The Fog of Innovation: Does Uncertainty from R&D Cloud the Horizon?

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Abstract

Not all uncertainty shocks are alike. We isolate measures of uncertainty stemming from R&D activity (the "fog of innovation") and show they can have starkly different macroeconomic effects compared to measures of aggregate uncertainty. We build these measures from micro-foundations using analyst forecasts. First, we find that firm-level R&D is related to increased uncertainty at forecast horizons of up to several years. We then construct measures of aggregate and R&D-driven uncertainty, finding that, while aggregate uncertainty has a *negative* impact on industrial production consistent with a negative demand shock, measures of R&D-based uncertainty have contrasting effects. In particular, while a measure of R&D-based uncertainty based on analyst disagreement acts like a negative demand shock, a measure based on forecast errors has a *positive* impact on industrial production, consistent with a positive supply shock. Our aggregate and R&D-based uncertainty are thus useful for forecasting both microeconomic and macroeconomic outcomes at different horizons.

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1 Introduction

An essential feature of innovative activity is that it is a step into the unknown – see Knight (1921). R&D may turn out to be unexpectedly fruitful or unfruitful, depending on the nature of any discovery. As a result, it is an act that could lead to inherent *uncertainty* regarding firm outcomes – which we term the "fog of innovation." This fog of innovation could have an impact on uncertainty about outcomes at the level of the firm conducting R&D. In addition, the uncertainty stemming from R&D activity could also have an aggregate impact – an impact that could be very different from that of more typical sources of aggregate uncertainty. In particular, aggregate uncertainty is generally viewed as acting like a negative demand side shock, whereas R&D is related to productivity and is thus closer to supply side conditions.

Consistent with the hypothesis that R&D generates fog, Kothari et al (2002) find that the returns to investments in R&D are more volatile than the returns to investments in physical capital, and Chan et al (2001) find that firms that perform R&D have more volatile returns than others. However, uncertainty is fundamentally about the difficulty of making accurate forecasts about future outcomes – see for example Jurado et al (2015) and Ma and Samaniego (2019) – so that the volatility of ex-post economic and financial variables are at best a proxy for uncertainty, rather than being an indicator of informational conditions resulting from R&D.

In this paper we study the link between R&D and uncertainty by using *analyst forecasts*. The properties of these forecasts, such as their accuracy and dispersion, allow us to link R&D to the informational conditions it creates more directly. Analysts report forecasts about firm-specific earnings-per-share (EPS) ratios, and those forecasts are statements about anticipated firm outcomes based on information at the time the forecasts are made. They are forecasts about market outcomes, not market outcomes themselves, and are thus closer to the information used to generate

them at the time than to ex-post market conditions such as volatility. In addition, since forecasts are made at different time horizons, we can also investigate the *time frame* over which R&D creates firm-specific uncertainty – how long it takes for the fog to dissipate. We investigate the link between uncertainty and R&D using a panel of publicly traded firms using firm fixed effects, so that any link between R&D and these uncertainty measures relies on changes over time in R&D spending at the same firm. This procedure accounts for any firm characteristics that might be related to both uncertainty and R&D.

The premise behind our measurement strategy is that changes in uncertainty at a given point in time will be reflected in analysts having *greater difficulty* making accurate forecasts. We provide a microfoundation for this intuition by building on the rational forecaster framework of Lin (2001), and argue that greater uncertainty at the firm level should be related to analysts experiencing greater ex-post *forecast errors*, as well as greater *disagreement* among analysts about their forecasts. Furthermore, we argue that analyst forecasts are more likely to be *biased upwards* in the presence of greater uncertainty, as more uncertainty requires greater forecaster dependence on information from firms themselves for the development of their forecasts – information that will likely be biased in favor of the firms' positive prospects. If R&D is positively related to firm-level uncertainty, then we expect that R&D expenditures should be related to all of the following outcomes: greater forecast errors, greater disagreement among forecasters, and greater positive bias.

The evidence supports all of these hypotheses. We find a significant positive impact of R&D on firm-level uncertainty, even accounting for firm-level fixed effects. Furthermore, we find that R&D leads to increased bias in forecast errors. This is true for the mean and median forecast errors, but we also look at different percentiles of the forecast error distribution, finding that the entire distribution of forecast errors is spread out towards the left by R&D.

In addition, analyst forecasts are made for different forecast horizons, allowing us to calculate an impulse response function for R&D-driven uncertainty and bias at the firm level. We find that uncertainty from R&D peaks after about a year, after which it gradually fades away after about 3 years. The bias wears off faster, after a little over

a year. Using our conceptual framework, this suggests that potentially-biased insider information is required by analysts to make forecasts about the short-term impact of R&D, but that public information on the likely longer-term fruitfulness of the R&D rapidly becomes available and is relevant for longer term outcomes. This also suggests that public information is useful for understanding the likely *effectiveness* of R&D on company earnings, but that private information is useful for understanding the *timing* – as in whether or not it will pay off in the short run.

Finally, it is natural to ask whether the fog of innovation has any *macroeconomic impact* distinct from that of aggregate uncertainty. To explore this question, we develop an aggregate measure of R&D-based uncertainty. We do so using changes in the median analyst forecast errors among firms in high-R&D industries, an approach similar to how Ma and Samaniego (2019, 2020) measure aggregate uncertainty both on aggregate and for different sectors. We create measures of both aggregate uncertainty and of the fog of innovation, using a consistent methodology. We find that aggregate uncertainty has a negative impact on industrial production and prices, supporting the widespread interpretation of aggregate uncertainty as having the impact of a negative demand shock. In contrast, the fog of innovation has a positive impact on industrial production while lowering prices, effects more consistent with a positive supply shock. As a result, the fog of innovation stands out as a form of uncertainty that is distinct from aggregate uncertainty both in terms of its origins and in terms of its effects. Furthermore, we find that disagreement and bias do not appear to account for this distinct behavior of the fog of innovation, suggesting it is precisely the unpredictable component – the uncertainty – of the fog of innovation that is responsible for its macroeconomic impact.

We also generate similar measures using the mean analyst forecast errors, mean disagreement, and median bias. Disagreement-based fog of innovation turns out to have a persistent *negative* effect on aggregate activity, whereas bias-based fog of innovation has a shorter, sharper negative impact, and the measure based on mean forecast error has a mixed impact. The fact that, unlike fog of innovation based on forecast errors, the disagreement measure has a negative impact suggests that uncertainty as such about R&D has a similar negative impact to aggregate

uncertainty. In this sense, using disagreement to measure R&D-based uncertainty, the fog of innovation does cloud the horizon in the same way as general uncertainty. At the same time, unlike the measure based on median forecast errors, the measure based on bias does not have a positive impact, suggesting that it is not overoptimism that accounts for the positive impact of the "fog of innovation" measures based on forecast errors. We conclude that it is the unforecastable component of the fog of innovation that accounts for the positive impact of our baseline "fog of innovation" measure based on median forecast errors – rather than the bias – reflecting upside potential that can be expoited rather than downside risk which can be mitigated.

Our paper sits at the intersection of the economics of innovation, the economics of uncertainty and the economics of forecasting. As a result it has contributions related to various important strands in the literature, including many aspects of policy and management.

First, we contribute to the economics of innovation by showing that uncertainty is intrinsic to R&D activity. It is important to underline that uncertainty in our context is not about volatility: it is about the difficulty of making predictions, bias and disagreement. At the microeconomic level, we find that the fog of innovation has a life-cycle, increasing for about a year and wearing off after three or four years, which has implications for how the evaluation of innovation should be treated both internally by innovating entities and by funding agencies. Since R&D generates uncertainty, models for risk-evaluation that are used for capital investments may not be suitable for R&D projects, so that models that take into account R&D-based uncertainty (not just volatility) could be important to ensure proper decision-making.

Interestingly, we find that forecasts made at the time that firms perform more R&D are likely to be *biased upwards* – in other words, analysts tend to overshoot their earnings forecasts relative to times when the firm is not conducting R&D. We look at different moments of the forecast error distribution and find that, while the 95th percentile of forecast errors is unrelated to R&D, as we go down the distribution based on percentiles the coefficient becomes not just significant but takes on larger negative values. In other words, R&D spreads the distribution of forecast errors out towards the left. If we interpret analyst forecasts as representing their true unbiased

forecasts, such a bias is puzzling. Furthermore, given that the initial uncertainty generated by R&D is likely Knightian – in that the distribution of possible outcomes of R&D may not be known – this finding is even more puzzling, since the consensus in the literature is that agents are likely to weigh negative outcomes more heavily in the face of Knightian uncertainty.[1] In this case we would expect analysts to *undershoot* earnings forecasts in the presence of R&D, and for the distribution of forecast errors to be shifted towards the *right*, not towards the left. Our finding is, however, consistent with Lim (2001), who argues that rational forecasters will be over-optimistic to the extent that they depend on access to information from firms themselves to make forecasts, and this access likely leads to upward bias. We build on the Lim (2001) framework not only to interpret our findings but also to support our strategy for measuring uncertainty. The implication is that external evaluation of R&D projects is heavily dependent on information from inside the project, with implications for both management and for analysts themselves.

