtain $\frac{1}{8}\frac{\beta}{1-\beta}\sigma_c$. Thus, the net benefit of waiting increases in σ_c.

2.1.2 Analysis of Model 2

The analysis of Model 2 is almost identical to that of Model 1. The key difference is that if the firm invests at time 0, then the first revenue is only received at time 1. Similarly, if the firm chooses to wait, and exercises its growth option at time 1, then

[12]If "very good" news about the output price is realized, then there is no benefit in waiting for the price to drop. This is because the project is viable regardless of the input price.

its first revenue is only received at time 2. Consequently, the net benefit of waiting under Model 2 has a similar form and intuition to that from Model 1:

$$\text{NetBenefit(Wait,Model 2)} = \underbrace{\left(-\frac{1}{4}NPV_{0[P_c(B)]} - \frac{1}{4}NPV_{0[P_c(VB)]}\right)}_{\text{(I)}} + \underbrace{(\frac{1}{2} - \frac{3}{8}\beta)P_s + \frac{1}{8}\beta\sigma_s}_{\text{(II)}}$$
$$\underbrace{-\frac{1}{4}\beta(P_c + h\sigma_c - \omega) - \frac{1}{4}\beta(P_c + \sigma_c - \omega)}_{\text{(III)}} \underbrace{-\frac{1}{8}\frac{\beta^2}{1-\beta}(P_c + \sigma_c - \omega)}_{\text{(IV)}}. \tag{2}$$

For the purpose of brevity, we once again present the expressions for the NPV of exercising the option to invest now, denoted $NPV_0^{\text{Model 2}}$, and the NPV of delaying the option to invest, denoted $E_0[NPV_1^{\text{Model 2}}]$, in Section OA.1 of the Online Appendix.

Here, term (I) (term (II)) captures the benefit of waiting due to a "bad" ("good") news principle about the output (input) price. As explained in Section 2.1.1, these benefits rise with σ_c and σ_s, respectively. Term (IV) hinges on $\sigma_s > 0$ and, as in equation (1), captures the opportunity of cost of not investing at time 0. By not investing at time 0, and then learning that the input price has increased to $P_s + \sigma_s$ while the input price has increased to $P_c + \sigma_c$ in the $P_c(G)$ case, the project has an ex-post negative NPV and the firm loses the future positive revenue stream.

The key difference between equations (1) and (2) is related to term (III). This term captures an opportunity cost of waiting, and represents any forgone profits from inaction. In Model 1, the firm started generating revenues immediately, meaning that these foregone profits arose at time 0 and were non-stochastic. In Model 2, the forgone revenues from waiting are materialized at time 1 *after* the time-to-build period ends. As such, these foregone profits become a stochastic function of the output price at time 1, but do not depend on the input price. Moreover, the forgone profits are capped from below by the abandonment option. This means that these forgone profits are a convex function of $P_{c,1}$, and therefore increase with σ_c. We refer to this as the "good news" principle associated with downstream uncertainty.

Similar to Model 1, upstream uncertainty unambiguously delays investment by raising the benefit of waiting without affecting the opportunity cost. To understand the impact of downstream uncertainty, we collect the terms in equation (2) that depend on σ_c, and differentiate this expression with respect to σ_c:[13]

$$\frac{\partial \text{NetBenefit(Wait, Model 2)}}{\partial \sigma_c} = -\frac{1}{4}\beta h + \frac{1}{8}\frac{\beta^2}{1-\beta}$$

The firm term above is negative due to the forgone profits over the inaction period, and the second term is positive due to the "bad" news principle. Importantly, the net benefit of waiting can decrease in σ_c if $h > \frac{\beta}{2(1-\beta)}$. Intuitively, if h is sufficiently large, then the forgone profits in the $P_c(VG)$ case dominate the benefits of waiting. This makes the firm *hasten* its investment in the face of more downstream uncertainty.

We conclude with two key observations. First, unlike Model 1, in which both σ_s and σ_c suppress investment, the time-to-build in Model 2 reduces the benefits of waiting to resolve output price uncertainty. Therefore, there is an intrinsic asymmetry between the uncertainties. Upstream uncertainty should induce a negative effect on investment, while downstream uncertainty's effect is either weaker or even positive. Second, while the time-to-build period is strictly one period in this simplified discrete-time model, the parameter h captures the effect of longer-time-to-build in reduced form. With a longer investment lag (higher h), very good news can be more extreme. Thus, we expect downstream uncertainty to boost investment for longer time-to-build projects. We formalize this intuition in the continuous-time model below.

2.2 Dynamic and stochastic model

We consider a dynamic and stochastic version of the model with time-to-build from Section 2.1 to show that the asymmetry between upstream and downstream uncertainty is not an artifact of any simplifying assumption. The setup builds on the key ingredients of Kydland and Prescott (1982) and Bar-Ilan and Strange (1996), but deviates by introducing (i) a distinction between assets in place and growth option, (ii) heterogeneity between the customers and suppliers, and (iii) two types of uncertainty (i.e., upstream and downstream uncertainty).

2.2.1 Model setup

Time is continuous, and the firm has k_0 units of assets-in-place and a production technology that is linear in capital. Each unit of capital produces one units of output

[13] The relevant parts of terms (I), (III), and (IV) are $-\frac{1}{4}\beta h\sigma_c - \frac{1}{4}\beta\sigma_c + \frac{1}{4}\frac{\beta}{1-\beta}\sigma_c - \frac{1}{8}\frac{\beta^2}{1-\beta}\sigma_c$.

per unit of time. The output good is then sold to the firm's customer c for a price $P_{c,t}$. The firm is also endowed with a growth option. This growth option provides an opportunity to increase the productive capacity by purchasing k_g units of input (capital) from the supplier s. Thus, to exercise the option, the firm needs to invest an $P_{s,t} \cdot k_g$, where $P_{s,t}$ is the price of the input paid to the supplier s.

We assume that the output price fluctuates with customer demand and evolves as

$$\frac{dP_{c,t}}{P_{c,t}} = \mu_c dt + \sigma_c dW_{c,t},$$

where $\{W_{c,t}\}$ is a standard Wiener process. The input price $P_{s,t}$ evolves as a continuous Markov chain with states $\{P_{s,H}, P_{s,M}, P_{s,L}\}$ and transitions over dt given by

$$\begin{bmatrix} 1-(\lambda_1+\lambda_2)dt & \lambda_1 dt & \lambda_2 dt \\ \frac{\lambda_1+\lambda_2}{2}dt & 1-(\lambda_1+\lambda_2)dt & \frac{\lambda_1+\lambda_2}{2}dt \\ \lambda_2 dt & \lambda_1 dt & 1-(\lambda_1+\lambda_2)dt \end{bmatrix}.$$

The three possible values of P_s are $P_{s,H} = 1 + \sigma_s$, $P_{s,M} = 1$, and $P_{s,L} = 1 - \sigma_s$. By construction, the unconditional input price from the supplier is normalized to one (without loss of generality). The volatility of $dP_{s,t}$ is higher whenever σ_s is higher. Lastly, we assume that $P_{s,0} = P_{s,M}$, so the input price from the supplier starts at its steady-state value. Future profits are discounted at a rate $\rho > \mu_c$.

Upon exercising the growth option, the firm immediately pays the cost of the input to the supplier. The input is then converted into a production line that produces final output after $h > 0$ periods of time-to-build. That is, if investment is made at time t, the new capital k_g only becomes productive at time $t + h$. Once the time-to-build period is completed, the firm is endowed with $k_0 + k_g$ units of productive capital. The technology remains linear in capital, resulting in a flow of $k_0 + k_g$ units of output per unit of time, and a revenue stream of $P_{c,t}(k_0 + k_g)$ per unit of time. The marginal labor cost of production under an active growth option is ω. One unit of output requires one unit of labor, suggesting the labor cost is $\omega(k_0 + k_g)$.

If the investment option is exercised at time t, the firm must commit to the build-up stage of the project. However, the firm can choose to abandon its investment project for a cost $a \geq 0$ at any time τ after the time-to-build period is over, when

$\tau \geq t + h$. Upon abandonment, the firm's capital reverts to the original assets-in-place k_0. For tractability, and without loss of generality, the price of the capital input also reverts to its initial level $P_{s,0}$. After abandonment, the firm retains the option to re-activate the investment project in the futureyby purchasing the required inputs from its supplier at the future re-entry time $\tau' \geq \tau$, for a cost $P_{s,\tau'} k_g$.

2.2.2 Numerical illustration

The model's solution is outlined in Appendix OA.2. We conjecture, and then verify, that prior to the adoption of the growth option, the firm's value is

$$V_0(P_{c,t}, P_{s,t}) = \underbrace{B_1(P_{s,t}) \cdot (P_{c,t})^{\beta_1} + B_2(P_{s,t}) \cdot (P_{c,t})^{\beta_2} + B_3(P_{s,t}) \cdot (P_{c,t})^{\beta_3}}_{\text{Growth option value}} + \underbrace{\frac{P_{c,t} k_0}{\rho - \mu_c}}_{\text{Assets in place value}}.$$

Here, $\beta_1, \beta_2, \beta_3$ are positive scalars, and $B_i(P_{s,t})$ for $i = 1, 2, 3$ are scalars that depend on the input price $P_{s,t}$. The investment policy is then given by thresholds $\overline{\xi}(P_s)$ that depend on the input price P_s. It is optimal to exercise the growth option at time t when $P_{s,t} \in \{P_{s,L}, P_{s,M}, P_{s,H}\}$ if and only if $P_{c,t} \geq \overline{\xi}(P_{s,t})$. These optimal investment thresholds cannot be solved in closed form, but can be obtained numerically.

We illustrate the effects of each uncertainty on investment by obtaining the optimal thresholds with the following parameter values. The annual real interest ρ is 2.5%, the average annual appreciation of the output price μ_c is 2%, and the marginal cost of labor is set to $\omega = 0.5$. We normalize assets-in-place to $k_0 = 1$, and set $k_g = 1$ so that exercising the growth option doubles the firm's capital. Lastly, the Markov chain that governs the dynamics of the input prices evolves with $\lambda_1 = \frac{1}{3}$ and $\lambda_2 = \frac{1}{6}$.[14]

Given the parameters above, we consider the optimal investment thresholds for all combinations of $\sigma_s \in \{0.02, 0.03, 0.04, 0.05\}$ and $\sigma_c \in \{0.02, 0.03, 0.04, 0.05\}$. Moreover, beyond allowing upstream and downstream uncertainty to take on a wide range of values, we also consider two cases for the length of the time-to-build period. Specifically, we consider the investment thresholds under both a long (short) time-to-build period in which h is set equal to eight (one) periods. Table 1 reports the steady-state investment thresholds for each case (i.e., $\overline{\xi}$ when $P_s = P_{s,M} = P_{s,0}$).

[14]Without loss of generality, we assume $a = 0$ in the remainder of the analysis. Abandonment is still effectively costly, because re-entry requires an additional cost.

Table 1: Optimal investment thresholds under supply-chain uncertainties
The table reports the optimal investment thresholds from the continuous-time model of Section 2.2. Specifically, the table reports the critical value of the output price $P_{c,t}$ required to induce the firm to exercise its growth option given (i) the degree of upstream uncertainty (σ_s), (ii) the degree of downstream uncertainty (σ_c), and (iii) the length of the time-to-build period (h). In each panel of the table σ_s and σ_s can each take on values in the set {0.02,0.03,0.04,0.05}. In Panel A (Panel B) the length of the time-to-build period is set to eight (one) periods.

(a) Time-to-build stage of $h = 8$ periods

σ_c \ σ_s	0.020	0.030	0.040	0.050
0.020	0.9872	0.9908	0.9960	1.0031
0.030	0.9797	0.9843	0.9912	1.0007
0.040	0.9693	0.9745	0.9825	0.9940
0.050	0.9586	0.9642	0.9729	0.9856

(b) Time-to-build stage of $h = 1$ periods

σ_c \ σ_s	0.020	0.030	0.040	0.050
0.020	1.2471	1.2473	1.2475	1.2478
0.030	1.2974	1.2975	1.2977	1.2980
0.040	1.3375	1.3377	1.3379	1.3381
0.050	1.3716	1.3718	1.3720	1.3722

Table 1 shows that controlling for σ_c, upstream uncertainty increases the investment threshold $\overline{\xi}$ regardless of h. This shows that, all else equal, upstream uncertainty delays investment. The result is consistent with the simple model in Section 2.1: delaying investment when σ_s increases is optimal because of a "good news" principle. Waiting entails the benefit of learning that the input price has fallen.

Panel A shows that controlling for σ_s, higher downstream uncertainty (σ_c) can *lower* the investment threshold. Thus, unlike σ_s, σ_c can hasten investment. Consistent with Section 2.1.2, this occurs for two reasons related to a "good news" principle. First, the opportunity cost of waiting increases in σ_c because the forgone profits over the inaction period are a convex and stochastic function of the output price. These foregone profits can become more extreme with higher σ_c, while the downside is capped by the abandonment option. Second, input price uncertainty can make the project uneconomical in the future, even if the output price appreciates. The potential loss of a positive revenue stream from waiting, and then learning that the input price has increased, becomes larger with higher σ_c.

However, downstream uncertainty only hastens investment if the time-to-build period is large enough. Panel B shows that when $h = 1$, the investment threshold increases with downstream uncertainty, similar to the effect of upstream uncertainty. Intuitively, if time-to-build is short, then the opportunity cost of missing out on profits during the build time cannot become too extreme. This allows the benefit of waiting – avoiding learning bad news about the output price – to dominate. Thus, the analysis in Sections 2.1 and 2.2 generates the following hypotheses.

Hypothesis (i). *The association between upstream (supplier-level) uncertainty and investment is unambiguously negative.*

Hypothesis (ii). *The association between downstream (customer-level) uncertainty and investment is weaker in absolute value, but can even be positive.*

Below, we confirm these conjectures using micro- and macro-level data.

3 Micro-level evidence

We use granular and dynamic data on supplier-customer relationships to provide novel empirical evidence that is consistent with the model from Section 2. We find that (i) the association between upstream (i.e., supplier-level) uncertainty and investment, sales, and stock price is negative and statistically significant, while (ii) the association between downstream (i.e., customer-level) uncertainty and investment is either statistically insignificant, or positive and significant. We describe the construction of the firm-level upstream and downstream uncertainty measures in Section 3.1. Using these measures, Sections 3.2 and 3.3 document the asymmetry between the two uncertainties for firms' investment rates and valuations. We also show that, in line with the model, the positive effects of downstream uncertainty are concentrated among firms that have longer time-to-build (Section 3.4), and greater investment reversibility (Section 3.5). We establish the robustness of the asymmetric impact of the two uncertainties for other firm-level outcome variables in Section 3.6.

3.1 Data

Sample. Our sample includes all firms in the CRSP/Compustat universe listed on the NYSE/AMEX/NASDAQ exchanges, excluding financial firms (SIC 6000 - 6999), public utilities (SIC 4900 - 4999), and firms belonging to the healthcare industry according to the Fama and French 10 industry group classification. We exclude these firms since their supply-chain environments are significantly different from those underlying our production model. The firm-level analyses range from 1976 to 2018 due to the availability of granular data on inter-firm relationships.

Identifying customers and suppliers. We construct the upstream and downstream uncertainties by dynamically identifying the sets of firms that supply to (i.e., are upstream from) and buy from (i.e., are downstream from) each firm in our sample.

To this end, we employ two datasets on supplier-customer relationships: Compustat Segments and the FactSet Revere Relationship database. By combining these sources we overcome the limitations associated with each specific dataset, and produce a comprehensive network that spans the longest time period possible.[15]

We combine both datasets to construct our panel of inter-firm links between 1976 and 2018 as follows. First, for firm-year observations between June 2003 and June 2018, we start by looking for each firm's suppliers and customers in the FactSet data. By using FactSet data in the first step, we obtain the most comprehensive coverage of firms' supplier-customer relationships for the most recent part of our sample period. Next, for the years prior to 2003 (when FactSet is unavailable), we obtain firms' suppliers and customers from the Compustat Segment database. Importantly, using FactSet data for the period in which the two data sources overlap ensures that we capture the union of both datasets, because the links reported in the Compustat Segment data are a *subset* of those reported in the FactSet data.

Measuring uncertainty. The model in Section 2 assumes that uncertainty exists over some economic fundamentals of suppliers, z_s, and customers, z_c. Market clearing immediately yields that $Var[z_{s,t+1}]$ ($Var[z_{c,t+1}]$) is positively related to input (output) price uncertainty. While granular data on relative prices is unobservable (at least at high-frequency), $Var[z_{s,t+1}]$ ($Var[z_{c,t+1}]$) is directly related to uncertainty over suppliers' (customers') valuations in equilibrium. This is becuase changes in firm valuations reflect changes in fundamentals, implying that relative input (output) price uncertainty is positively correlated with the return volatility of supplier (customer) firms. We verify this assumption in Online Appendix OA.5 using the NBER-CES database. The average correlation between input price uncertainty and supplier return volatility is positive and significant (about 0.3). We obtain a similar result for the correlation between output price uncertainty and customer return volatility.

We construct our baseline measures of uncertainty as follows. First, for each firm-year observation between June 1976 and June 2018, we identify the customers and

[15] On the one hand, Compustat Segments data contains considerably fewer links between firms than FactSet. This is because firms are only required to disclose relationships with customers that account for at least 10% of total sales at the annual frequency. However, the Compustat data is available for an extended time period, starting in 1976. On the other hand, FactSet contains around ten times as many links as Segments, as inter-firm relationships in FactSet are obtained using comprehensive data from accounting statements, press releases, interviews, and firms' websites, among other sources. However, this FactSet data is only available from 2003 to 2018.

suppliers associated with firm i in year t, as described above. Second, for each supplier (customer) firm linked to firm i, we use CRSP daily data to compute the volatility of the supplier's (customer's) daily stock returns in the year preceding time t.[16] We then compute the average stock return volatility across all suppliers (customers) that trade with firm i at time t, and refer to this average as the upstream (downstream) uncertainty of firm i. Finally, we control for firm i's own inherent uncertainty (i.e., the uncertainty that is potentially unrelated to the firm's trading partners) by computing the realized daily stock return volatility of the firm over the past year.

Importantly, while the above measures of uncertainty are backwards looking by construction, the fact that we define uncertainty using variation in *realized* rather than *expected* stock returns does not drive our results. First, since the time series of uncertainty measures are typically highly persistent, ex-post volatility is highly correlated with ex-ante uncertainty, but does not rely on parametric assumptions. Second, for robustness, we repeat our analyses using forward-looking measures of uncertainty extracted from option prices (discussed and reported in Section 3.6). Since using option price data significantly truncates both the time-series and cross-sectional dimensions of our analyses,[17] yet deliver consistent results to those obtained using realized volatility, we base our benchmark results on realized volatility.

3.2 Firm-level investment under supply-chain uncertainty

We verify the predictions of the real-option model. We find that upstream and downstream uncertainty have (i) *independent* interaction with firms' decisions to invest, beyond a firm's own uncertainty, and (ii) an *asymmetric* effect on firms' investment. Upstream (downstream) uncertainty suppresses (never depresses; potentially raises) investment. We document these effects via a panel regression:

$$\begin{aligned} y_{i,t} = \alpha_i + \delta_t + \beta_1 \sigma(\text{Own})_{i,t} + \beta_2 \sigma(\text{Upstream})_{i,t} + \beta_3 \sigma(\text{Downstream})_{i,t} \\ + \boldsymbol{\nu}' \boldsymbol{N}_{i,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

[16] We calculate these stock return volatilities by (i) adjusting returns for delisting events, and (ii) requiring that each firm has at least 200 non-missing daily stock returns over the previous year.

[17] There are two costs of using the forward-looking measure of uncertainty extracted from options prices. First, the sample period is significantly truncated, as OptionMetrics only begins reporting option price data in January 1996. Second, the use of option-implied volatility places significantly more restrictive filters on the sample. A firm will only enter the sample if (i) it has options written on its stock, and (ii) its customers and suppliers also have options written on their stocks.

Here, $y_{i,t}$ is the investment rate of firm i at time t, defined in accordance with Belo, Lin, and Bazdresch (2014), α_i is a firm fixed effect, and δ_t is a time fixed effect that subsumes common shocks to all firms in a given time period (e.g., the Great Recession). Our key variables of interest are $\sigma(\text{Upstream})_{i,t}$ and $\sigma(\text{Downstream})_{i,t}$. These variables denote the uncertainty of firm i's suppliers (upstream uncertainty) and the uncertainty of firm i's customers (downstream uncertainty) at time t, respectively.

$\sigma(\text{Own})_{i,t}$ denotes the firm i's own uncertainty at time t, and is an economically important control. For tractability, the models in Section 2 assume that $\sigma(\text{Upstream})_{i,t}$ and $\sigma(\text{Downstream})_{i,t}$ are orthogonal. In reality, however, both uncertainties can be correlated, as fundamental shocks that are specific to firm i's own uncertainty can simultaneously propagate up- and downstream, and impact both the firm's upstream (input price) uncertainty and downstream (output price) uncertainty. Including $\sigma(\text{Own})_{i,t}$ in equation (3) accounts for any common shocks to $\sigma(\text{Downstream})_{i,t}$ and $\sigma(\text{Upstream})_{i,t}$ that originate from their common trading partner: firm i.

In the regression above, $\boldsymbol{N}_{i,t}$ is a vector that includes the numbers of suppliers and customers linked to firm i in year t. The number of suppliers (customers) is included as a control variable in all regressions that feature upstream (downstream) uncertainty. $\boldsymbol{Z}_{i,t}$ is a vector of time-varying firm-level controls that contains the book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. These variables capture relevant aspects of a firm's economic environment, other than uncertainty, that can influence its decision to invest. Details on the construction of each variable are provided in Section OA.3 of the Online Appendix.

Panel A of Table 2 reports the results of estimating equation (3). In Table 2, and all following firm-level results, we scale each independent variable by its unconditional standard deviation to aid interpretation, and cluster standard errors at the firm level. In all projections, observations are measured in June (i.e., time t refers to June of the given year) to ensure that accounting data are publicly available for all firms.

Columns one and two of the table show that, before accounting for the supply-chain uncertainties, higher firm-level uncertainty is associated with a decrease in investment. Specifically, without the additional controls $\boldsymbol{Z}_{i,t}$, a one standard deviation in a firm's own uncertainty is associated with a statistically significant decrease in its investment rate by 0.13. This result is consistent with the wide-held notion that

Table 2: Firm-level investment and valuation under supply-chain uncertainties
The table reports the relation between a firm's investment rate (Panel A) or price-to-earnings ratio (Panel B) and the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers), the firm's downstream uncertainty (uncertainty of the firm's customers), and the firm's own uncertainty. The results are based on estimating regression (3), where $y_{i,t}$ is firm i's investment rate or price-to-earnings ratio obtained from the most recent annual report as measured at time t. The benchmark upstream and downstream uncertainty are constructed at time t following the procedure outlined in Section 3.1. In all specifications we include firm and year fixed effects. In all specifications that feature upstream (downstream) uncertainty we control for the number suppliers (customers) of each firm. In even column we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. All regressions are estimated using a panel of firm-year observations ranging from 1976 to 2018. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Investment rates							
σ(Own)	-0.13	-0.06	-0.09	-0.08	-0.08	-0.07	-0.06	-0.01
	(-19.31)	(-8.56)	(-6.11)	(-5.42)	(-3.80)	(-3.20)	(-3.51)	(-0.71)
σ(Upstream)			-0.03	-0.03			-0.02	-0.02
			(-3.35)	(-3.53)			(-1.78)	(-1.98)
σ(Downstream)					0.03	0.03	-0.00	-0.01
					(4.00)	(3.18)	(-0.36)	(-0.64)
Adj.-R^2	0.33	0.37	0.50	0.51	0.40	0.41	0.48	0.52
Obs.	160829	149102	18794	17703	32253	30392	12164	11531
	Panel B: Valuation ratios							
σ(Own)	-0.06	-0.04	-0.05	-0.05	-0.04	-0.05	-0.02	-0.00
	(-12.04)	(-5.84)	(-3.07)	(-3.01)	(-3.97)	(-3.87)	(-0.99)	(-0.16)
σ(Upstream)			-0.02	-0.02			-0.03	-0.03
			(-2.01)	(-1.96)			(-2.28)	(-1.90)
σ(Downstream)					0.01	0.01	0.00	-0.00
					(1.40)	(0.60)	(0.17)	(-0.35)
Adj.-R^2	0.15	0.14	0.15	0.15	0.14	0.14	0.13	0.14
Obs.	1679710	129745	18449	17398	31058	29276	11918	11310
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

uncertainty is negatively related to investment (e.g., Bloom (2009)).

Columns three and four extend the aforementioned analysis by considering the effect of upstream uncertainty on firms' investment rates. Upstream uncertainty is negatively related to investment, beyond the negative impact of the firm's own uncertainty. For instance, column four indicates that, conditioning on a firm's own uncertainty and the control variables $\boldsymbol{Z}_{i,t}$, a one standard deviation increase in upstream uncertainty decreases investment rates by an additional 3%. This effect is significant at better than the 1% level, and consistent with the prediction of the models in Section 2 regarding the impact of upstream uncertainty.

By contrast, columns five and six show that higher downstream uncertainty is positively and statistically related to investment. A one standard deviation increase in downstream uncertainty *increases* a firm's investment rate by 3%, controlling for the firm's own uncertainty and $\boldsymbol{Z}_{i,t}$. This positive association between downstream uncertainty and investment is in line with hypothesis (ii) of the model in Section 2.2.

Finally, columns seven and eight consider the incremental effect of each type of uncertainty on investment, controlling for all three uncertainties (own, upstream, and downstream) jointly. The asymmetry between upstream and downstream uncertainty is still manifested, and consistent with the predictions of the model: (i) Upstream uncertainty suppresses investment, beyond the effects of the other uncertainties; (ii) While the effect of downstream uncertainty is no longer positive and statistically significant, its marginal effect is small in absolute value, and indistinguishable from zero. Importantly, downstream uncertainty does not dampen investment. Comparing the results of columns (7) and (8) to those of columns (1) and (2) shows that the effect of a firm's own uncertainty on investment is overstated when not controlling for the supply-chain uncertainties. In Column (8), only the slope coefficient on upstream uncertainty is statistically significant.

3.3 Firm-level valuation under supply-chain uncertainty

Production-based asset pricing models typically predict that firms' investment and stock prices comove (see, e.g., Zhang (2005)). Consistent with the results of Section 3.2, and coupled with standard q-theory, we show that the asymmetry between upstream and downstream uncertainty also applies to firm-level valuation ratios. We estimate equation (3) after replacing $y_{i,t}$ with firm i's valuation ratio at time t, measured using price-to-earnings (see Section OA.3 of the Online Appendix for details).

The results are shown in Panel B of Table 2. Columns one and two show that *without* controlling for upstream or downstream uncertainty, an increase in a firm's own uncertainty leads to significantly lower valuations. We consider the marginal effect of upstream (downstream) uncertainty in columns three and four (five and six).

In line with Panel A, the slope coefficient on upstream (downstream) uncertainty is negative (positive). While the negative relation between upstream uncertainty and valuations is statistically significant and sizable around 2%, the positive relation between downstream uncertainty and valuations is indistinguishable from zero. Finally, columns seven and eight report the results of horse-race regressions in which all three uncertainties are included simultaneously. Upstream uncertainty plays the traditional role of reducing valuations, and crowds out the impact of a firm's own uncertainty. In contrast, downstream uncertainty has a non-negative relation to firm value.

3.4 Downstream uncertainty and time-to-build

The model in Section 2.2 predicts that the asymmetry between upstream and downstream uncertainty is more pronounced for firms facing longer time-to-build. With enough build time, downstream uncertainty can hasten investment. We verify this prediction empirically. Using a firm's sector as a proxy for its time-to-build, we find that the positive interaction between downstream uncertainty and investment is almost *twice* as large for firms with longer time-to-build periods. We test the interaction between downstream uncertainty and time-to-build via the panel regression

$$\begin{aligned} y_{i,t} = \alpha_i + \delta_t + \beta_1 \sigma(\text{Own})_{i,t} + \beta_2 \sigma(\text{Downstream})_{i,t} \times \mathbb{I}\left[\text{Long}\right]_{i,t} \\ + \beta_3 \sigma(\text{Downstream})_{i,t} \times \mathbb{I}\left[\text{Short}\right]_{i,t} + \nu N_{c,i,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $\mathbb{I}\left[\text{Long}\right]_{i,t}$ ($\mathbb{I}\left[\text{Short}\right]_{i,t}$) denotes an indicator variable that takes on a value of one if firm i is defined as having a long (short) time-to-build at time t, and zero otherwise. All other variables in equation (4) follow the same definitions as equation (3).[18]

Since firm-level measures of time-to-build are unobservable, we split our sample into two groups using an intuitive yet conservative approach that is based on the sectoral classification of Gomes, Kogan, and Yogo (2009). By and large, perishable goods involve a shorter construction time than durable goods. Thus, the short time-to-build group is comprised of firms that belong to industries that produce non-durable consumption goods or services, while the long time-to-build group includes

[18] Note that we omitted the term related to upstream uncertainty. We do so because the time-to-build assumption affects only the opportunity cost of waiting for downstream uncertainty, but not for upstream uncertainty. Moreover, the model predicts that downstream uncertainty should induce a non-negative impact on investment, even if upstream uncertainty is fixed or time-varying.

firms operating in other sectors (e.g., investment-goods or durable consumption goods producers). We conjecture that β_2 is qualitatively and quantitatively larger than β_3. The results for these slope coefficients are reported in Table 3.

Table 3: Investment, supply-chain uncertainties, and time-to-build
The table reports the relation between a firm's investment rate and the contemporaneous level of the firm's downstream uncertainty (uncertainty of the firm's customers), conditioning on a proxy for the firm's time-to-build period based on the sectoral classification of Gomes et al. (2009). The results are based on estimating regression (4), where $y_{i,t}$ is firm i's investment rate obtained from the most recent annual report as measured at time t, the "Short" dummy takes the value of one for firms that produce perishables (non-durable consumption goods or services), while the "Long" dummy takes the value of one for firms operating in other sectors (e.g., investment-good producers and durable consumption goods producers). Downstream uncertainty is constructed at time t following the procedure outlined in Section 3.1. We include year fixed effects in columns (1)-(4), and firm fixed effects in columns (3) and (4). We control for each firm's number customers in all columns, and in columns (2) and (4) we include each firm's book-to-market ratio, return momentum, financial constraints index, profitability, and Tobin's q as additional control variables. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level. The table also reports the p-value from a Wald test on the null hypothesis that the relation between downstream uncertainty and investment is the same for both short and long time-to-build firms ($H_0 : \beta_2 = \beta_3$ in equation (4)).

	(1)	(2)	(3)	(4)
σ(Downstream) $\times$ Short	0.03	0.02	0.02	0.01
	(3.17)	(2.04)	(1.78)	(1.33)
σ(Downstream) $\times$ Long	0.08	0.05	0.04	0.03
	(7.55)	(4.60)	(4.05)	(2.56)
F(Long=Short)	22.02	6.52	3.87	1.06
p(Long=Short)	0.00	0.01	0.05	0.30
Controls	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj.-R^2	0.04	0.16	0.40	0.44
Obs.	33351	31485	32253	30392

Columns one and two report the results without firm fixed effects. While an increase in downstream uncertainty is associated with higher investment rates among all firms, the effect of downstream uncertainty on investment is over twice as large in magnitude for the long time-to-build group. For example, column one (two) estimates equation (4) without (with) additional controls and shows that a one standard deviation increase in downstream uncertainty increases investment rates by 8% (5%)

among firms with long time-to-build. In contrast, downstream uncertainty only increases investment by 3% (2%) among firms with short time-to-build.