Furthermore, we contribute to the literature on the macroeconomics of uncertainty. The link between R&D and uncertainty has previously focused on how macroeconomic or market conditions affect R&D – see for example Bloom (2007) or Oriani and Sobrero (2008). Our work begins from the idea that *the reverse* should also be the case due to the nature of R&D: more R&D should lead to greater uncertainty, at least at the firm conducting it. Establishing whether this is the case is important for understanding R&D as a factor of firm dynamics, as well as for understanding how analysts respond to this uncertainty, how investment behavior might respond to this uncertainty, and what are the aggregate consequences of R&D – not just by improving productivity (see Romer (1990)) but by potentially *increasing uncertainty*. We also show that different sources of uncertainty can have significantly different effects, as it turns out that the impact of R&D-based uncertainty on aggregates can be positive – not as large as that of aggregate uncertainty, but of the opposite sign. Furthermore, we find that the fog of innovation increases and then dissipates over the forecast horizon. This suggests a time-line of about 3 years over which R&D creates uncertainty about earnings outcomes. This number is a

[1] See for example Schmeidler (1989) and Gilboa and Schmeidler (1989).

potentially useful input for models of R&D, since quantitatively implementing such models requires information regarding the time it takes for R&D spending to yield concrete results. Models of gradual physical investment assume a "time-to-build" of four to six quarters:[2] our work finds that "time-to-build" for R&D projects is likely longer, suggesting that time-to-build is an element that could be useful to introduce into business cycle models or models of firm dynamics with R&D. In addition, our measures of R&D-based uncertainty could thus be useful tools for forecasting, both at the microeconomic and the macroeconomic level.

The idea that success or failure in R&D could have implications for macroeconomic fluctuations is present in the endogenous growth literature since at least Aghion and Howitt (1992). However, since the focus of such models is on understanding the process of economic growth, such models tend to feature an aggregate steady state. In turn, the literature on the cyclicality of R&D has focused on understanding how R&D responds to macroeconomic conditions, e.g. Barlevy (2007) and Bloom (2007), rather than how R&D might itself affect macroeconomic fluctuations. Fatás (2000) and Ma and Samaniego (2026) argue that the process of R&D creates an endogenous propagation mechanism for shocks, and the model of Ma and Samaniego (2026) features shocks to the productivity of R&D, but to our knowledge our work is the first to estimate the macroeconomic impact of *uncertainty* stemming from the R&D process itself.

We also contribute to the literature on the measurement of uncertainty. Ma and Samaniego (2019, 2020) use analyst forecasts to measure aggregate uncertainty, as well as uncertainty in different sectors of the economy. Here we use a similar approach to measuring uncertainty at the *firm* level, identifying R&D as a factor thereof.

Our work contributes to the literature on R&D and firm valuations. Our finding that analysts performing R&D tend to overshoot their EPS forecasts may appear inconsistent with Gu (2005), who argues that investors and analysts tend to undervalue patents. However, this could be accounted for by selection bias: patents represent the successes of R&D, whereas at the time the R&D is conducted the extent of success or failure has yet to be fully realized. Stevens and Burley (1997) argue that

[2]See for instance Kydland and Prescott (1982) and Zhou (2000).

the number of product successes is 3 orders of magnitude smaller than the number of potential ideas, and the number of ideas that are explored formally (i.e. some resources are devoted to their initial development) is about 2 orders of magnitude smaller: the point at which significant R&D is performed is likely somewhere in this range, whereas patent applications would be near the end and a successful patent award would be even later in the innovation process. Similarly, Eberhart et al (2004) argue that investors undervalue R&D spending: while Feng et al (2020) argue this finding can be accounted for by an expanded set of return factors, an alternative explanation is that R&D comes with greater return opportunities but also greater uncertainty and risk, something that our measures of uncertainty based on analyst forecasts convey.

We also contribute to the literature on R&D and firm dynamics. Quality ladder models such as Klette and Kortum (2004) underline the idea that R&D success is probabilistic in nature. Our paper shows that firm earnings become more difficult to forecast when firms perform R&D, so that a trade-off between uncertainty and R&D could be a useful and empirically-relevant component of such models.

Finally, we contribute to the literature on the factors of aggregate uncertainty. We confirm the well known fact that aggregate uncertainty behaves as a negative demand shock, see for example Bloom (2009) , Bachmann et al. (2013) and Jurado et al. (2015). We find that the impact of uncertainty stemming from forecast errors in high-R&D sectors on aggregates is consistent with a positive supply shock, although it is smaller in impact than overall uncertainty. In addition, R&D uncertainty based on disagreement behaves like a negative demand shock. More broadly, the implication is that uncertainty is multi-dimensional, so that it has potentially independent elements related to both demand and supply factors, with different macroeconomic implications as a result.

Section 2 introduces our conceptual framework. Section 3 introduces our empirical specification for the firm level data and describes our data. Section 4 describes our firm-level findings, and Section 5 discusses the macroeconomic implications. Section 6 concludes.

2 Conceptual framework

The premise behind our measurement strategy is that changes in uncertainty will be reflected in analysts having greater difficulty making forecasts. This should be reflected in the being of lower accuracy than usual, in greater disagreement, and in more significant bias in their forecasts.

To substantiate this intuition, we begin with a simple model of forecaster behavior in the face of uncertainty, building on the framework of Lim (2001). We do so to illustrate the idea that it is reasonable to measure firm level uncertainty using disagreement among forecasters, as well as realized forecast errors. Notably, the framework also underlines the possibility that rational analysts may generate biased optimal forecasts, and that this is more likely in the presence of greater uncertainty.

Suppose that an analyst seeks to generate a forecast of firm earnings per share X, with the aim of minimizing the conditional expected squared error of the forecast. The presumption is that their compensation is related to the accuracy of their forecasts, so they have an economic incentive to minimize this error.

Using the information set I, the analyst produces optimal forecast $\hat{X}^*$ using the following objective function V:

$$\hat{X}^* = \arg\min_{\hat{X}} E\left[\left(\hat{X} - X\right)^2 | I\right]$$

Note that this can be rewritten as choosing the optimal bias b^* according to:

$$b^* = \arg\min_{b} \left\{b^2 + \sigma^2\left(X|I\right)\right\}$$

where $b \equiv \hat{X} - E\left[X|I\right]$ is the conditional bias of the forecast $\hat{X}$ and σ^2 is the variance.

This information set I is generated using a combination of analyst research, company visits, and contact with the company's managers. A key assumption is that, while all of these acts are costly, getting information from the company themselves is easier if, implicitly or otherwise, the managers expect the analyst to generate an earnings forecast with a positive bias. Alternatively, it might be that, while access

to the managers increases the precision of the forecast $\hat{X}$, managers necessarily also provide a rosy picture of the firm's operations, which introduces bias. This creates a trade-off for the analyst between bias and precision, even though the analyst is rational.

Define the *precision* $\pi(\cdot)$ of the forecast to be the inverse of $\sigma^2(X|I)$, and suppose that the precision of the forecast takes the form $\pi(b) = c \times \tau(b)$. The function $\tau(\cdot)$ is a strictly increasing positive and concave function of the forecast bias $b : \tau'(\cdot) > 0$, $\tau''(\cdot) < 0$. This captures the idea that by increasing upwards bias the analyst can receive more precise information from the firm managers, and that this effect experiences decreasing returns. We interpret the parameter c as an index of certainty, since a high value of c implies that little effort is required to obtain high precision – i.e. the trade-off between bias and precision is weaker. The analyst's problem then becomes:

$$b^* = \arg\min_b \left\{ b^2 + \frac{1}{c \times \tau(b)} \right\}$$

Proposition 1 *The optimal bias b^* is strictly positive. Moreover, greater certainty c reduces optimal bias. Conversely, greater uncertainty increases the optimal bias b^*.*

Proof. For all proofs, see Appendix A. ■

Recall that precision equals $\pi(b) = c \times \tau(b)$. Our strategy for measuring uncertainty is to use the variance among forecasters regarding earnings at a given firm. This relationship could hold for two different reasons. One is if R&D means that forecasters do not necessarily share the same information set I, leading to divergent forecasts. Another reason is that, even if analysts do share the same information set I, their forecasts $\hat{X}$ nonetheless have a larger variance σ^2 – i.e. a lower precision π.

Note that

$$\left.\frac{d\pi(b)}{dc}\right|_{b=b^*} = \underbrace{\tau(b^*)}_{\text{Direct effect}} + \underbrace{c \times \tau'(b^*) \frac{\partial b^*}{\partial c}}_{\text{Offsetting effect}}$$

Thus, as certainty c rises, there are two effects on precision. One is the direct effect, which leads the precision to rise. However, since $\frac{\partial b^*}{\partial c} < 0$, there is a second

offsetting effect because higher precision leads agents to invest less in the relationship with managers, which results in a lower bias and also a loss of precision. However, we expect this second effect to be of second-order.

To proceed further, we note that, at least locally, it is likely that the elasticity of precision with respect to bias is not something that changes dramatically, so let us formalize this assumption:

Condition 1 Precision π has a constant elasticity $\alpha > 0$ with respect to bias b.