The fact that downstream uncertainty induces a more positive effect on investment for long time-to-build firms is qualitatively unchanged when we include firm fixed effects. Column three (four) shows that without (with) additional controls, a one standard deviation increase in downstream uncertainty is associated with 4% (3%) increase in investment for long time-to-build firms, and β_2 is statistically significant. For short time-to-build firms, downstream uncertainty increases investment by only 2% (1%), and β_3 is indistinguishable from zero. Relatedly, a Wald test on the null hypothesis that $\beta_2 = \beta_3$ is rejected at 5% level or better in most columns.

3.5 Supply-chain uncertainty and investment reversibility

A key ingredient of the models in Section 2 is that the firm holds an option to abandon the project in "very bad" states of the world. The cost of exercising this abandonment option controls the project's reversibility, and has a direct impact on the net benefit of waiting to invest if either upstream or downstream uncertainty rise.

On the one hand, if the abandonment cost is sufficiently large, then abandoning the project in the "very bad" state may no longer be possible. This makes the investment irreversible. In this case, higher upstream uncertainty magnifies the "bad news" principal, as waiting allows the firm to avoid losses in both the "bad" and "very bad" states of the world. These losses intensify with more upstream uncertainty, so the benefit of waiting following an upstream uncertainty shock is larger when the abandonment cost is higher. On the other hand, if the abandonment cost is sufficiently low, then abandoning the project in the "bad" state becomes possible. This magnifies the "good news" principle associated with downstream uncertainty. By not investing immediately, the firm forgoes the next period's truncated profit, which only rises with more downstream uncertainty. As such, the cost of waiting following a downstream uncertainty shock is larger when the abandonment cost is lower.

To check these predictions of the model, we split the effects of up- and downstream uncertainty across firms with high and low investment reversibility. Specifically, we estimate projections that are similar to equation (4), but interact each supply-chain uncertainty of interest with an indicator that classifies each firm as facing high or low reversibility. We use the asset redeployability measure of Kim and Kung (2017) as our proxy of reversibility. Firms with a below-median value of redeployability have less reversibility, corresponding to a higher abandonment cost.

The results in Table OA.6.2 of the Online Appendix confirm both predictions. First, upstream uncertainty is more negatively associated with investment for firms with harder-to-abandon projects. Second, downstream uncertainty has a more positive effect on the investment rates of firms with easier-to-reverse investment projects.

3.6 Robustness of firm-level results

Our firm-level results for investment and valuation under supply-chain uncertainty are robust to using: (1) alternative uncertainty measures (e.g., forward-looking option-implied volatility); (2) other firm-level outcomes beyond investment rates, such as real sales and inventory growth; and (3) an alternative subsample period.

For instance, since the models in Section 2 motivate the empirical analysis, the models are primarily concerned with the effects of up- and downstream uncertainties on firms' investment rates. Since investment is correlated with other firm outcomes, we extend the empirical analysis to consider the interaction between the supply-chain uncertainties and related firm-level outcomes. Table OA.6.1 examines how upstream and downstream uncertainty affect firms' real sales and inventory growth rates. In line with the results for investment, upstream and downstream uncertainty have an asymmetric impact on each outcome. An increase in upstream uncertainty is associated with reductions of both sales and inventory growth rates, whereas downstream uncertainty either induces a positive or a zero effect on these growth rates. We report other robustness checks in Section OA.6 of the Online Appendix.

4 Macro-level evidence

This section shows that the micro-level results documented in Section 3 also hold at the macro-level. That is, the asymmetric response of firm-level investment and valuations to changes in upstream and downstream uncertainty carries over to the macroeconomy. Intuitively, since supplier-specific (customer-specific) uncertainty is associated with decreased (increased) economic activity, common uncertainty shocks to firms that tend to operate relatively upstream (downstream) should induce a positive (negative) effect on most other firms, as most links in the production network point downstream. We construct *macro-level* measures of supply-chain uncertainty in Section 4.1. Section 4.2 then shows that shocks to macro-level upstream (downstream) uncertainty lead to a deterioration (improvement) in aggregate growth and asset prices. Moreover, Section 4.3 demonstrates that macro-level upstream (downstream) uncertainty is associated with higher (lower) marginal utility of investors.

4.1 Data

Our macro-level analysis uses the same universe of firms described in Section 3.1. Unlike our firm-level tests that begin in 1976, our macro-level results begin in 1974. We choose this slightly earlier start date since we can compute the macro-level measures of supply-chain uncertainty over a longer time period, as described below.[19]

Constructing vertical position. The macro-level analysis of supply-chain uncertainties requires to move beyond the "upstream" and "downstream" metrics used in Section 3, due to the need to consider the *absolute* vertical position of each firm in the production network, rather than the *relative* position of a firm in a given supply chain.[20] To see why, consider a firm i that has a high vertical position (i.e., is further from final consumers). In the firm-level analysis, it was sufficient to define any supplier firm s that sells to firm i as an upstream firm with respect to i. However, firm s is not necessarily more upstream than firm i in an absolute sense. For example, while s may sell some of its output to i, firm s may sell most of its goods to final consumers. Therefore, while firm s is *relatively* upstream from the perspective of firm i (i.e., in a specific supply chain), firm s may still have a lower *absolute* vertical position when considering the production network as a whole.

We measure the vertical position of firms in the production network using the Input-Output (I-O) tables constructed by the Bureau of Economic Analysis (BEA). These tables, which are also referred to as the BEA's Make and Use tables, record the dollar flows of commodities between industries, and their usage for final consumption. There are two primary benefits of using the BEA I-O tables rather than Computstant Segments or FactSet data to measure absolute vertical position. First, the I-O tables span a significantly longer time period than either alternative dataset, allowing us to

[19]While this slightly earlier start date allows us to begin the sample period around the time that NASDAQ-listed firms appear in CRSP, this start date does not influence our macro-level results.

[20]Following Gofman et al. (2020), we use the term "vertical position" or "upstreamness" to denote the distance of a firm from final consumption good production.

measure the vertical positions of firms as far back as the 1970s.[21] Second, the I-O tables account for the *existence* and the *importance* of inter-industry links, as they record the dollar flows of goods between different parts of the economy.[22] Nonetheless, the I-O tables are only published once every five years.

The intuition behind the vertical position measure based on the BEA's Make and Use tables is that industries that produce a higher (lower) dollar value of commodities that flow to final consumers are less (more) upstream in the production network. With this intuition in mind, we follow Antràs and Chor (2018) to combine the normalized Make and Use tables, denoted by $\tilde{M}$ and $\tilde{U}$, respectively, to compute a vertical position (upstreamness) score for each industry. Specifically, the upstreamness score of industry k at time t is the k^{th} element of

$$VP_t = \left(I_{N_t \times N_t} - \tilde{M}_{N_t \times C_t} \times \tilde{U}_{C_t \times N_t} \right)^{-1} \iota. \tag{5}$$

Here, VP_t is a $N_t \times 1$ vector of vertical position scores, I is an identity matrix, ι is a vector of ones, and the subscripts N_t and C_t represent the total number of industries and commodities in the BEA tables at time t, respectively. The Leontief inverse in equation (5) captures the importance of each industry as a *direct* and *indirect* supplier to all other industries (Carvalho and Tahbaz-Salehi, 2019).[23]

We apply the procedure underlying equation (5) to the BEA Make and Use tables reported for years 2012, 2007, 2002, 1997, 1992, 1987, 1982, and 1977. For observations preceding (proceeding) 1977 (2012), we assume that an industry's vertical position is identical to that in 1977 (2012). For observations between successive releases of the I-O tables, we assume that an industry's vertical position in year t is the same as that based on the previously released Make and Use tables. For the purpose

[21] While Compustat Segments contains a small number of observations for the 1970s, there is an insufficient number of inter-firm links to compute absolute measures of upstreamness. For instance, there are only 1087 links in Compustat Segments for the entire $1976 - 1979$ period.

[22] While Compustant Segments data also contains information on the flow of sales between a firm and its most critical customers, this data is limited to the small set of firms that appear in the Segments data. Similar data on flows is unavailable for the more comprehensive FactSet dataset.

[23] The properties of this matrix satisfy the conditions listed in Carvalho and Tahbaz-Salehi (2019) for this matrix's inverse to exist. Therefore, defining $T_t \equiv \tilde{M}_{N_t \times C_t} \times \tilde{U}_{C_t \times N_t}$, and noting that $(I_{N_t} - T_t)^{-1} = \sum_{z=0}^{\infty} T_t^k$, we can write element (i, j) of $(I_{N_t} - T_t)^{-1}$ as $t_{i,j} + \sum_{k=1}^{N_t} t_{i,k} t_{k,j} + \ldots$. Here, the first term reflects the importance of industry j as a supplier to industry i, the second term accounts for links between industry j, and each industry r that, in turn, supplies to industry i, and the ellipses account for all other indirect links between industry j and industry i.

of brevity, we provide a detailed description of how we clean, filter, and normalize the BEA I-O tables, and then match the resulting industry-level vertical position scores to the CRSP/Compustat universe, in Section OA.4 of the Online Appendix.

Constructing macro-level uncertainties. At the end of each month between January 1974 and December 2018, we sort firms into two groups based on the cross-sectional distribution upstreamness scores from equation (5). Firms that belong to industries with a vertical position score above (below) the 90^{th} (10^{th}) percentile of the distribution of vertical position scores are considered upstream (downstream) firms. While these cutoffs may appear relatively extreme, they provide a clear distinction between firms that are considered upstream and downstream. Furthermore, these breakpoints produce portfolios that contain hundreds of individual firms.[24]

To parallel our micro-level measures of upstream- and downstream uncertainty from Section 3, we construct our baseline measures of macro-level upstream and downstream uncertainty using the realized volatility of firm-level stock returns. We compute the realized stock return volatility of each firm assigned to each of the upstream and downstream portfolios. The volatility of firm i in month t is the standard deviation of the firm's daily stock returns in month t.[25] We then compute the value-weighted average realized stock return volatility across all firms in a given portfolio. This procedure yields a monthly time-series of aggregate uncertainty for both upstream and downstream firms. Finally, since most macroeconomic variables of interest are recorded at a lower frequency than stock returns, we aggregate the monthly time series of upstream and downstream uncertainties into quarterly time series. This is achieved by computing the time-series mean of upstream (downstream) uncertainty over the three months preceding the end of each quarter t.[26]

We also ensure that our macro-level results are robust to using forward-looking measures of uncertainty. For instance, in Section 4.3 we extract the time-t measurable component of future realized stock return volatility. The results based on

[24] Untabulated analyses show our results are robust to using the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of vertical position scores to define upstream and downstream firms.

[25] To compute these measures of volatility we (i) adjust stock returns in CRSP daily for delisting returns, and (ii) require that each firm has at least 15 valid stock returns in a given month.

[26] Rather than averaging uncertainty over the three months in a given quarter, an alternative approach is to define the uncertainty associated with quarter t as the value of uncertainty in the final month of quarter t. Untabulated analyses show that our results are robust to this alternative method for converting the monthly measure of uncertainty into a quarterly measure.

these forward-looking measures are in line with those based on realized stock return volatility. Moreover, in untabulated robustness checks we also show our results are materially unchanged when measuring aggregate supply-chain uncertainty using (i) forward-looking option-implied volatility, and (ii) idiosyncratic stock return volatility.

4.2 Upstream and downstream uncertainty: aggregate IRFs

We show that macro-level upstream (downstream) uncertainty negatively (positively) affects aggregate growth and asset prices by estimating IRFs that determine how macro-level uncertainty shocks impact key variables of interest.

The IRFs are estimated using the Smooth Local Projections (SLP) method described by Barnichon and Brownlees (2019). Unlike IRFs from the local projection (LP) method of Jordà (2005), which requires the estimation of *separate* predictive regressions for each forecast horizon of interest, SLPs assume that impulse responses are a *smooth* function of the forecast horizon. This allows SLPs to strike a balance between the benefits of IRFs from vector autoregressions, which are efficient for correctly specified models, and IRFs from LPs, which are more robust to model misspecification but are potentially noisy.[27] Specifically, our IRFs are based on the following h-step ahead predictive regressions for horizons of $h \in \{1, ..., H\}$ quarters

$$y_{t+h} = \beta_{0(h)} + \beta_{1(h)} y_t + \beta_{2(h)} \sigma_{U,t} + \beta_{3(h)} \sigma_{D,t} + \sum_{p=1}^{P} \boldsymbol{\gamma}'_{p(h)} \boldsymbol{\Gamma}_{t-p} + \varepsilon_{t+h}. \quad (6)$$

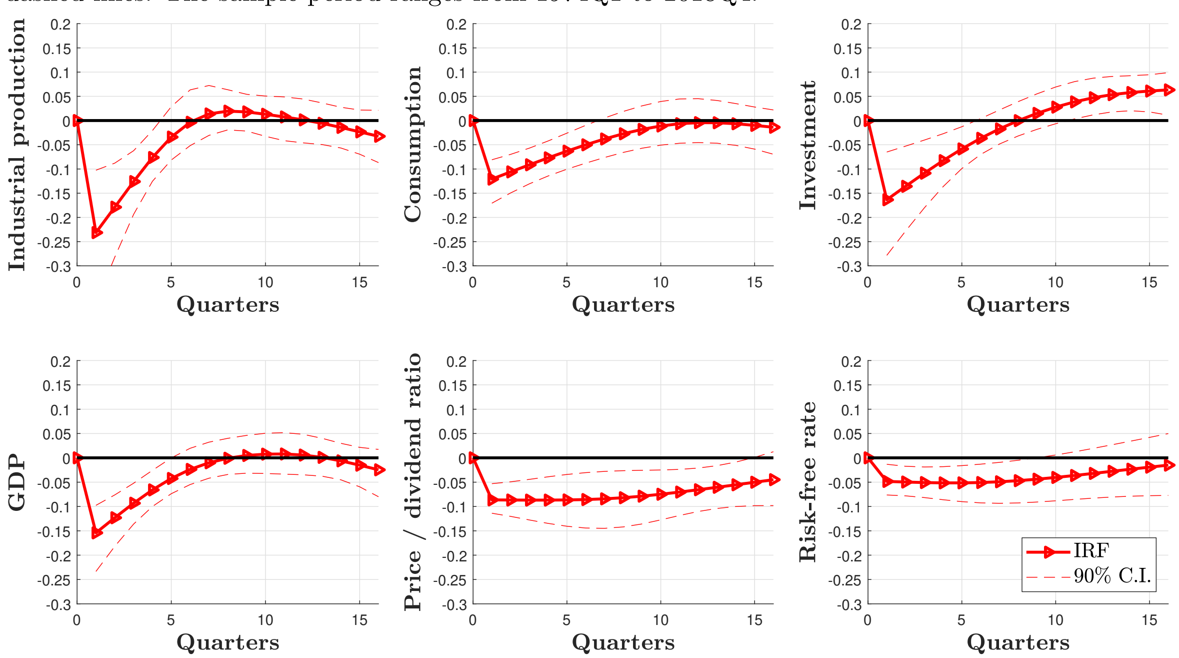
Here, y_{t+h} denotes one of the six following aggregate-level variables at time $t+h$: the quarterly real growth rates of industrial production, consumption, private investment, gross domestic product, the level of the market's price-dividend ratio, and the risk-free rate. $\sigma_{U,t}$ ($\sigma_{D,t}$) denotes macro-level upstream (downstream) uncertainty at time t, constructed following the procedure in Section 4.1, and $\boldsymbol{\Gamma}_{t-p}$ is a vector of controls in quarter $t-p$. These controls include the dependent variable of interest, the two macro-level supply-chain uncertainties, the excess market return, the term spread, the default spread, and the inflation rate. These last four variables are included to account for the negative correlation between the level of macroeconomic activity and macroeconomic uncertainty. We set P equal to one, but results are also robust

[27] Barnichon and Brownlees (2019) strike a balance between VARs and LPs by estimating LPs, and then using penalized B-splines to shrink the resulting IRF towards a smooth polynomial function.

to setting P equal to four. Moreover, our results are robust to controlling for the contemporaneous values of the various controls in $\mathbf{\Gamma}_t$. Finally, we standardized all variables in equation (6) for ease of interpretation and comparability between figures.

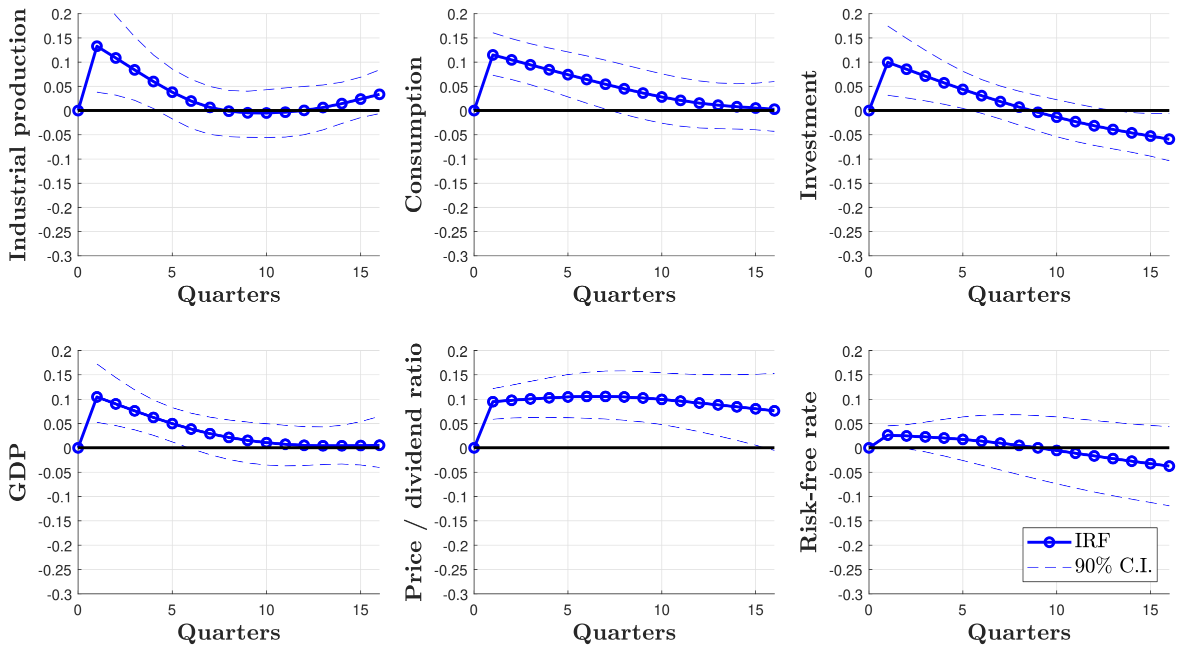
Figure 2 (Figure 3) shows the impulse response functions for the six outcome variables with respect to a one standard deviation increase in macro-level upstream (downstream) uncertainty. Each figure displays the mean response of each variable to the given shock (solid lines), alongside the 90% confidence interval (dashed lines).

Figure 2: Impulse responses from macro-level upstream uncertainty shocks
The figure shows impulse response functions (IRF) from a one standard deviation shock to macro-level upstream uncertainty $\sigma_{U,t}$ to the quarterly growth rates of industrial production, real consumption, real investment, real GDP, and the levels of the aggregate price-dividend ratio and the risk-free rate. We estimate the IRFs using smooth local projection (Barnichon and Brownlees (2019)) method of Equation (6) for horizons that range from one to 16 quarters ahead. We measure macro-level upstream uncertainty by following the procedure described in Section 4.1. Detailed descriptions on the variables included in equation (6) are provided in Section OA.3.2 of the Online Appendix. The estimated IRFs are denoted by solid lines, while 90% confidence intervals are represented by the dashed lines. The sample period ranges from 1974Q1 to 2018Q4.



The IRFs from macro-level upstream uncertainty to all variables of interest are negative and significant, as shown in Figure 2. That is, higher upstream uncertainty leads to a contraction. One quarter after an upstream uncertainty shock, industrial production and consumption growth drop by approximately 0.25 and 0.15 standard

Figure 3: **Impulse responses from macro-level downstream uncertainty shocks**
The figure shows impulse response functions (IRF) from a one standard deviation shock to macro-level downstream uncertainty $\sigma_{D,t}$ to the quarterly growth rates of industrial production, real consumption, real investment, real GDP, and the levels of the aggregate price-dividend ratio and the risk-free rate. We estimate the IRFs using smooth local projection (Barnichon and Brownlees (2019)) method of Equation (6) for horizons that range from one to 16 quarters ahead. We measure macro-level downstream uncertainty by following the procedure described in Section 4.1. Detailed descriptions on the variables included in equation (6) are provided in Section OA.3.2 of the Online Appendix. The estimated IRFs are denoted by solid lines, while 90% confidence intervals are represented by the dashed lines. The sample period ranges from 1974Q1 to 2018Q4.



deviations, respectively. These effects are statistically significant and persist for about seven quarters ahead. Higher upstream uncertainty also drops the market's valuation ratio and the risk-free rate. The reduction in the valuation ratio (the risk-free rate) persists for around 12 (six) quarters. Together, these results echo the firm-level findings for upstream uncertainty, and are consistent with the traditional negative association between uncertainty and economic growth (e.g., Ramey and Ramey (1995)).

In contrast to upstream uncertainty, Figure 3 shows that macro-level downstream uncertainty shocks have an expansionary impact, leading to higher future real economic growth. A one standard deviation shock to macro-level downstream uncertainty increases one-quarter ahead industrial production growth, consumption growth, and investment growth by about 0.1 standard deviations. Likewise, the market's price-dividend ratio rises by a similar, and statistically significant, amount and remains elevated for almost 16 quarters ahead. However, the risk-free rate is largely unaffected. Overall, the positive impact of downstream uncertainty is even more pronounced at the macro-level than the firm-level.

Comparing the IRFs in Figures 2 and 3 shows that macro-level upstream and downstream uncertainty have an *asymmetric* effect on aggregate variables in terms of signs and magnitudes. The positive impacts of macro-level downstream uncertainty shocks are quantitatively more muted, in absolute value, than the negative impacts of macro-level upstream uncertainty shocks. In general, a one standard deviation shock to upstream uncertainty leads to responses that are around 50% to 100% larger in magnitude than the responses to downstream uncertainty shocks. These differences in the sign and the magnitude of the supply-chain uncertainty shocks are broadly consistent with the implications of the micro-level models in Section 2.

By jointly controlling for upstream and downstream uncertainty in equation (6), we isolate the component of downstream uncertainty that is orthogonal to upstream uncertainty. This orthogonal component is procyclical, reconciling the positive impact of downstream uncertainty on economic growth. We show this in Section 4.4.[28]

Robustness. We conduct a host of robustness checks showing that we obtain similar IRFs when we: (1) use the predictable component of the macro-level uncertainties; (2) use either option-implied volatility or idiosyncratic stock return volatility to measure uncertainty; (3) include additional lags of control variables (i.e., increasing P in equation (6)) or estimate the IRFs using the local projection method of Jordà (2005); or (4) use the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of vertical position scores to define the sets of upstream and downstream firms. We do not tabulate these results for the purpose of brevity.

[28]Untabulated results verify that the asymmetric effects of the two macro-level uncertainties arise even if we only control for one facet of uncertainty at a time in equation (6). We re-estimate the IRFs associated with upstream (downstream) uncertainty after removing all contemporaneous and lagged terms associated with downstream (upstream) uncertainty. While these restricted specifications are misspecified (Section 4.3 shows that both facets of uncertainty impact marginal utility), the IRFs based on these restricted regressions deliver a consistent conclusion to the IRFs from the unrestricted regressions – reported in Figures 2 and 3. Qualitatively, we still obtain negative (insignificant or positive) impulse responses from upstream (downstream) macro-level uncertainty shocks. Quantitatively, the results of the restricted projections are weaker. By not controlling for the two types of uncertainty, the impulse responses to downstream uncertainty incorporate the impact of the joint component between the two uncertainties, as well as the impact of the orthogonal component.

4.3 Upstream and downstream uncertainty: prices of risk

We show that macro-level upstream (downstream) uncertainty shocks are associated with an increase (decrease) in the marginal utility of investors. This finding is consistent with the former section that shows that macro-level upstream (downstream) uncertainty decreases (increases) future consumption growth.

Ex-ante uncertainty. As investors are concerned about variation in *expected* outcomes, we compute the market prices of risk of a forward-looking versions of aggregate upstream and downstream uncertainty. Specifically, we consider the time-t predictable component of each future volatility measure. We extract these ex-ante (predictable) components by projecting the logarithm of realized volatility of aggregate upstream (downstream) uncertainty at time $t+1$ on a set of time-t predictors:

$$\ln(\sigma_{x,t+1}) = \beta_0 + \boldsymbol{\beta}\boldsymbol{\Gamma}_t' + \varepsilon_{x,t+1} \quad \text{for } x \in \{U, D\}, \tag{7}$$

and define the ex-ante component, denoted by $\tilde{\sigma}_{x,t} = \exp\left(\hat{\beta}_0 + \hat{\boldsymbol{\beta}}\boldsymbol{\Gamma}_t'\right)$ for $x \in \{U, D\}$. Taking the logarithm above ensures the ex-ante uncertainty measures are strictly positive. We estimate these projections at the monthly frequency using data between January 1974 and December 2018. Our baseline specifications includes the following control variables in $\boldsymbol{\Gamma}_t$: both upstream and downstream macro-level uncertainty, the market's price-dividend ratio, the term and default spreads, and the inflation rate.[29]

Market prices of risk. We estimate the market prices of risk of the predictable components of macro-level upstream and downstream uncertainty by assuming that the stochastic discount factor (SDF) that prices all assets in the economy is:

$$M_t = 1 - b_{MKT} MKTRF_t - b_U \Delta\tilde{\sigma}_{U,t} - b_D \Delta\tilde{\sigma}_{D,t}. \tag{8}$$

The parameter b_U (b_D) measures the market price of upstream (downstream) un-

[29] Prior to estimating the market prices of risk associated with ex-ante upstream and downstream uncertainty measures, we first confirm that the impulse responses from these uncertainties to aggregate variables are consistent with the baseline results of Section 4.2. We replace the quarterly measures of $\sigma_{U,t}$ and $\sigma_{D,t}$ in equation (6) with the ex-ante measures of upstream and downstream uncertainty – $\tilde{\sigma}_{U,t}$ and $\tilde{\sigma}_{D,t}$, respectively. The results, reported in Figures OA.7.2 and OA.7.3 of the Online Appendix, show that using ex-ante measures of macro-level uncertainties supports the conclusion that macro-level upstream (downstream) uncertainty is associated with a deterioration (improvement) in macroeconomic conditions and asset prices.

certainty, and b_{MKT} reflects the price of risk associated with the market portfolio, which we proxy using the excess market return from the Fama and French (1993) three-factor model. We demean all variables included in equation (8), and estimate $[b_{MKT}\ b_U\ b_D]'$ via generalized method of moments (GMM) using the Euler condition $\mathbb{E}\left[M_t r^e_{i,t}\right] = 0$, where $r^e_{i,t}$ denotes the excess return of test asset i at time t.

We employ two menus of test assets to estimate the loadings in equation (8): (1) the monthly returns of 25 value-weighted portfolios double sorted on size and book-to-market, and (2) following the suggestions of Lewellen, Nagel, and Shanken (2010), we also estimate the loadings using a set of 42 portfolios that augments the first set of assets with the monthly value-weighted returns of the Fama-French 17 industry portfolios. This helps to break the strong factor structure inherent in the returns of the first set of test assets. In robustness checks discussed below we also show that our results hold when using even more comprehensive menu comprised of 92 test assets.[30]

Table 4: Market price of risk of macro-level upstream and downstream uncertainty
The table reports the market prices of risk associated with macro-level upstream and downstream uncertainty (σ_U and σ_D, respectively). We estimate these market prices of risk via a generalized method of moments procedure based on the stochastic discount factor (SDF) given by equation (8) and the Euler equation given by $\mathbb{E}\left[M_t r^e_{i,t}\right] = 0$. When estimating these prices of risk we use the ex-ante (predictable) components of future macro-level upstream and downstream realized volatility, obtained via equation (7) at the monthly frequency. We control for excess market returns as a risk factor, capturing first-moment fluctuations in productivity. We use two different sets of value-weighted test assets. In Panel A the set of test assets is comprised of the monthly returns of 25 portfolios sorted on size and book-to-market. In Panel B, the set of test assets in Panel A is augmented by including the monthly returns of the 17 Fama-French industry portfolios. The t-statistic associated with each factor risk premium is reported in parentheses, and the mean absolute error (MAE) from each estimation procedure is reported in the bottom row of each panel. Monthly data spanning February 1974 to December 2018 is used to estimate each model.

	Panel A: 25 portfolios				Panel B: 42 portfolios			
MKTRF	3.64	2.76	3.85	2.97	3.40	2.79	3.55	3.03
	(3.47)	(2.40)	(3.51)	(2.24)	(3.30)	(2.57)	(3.32)	(2.66)
σ_U		-0.67		-2.42		-0.46		-1.41
		(-2.44)		(-3.59)		(-2.34)		(-3.07)
σ_D			0.40	4.90			0.28	2.93
			(0.70)	(3.28)			(0.60)	(2.73)
MAE	0.98	1.03	0.97	0.93	1.01	1.01	1.00	0.97

[30] We obtain the monthly returns of all test assets from Ken French's data library. We thank Ken French for making this data available.

Table 4 reports the loading associated with each source of risk included in equation (8) across the two sets of test assets, and the mean absolute pricing error (MAE) from each GMM estimation. Panel A is based on the set of 25 test assets. When b_D (b_U) is restricted to zero, upstream (downstream) uncertainty has a negative (positive) and statistically significant (insignificant) price of risk. When both coefficients are unrestricted in the rightmost column of Panel A, then upstream (downstream) uncertainty has a negative (positive) price of risk, and each of these slope coefficients is statistically significant at better than the 1% level. Economically, states of high upstream (downstream) macro-level uncertainty are associated with bad (good) times for investors. The results in Panel B, which are based on a more comprehensive set of test assets, mirror those in Panel A. Thus, the table documents that marginal utility increases (decreases) with higher macro-level upstream (downstream) uncertainty.

Robustness. Table OA.7.6 of the Online Appendix shows that the market prices of risk the aggregate supply-chain uncertainties are robust along two dimensions. First, estimating these prices of risk using more comprehensive sets of 62 or 92 tests assets produces qualitatively and quantitatively similar results. Second, perturbing the set of predictors $\mathbf{\Gamma}_t$ used in equations (6) does not change our results.

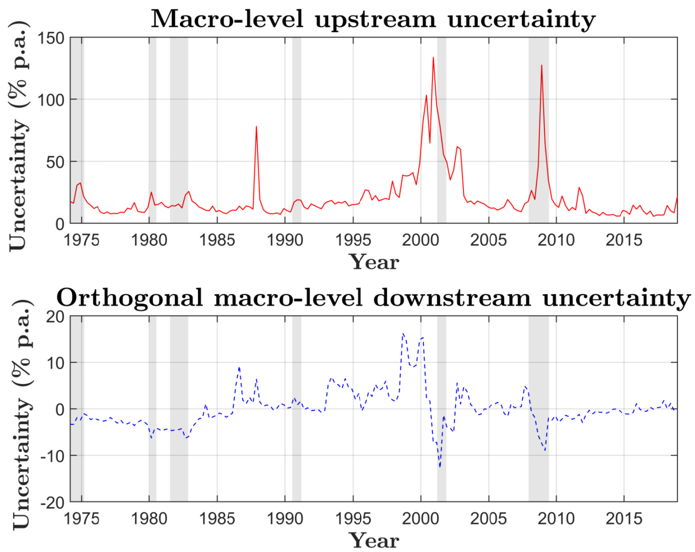
4.4 Supply-chain uncertainties and the COVID-19 crisis

Cyclicality. By jointly controlling for upstream and downstream uncertainty in equation (6), we effectively isolate the component of downstream uncertainty that is orthogonal to upstream uncertainty. This orthogonal component is procyclical. To illustrate this point, Figure 4 plots the time series of both macro-level upstream uncertainty (top panel) and the orthogonal component of downstream uncertainty (bottom panel). The orthogonal component is computed by projecting downstream uncertainty on contemporaneous upstream uncertainty, and computing the residuals.