Proposition 2 *Under Condition* 1*, higher certainty (lower certainty c) is related to less variation among forecasts. Conversely, lower certainty is related to less precision and thus greater variance among forecasts.*

Finally, since the distribution of actual forecast errors will have precision $\pi(b^*)$, and the actual forecasts will be distributed with variance $1/\pi(b^*)$, it follows that:

Proposition 3 *The average forecast error will be greater when c is lower.*

This framework thus serves to motivate our approach to measuring uncertainty at the firm level. To sum up, our conceptual framework tells us that, *if R&D increases firm-level uncertainty*, at times of high R&D activity we should expect to see:

1. larger forecast errors
2. larger disagreement among analysts
3. forecasts more likely to be biased upwards.

In the next section, we investigate these three predictions.

3 Empirical Approach

3.1 Specification

We wish to relate firm level uncertainty about future outcomes based on the R&D that they conduct. Consider firm i in year t, and let $Uncertainty^h_{i,t}$ be a measure

for uncertainty for that firm, based on information available at time t regarding date $t+h$, so $h > 0$ is the forecast horizon. Let δ_i be a firm fixed effect, and let $\log RND_{i,t}$ be the natural logarithm of R&D spending conducted by the firm. We estimate the following specification:

$$Uncertainty^h_{i,t} = \delta_i + \delta_t + \beta \times \log RND_{i,t} + Controls_{i,t} + \epsilon_{i,t}$$

where δ_t is a date-specific fixed effect, to control for aggregate conditions – including aggregate uncertainty – and $Controls_{i,t}$ is a series of firm-level controls. Since R&D activity is persistent over time, we allow for the possibility of autocorrelation by clustering errors at the firm level.

The fact that we control for firm fixed effects δ_i implies that our identification relies on changes in R&D over time at the same firm, not on comparisons across firms. This in turn implies that any firm-level determinants of research activity or of uncertainty are accounted for in the estimation.

We include additional controls to be discussed below. One control variable that could be important for theoretical reasons is R&D performed by the firm's competitors. There are two reasons why we include this control: there could be spillovers from their activity affecting both the outcome and the uncertainty of firm i's R&D, and there could be duplication which could add uncertainty as to who will be the winner of the R&D race – see Jones (1995) and Reinganum (2018). Suppose $j(i)$ is the industry where firm i operates: then we define $\log RND_{j(i)\setminus i,t}$ as R&D performed by firms in industry $j(i)$ other than firm i itself.

Conditioning on *date* fixed effects δ_t controls for aggregate uncertainty, so in this way we already account for the possibility of reverse causality between uncertainty and R&D. At the same time, the possibility of reverse causality suggests that we may require an instrument to isolate the exogenous impact of R&D spending on *firm-level* uncertainty. There could be sources of firm-specific uncertainty that have an impact on R&D spending by the firm, to the extent that uncertainty affects R&D (whether positively or negatively). Bloom (2007) argues that exogenous uncertainty should suppress R&D, so any bias resulting from such endogeneity would lead to attenuation

bias, meaning that any finding that R&D affects uncertainty would *understate* the effect. Nonetheless, this suggests that more accurate estimates could be obtained with the use of appropriate instruments.

We construct instruments by drawing on the theory of *absorptive capacity*, introduced by Cohen and Levinthal (1989, 1990). According to this theory, a firm's tendency to innovate is related to relevant information it receives from outside sources, and to the firm's capacity to utilize this information – its absorptive capacity. This suggests that we can develop instruments by positing two factors: a time-varying factor T_t that might contribute to R&D at a particular date, and a pre-determined indicator of the firm's absorptive capacity $AC_{i,t-1}$, and . The instrument then combines firm characteristics with a time-varying exposure measure:

$$Instrument_{it} = AC_{i,t-1} \times T_t$$

3.2 Data

3.2.1 Firm uncertainty

Key to our study is identifying measures of firm level uncertainty $Uncertainty^h_{i,t}$. For this purpose we draw on the IBES database, which compiles earnings-per-share (EPS) forecasts made by financial analysts for publicly traded firms.

We measure uncertainty about a given firm i in year t using the absolute value of the median realized forecast error about a given firm. The idea is that, if forecasts made at date t about date $t + h$ are inaccurate, this indicates that at time t there was uncertainty about factors that were important for the realization of earnings h periods ahead. Taking absolute values means that the resulting uncertainty measure is neutral regarding the sign of the error (i.e. overoptimism and underoptimism are treated symmetrically), as per our conceptual framework. Our benchmark measure is the one-year-ahead log EPS forecasts provided by IBES, but we also examine other forecast horizons. Taking logs of nominal variables ensures that our measures are scale-independent, and that any price level variation over time is absorbed by time

dummies.[3]

For robustness, we use two alternative measures of uncertainty about a given firm i in year t. One is the mean realized forecast error, instead of the median – we prefer the median as it is less sensitive to outliers and is consistent with the strategy followed in Ma and Samaniego (2019, 2020) for measuring sectorial uncertainty, but our results are robust to using means instead. Following Proposition 3, we expect an estimated coefficient $\beta > 0$ for this measure of $Uncertainty_{i,t}^{h}$ if R&D leads to greater uncertainty.

An alternative measure is the *standard deviation* of log EPS forecasts h periods ahead made about firm i in a given year t. The idea is that the lack of consensus among analysts is an indicator of uncertainty regarding the firm's future. Note that all of these measures are consistent with our conceptual framework. Following Proposition 2, we expect an estimated coefficient $\beta > 0$ for this measure of $Uncertainty_{i,t}^{h}$ if R&D leads to greater uncertainty.

Finally, we also look at the forecast errors *without* taking absolute values, so that the measure of $Uncertainty_{i,t}^{h}$ is the median (or mean) of the realized log EPS value minus the log forecast value. This measure is not so much related to uncertainty but related to potential bias in forecasts made at a given date t – which is of independent interest, as discussed in our conceptual framework. Following Proposition 1, we expect an estimated coefficient $\beta < 0$ for this measure of $Uncertainty_{i,t}^{h}$ if R&D leads to greater upward bias in forecasts, i.e. a tendency towards overshooting.

3.2.2 Firm behavior

To identify firm behavior we draw on the Compustat database, which contains information from firm balance sheets and income statements from publicly traded firms.

Our key dependent variable is R&D spending by a given firm. We focus on the natural logarithm of R&D spending $\log RND_{i,t}$, as taking logarithms makes the measure independent of the firm's scale.

[3]Also, earnings-per-share statistics depend on the granularity of a share, which varies across firms: again, taking logs makes scale irrelevant, as does having firm fixed effects.

As discussed, a potentially important control is R&D performed by similar firms to firm i. If $j(i)$ is the industry j where firm i operates, then $\log RND_{j(i)\backslash i,t}$ is log R&D spending by other firms in the same industry, as measured by using the NAICS code reported for the firm in Compustat.

In addition, we use a variety of further controls. We include dummies for each year t, to control for date-specific factors, including business cycle conditions, macroeconomic uncertainty, inflation, etc. We control for firm size using log sales. We also control for capital expenditures, since Kothari et al (2002) find that capital investments are themselves a potential factor of uncertainty.

As discussed, we check the robustness of our results using instrumental variables based on the product of an indicator of the firm's absorptive capacity $AC_{i,t-1}$ and a time-varying stimulus to innovation T_t. Cohen and Levinthal (1989, 1990) argue that R&D itself is a key determinant of a firm's absorptive capacity, so we set $AC_{i,t-1}$ equal to lagged R&D $\log RND_{i,t-1}$. Then, we measure a time varying factor of R&D T_t using federal R&D spending. We distinguish between military and non-military R&D spending, so as to create two separate instruments, since the extent to which these influence private R&D may not be similar. The use of federal R&D is arguably exogenous since it depends on basic science and military priorities rather than immediate commercial applications of R&D. We call them $Inst_{i,t}^{Mil}$ and $Inst_{i,t}^{NonMil}$ respectively. Both perform well as instruments for $\log RND_{i,t}$ in the first stage, see Table 1.

4 Empirical Findings

4.1 R&D and Uncertainty

Table 2 displays our baseline results. Our benchmark uncertainty measure is the median forecast error for the 1-year ahead EPS forecast, the most common forecast in the database. However, the results are robust to measuring uncertainty with the mean forecast error, or with analyst disagreement: in all cases, the estimated coefficient on log R&D spending is positive and highly statistically significant, consistent

Table 1: First stage regressions with instrumental variables. One, two and three asterisks indicate statistical significance at the 10, 5 and 1 percent levels henceforth.

Instrument	$\log RND_{i,t}$
$Inst_{i,t}^{Mil}$	0.0365^{***}
S.d.	0.0070
$Inst_{i,t}^{NonMil}$	0.0734^{***}
S.d.	0.0073
Controls	Yes
Fixed effects	Yes
Kleibergen-Paap rk LM statistic (Underidentification test)	306.644
Kleibergen-Paap rk Wald F statistic (Weak identification test)	760.377
Hansen J statistic (overidentification test of all instruments)	1.919
R^2	0.8491
Obs	$110,256$

Table 2: Estimates of the impact of R&D on different measures of firm uncertainty. Baseline results.

$Uncertainty^h_{i,t}$	Median Err	Mean Err	Disag
log R&D	0.0608^{***}	0.0571^{***}	0.0661^{***}
S.d.	0.0078	0.0075	0.0059
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
IV	No	No	No
R^2	0.0339	0.0407	0.0621
Obs	36,721	36,721	38,502

with Propositions 2 and 3 of our conceptual framework.