Macro-level upstream uncertainty is countercyclical, typically rising around NBER recession, and reaching peaks in the periods surrounding the Great Recession, the dot-com crash, and the 1987 stock market crash. In contrast, the orthogonal downstream uncertainty typically declines in recessions, and rises during the technological boom of late 1990s. The counter- (pro-) cyclicality of upstream (orthogonal downstream) macro-level uncertainty is in line with the IRFs in Section 4.2.

COVID-19. The recent COVID-19 pandemic has brought an almost unprece-

Figure 4: Macro-level upstream uncertainty, and orthogonal downstream uncertainty The figure shows the quarterly time series of macro-level upstream uncertainty (top panel) and the orthogonal macro-level downstream uncertainty (bottom panel). We compute the macro-level uncertainties following the procedure described in Section 4.1. The orthogonal component represents the residuals from a projection of macro-level upstream uncertainty $\sigma_{U,t}$ onto downstream uncertainty $\sigma_{D,t}$. Each time series spans 1974Q1 to 2018Q4. Shaded regions represent NBER recessions.



dented level of uncertainty to financial markets. This was particularly manifested by the VIX index, displayed in the top panel of Figure OA.7.4. The VIX increased by nearly 200% in the first quarter of 2020. While part of this increase likely reflects higher risk aversion, there is little doubt that the global pandemic was both a negative first-moment shock and a positive second-moment shock. At the onset of the pandemic, macroeconomic uncertainty spiked, for example, due to the unknown nature of the disease, duration of imposed shutdowns, and timing of a potential vaccine.

Was the uncertainty shock associated with COVID-19 driven by macro-level upstream or downstream uncertainty? We check this by extending the time-series of each uncertainty to October 2020. Because the BEA I-O tables for 2017 are unavailable (these tables are published with five year lag), we assume that industries' vertical positions in 2020 are identical to those implied by the I-O tables for 2012. We extend these time series by following the same producures described in Section 4.1.

The middle panel of Figure OA.7.4 shows the component of downstream uncertainty that is orthogonal from upstream uncertainty around the onset of the COVID-19 crisis. By construction, the average level of the orthogonal downstream uncertainty is zero and, as discussed earlier, this orthogonal component turns negative in most past recessions. Notably, we find that the orthogonal downstream uncertainty spikes during March 2020. Thus, while downstream uncertainty was dominated by upstream uncertainty in most past contractions, the opposite is true for the recent crisis.

This result sheds light on the potential origins of the economic recession and its prognosis. First, a priori, it is unclear whether the COVID-19-induced contraction represents a supply- or demand-side shock. Our results suggest that the latter is more likely. A possible narrative is that the sharp decline in economic activity during the first half of 2020 was largely driven by lockdown restrictions, and precautionary consumer behavior. This negative demand shock propagated upstream, but primarily affected downstream firms. Second, our findings in Section 4.2 suggest that higher downstream uncertainty positively predicts future economic growth. Consistent with these findings, along with the fact that downstream uncertainty was more dominant at the onset of the COVID-19 recession, the bottom panel of Figure OA.7.4 shows that while industrial production dropped from January to April of 2020, output largely recovered by July of 2020. Put differently, unlike upstream uncertainty, downstream uncertainty shocks do not deepen recessions, and may even hasten recovery. This seems to be the case thus far in the data. As of Q3 of 2020, the orthogonal component of downstream uncertainty is roughly zero, though slightly negative. So long as this orthogonal component does not fall significantly, the evidence presented in this study suggets that a full economic recovery should not be hindered by uncertainty.

5 Conclusion

We examine the theoretical and empirical implications of uncertainties that originate in different locations of firms' supply-chain environments on firms' real economic activity and financial valuation. Higher upstream (downstream) uncertainty, stemming from suppliers (customers), is negatively (positively) related to firms' investment and valuations. This asymmetry holds at the micro-level (i.e., firm-level), and even more strongly at the aggregate-level. Specifically, macro-level upstream (downstream) uncertainty leads to a decline (increase) in key macroeconomic and financial market variables, such as output, consumption, investment, and the market's price-to-dividend ratio, and increases (decreases) the marginal utility of investors.

On the theoretical front, we construct a real-option model that predicts the aforementioned asymmetry. The key feature of the model is the realistic delay between the times when a firm initiates an investment project and when the firm receives its first revenue. This "time-to-build" period implies that downstream (upstream) uncertainty, related to input prices from suppliers (output price to customers), impacts the firm in the short (long) run. Upstream uncertainty depresses investment due to the traditional "bad news principle," while downstream uncertainty can sharply increase the opportunity cost of waiting via "growth option" channels and hasten investment.

On the empirical front, we take a "bottom-up" approach to examine the relation between the two types of uncertainty and firm-level outcomes. We find that higher upstream uncertainty supresses investment and valuations, whereas higher downstream uncertainty never decreases, and often increases, these variables. Moreover, the positive link between downstream uncertainty and investment *increases* for longer time-to-build industries. These results are in line with our real-option model. We also construct *aggregate* measures of the supply-chain uncertainties and show that the micro-level results aggregate up to the macro-level.

Overall, our findings suggest that while higher uncertainty is often associated with lower investment and asset prices, the effects of uncertainty are more nuanced. Although upstream uncertainty is associated with contractions, downstream uncertainty may have an *expansionary* impact. This finding bears implications for policymakers who may opt to react to the two supply-chain uncertainties differently. For example, as the COVID-19 crisis was accompanied by a rise in downstream uncertainty, the effects of which are larger for longer time-to-build projects, policies that increase the time required to enter the product market (e.g., more trials and testing) may *promote* investment. We leave the theoretical exploration of such policies for future research.

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A Online appendix

OA.1 Static model solution

OA.1.1 Model 1

The NPV for exercising the option to invest at time 0 is:

$$
\begin{aligned}
NPV_0^{\text{Model 1}} =& \frac{1}{4}\underbrace{\left\{-P_s + P_c - \omega + \frac{\beta}{1-\beta}(P_c + h\sigma_c - \omega)\right\}}_{NPV_{0[P_c(VG)]}>0} \\
&+ \frac{1}{4}\underbrace{\left\{-P_s + P_c - \omega + \frac{\beta}{1-\beta}(P_c + \sigma_c - \omega)\right\}}_{NPV_{0[P_c(G)]}>0} \\
&+ \frac{1}{4}\underbrace{\left\{-P_s + P_c - \omega + \frac{\beta}{1-\beta}(P_c - \sigma_c - \omega)\right\}}_{NPV_{0[P_c(B)]}<0} + \frac{1}{4}\underbrace{\left\{-P_s + P_c - \omega - \beta a\right\}}_{NPV_{0[P_c(VB)]}<0},
\end{aligned}
$$

The NPV for of waiting to invest at time 1 is:

$$
\begin{aligned}
E_0[NPV_1^{\text{Model 1}}] =& \frac{\beta}{8}\underbrace{\left\{-(P_s - \sigma_s) + \frac{1}{1-\beta}(P_c + h\sigma_c - \omega)\right\}}_{NPV_{1[P_c(VG),P_s(down)]}>0} \\
&+ \frac{\beta}{8}\underbrace{\left\{-(P_s - \sigma_s) + \frac{1}{1-\beta}(P_c + \sigma_c - \omega)\right\}}_{NPV_{1[P_c(G),P_s(down)]}>0} \\
&+ \frac{\beta}{8}\underbrace{\left\{-(P_s + \sigma_s) + \frac{1}{1-\beta}(P_c + h\sigma_c - \omega)\right\}}_{NPV_{1[P_c(VG),P_s(up)]}>0}.
\end{aligned}
$$

OA.1.2 Model 2

$$
NPV_0^{\text{Model 2}} = \frac{1}{4}\underbrace{\left\{-P_s + \frac{\beta}{1-\beta}(P_c + h\sigma_c - \omega)\right\}}_{NPV_{0[P_c(VG)]}>0} + \frac{1}{4}\underbrace{\left\{-P_s + \frac{\beta}{1-\beta}(P_c + \sigma_c - \omega)\right\}}_{NPV_{0[P_c(G)]}>0}
$$

$$+\frac{1}{4}\underbrace{\left\{-P_s+\frac{\beta}{1-\beta}(P_c-\sigma_c-\omega)\right\}}_{NPV_{0[P_c(B)]}<0}+\frac{1}{4}\underbrace{\{-P_s-\beta a\}}_{NPV_{0[P_c(VB)]}<0},$$

$$\begin{aligned}E_0[NPV_1^{\text{Model 2}}]=&+\frac{1}{8}\beta\underbrace{\left\{-(P_s-\sigma_s)+\frac{\beta}{1-\beta}(P_c+h\sigma_c-\omega)\right\}}_{NPV_{1[P_c(VG),P_s(down)]}>0}\\&+\frac{1}{8}\beta\underbrace{\left\{-(P_s-\sigma_s)+\frac{\beta}{1-\beta}(P_c+\sigma_c-\omega)\right\}}_{NPV_{1,[P_c(G),P_s(down)]}>0}\\&+\frac{1}{8}\beta\underbrace{\left\{-(P_s+\sigma_s)+\frac{\beta}{1-\beta}(P_c+h\sigma_c-\omega)\right\}}_{NPV_{1,[P_c(VG),P_s(up)]}>0}.\end{aligned}$$

OA.2 Dynamic model solution

We outline the solution to the model in Section 2.2. Let $V_0(P_{c,t}, P_{s,t})$ denote the value of the firm that produces using only assets-in-place and has not (yet) exercised its growth option. $V_1(P_{c,t})$ denotes the value of a firm with an active (productive) growth option and, finally, let $V_2(P_{c,t}, \theta)$ represent the value of a firm with a project under construction, where θ is the elapsed time-to-build.

We conjecture and verify that the value of the firm that produces using only assets-in-place is

$$V_0(P_{c,t},P_{s,t})=\underbrace{B_1(P_{s,t})\cdot(P_{c,t})^{\beta_1}+B_2(P_{s,t})\cdot(P_{c,t})^{\beta_2}+B_3(P_{s,t})\cdot(P_{c,t})^{\beta_3}}_{\text{Growth option value}}+\underbrace{\frac{P_{c,t}k_0}{\rho-\mu_c}}_{\text{Assets in place value}},$$

where $\beta_1, \beta_2, \beta_3$ are positive scalars, and where $B_i(P_{s,t})$ for $i = 1, 2, 3$ are scalars that depend on the current input price state $P_{s,t} \in \{P_{s,L}, P_{s,M}, P_{s,H}\}$. Similarly, we conjecture and verify that the value of a firm with an active growth opportunity is:

$$V_1(P_{c,t})=\underbrace{A(P_{c,t})^{\alpha}}_{\text{Abandonment option value}}+\underbrace{\frac{P_{c,t}(k_0+k_g)}{\rho-\mu_c}-\frac{\omega(k_0+k_g)}{\rho}}_{\text{Augmented value from installed capital}},$$

where $\alpha < 0$, and A is a constant. The value function of a firm in the time-to-build stage, where θ units of the build period have passed, is given by:

$$V_2(P_{c,t},\theta) = \underbrace{E\left[\int_t^{t+\theta} e^{-\rho s}(P_{c,s}-\omega)k_0 ds\right]}_{\text{(I)}} + \underbrace{e^{-\rho\theta}E\left[V_1(P_{c,t+\theta})|\, P_{c,t+\theta} > \underline{\xi}\right]}_{\text{(II)}}$$
$$+ \underbrace{e^{-\rho\theta}E\left[V_0(P_{c,t+\theta})|\, P_{c,t+\theta} < \underline{\xi}\right]}_{\text{III}},$$

where in the equation above, term (I) is the discounted profits before the time-to-build is complete, obtained from existing assets in place only, term (II) is the discounted value of the firm it is chooses to operate the new project when time-to-build is over, and term (III) is the discounted value of the firm if it chooses to abandon immediately when the time-to-build period is over. $\underline{\xi}$ is the endogenous abandonment threshold for the output price. With some algebra, V_2 can be simplified to:

$$\begin{aligned} V_2(P_{c,t},\theta) &= (1-\Phi(u(P_{c,t},\theta)-\alpha\sigma_c))A(P_{c,t})^{\alpha}e^{\alpha(\mu_c-\frac{\sigma_c^2}{2})\theta+\frac{\alpha^2\sigma_c^2\theta}{2}-\rho\theta} \\ &\quad +(1-\Phi(u(P_{c,t},\theta)-\sigma_c))\frac{P_{c,t}k_g}{\rho-\mu_c}e^{\mu_c\theta-\rho\theta}-(1-\Phi(u(P_{c,t},\theta)))\frac{\omega(k_0+k_g)}{\rho}e^{-\rho\theta} \\ &\quad +\Sigma_{i=1}^3\Phi(u(P_{c,t},\theta)-\beta_i\sigma_c)B_i(P_{s,M})(P_{c,t})^{\beta_i}e^{\beta_i(\mu_c-\sigma_c^2/2)+\frac{\beta_i^2\sigma_c^2\theta}{2}-\rho\theta}+\frac{P_{c,t}k_0}{\rho-\mu_c} \end{aligned}$$

where

$$u(P_{c,t},\theta) = \frac{log\underline{\xi} - logP_{c,t} - (\mu_c - \sigma_c^2/2)\theta}{\sigma_c\sqrt{\theta}}$$

The optimal investment rule is given by investment thresholds $\overline{\xi}(P_s)$ that depends on the state of the input price $P_s \in \{P_{s,L}, P_{s,M}, P_{s,H}\}$. It is optimal to exercise the growth option at time t when $P_{s,t} = P_s \in \{P_{s,L}, P_{s,M}, P_{s,H}\}$ if and only if $P_{c,t} \geq \overline{\xi}(P_s)$. The coefficients $\{\beta_i, B_i(P_s)\}_{\{i=1,2,3\}}$ and the optimal exercise thresholds $\overline{\xi}(P_s)$ are jointly determined by value-matching and smooth-pasting conditions:

$$\begin{aligned} V_0(\overline{\xi}(P_s),P_s) &= V_2(\overline{\xi}(P_s),h)-P_sk_g, \quad \text{for } P_s \in \{P_{s,L},P_{s,M},P_{s,H}\} \\ \frac{\partial}{\partial P_c}V_0(\overline{\xi}(P_s),P_s) &= \frac{\partial}{\partial P_c}V_2(\overline{\xi}(P_s),h). \end{aligned}$$

Similarly, the optimal abandonment rule is given by an abandonment threshold $\underline{\xi}$, such that it is optimal abandon if and only if $P_c \leq \underline{\xi}$. The coefficients A, α, along with the optimal abandonment threshold are jointly determined by value-matching and smooth-pasting conditions:

$$\begin{aligned} V_1(\underline{\xi}) &= V_0(\underline{\xi},P_{s,M}) \\ \frac{\partial}{\partial P_c}V_1(\underline{\xi}) &= \frac{\partial}{\partial P_c}V_0(\underline{\xi},P_{s,M}). \end{aligned}$$

OA.3 Variable description and construction

OA.3.1 Micro-level variables

Book-to-market ratio. A firm's book-to-market ratio is constructed by following Daniel and Titman (2006). Book equity is defined as shareholders' equity minus the value of preferred stock. If available, shareholders' equity is set equal to stockholders' equity (Compustat Annual item SEQ). If stockholders' equity is missing, then common equity (Compustat Annual item CEQ) plus the par value of preferred stock (Compustat Annual item PSTK) is used instead. If neither of the two previous definitions of stockholders' equity can be constructed, then shareholders' equity is the difference between total assets (Compustat Annual item AT) and total liabilities (Compustat Annual item LT). For the value of preferred stock we use the redemption value (Compustat Annual item PSTKRV), the liquidating value (Compustat Annual item PSTKL), or the carrying value (Compustat Annual item PSTK), in that order of preference. We also add the value of deferred taxes and investment tax credits (Compustat Annual item TXDITC) to, and subtract the value of post-retirement benefits (Compustat Annual item PRBA) from, the value of book equity if either variable is available. Finally, the book value of equity in the fiscal year ending in calendar year $t-1$ is divided by the market value of common equity from December of year $t-1$.