Table 3 displays the results with instrumental variables. Once again we find positive and statistically significant coefficients. Consistent with our hypothesis that attenuation bias is possible in the basic estimation, the coefficients are almost double the size of the coefficients without instrumental variables.

4.2 Structural break

Before moving on to other dependent variables, we ask whether the relationship between uncertainty and R&D is different up to 2008 compared to after 2008. The reason is that the literature on uncertainty views 2008 as a large uncertainty shock (see Bloom et al 2018). As a result, it is of interest to see whether the coefficient on uncertainty varies over these two separate periods, or is due only to events on or around 2008. Table 4 shows that the pre-financial crisis relationship between R&D and uncertainty is more significant than in the baseline results. In contrast, after 2008 the results becomes weaker – although it remains highly statistically significant.

Table 3: Estimates of the impact of R&D on different measures of firm uncertainty. Instrumental variables.

$Uncertainty^h_{i,t}$	Median Err	Mean Err	Disag
log R&D	0.1027***	0.0996***	0.1268***
S.d.	0.0140	0.0134	0.0103
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
IV	Yes	Yes	Yes
R^2	0.0117	0.0131	0.0166
Obs	34,585	34,585	36,197

Table 4: Estimates of the impact of R&D on different measures of firm uncertainty. Instrumental variables, 2008 and before.

	Up to 2008			After 2008		
$Uncertainty^h_{i,t}$	Median Err	Mean Err	Disag	Median Err	Mean Err	Disag
log R&D	0.1403***	0.1353***	0.1680***	0.0806***	0.0776***	0.1125***
S.d.	0.0222	0.0209	0.0155	0.0235	0.0217	0.0180
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
IV	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0079	0.0085	0.0049	0.0137	0.0161	0.0167
Obs	20,688	20,688	21,429	13,722	13,722	14,559

Table 5: Estimates of the impact of R&D on bias, with/without instrumental variables. A negative sign implies a systematic overshooting of the forecast above the eventual realization.

$Uncertainty^h_{i,t}$	Median bias		Mean bias	
Specification	OLS	IV	OLS	IV
log R&D	-0.0538^{***}	-0.0806^{***}	-0.0515^{***}	-0.0729^{***}
S.d.	0.0084	0.0149	0.0082	0.0144
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
IV	No	Yes	No	Yes
R^2	0.0063	0.0075	0.0086	0.0089
Obs	36,721	34,585	36,721	34,585

4.3 R&D and Forecast bias

Table 5 displays our results for the actual forecast errors (the realization minus the forecast). A negative coefficient implies that the forecasts are more likely to overshoot in the presence of R&D, relative to whatever the baseline extent of bias there might be. This is exactly what we find in Table 5, consistent with Proposition 1 our conceptual framework.

In Figure 1, we look at moments of the forecast error distribution other than the median. Interestingly, the evidence is that the entire distribution of forecast errors is spread out towards the left in the presence of R&D, as all percentiles have coefficients significantly lower than zero. Furthermore, the deviation from zero decreases with the percentile, indicating that the distribution of forecast errors is skewed towards the left by R&D, consistent with Proposition 1.

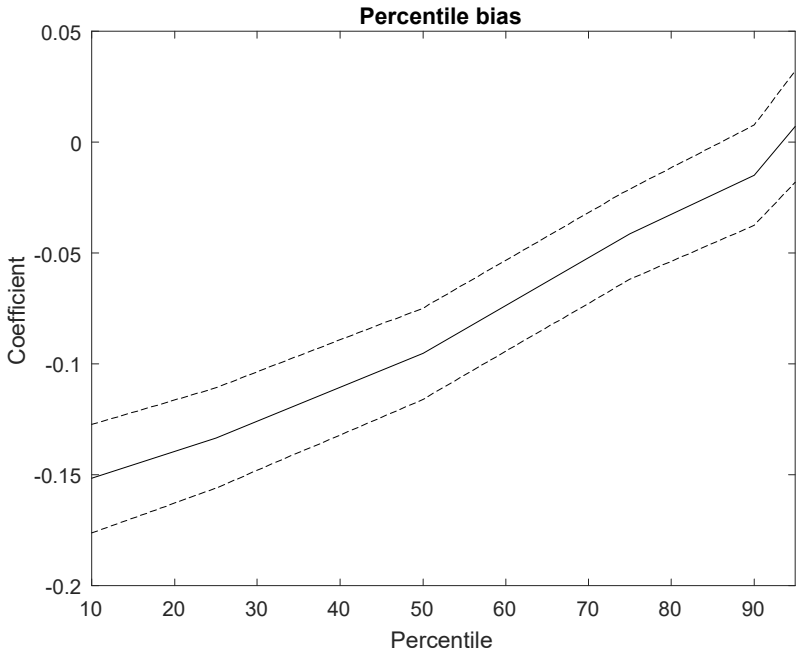


Figure 1 – Firm level uncertainty measured over different percentiles of the forecast error. Estimates include full controls and instrumental variables.

4.4 Forecast horizons

Our baseline results above all concern the 1-year EPS forecasts. Here we examine forecasts of different time horizons h. Specifically, we examine forecasts made at 1,

2, 3, 4, 8, 12, 16 and 20 quarter horizons.

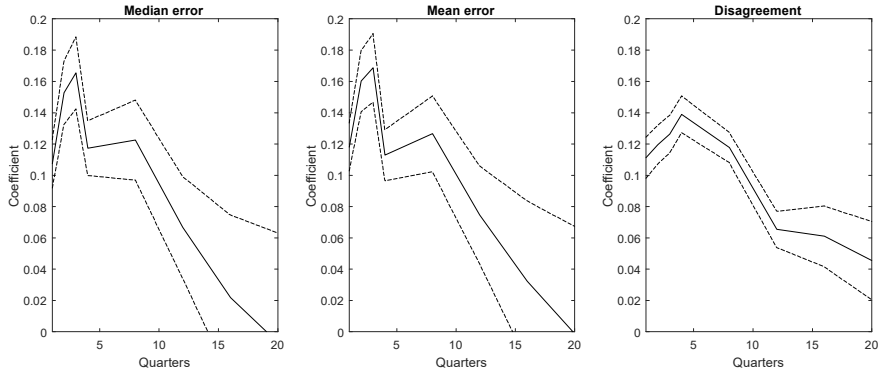


Figure 2 – Firm level forecast uncertainty over different forecast horizons.

Figure 2 displays the "impulse responses" for uncertainty at different forecast horizons. Based on the Figure 2, uncertainty rises sharply and peaks at the 4-quarter horizon. It then decays rapidly so that it is not significantly different from zero after about 15 quarters, or under 4 years. Thus, the uncertainty generated by R&D rises rapidly and decays gradually. This pattern is clearest in the case of the disagreement-based measure, which decays more slowly than the others.

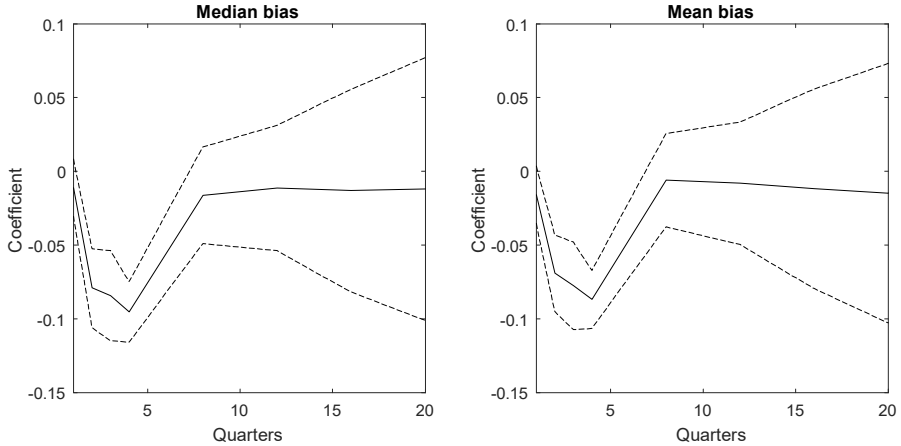


Figure 3 – Firm level forecast bias over different forecast horizons.

Figure 3 displays the impulse responses for the bias variables. Interestingly the bias decays more rapidly than the forecast errors, at least in terms of the estimate. Our conceptual framework suggests that the bias is due to analysts relying on potentially biased information from firms in order to generate their forecasts, this suggests that such inside information is only important at the early stages of R&D. This also offers an explanation for why the disagreement-based measure decays more slowly than the others: After 2 or 3 years information about the R&D may remain difficult to assess due to the fog of innovation, but analysts becomes less reliant on information from firms themselves,

To summarize, we have shown that R&D activity is strongly empirically related to difficulty making earnings forecasts. This uncertainty persists for three or four years, after which it decays to background levels. Whether this uncertainty has any independent macroeconomic impact independent from macroeconomic uncertainty more generally is thus a question of interest, a question which we address in the remainder of the paper.

5 Macroeconomic Implications

In this section, we develop indicators of macroeconomic uncertainty stemming from R&D activity, the fog of innovation. In each case we will develop a parallel indicator of aggregate uncertainty, and compare their behavior.