Downstream uncertainty (stock return volatility). Our primary measure of the uncertainty of the customers of firm i at time t, based on realized stock return volatility, is computed three steps. First, we identify the customers associated with firm i at time t using the procedure outlined in Section 3.1. Second, for each customer associated with firm i at time t, we compute the standard deviation of the daily stock returns of each customer in the year preceding time t. When calculating these standard deviations we (i) adjust daily stock returns for delisting events, and (ii) require that each customer firm has at least 200 non-missing daily stock returns in the previous year. Third, we calculate the equal-weighted average of all standard deviations computed in the previous step of the procedure.

Downstream uncertainty (idiosyncratic stock return volatility). We construct an additional proxy of the uncertainty of the customers of firm i at time t using the idiosyncratic volatility of daily stock returns. This alternative measure of customer-level uncertainty is computed three steps. First, we identify the customers associated with firm i at time $t$using the procedure outlined in Section 3.1. Second, for each customer associated with firm i at time t, we compute the idiosyncratic volatility of the firm's stock returns by following Ang, Hodrick, Xing, and Zhang (2006). That is, we project each customer's (de-listing adjusted) excess daily stock returns in the year preceding time t on the Fama and French (1993) factors, provided there are at least 200 valid daily returns in the previous year. We then compute the standard deviations of the residuals obtained from the aforementioned regression. Third, we calculate the equal-weighted average idiosyncratic return volatility across all customers identified in the previous steps.

Downstream uncertainty (implied volatility). We construct an additional proxy of the uncertainty of the customers of firm i at time t using the implied volatility of each customer firm's out-of-the-money put options. This alternative measure of customer-level uncertainty is computed three steps. First, we identify the customers associated with firm i at time t using the procedure outlined in Section 3.1. Second, for each customer associated with firm i at time t, we compute the daily mean implied volatility of the firm by taking the equal-weighted average implied volatility across all put options with between seven and 365 calendar days to maturity, and with a moneyness between 0.80 and 0.95. We then compute the time-series average of this implied volatility over all days in the year preceding time t. Finally, we then calculate the equal-weighted average implied volatility across all customers identified in the previous steps. We use option data from OptionMetrics to construct this proxy of customer-level uncertainty.

Financial constraints. We measure a firm's financial constraints by constructing the Kaplan and Zingales (1997) index in the way described by Lamont, Polk and Saaa-Requejo (2001). That is, we use the estimated ordered logit coefficients in Table 9 of Lamont et al. (2001) to construct our firm-level index of financial constraints.

Investment rate. Following Belo et al. (2014), the investment rate is computed as capital expenditure (Compustat Annual item CAPX) minus the sales of property, planet, and equipment (Compustat Annual item SPPE) scaled by the average net property, planet, and equipment in years t and $t-1$ (Compustat Annual item PPENT). Missing values of SPPE are set to zero.

Momentum. A firm's past return momentum in month t is defined as its cumulative return between months $t-11$ and $t-1$ Jagadeesh and Titman (1993). This measure is constructed using CRSP Monthly return data that is adjusted for de-listing events.

Number of customers. We compute the number of customers associated with firm i in year t as follows. First, we use the FactSet Relationship databse to identify all customers in each year between 2003 and 2018. Second, we use the Compustat Segments data from Barrot and Sauvagnat (2016) to count the number of customers associated with firm i in each year prior to 2003 (when FactSet data is unavailable).

Number of suppliers. We compute the number of suppliers associated with firm i in year t as follows. First, we use the FactSet Relationship databse to identify all suppliers in each year between 2003 and 2018. Second, we use the Compustat Segments data from Barrot and Sauvagnat (2016) to count the number of suppliers associated with firm i in each year prior to 2003 (when FactSet data is unavailable).

Own uncertainty (stock return volatility). Our primary measure of the uncertainty of firm i at time t is the standard deviation of the firm's daily stock returns in the year preceding time t. To compute this standard deviation we adjust daily stock returns for delisting events and also require that each firm has at least 200 non-missing daily stock returns in the previous year.

Own uncertainty (idiosyncratic stock return volatility). We construct an additional proxy of the uncertainty of firm i at time t using the idiosyncratic volatility of the firm's daily stock returns in the year preceding time t. Here, we measure idiosyncratic volatility in accordance with Ang et al. (2006). Specifically, we project the firm's daily excess stock returns on the Fama and French (1993) factors, provided there are at least 200 valid daily returns in the previous year. We then compute the standard deviations of the residuals obtained from the aforementioned regression. In constructing this measure of idiosyncratic volatility we adjusted daily stock returns for delisting events.

Own uncertainty (implied volatility). We construct an additional proxy of the uncertainty of firm i at time t using the average implied volatility of the firm's out-of-the-money put options over the year preceding time t. To compute the average implied volatility of each firm on each day we take the equal-weighted average implied volatility across all put options with between seven and 365 calendar days to maturity, and with a moneyness between 0.80 and 0.95. We use option data from OptionMetrics to construct this proxy of firm-level uncertainty.

Price-earnings ratio. We measure the price-to-earnings rate of firm i at time t by scaling the firm's stock price from CRSP at time t by the firm's earnings per share excluding extraordinary items (Compustat Annual item EPSFX). We draw these price-earnings ratio from the firm-level financial ratios dataset on WRDS.

Profitability. A firm's profitability, as measured by return on assets, is computed as net income (Computat Annual item NI) divided by total assets (Compustat Annual item AT).

Real sales growth. The real sales growth rate is defined as the growth rate of real sales between years $t-1$ and t.

Real inventory growth. The inventory growth rate is defined following Belo and Lin (2012). That is, we compute the annual percentage change in each firm's inventory holdings (Compustat Annual item INVT) after converting the value of inventories to real terms.

Tobin's *q*. We define Tobin's q as the book value of assets (Compustat Annual Item AT) minus the book value of common equity (Compustat Annual Item CEQ) plus the market value of common equity (Compustat Annual Item CSHO), divided by the book value of assets.

Upstream uncertainty (stock return volatility). Our primary measure of the uncertainty of the customers of firm i at time t, based on realized stock return volatility, is computed three steps. First, we identify the suppliers associated with firm i at time t using the procedure outlined in Section 3.1. Second, for each supplier associated with firm i at time t, we compute the standard deviation of the daily stock returns in the year preceding time t. When calculating these standard deviations we (i) adjust daily stock returns for delisting events, and (ii) require that each supplier firm has at least 200 non-missing daily stock returns in the previous year. Third, we calculate the equal-weighted average of all standard deviations computed in the previous step of the procedure.

Upstream uncertainty (idiosyncratic stock return volatility). We construct an additional proxy of the uncertainty of the suppliers of firm i at time t using the idiosyncratic volatility of daily stock returns. This alternative measure of suppliers-level uncertainty is computed three steps. First, we identify the suppliers associated with firm i at time t using the procedure outlined in Section 3.1. Second, for each supplier associated with firm i at time t, we compute the idiosyncratic volatility of the firm's stock returns by following Ang et al. (2006). That is, we project each supplier's (de-listing adjusted) excess daily stock returns in the year preceding time t on the Fama and French (1993) factors, provided there are at least 200 valid daily returns in the previous year. We then compute the standard deviations of the residuals obtained from the aforementioned regression. Third, we calculate the equal-weighted average idiosyncratic return volatility across all suppliers identified in the previous steps.

Upstream uncertainty (implied volatility). We construct an additional proxy of the uncertainty of the suppliers of firm i at time t using the implied volatility of each supplier firm's out-of-the-money put options. This alternative measure of supplier-level uncertainty is computed three steps. First, we identify the suppliers associated with firm i at time t using the procedure outlined in Section 3.1. Second, for each supplier associated with firm i at time t, we compute the daily mean implied volatility of the firm by taking the equal-weighted average implied volatility across all put options with between seven and 365 calendar days to maturity, and with a moneyness between 0.80 and 0.95. We then compute the time-series average of this implied volatility over all days in the year preceding time t. Finally, we then calculate the equal-weighted average implied volatility across all suppliers identified in the previous steps. We use option data from OptionMetrics to construct this proxy of supplier-level uncertainty.

OA.3.2 Aggregate uncertainty variables

Default spread. The default spread at time t is defined as the difference between yields on AAA-rated corporate bonds and the yields on BAA-rated yields at the same point in time. We draw the default spread from the updated dataset corresponding to Welch and Goyal (2008), which is available on Amit Goyal's website.

Downstream stock return volatility. Our primary measure of aggregate downstream uncertainty at time t, based on realized stock return volatility, is computed as follows. First, we calculate the vertical position of each industry at a given point in time following the procedure outlined in 4.1, and map these industry-level vertical position scores to the firm-level. Second, define downstream firms as those firms with a vertical position score that is below the 10^{th} percentile of the cross-sectional distribution of vertical position scores at the given point in time. Third, we compute the realized stock return volatility of each firm assigned to the downstream portfolio in month t. When computing these monthly measures of realized stock return volatility we (i) adjust the CRSP daily stock return data for delisting events, and

(ii) require that each firm has 15 valid returns in each month. Fourth, we then take the value-weighted average realized stock return volatility across all firms assigned to the downstream portfolio in month t. In applications that require a monthly measure of aggregate downstream uncertainty, we end the procedure here. In applications that require a quarterly measure of aggregate downstream uncertainty, we define downstream uncertainty in quarter t as the time-series average value of monthly aggregate downstream uncertainty over the three month in quarter t.

Excess market returns. We obtain the quarterly excess returns of the market portfolio using data on the market factor underlying the Fama and French (1993) three-factor model. Specifically, we compound the monthly returns associated with the excess market return factor to the quarterly frequency. We implement this calculation using factor return data drawn from Ken French's data library.

Industrial production. We measure the quarterly growth rate of industry production at time t using the logarithmic growth rate of the Board of Governors of the Federal Reserve System's industrial production index. We obtain our data on the industrial production index from FRED, and express the quarterly growth rate as a percentage.

Inflation rate. The inflation rate at time t is computed using the consumer price index for all urban consumers constructed by the Bureau of Labor Statistics. We draw this inflation rate date from the updated dataset corresponding to Welch and Goyal (2008), which is available on Amit Goyal's website.

Price-dividend ratio. We compute the price-divided ratio of the S&P 500 index at time t by dividing the price index of the S&P 500 at time t by the twelve-month moving sum of dividends paid by the constituents of the S&P 500 index over the 12 months preceding time t. We obtain data on both components of the price-dividend ratio from the updated dataset corresponding to Welch and Goyal (2008), which is available on Amit Goyal's website.

Real consumption growth. We construct the quarterly growth rate of real consumption at time t in four steps. First, we compute the sum of personal consumption expenditures on non-durable goods and personal consumption expenditures on services. Each of these components of personal consumption expenditure is constructed by the Bureau of Economic Analysis, and is expressed in nominal terms in units of billions of dollars. Second, we deflate the nominal values of personal consumption expenditures by the consumer price index deflator to express consumption expenditures in real terms. Specifically, we use the deflator associated with the consumer price index for all urban consumers constructed by the Bureau of Labor Statistics. Third, we scale real personal consumption expenditures at each point in time by the size of the U.S. population, as reported by the Bureau of Economic Analysis. Finally, to compute the quarterly growth rate of real consumption expenditures, we begin by aggregate consumption expenditures from the monthly frequency to the quarterly frequency. This is done by computing the average value of real consumption expenditures per capita per quarter. We then compute the logarithmic growth rate of this quarterly real consumption expenditures per capita series. We obtain each of the aforementioned series from FRED, and express the quarterly growth rate of real consumption as a percentage.

Real gross domestic product. We construct the quarterly growth rate of real gross domestic production (GDP) at time t by computing the logarithmic growth rate of real gross domestic product per capita, as constructed and reported by the Bureau of Economic Analysis. We obtain our data on real GDP per capita from FRED, and express the quarterly growth rate as a percentage.

Real private investment. We construct the quarterly growth rate of real private investment at time t in three steps. First, we compute the sum of private non-residential fixed investment and private residential fixed investment. Each of these series is constructed by the Bureau of Economic Analysis and expressed in nominal terms in units of billions of dollars. Second, we deflate the nominal values of private investment by the consumer price index deflator to express consumption expenditures in real terms. Specifically, we use the deflator associated with the consumer price index for all urban consumers constructed by the Bureau of Labor Statistics. Finally, we compute the logarithmic quarterly growth rate of this real private investment series. We obtain each of the aforementioned series from FRED, and express the quarterly growth rate of real private investment as a percentage.

Risk-free rate. We use the Treasury-bill rate as our proxy for the risk-free rate at time t. We obtain data on the risk-free rate from the updated dataset corresponding to Welch and Goyal (2008), which is available on Amit Goyal's website.

Term spread. The term spread at time t is defined as the difference between the yield on long-term Treasury bonds and the Treasury-bill rate. We draw the term spread from the updated dataset corresponding to Welch and Goyal (2008), which is available on Amit Goyal's website.

Upstream stock return volatility. Our primary measure of aggregate upstream uncertainty at time t, based on realized stock return volatility, is computed as follows. First, we calculate the vertical position of each industry at a given point in time following the procedure outlined in 4.1, and map these industry-level vertical position scores to the firm-level. Second, define upstream firms as those firms with a vertical position score that exceeds the 90^{th} percentile of the cross-sectional distribution of vertical position scores at the given point in time. Third, we compute the realized stock return volatility of each firm assigned to the upstream portfolio in month t. When computing these monthly measures of realized stock return volatility we (i) adjust the CRSP daily stock return data for delisting events, and (ii) require that each firm has 15 valid returns in each month. Fourth, we then take the value-weighted average realized stock return volatility across all firms assigned to the upstream portfolio in month t. In applications that require a monthly measure of aggregate upstream uncertainty, we end the procedure here. In applications that require a quarterly measure of aggregate upstream uncertainty, we define upstream uncertainty in quarter t as the time-series average value of monthly aggregate upstream uncertainty over the three month in quarter t.

OA.4 Cleaning BEA Input-Output tables

We use the BEA Make and Use tables for years 2012, 2007, 2002, 1997, 1992, 1987, 1982, and 1977 to measure industry-level vertical position using equation (5). For each set of tables we define N_t (C_t) as the number of industries (commodities) that exist within the BEA tables in year t. The dimensions of the Make table, which we denote by M_t, are $N_t \times C_t$. Similarly, the dimensions of the Use table, which we denote by U_t, are $C_t \times (N_t + 1)$. The first N_t columns of U_t contain the dollar flow of a commodity into each industry (i.e., record the value of the commodity used by the industry as an input), while the last column of U_t contains the dollar value of the commodity used for final consumption.

Next, we normalize the Make and Use tables so that the sum of each row is one. Specifically, we define the matrices $\tilde{M}_t$ and $\tilde{U}_t$ such that

$$\tilde{M}_{j,i,t} = M_{j,i,t} \bigg/ \left(\sum_{z=1}^{C_t} M_{j,z,t} \right), \quad \forall i \in \{1, \ldots, N_t\} \text{ and } j \in \{1, \ldots, C_t\}$$

$$\tilde{U}_{i,j,t} = U_{i,j,t} \bigg/ \left(\sum_{z=1}^{N_t+1} U_{i,z,t} \right), \quad \forall i \in \{1, \ldots, N_t\} \text{ and } j \in \{1, \ldots, C_t\}.$$

Here, element (j, i) in $\tilde{M}$ captures the share of commodity i produced by industry j, and element (i, j) in $\tilde{U}_t$ represents the share of commodity i used by industry j. When computing these shares we take the possibility that some of the commodity may be used for final consumption into account. We remove industries related to the state, local, and Federal government (denoted by entries S001-S007) and Other Services (denoted by NAICS code 81). The final consumption use of each commodity (i.e., the final column of each Use table) is drawn from the Personal Consumption Expenditure columns of the BEA USe files (denoted by F01000 or 910000).