5.1 Forecast-based uncertainty

Ma and Samaniego (2019) generate an aggregate uncertainty measure by using the median forecast error in the IBES database for each month, finding that such a measure behaves very similarly with other macroeconomic uncertainty measures. As in the previous section, the premise behind this strategy is that uncertainty is reflected in analysts having greater difficulty than usual making earnings forecasts. This will be our baseline measure of aggregate uncertainty.

In addition, Ma and Samaniego (2019) measure uncertainty in different subsets

of the economy by restricting the set of firms for which they compute forecast errors before drawing the median value. We use this approach to measure R&D-based uncertainty, by restricting the sample of firms from which we take the median to firms in high-R&D industries. Thus, this measure of the fog of innovation does so by focusing on uncertainty surrounding firms in the most R&D-active sectors. To isolate the component of this uncertainty that is not related to aggregate uncertainty, we define the fog of innovation as the component of this series that is not predicted by aggregate uncertainty.

We then introduce our uncertainty measures – aggregate and R&D-based – into a vector autoregression system similar to that used in the related literature to study the macroeconomic impact of uncertainty. If our aggregate uncertainty measure behaves similarly to other measures in the literature, it validates our measurement strategy and gives us confidence that our results using R&D-based uncertainty (fog of innovation) are reliable also.

We identify high-R&D industries as follows. First, for each industry, we average R&D spending over time at each firm as a share of sales, and find the median firm value. We think of this as the industry's R&D intensity, following the approach in Rajan and Zingales (1998) for measuring industry characteristics. We do this twice: once by treating missing values as zeroes, and a second time discarding missing values. Then, we consider an industry a high-R&D industry if it is above the median according to *both* criteria. We wish for an exclusive rather than an inclusive list due to the highly skewed distribution of R&D across industries, see Samaniego (2013). The resulting list of R&D-intensive industries is primarily related to computing, electronics, chemicals, business services and professional services.

Our benchmark approach is to measure uncertainty using the median forecast error, both on aggregate and among R&D-intensive sectors. In addition to this approach, we generate additional measures of aggregate and R&D-based uncertainty. One measure uses the mean forecast error instead of the median, for robustness. Another uses the mean disagreement among analyst forecasts. Finally we also use the median *bias*. These measures capture specific aspects of uncertainty and of R&D-based uncertainty. The measures based on forecast errors capture unforecastability.

The measure based on disagreement captures noise, and the measure based on bias captures the extent of distortion of the point-estimates.

In each case the aggregate measure is computed using the entire sample, and the R&D-based measure – fog of innovation – uses the unpredicted component of computing the measure using only firms in high-R&D industries.

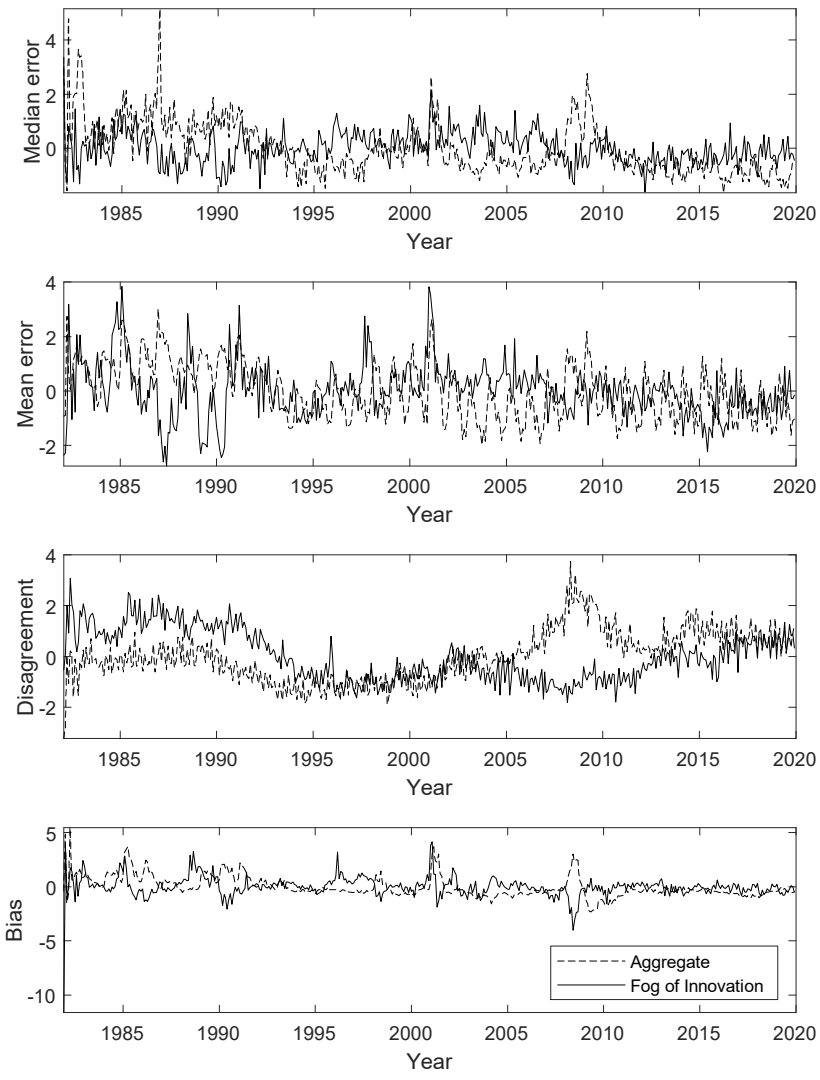


Figure 4 – Forecast-based uncertainty measures. The dashed line represents the aggregate measure, and the full line represents R&D-based measure. Measures are standardized to have mean zero and variance of one.

Table 6: Correlations between aggregate and R&D-based uncertainty measures.

Aggregate			
Measure	Mean Err	Disag	Bias
Median Err	0.60^{***}	-0.13^{***}	0.84^{***}
Mean Err	–	0.02	0.57^{***}
Disag	–	–	-0.23^{***}

R&D-based			
Measure	Mean Err	Disag	Bias
Median Err	0.53^{***}	-0.13^{***}	0.24^{***}
Mean Err	–	-0.01	0.37^{***}
Disag	–	–	0.09^{*}

Figure 4 displays the resulting series. For the measures based on median forecast errors, the aggregate and R&D-based series have a correlation of zero by construction. The two series thus have independent dynamics. For example, the R&D-based uncertainty reacts less to the financial crisis of 2008 as well as to the uncertainty that came with the COVID shock in 2020. In contrast, in 2001 R&D-based uncertainty reacts more strongly than aggregate uncertainty to the bursting of the tech-bubble. The measures based on mean forecast errors are much more volatile, which is consistent with our choice of the median as a benchmark for being potentially less driven by outliers.

Table 6 displays the correlations between different uncertainty measures. Among the aggregate uncertainty measures, the median and mean measures are highly correlated with each other, as is the bias measure. However, the disagreement measure appears to capture very different information, being correlated with the other measures either not at all or negatively. The same pattern is seen among the R&D-based uncertainty measures: all are highly positively correlated, except for the R&D-based disagreement measure.

5.2 Empirical specification

To estimate the macroeconomic impact of the fog of innovation, we employ a structural vector autoregression (SVAR) specification similar to that in Bloom (2009), regarding the variables to include in the system and their ordering. We use 12 lags of monthly data of the log S&P 500 index, federal funds rate,[4] log wages, log CPI,

[4]We use the official rate except for close to the periods when interest rates were essentially zero and quantitative easing continued to loosen monetary conditions (GFC and COVID), where we use

log hours worked in the manufacturing sector, log employment for the manufacturing sector, and log industrial production between 1982m1 and 2019m12.

Although we have data up to 2025, to maintain comparability with the existing macro-uncertainty literature and to avoid distortion from exceptional policy and financial conditions in recent years, our benchmark SVAR is estimated using data up to 2019, excluding the COVID-19 period and subsequent years. The pandemic and its aftermath introduced unprecedented structural changes in both macroeconomic dynamics and financial markets, where policy rates reached the effective zero lower bound, monetary interventions expanded beyond their conventional toolkit, equity valuations displayed atypical risk–return patterns, and supply-side disturbances interacted with policy uncertainty in ways not observed in earlier decades. These features imply that the period after early 2020 may not be governed by the same policy reaction functions, shock transmission mechanisms, and financial-market pricing behavior that characterize the pre-pandemic era. As a result, the main analysis has been limited to the pre-2020 sample, where policy responses and market dynamics are more stable and comparable across studies (e.g., Bloom 2009; Jurado et al. 2015). We report results with the entire sample in the Appendix, finding that our key results hold: aggregate uncertainty behaves like a negative demand shock, and the fog of innovation behaves like a positive supply shock.

The variables are ordered as follows in our VAR, with the stock market index is placed first to ensure that potentially anticipatory market behavior is taken into account when considering the effect of uncertainty:

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the Wu Xia (2016) shadow rate.

$$\begin{bmatrix} \log(\text{S\&P 500 Index}) \\ \text{Aggregate Uncertainty} \\ \textit{Fog of innovation} \\ \text{Federal Funds Rate} \\ \log(\text{Wages}) \\ \log(\text{CPI}) \\ \text{Weekly Working Hours} \\ \log(\text{Employment}) \\ \log(\text{Industrial Production}) \end{bmatrix}$$

This specification differs from that in Bloom (2009) in that there are two measures of uncertainty, aggregate uncertainty and the fog of innovation. In our specification aggregate uncertainty precedes the fog of innovation, capturing the notion in the literature that aggregate uncertainty may affect innovative activity and thus the fog of innovation itself. In the Appendix we switch the positions in the VAR of the fog of innovation and aggregate uncertainty, finding consistent results.

Following Jurado et al. (2015), we estimate an unrestricted VAR with all variables in levels, not in HP-filtered form as in Bloom (2009). Based on Sims (1980) and others, using non-stationary data can reveal dynamic relationships between uncertainty and macroeconomic variables that stationary specifications might obscure. Our 12-lag structure accounts for serial correlation, ensuring consistent estimation of impulse responses and forecast error variance decompositions.[5] Conversely, HP-filtering removes low-frequency, long-term information and uses the entire sample in its detrending procedure, which can distort the interpretability of the dynamic relations. We use 12 monthly lags and identify structural shocks by a recursive (Cholesky) decomposition.

[5]See Toda and Yamamoto (1995), inter alia.

5.3 Results

First we study the impact of the different aggregate uncertainty shocks, and then turn to the impact of the different "fog of innovation" shocks.

5.3.1 Aggregate Uncertainty Shocks

Median forecast errors We begin by examining the dynamic impact of macroeconomic uncertainty, measured using the median forecast error among analysts in a given month.

Figure 5 plots the impulse responses of the federal funds rate, price level, industrial production, employment, average weekly working hours, stock market index (S&P 500 Index), wage, and forecast-based R&D uncertainty (micro-uncertainty) to the aggregate uncertainty from median forecast errors.

The shaded area represents +/- one standard error confidence bands estimated from the VAR system. The units for all the variables are proportional deviations from their respective long run trends. The impulse responses in Figure 5 show that a positive aggregate uncertainty shock is followed by persistent declines in industrial production and employment, consistent with the interpretation of aggregate uncertainty as a negative demand shock. The peak output decline occurs within the first two to three years, after which responses gradually revert toward zero.

Furthermore, stock market valuations also decline following an aggregate uncertainty shock, although the magnitude is smaller and confidence intervals widen at longer horizons. This pattern is similar to the standard findings for aggregate uncertainty shocks in the literature (e.g., Bloom 2009; Bachmann et al. 2013; Jurado et al. 2015, Ma and Samaniego 2019), where uncertainty temporarily lowers real activity (e.g. industrial production, employment), and leads investors to mark down equity prices in anticipation of weaker earnings prospects. The monetary policy response complements this interpretation. The federal funds rate falls sharply on impact, which is consistent with policy easing in response to a deterioration in economic conditions. CPI falls gradually, suggesting deflationary pressures again consistent with a negative demand shock, while employment falls persistently as output contracts.

In conclusion, these responses indicate that shocks to our measure of macroeconomic uncertainty behave as macro uncertainty shocks elsewhere in the literature, affecting both financial conditions and real activity in line with prior work and with the conceptual view that heightened uncertainty depresses investment and postpones hiring decisions. Our findings thus show that our measure based on median forecast errors provides a bridge between firm-level informational frictions and aggregate cyclical uncertainty, supporting the finding that uncertainty measured through forecast errors captures broad informational deterioration rather than merely statistical volatility. Overall, we found out that forecast-based aggregate uncertainty plays like a negative demand shock to the macroeconomy.

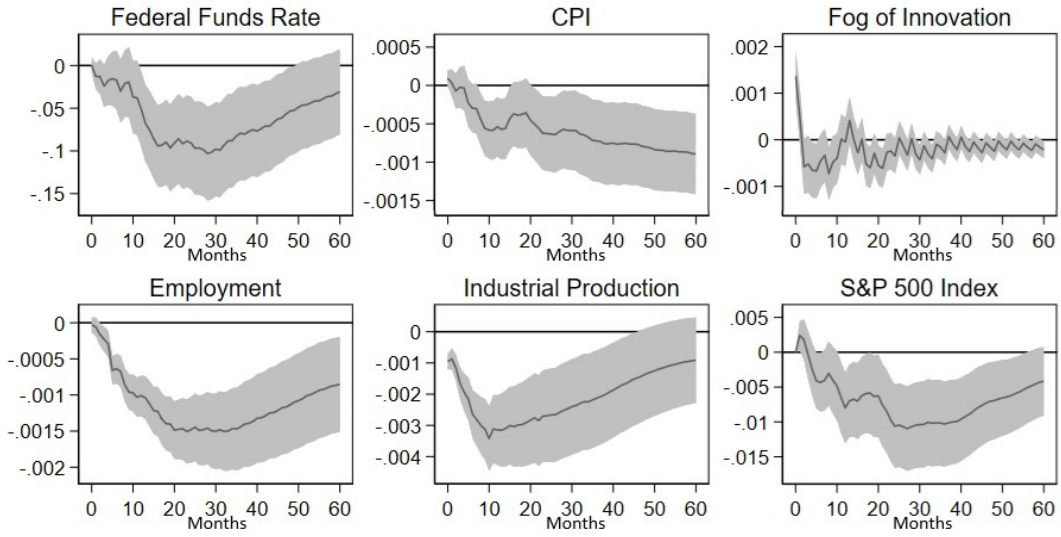


Figure 5 – Impulse response from aggregate uncertainty shocks measured using the median forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

Mean forecast errors Next we examine the dynamic impact of macroeconomic uncertainty, measured using the *mean* forecast error among analysts in a given month. As mentioned, we believe the median forecast error provides a more robust indicator of uncertainty than the mean, which could be subject to influence by outliers and errors, but as we will see many broad patterns are consistent nonetheless.

Figure 6 presents the impulse response functions form a shock to mean of forecast-based macroeconomic uncertainty, using the same VAR structure as before. The units for all variables are proportional deviations from their respective long-run trends.

The impulse responses again show that a positive aggregate uncertainty shock triggers a pronounced and persistent decline in employment and industrial production. The peak contraction in industrial output occurs within the first year, after which it begins a gradual, multi-year recovery, though employment effects appear more sustained.

Financial markets react in tandem with the real economy. The stock market, as measured by the S&P 500, declines on impact, reflecting investors' downward revisions to future earnings prospects amid heightened uncertainty. Prices also decline. The monetary policy response is swift and accommodative; the federal funds rate falls sharply upon impact, indicating a policy easing aimed at counteracting the deteriorating economic conditions. Notably, the "Fog of Innovation" measure also fluctuating around zero but more on negative side, suggesting that uncertainty shocks may depress longer-term growth investments and inventive output.

In conclusion, these responses indicate that shocks to our forecast-based measure of uncertainty behave consistently with the the results from median forecast, in that aggregate uncertainty behaves like a negative demand shock, with lower output, input use and prices, along with monetary policy accommodation.

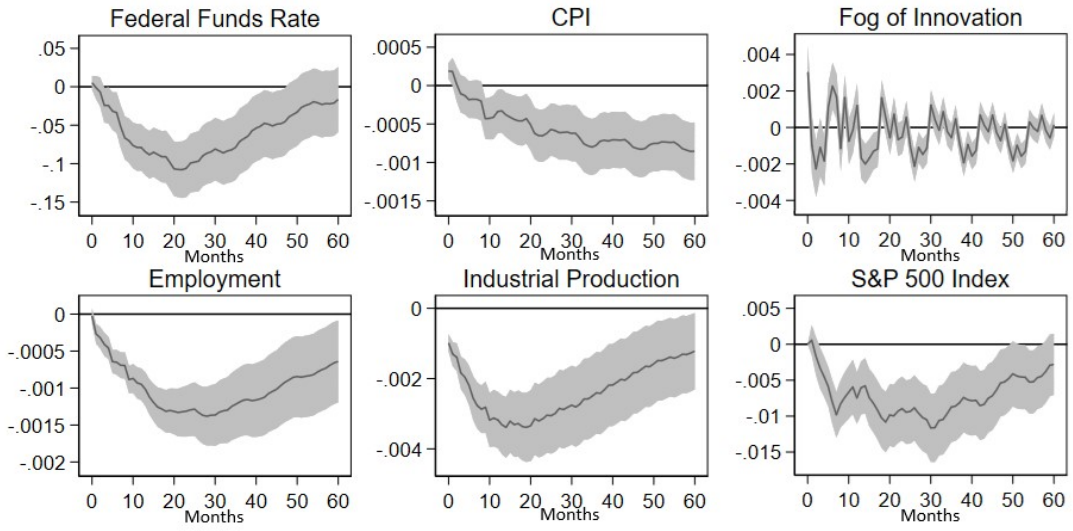


Figure 6 – Impulse response from aggregate uncertainty shocks measured using the mean forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

Aggregate Bias shocks Next we examine the dynamic impact of macroeconomic uncertainty, measured using the median forecast *bias* among analysts in a given month.

Tme impulse responses in Figure 7 reveal a distinct pattern again consistent with a significant negative economic shock. The federal funds rate declines sharply after the shock, falling by 0.2 percentage point within the first ten months and then moderately recovers over the next months.

Real economic activity shows a contractionary profile. Industrial production, employment, and the S&P 500 index all drop immediately upon impact, reflecting an instantaneous contraction in output and a market reassessment of future earnings. While Industrial production and the S&P 500 index begin a gradual recovery within

the first year, it takes almost two years for employment to start the recovery, suggesting the labor market adjustment may be lagged or more sensitive to this specific shock.