If the sum of a particular row of the Use table, denoted by the matrix U_t, is zero, then we set the respective rows of the normalized Use table, denoted by $\tilde{U}_t$, to zero also. Likewise, when we compute the normalize Use matrix $\tilde{U}_t$ we remove industries that supply for than 90% of their output to themselves. That is, we exclude any industries for which $\tilde{U}_{t,(i,i)} > 0.90$. We apply this filter because these industries are essentially disconnected from the broader economy, yet have extremely high vertical position scores. If we were to include these few but extreme industries in our calculations of vertical position, then the vertical positions of the relatively few industries that supply to these disconnected industries, either directly or indirectly, would become elevated. Also note that equation (5) features a $N_t \times N_t$ matrix $T_t \equiv \tilde{M}_{N_t \times C_t} \times \tilde{U}_{C_t \times N_t}$, where element (i, j) of matrix T_t contains the amount transfered from industry i to industry j. For each row i in T_t, if the element (i, j) is less than 1%, we set this element equal to zero and distribute this small amount among the non-negligible elements of row i. This filter allows us to minimize any noise in the Make and Use tables, and allows us to focus on the most economically important inter-industry transfers. We then use these definitions of $\tilde{M}_t$ and $\tilde{U}_t$ to compute the vertical position scores using equation (5).

In order to link the BEA-implied vertical position measures to the CRSP/Compustat universe of firms we make use of data provided by the BEA to map industry codes in the Make and Use tables to NAICS codes (for the 1997, 2002, 2007, and 2012 tables) and to SIC codes (for the 1977, 1982, 1987, and 1992 tables). For the NAICS-based tables in the post-1997 period, we map NAICS codes to the CRSP/Compustat universe as follows. First, we try to match each firm's six-digit NAICS code to the six-digit NAICS codes of the available industries. If no matches are found, we then try to match each firm's five-digit NAICS code to the five-digit NAICS codes of the available industries. If no matches are found, we then apply this same process to four-digit, three-digit, and two-digit NAICS codes (in that order). Likewise, for the pre-1997 period, we first try to match each firm to an industry using four-digit SIC codes. For the firms that remain unmatched, we then try to match each firm to an industry based on three-digit, or two-digit SIC codes (in that order).

OA.5 Input/Output Price Uncertainty versus Supplier/Customer Return Volatility

In this section we provide empirical evidence to support the assumption that input (output) price uncertainty is positively related to uncertainty over the valuations of a firm's suppliers (customers). We obtain annual time-series for output prices (PISHIP) and input prices (PIIINV) that are specific to a cross-section of 473 manufacturing industries covered by the NBER-CES Manufacturing Industry Database (using the 1997 NAICS industry classification). These time-series span year $\tau \in \{1958, \ldots, 2018\}$. For each industry i, we model the annual log growth in PISHIP and PIINV using a GARCH(1,1) model to obtain the output and input price uncertainty, denoted by $\hat{\sigma}_{P(\text{Output}),i,\tau}$ and $\hat{\sigma}_{P(\text{Input}),i,\tau}$, respectively.

For each industry i we use the 1997 BEA Make and Use Tables, described in Section OA.4, to compute the flow-weighted stock returns of the industry's customers and suppliers. Below, we let N (C) denote the number of industries (commodities) that exist within the BEA Make and Use tables. In line with the notation in Section OA.4, we refer to the Make matrix as $M_{N\times C}$ and the Use matrix as $U_{C\times N}$. The flow of inputs from industry i to industry j is then recorded in element

$$A(i,j) = \sum_{c=1}^{C} M(i,c)\left(\frac{U(c,j)}{\sum_{k=1}^{N} U(c,k)}\right)$$

of matrix $A_{N\times N}$. Given $A_{N\times N}$, we construct the monthly time-series of the returns of industry i's customers as

$$r_{i,t}^{\text{Customer}} = \sum_{j=1}^{N} w_j^{c,i} r_{j,t}, \quad \text{where } w_j^{c,i} = A(i,j) / \sum_k A(i,k).$$

Similarly, the monthly time-series of the returns of industry i's suppliers is

$$r_{i,t}^{\text{Supplier}} = \sum_{j=1}^{N} w_j^{s,i} r_{j,t}, \quad \text{where } w_j^{s,i} = A(j,i) / \sum_k A(k,i).$$

Next, in December of each year τ we construct the realized return volatility of $r_{i,t}^{\text{Customer}}$ and $r_{i,t}^{\text{Supplier}}$ over the last M months, denoted by $RV_{\text{Customer},i,\tau}$ and $RV_{\text{Supplier},i,\tau}$. In the benchmark case we set $M = 3$ to encompass the latest quarter, but we obtain very similar results for $M = 6$ and $M = 12$.

We then focus on industries in our sample that overlap with the NBER-CES database, represented by N_{CES}. For each $i \in N_{CES}$ we compute two time-series correlations: (i) the correlation between the industry's output price uncertainty and the industry's customer return volatility, $\rho^i_{P(\text{Output}),R(\text{Customer})} = \rho(\hat{\sigma}_{P(\text{Output}),i,\tau}, RV_{\text{Customer},i,\tau})$, and (ii) the correlation between the industry's input price uncertainty and the industry's supplier return volatility, $\rho^i_{P(\text{Input}),R(\text{Supplier})} = \rho(\hat{\sigma}_{P(\text{Input}),i,\tau}, RV_{\text{Supplier},i,\tau})$. We only compute these correlation for industries for which there are at least ten overlapping years of price uncertainty and return volatility data.

Panel A (Panel B) of Figure OA.5.1 shows the histogram of $\rho^i_{P(\text{Output}),R(\text{Customer})}$ $\left(\rho^i_{P(\text{Input}),R(\text{Supplier})}\right)$. Consistent with assumption posited in the empirical analysis, both $\rho^i_{P(\text{Output}),R(\text{Customer})}$ and $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ are positive and sizable for almost all industries. Both distributions are right-skewed. The cross-sectional average of $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ is 0.31 with a t-statistic of 45.41. Likewise, the cross-sectional average of $\rho^i_{P(\text{Output}),R(\text{Customer})}$ is 0.21 with a t-statistic of 28.27.[31]

[31] As mentioned above, we obtain similar results for other choices of M. For example, if $M = 6$, then $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ averages 0.18, with a t-statistic of 30.43, while $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ averages 0.14, with a t-statistic of 18.73.

(a) Input price and supplier return correlations **(b)** Output price and customer return correlations

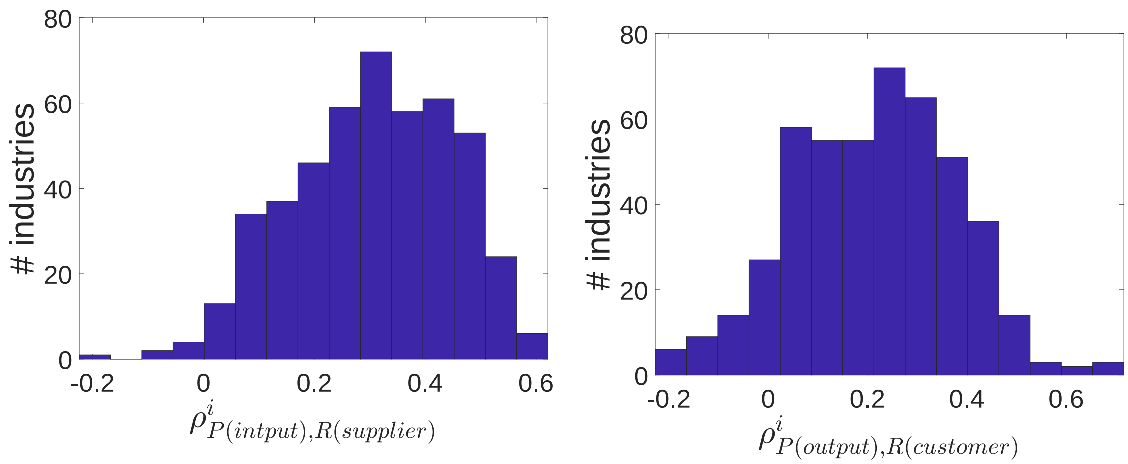

Figure OA.5.1: Cross-sectional correlation: price versus return uncertainty
Panel A shows the histogram of $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ and Panel B the histogram of $\rho^i_{P(\text{Output}),R(\text{Customer})}$. $\rho^i_{P(\text{Output}),R(\text{Customer})}$ is the correlation between industry i's output price uncertainty and the industry's customer return volatility. $\rho^i_{P(\text{Input}),R(\text{Supplier})}$ is the correlation between industry i's input price uncertainty and the industry's supplier return volatility. The sample period ranges from 1958 to 2018.

OA.6 Additional micro-level results

OA.6.1 Supplementary tables

Table OA.6.1: Firm-level sales and inventory growth under supply-chain uncertainties

The table reports the relation between a firm's real sales growth rate (Panel A) or real inventory growth rate (Panel B) and the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers), the firm's downstream uncertainty (uncertainty of the firm's customers), and the firm's own uncertainty. The results are based on estimating regression (3), where $y_{i,t}$ is firm i's sales growth rate or inventory growth rate obtained from the most recent annual report as measured at time t. The benchmark upstream and downstream uncertainty are constructed at time t following the procedure outlined in Section 3.1. In all specifications we include firm and year fixed effects. In all specifications that feature upstream (downstream) uncertainty we control for the number suppliers (customers) of each firm. In even column we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. All regressions are estimated using a panel of firm-year observations ranging from 1976 to 2018. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Real sales growth				
σ(Own)	-0.17	-0.06	-0.14	-0.12	-0.11	-0.10	-0.15	-0.01
	(-16.91)	(-6.31)	(-6.42)	(-5.32)	(-4.33)	(-3.64)	(-5.14)	(-0.36)
σ(Upstream)			-0.05	-0.04			-0.03	-0.03
			(-3.64)	(-3.38)			(-1.72)	(-1.96)
σ(Downstream)					-0.00	0.00	-0.01	-0.01
					(-0.04)	(0.03)	(-0.56)	(-0.39)
Adj.-R^2	0.14	0.20	0.19	0.19	0.15	0.15	0.20	0.26
Obs.	148120	140768	18221	17304	30803	29323	11902	11336
				Panel B: Real inventory growth				
σ(Own)	-0.11	-0.04	-0.08	-0.05	-0.08	-0.07	-0.08	-0.02
	(-13.82)	(-4.66)	(-4.62)	(-2.78)	(-5.39)	(-5.17)	(-3.98)	(-0.88)
σ(Upstream)			-0.02	-0.03			-0.02	-0.02
			(-2.20)	(-2.61)			(-0.95)	(-1.33)
σ(Downstream)					0.02	0.02	0.00	0.00
					(1.84)	(1.52)	(0.03)	(0.07)
Adj.-R^2	0.10	0.13	0.12	0.12	0.12	0.12	0.12	0.13
Obs.	125896	120157	14925	14262	25102	24023	9797	9386
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table OA.6.2: Investment, supply-chain uncertainties, and reversibility
The table reports the relation between a firm's investment rate and the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers) and downstream uncertainty (uncertainty of the firm's customers), conditioning on a proxy for the firm's investment reversibility. The proxy is based on capital redeployability measure of Kim and Kung (2017). The results are based on estimating regression (4), where $y_{i,t}$ is firm i's investment rate obtained from the most recent annual report as measured at time t, the "HighReverse" ("LowReverse") dummy takes the value of one for firms that have above (below) median values of the capital redeployability proxy. The benchmark uncertainty measures are constructed at time t following the procedure outlined in Section 3.1. We include a year fixed effect in all columns, and a firm fixed effect in odd-numbered columns. In all columns we control for the number customers for each firm, and in columns (3), (4), (7) and (8) we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	Panel A: Supplier-level				Panel B: Customer-level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ(Own)	0.13	-0.09	0.17	-0.04	0.09	-0.07	0.12	-0.04
	(8.62)	(-6.14)	(10.48)	(-2.93)	(8.60)	(-3.79)	(8.75)	(-1.87)
σ(Upstream) $\times$ HighReverse	-0.01	-0.03	-0.03	-0.03				
	(-0.91)	(-2.34)	(-2.33)	(-2.69)				
σ(Upstream) $\times$ LowReverse	-0.07	-0.04	-0.08	-0.04				
	(-4.81)	(-3.20)	(-5.72)	(-3.54)				
σ(Downstream) $\times$ HighReverse					0.09	0.03	0.04	0.02
					(7.29)	(2.91)	(3.92)	(1.60)
σ(Downstream) $\times$ LowReverse					0.00	0.02	-0.02	0.00
					(0.17)	(1.56)	(-1.65)	(0.44)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.03	0.50	0.15	0.53	0.04	0.40	0.16	0.44
Obs.	19456	18794	18375	17703	33339	32240	31473	30379

OA.6.2 Additional robustness

Alternative measures of uncertainty. We consider alternative uncertainty proxies. First, while the realized volatility used in the benchmark case is highly persistent, and thus, proxies for expected volatility, we consider a separate uncertainty measure that is forward looking. This helps to further tighten the link between the model's predictions and our empirical results. Specifically, we construct an ex-ante measure of upstream and downstream uncertainty using the implied volatility extracted from options written on each firm's stock. While using option-implied volatility is theoretically appealing, the use of options data has two costs: (i) the time series of our sample is truncated, since option data are only available from 1996 onward; and (ii) the cross section of our sample is also reduced to firms that are optioned *and* have a supplier or customer that has options traded on its stock. Second, we measure upstream and downstream uncertainty using each firm's *idiosyncratic* stock return volatility (IVOL), as defined by Ang et al. (2006). While IVOL is also a backwards-looking proxy, the use of idiosyncratic (rather than total) stock return volatility removes some part of the common variation in stock returns, and typically lowers the correlation between upstream and downstream uncertainty. Details on the construction of each alternative measure are provided in Section OA.3 of the Online Appendix.

We re-estimate equation (3) using each alternative measure of uncertainty, and report the results for IVOL (implied volatility) in Panel A (Panel B) of Table OA.6.3. Regardless of which measure of uncertainty we employ, we draw the same conclusions as those obtained from the baseline analysis. That is, higher firm-specific upstream (downstream) uncertainty suppresses (spurs) investment. In Panel A, the negative and positive effects of both upstream and downstream uncertainty, respectively, are both statistically significant, and incremental to the negative effect of a firm's own uncertainty on its investment rate. In Panel B, which employs implied volatility as a measure of uncertainty, the qualitative takeaways are identical to those in Panel A, although the statistical significance of the results is reduced. This lower degree of statistical power is expected since the number of firm-year observations in Panel B is roughly 50% lower than the number of firm-year observations in Panel A.

In Table OA.6.5 of Online Appendix we consider another modification to the benchmark uncertainty measures. When constructing upstream uncertainty, we weigh each supplier based on the relative size of its sales. When constructing downstream uncertainty, we weigh each customer based on the relative magnitude of its cost of goods solds (COGS). The results are qualitatively and quantitatively similar to the benchmark case.

Sub-sample evidence. To ensure our results are not driven by the early part of our sample period (for which Factset data is not available), Table OA.6.4 in the Online Appendix considers the effects of upstream and downstream uncertainty on firm-level investment rates in the most recent half of our sample period. That is, we report the results of estimating equation (3) using data from June 1997 to June 2018 only. The results are qualitatively and quantitatively similar to the full-sample results in Table 2.