Price and innovation dynamics are broadly consistent with this measure of uncertainty also representing a negative demand shock. The CPI exhibits a steady and persistent decline, signaling strong deflationary pressures that build over the entire horizon. Similarly, the "Fog of Innovation" measure falls sharply after the aggregate shock, indicating a reaction to any R&D or innovative activity decisions. This suggests the shock damages not only current economic conditions but also the economy's longer-term growth potential by curtailing investment in knowledge creation.

In conclusion, the responses to an aggregate bias shock indicate an economic scenario characterized by monetary policy easing, deflationary pressures, a sharp but partially recovering hit to employment, industrial production, and the stock market. This pattern indicates that shocks to the forecast bias function plays once more as a negative demand shock.

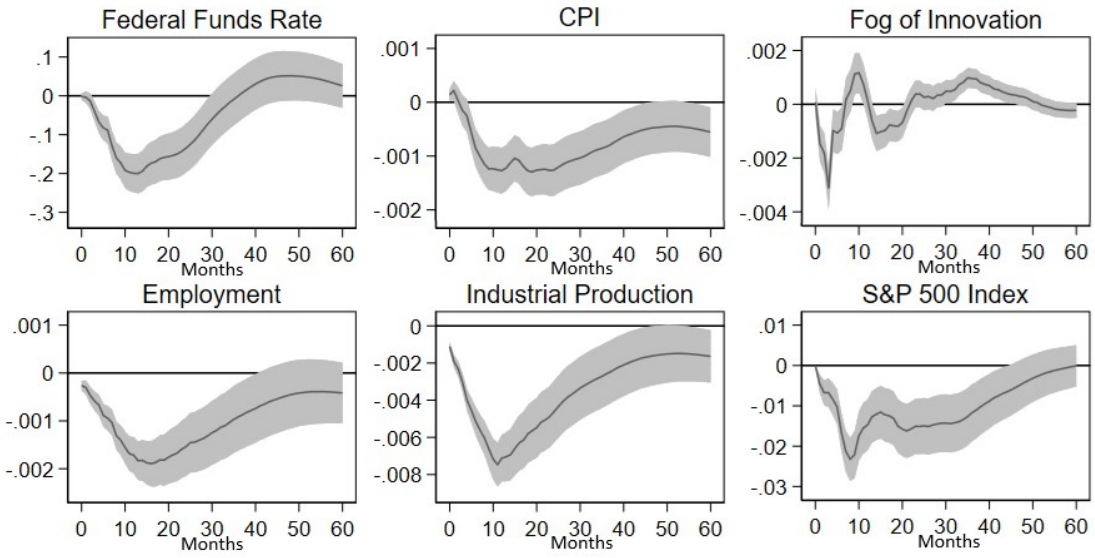


Figure 7 – Impulse response from aggregate uncertainty shocks measured using aggregate bias. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

Aggregate disagreement shocks The impulse responses in Figure 8 show that a positive disagreement shock generates a clear contractionary pattern. Employment declines immediately and persistently, with the negative effect deepening for several periods before stabilizing at a significantly lower level. This is consistent with firms postponing hiring decisions in the face of heightened disagreement, similar to the uncertainty. Industrial production shows a more modest initial decline but follows a similar persistent negative trajectory, corroborating a slowdown in real economic activity.

The monetary and price responses align with this interpretation of a negative demand shock. The federal funds rate rises slightly on impact before turning negative,

indicating an initial possible tightening or neutral stance followed by subsequent policy easing as the economic deterioration becomes apparent. The CPI declines steadily and persistently after the shock, indicating strong deflationary or deflationary pressures that build over time, which indicate a significant negative aggregate demand shock.

Financial and innovation markets react as anticipated. The S&P 500 index falls on impact and continues to decline gradually, reflecting a downward reassessment of corporate earnings and/or increased risk premia.

In conclusion, these responses suggest that shocks to the disagreement-based measure behave similarly to the other macroeconomic uncertainty shocks. They trigger a co-movement of declining real activity (employment and production), falling asset prices, disinflation, a dampening of innovative capacity, and an eventual accommodative monetary policy shift. This pattern is consistent with the established results in the median forecast uncertainty, mean forecast uncertainty and aggregate bias. All four aggregate indicators thus behave in a consistent fashion.

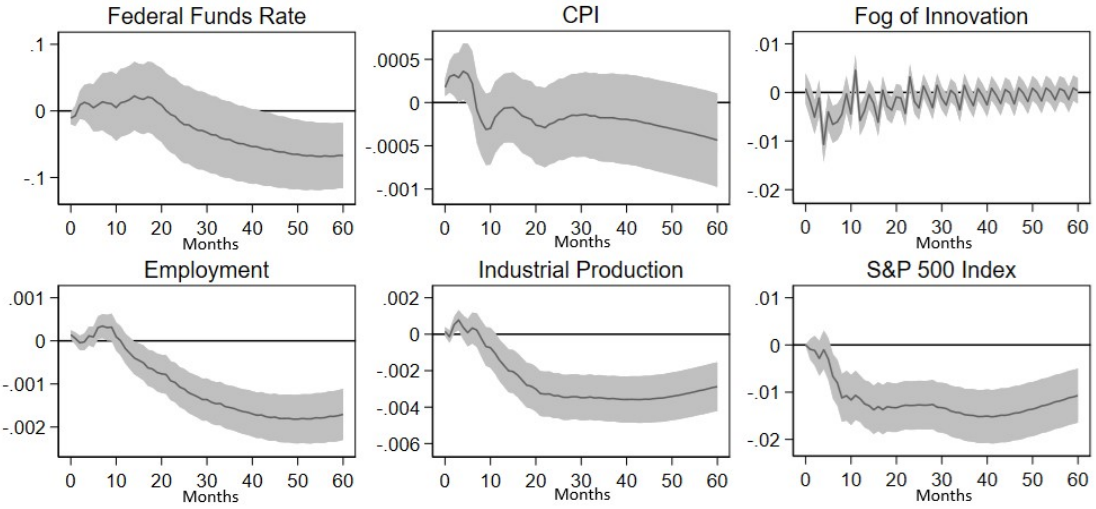


Figure 8 – Impulse response from aggregate uncertainty shocks measured using aggregate disagreement. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

5.3.2 "Fog of Innovation" Shocks

In the next step, we examine how macroeconomic activity responds to "fog of innovation" shocks, i.e. shocks in our measure of uncertainty derived specifically from forecasts in high-R&D industries. Note that the ordering of variables remains as in the benchmark specification.

Median "fog of innovation" (baseline) The responses in Figure 9 suggest that the character of R&D-related uncertainty (fog of innovation) shocks is quite different from that of aggregate uncertainty shocks. A shock to R&D uncertainty from forecasts generates a gradual *increase* in industrial production, with the response declining gradually after about 20 months. In employment, the first response to the

RND uncertainty starts with a slight negative response, becoming broadly positive after that. That said, the impact is smaller in magnitude than that of aggregate uncertainty. This finding suggests that R&D-induced uncertainty identified in Section 3 is predominantly a firm-level informational phenomenon, with a limited but *positive* impact on the aggregate economy.

The reason that the impact is limited is likely that, while R&D generates informational frictions at the firm level, these idiosyncratic uncertainties do not necessarily aggregate into systematic macro uncertainty. For example, suppose that several firms engage in a patent race, in the knowledge that one of them will win but with the identity of the winner as-yet unknown. At the microeconomic level this will create significant uncertainty for the participants in the race, but from the macroeconomic perspective who wins is irrelevant and there could be no uncertainty. Of course, for well-diversified investors, the existence of the patent race would be a boon, which explains the fact that the aggregate impact of the fog of uncertainty shock is positive.

The response of stock market prices further supports such an interpretation. Whereas aggregate uncertainty shocks are associated with a decrease in stock valuation, fog of innovation is associated with an increase, aligning with the *positive* impact of shocks from R&D uncertainty on industrial production and employment. This is consistent with the idea that uncertainty stemming from R&D reflects possibilities for upside rather than generalized risk, and equity markets respond accordingly. For example, successful R&D presents upside opportunities, whereas if an R&D endeavor fails firms still have their pre-existing knowledge and product portfolio to use to generate earnings. Finally, the shocks from R&D uncertainty from forecasts generate only softened monetary policy responses, consistent with their smaller real-side effects. The fall in the federal funds rates is limited relative to the benchmark median forecast errors shock, indicating that micro R&D-driven uncertainty does not systematically loosen nor tighten financial conditions at the macro level. Fog of innovation shocks also lead to a decrease in prices. To sum up, in contrast to aggregate uncertainty, which acts like a negative demand shock, we find that uncertainty measured using forecast errors in high-R&D industries acts more like a *positive supply shock* to the macroeconomy, increasing output and input use, as well as the stock market,

while decreasing prices.