Table OA.6.3: Investment and alternative measures of supply-chain uncertainties
The table reports the relation between a firm's investment rate and alternative uncertainty measures, capturing the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers), the firm's downstream uncertainty (uncertainty of the firm's customers), and the firm's own uncertainty. The results are based on estimating regression (3), where $y_{i,t}$ is firm i's investment rate obtained from the most recent annual report as measured at time t. In Panel A, the uncertainty measures are based on the idiosyncratic return volatility stock returns. In Panel B, the uncertainty measures are based on the implied volatility extracted from of out-of-the-money put options written on each firms' stocks. Given the alternative measures, we construct the uncertainty for each firm, its suppliers and its customers following the procedure outlined in Section 3.1. In all specifications we include firm and year fixed effects. In all specifications that feature upstream (downstream) uncertainty we control for the number suppliers (customers) of each firm. In even column we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. The regressions in Panel A (Panel B) are estimated using an unbalanced panel of firm-year observations ranging from 1976 (1996) to 2018. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	Panel A: IVOL				Panel B: Implied volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ(Own)	-0.09	-0.09	-0.09	-0.09	-0.05	-0.05	-0.00	-0.00
	(-6.79)	(-6.25)	(-4.12)	(-3.47)	(-2.51)	(-2.90)	(-0.18)	(-0.00)
σ(Upstream)	-0.03	-0.03			-0.02	-0.03		
	(-3.60)	(-3.66)			(-1.98)	(-2.24)		
σ(Downstream)			0.02	0.02			0.02	0.02
			(2.60)	(1.95)			(1.39)	(1.73)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.50	0.51	0.40	0.41	0.57	0.57	0.53	0.54
Obs.	18794	17703	32253	30392	10154	9545	10673	10065

Table OA.6.4: Investment under supply-chain uncertainty: recent subsample
The table reports the relation between a firm's investment rate and the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers), the firm's downstream uncertainty (uncertainty of the firm's customers), and the firm's own uncertainty. The results are based on estimating regression (3), where $y_{i,t}$ is firm i's investment rate obtained from the most recent annual report as measured at time t. The benchmark upstream and downstream uncertainty are constructed at time t following the procedure outlined in Section 3.1. In all specifications we include firm and year fixed effects. In all specifications that feature upstream (downstream) uncertainty we control for the number suppliers (customers) of each firm. In even column we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. All regressions are estimated using a panel of firm-year observations ranging from 1976 to 2018. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ(Own)	-0.06	-0.03	-0.09	-0.08	-0.04	-0.04	-0.06	-0.02
	(-6.10)	(-2.60)	(-6.23)	(-5.61)	(-1.85)	(-1.54)	(-3.63)	(-0.98)
σ(Upstream)			-0.03	-0.03			-0.02	-0.02
			(-3.36)	(-3.53)			(-1.77)	(-1.99)
σ(Downstream)					0.03	0.02	-0.00	-0.01
					(2.96)	(2.20)	(-0.30)	(-0.61)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.40	0.44	0.50	0.51	0.42	0.44	0.49	0.52
Obs.	65854	61173	18378	17294	23995	22622	11746	11121

Table OA.6.5: Investment and P/E under supply-chain uncertainty: weighted uncertainties

The table reports the relation between a firm's investment rate, P/E ratio, and the contemporaneous level of the firm's upstream uncertainty (uncertainty of the firm's suppliers), the firm's downstream uncertainty (uncertainty of the firm's customers), and the firm's own uncertainty. The results are based on estimating regression (3). In Column (1)–(4) $y_{i,t}$ is firm i's investment rate obtained from the most recent annual report as measured at time t. In Column (5)–(8) $y_{i,t}$ is firm i's P/E ratio at time t. Let $S_{i,t}$ be the set of suppliers of firm i at time t, and let $C_{i,t}$ be the set of its customers. Upstream uncertainty is defined by $\sigma(\text{Upstream})_{i,t} = \sum_{s \in S_{i,t}} w_{s,t}\sigma_{s,t}$, where $w_{s,t} = sale_{s,t}/\sum_{k \in S_{i,t}} sale_{k,t}$, and *sale* is the log of firm k sales. Downstream uncertainty is defined by $\sigma(\text{Downstream})_{i,t} = \sum_{c \in C_{i,t}} w_{c,t}\sigma_{c,t}$, where $w_{c,t} = cogs_{c,t}/\sum_{k \in C_{i,t}} cogs_{k,t}$, and *cogs* is the log of firm k cost of goods sold. Each firm's own uncertainty is constructed at time t following the procedure outlined in Section 3.1. In all specifications we include firm and year fixed effects. In all specifications that feature upstream (downstream) uncertainty we control for the number suppliers (customers) of each firm. In even column we include additional control variables including book-to-market ratio, stock return momentum, financial constraints index, profitability, and Tobin's q. The definitions of all variables are provided in Section OA.3.1 of the Internet Appendix. All regressions are estimated using a panel of firm-year observations ranging from 1976 to 2018. t-statistics reported in parentheses are based on standard errors that are clustered at the firm level.

	Panel A: I/K				Panel B: P/E			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ(Own)	-0.08	-0.03	-0.09	-0.04	-0.06	-0.04	-0.07	-0.05
	(-5.56)	(-2.22)	(-8.06)	(-3.08)	(-3.48)	(-2.17)	(-5.97)	(-3.88)
σ(Upstream)	-0.03	-0.03			-0.02	-0.02		
	(-3.00)	(-3.38)			(-1.96)	(-1.72)		
σ(Downstream)			0.04	0.03			0.02	0.02
			(4.88)	(3.26)			(2.26)	(1.55)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2	0.50	0.53	0.40	0.44	0.14	0.15	0.14	0.14
Obs.	18773	17683	32203	30346	18429	17379	31015	29237

OA.7 Additional macro-level results

Figure OA.7.2: Impulse responses using ex-ante macro-level upstream uncertainty
The figure shows impulse response functions (IRF) from a one standard deviation shock to macro-level upstream ex-ante uncertainty to the quarterly growth rates of industrial production, real consumption, real investment, real GDP, and the levels of the aggregate price-dividend ratio and the risk-free rate. We estimate the IRFs using smooth local projection (Barnichon and Brownlees (2019)) method of Equation (6) for horizons that range from one to 16 quarters ahead. The ex-ante (predictable) components of future macro-level upstream realized volatility is via equation (7). Detailed descriptions on the variables included in equation (6) are provided in Section OA.3.2 of the Online Appendix. The estimated IRFs are denoted by solid lines, while 90% confidence intervals are represented by the dashed lines. The sample period ranges from 1974Q1 to 2018Q4.

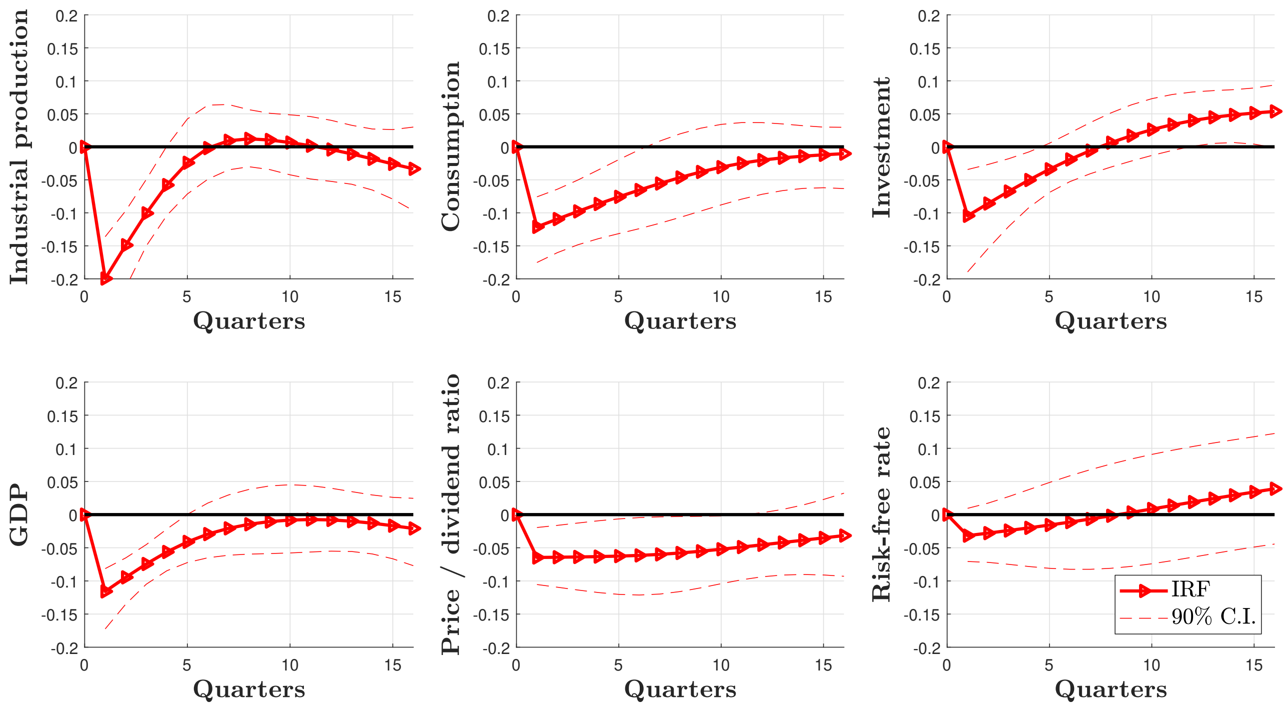

Figure OA.7.3: Impulse responses from ex-ante macro-level downstream uncertainty
The figure shows impulse response functions (IRF) from a one standard deviation shock to macro-level downstream ex-ante uncertainty to the quarterly growth rates of industrial production, real consumption, real investment, real GDP, and the levels of the aggregate price-dividend ratio and the risk-free rate. We estimate the IRFs using smooth local projection (Barnichon and Brownlees (2019)) method of Equation (6) for horizons that range from one to 16 quarters ahead. The ex-ante (predictable) components of future macro-level downstream realized volatility is via equation (7). Detailed descriptions on the variables included in equation (6) are provided in Section OA.3.2 of the Online Appendix. The estimated IRFs are denoted by solid lines, while 90% confidence intervals are represented by the dashed lines. The sample period ranges from 1974Q1 to 2018Q4.

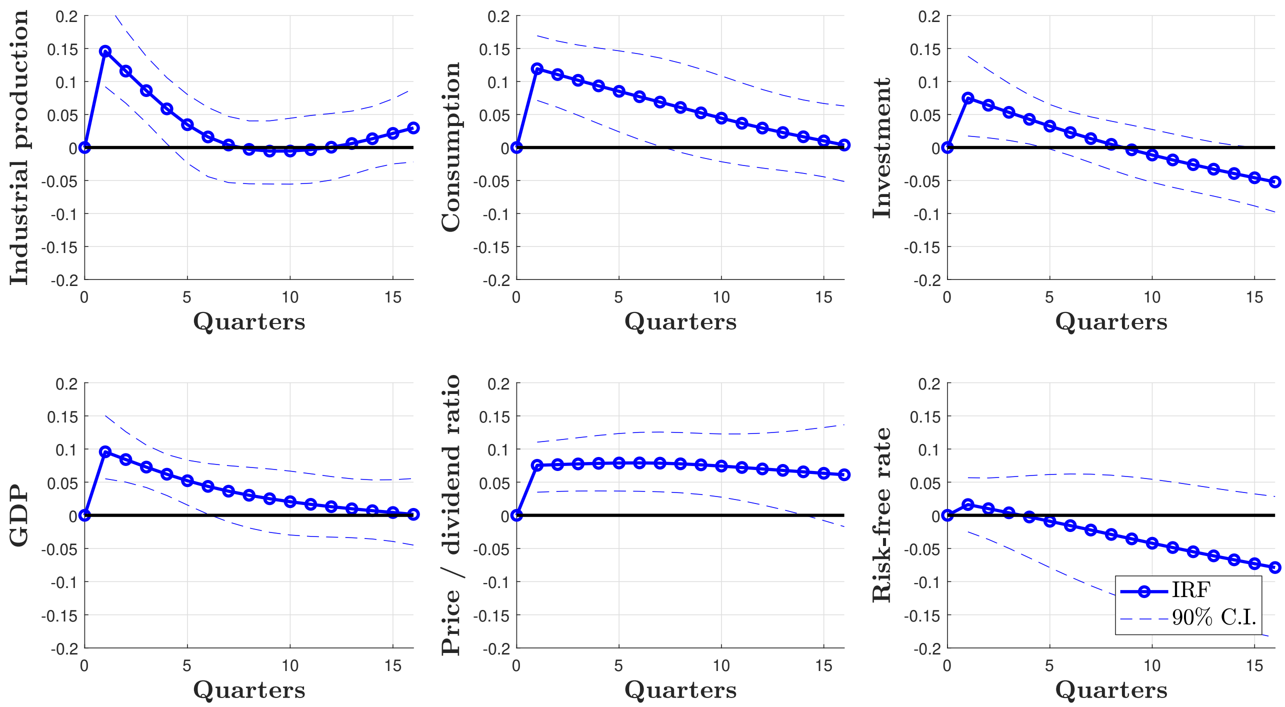

Table OA.7.6: Market price of risk of macro-level supply-chain uncertainties: robustness

The table reports robustness checks for the market prices of risk associated with macro-level upstream and downstream uncertainty (σ_U and σ_D, respectively). We estimate these market prices of risk via a generalized method of moments procedure based on the stochastic discount factor (SDF) given by equation (8) and the Euler equation given by $\mathbb{E}\left[M_t r^e_{i,t}\right] = 0$. When estimating these prices of risk we use the ex-ante (predictable) components of future macro-level upstream and downstream realized volatility, obtained via equation (7) at the monthly frequency. We control for excess market returns $MKTRF$ as a risk factor, capturing first-moment fluctuations in productivity. In Panel A, we use the same ex-ante macro-level uncertainties as in the benchmark analysis but we change the menu of testing assets. We use a set of 62 test assets, comprised of 25 portfolios sorted on size and book-to-market, the 17 Fama-French industry portfolios, 10 momentum-sorted portfolios, and 10 investment-sorted portfolios, or 92 test assets, comprised of the 62 aforementioned test assets plus 10 short-term reversal-sorted portfolios, 10 long-term reversal-sorted portfolios, and 10 profitability-sorted portfolios. In Panel B, we use the same menu of testing assets as in the benchmark analysis, but we change the predictors used to construct the exante uncertainties, $\mathbf{\Gamma}_t$, by (i) excluding downstream (upstream) volatility when measuring the ex-ante component of upstream (downstream) uncertainty, (ii) excluding the default spread and inflation rate, or (iii) excluding the price-to-dividend ratio and term spread, while retaining each of the remaining variables in $\mathbf{\Gamma}_t$. The t-statistic associated with each factor risk premium is reported in parentheses, and the mean absolute error (MAE) associated with each estimation procedure is reported in the bottom row of each panel. Monthly data spanning February 1974 to December 2018 is used to estimate each model.

	Panel A: Test assets		Panel B: Controls					
Excluded controls	None		Other vol.		DEF/INFL		PD/TERM	
Portfolios	62	92	25	42	25	42	25	42
MKTRF	2.05	1.94	3.10	3.07	3.25	3.16	3.01	3.03
	(1.85)	(1.86)	(2.39)	(2.71)	(2.57)	(2.80)	(2.28)	(2.67)
σ_U	-1.97	-1.79	-1.87	-1.17	-1.78	-1.17	-2.34	-1.41
	(-4.51)	(-5.19)	(-3.42)	(-3.09)	(-3.20)	(-3.01)	(-3.53)	(-3.11)
σ_D	2.70	2.20	3.87	2.50	3.52	2.40	4.66	2.90
	(2.68)	(2.83)	(3.13)	(2.70)	(3.01)	(2.72)	(3.23)	(2.77)
MAE	0.96	0.84	0.94	0.96	0.96	0.97	0.93	0.96

Figure OA.7.4: COVID-19 crisis: VIX, downstream uncertainty, and industrial production

The figure shows the monthly time series of (i) the VIX index (top panel), (ii) the orthogonal component of macro-level downstream uncertainty (middle panel), and (iii) the industrial production index (bottom panel). Data on the VIX and industrial production index from FRED. We compute the component of downstream uncertainty that is orthogonal to upstream uncertainty via the residuals from a contemporaneous projection of upstream uncertainty onto downstream uncertainty. Each time series spans from October 2019 to the end of September 2019.