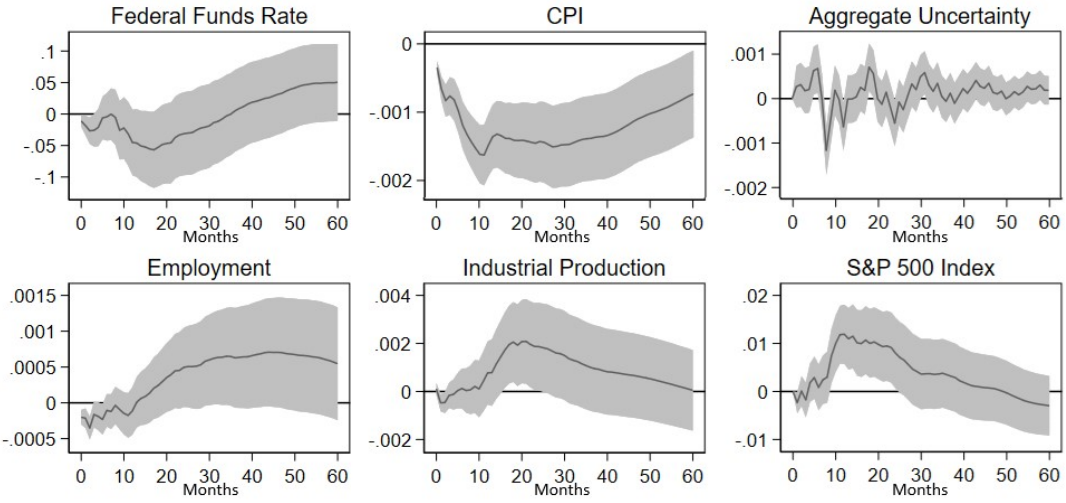


Figure 9 – Impulse response from fog of innovation shocks, measured as the median forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

In conclusion, these results complement the firm-level evidence, revealing that R&D raises uncertainty for the firms undertaking it, causing volatility in the informational environment, and contributing to forecast errors. Its aggregate consequences are modest compared to the impact of aggregate uncertainty shocks, suggesting that that the fog of innovation is most relevant for market participants and less so for economic aggregates, at least compared to aggregate uncertainty. That said, the fog of innovation still has aggregate impact of a form broadly consistent with a *positive supply shock*.

Mean "fog of innovation" In the next step, we examine how macroeconomic activity responds to "fog of innovation" shocks, this time derived from mean forecast-

errors in high-R&D industries. Again, we believe the median forecast error provides a more robust indicator of uncertainty than the mean, which could be subject to influence by outliers and errors and thus might be affected by the extent of disagreement and noise and not just by unforecastability.

The impulse responses in Figure 10 show that an increase in R&D-related uncertainty elicits only a modest macroeconomic reaction, and initially it is negative. Industrial production and employment decline for about a year before going back to the positive side, while the stock market (S&P 500) also falls briefly before turning positive over the next 4 years. The CPI declines gradually, suggesting deflationary pressure.

Again, these responses indicate that R&D-driven uncertainty shocks propagate to the real economy and financial markets, but with effects that are less abrupt and less severe than those of broader aggregate uncertainty shocks and less severe compared to the results for the median uncertainty measurement. This supports the interpretation that innovation-related uncertainty operates through distinct channels, reflecting firm-level informational frictions and sector-specific risks, without triggering the sharp, economy-wide contractions typically associated with general macroeconomic uncertainty. In the case of mean fog of innovation, the short run response is in fact contractionary and consistent with a *negative demand* shock, while some features of a positive supply shock (higher stock prices followed by higher employment and industrial production) emerge some years later. As we shall see, this is consistent with the mean fog of uncertainty measure combining the impact of the median fog of innovation – which is positive – with that of disagreement – which is negative.

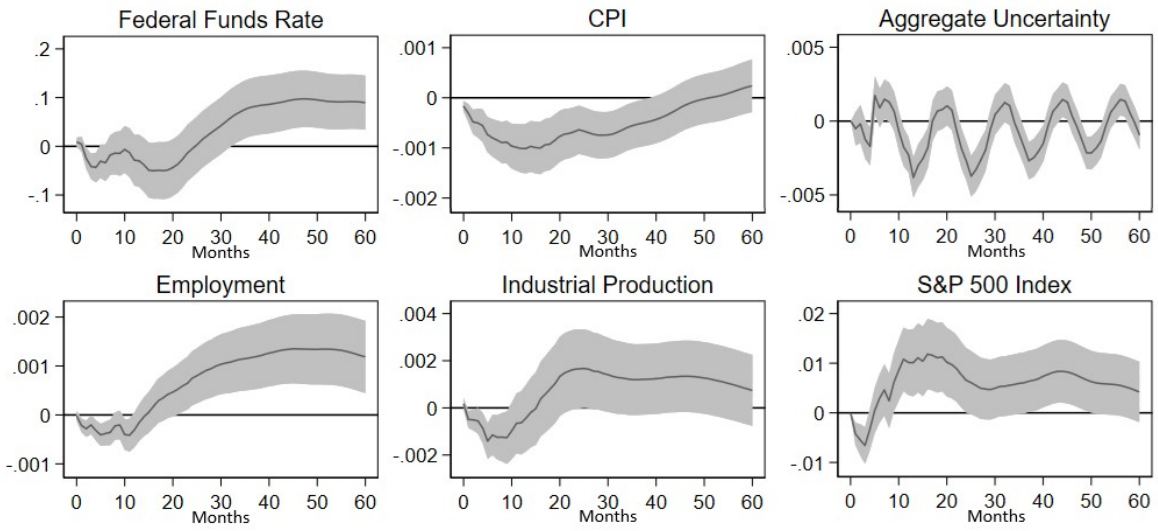


Figure 10 – Impulse response from fog of innovation shocks, measured as the mean forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

"Fog of innovation" bias Next, we repeat the analysis using uncertainty shocks measured using the fog of innovation computed using median *bias*. Based on the results presented in Figure 11, the macroeconomic response to a "fog of innovation" *bias* shock, derived from forecast bias in high-R&D industries, are characterized by limited aggregate propagation and subdued volatility.

The shock produces a negative response in industrial production, while the impact on employment is modestly positive. The magnitude of these real activity responses is notably smaller than those typically associated with broader aggregate uncertainty shocks, and also the results from the median and mean of forecast errors. The reaction of the Federal Funds Rate is also minimal with an easing monetary environment, as the short-run response followed by an increase in the federal funds rate, indicat-

ing a modest monetary policy response consistent with the shock's limited perceived threat to macroeconomic stability.

Notably, the shock coincides with a slight decline in the price level, as indicated by the negative CPI response. Furthermore, the S&P 500 shows a mild negative response over the first months, followed by a weak positive response in the long horizon. This pattern supports the interpretation that innovation-related bias, rooted in firm-level informational frictions and forecast bias, is associated with a very limited broader market reaction. Finally, the short-term impact of firm-level uncertainty on aggregate uncertainty is modest and positive, but this effect is temporary, and after a few months, it moves towards zero.

Overall, the evidence suggests that innovation bias shocks primarily act as firm-specific informational disturbances with weak spillovers to the aggregate economy. Their net effect resembles a short-lived negative demand shock. It is at odds with the behavior of the "fog of innovation" uncertainty shock, which acts as a mild positive supply shock in the median and mean forecast, indicating that those findings are accounted for by some aspect of uncertainty *other than the induced bias*.

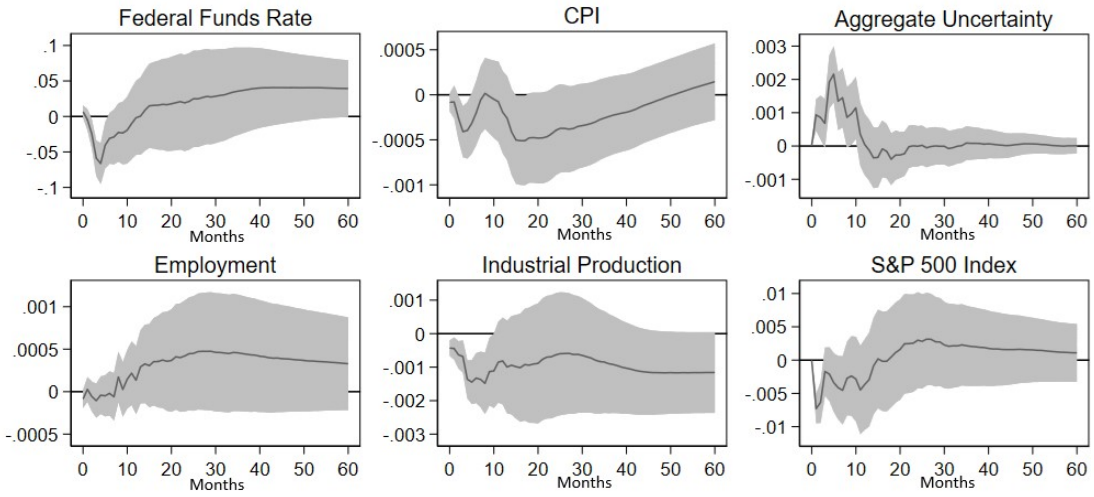


Figure 11 – Impulse response from fog of innovation shocks, measured as the median bias in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

"Fog of innovation" disagreement Finally, we repeat the analysis using uncertainty shocks measured using analyst disagreement. This exercise isolates the noise component of uncertainty, so examining its behavior helps understand the extent to which the above results are accounted for by *noise*.

Based on the results presented in Figure 12, the macroeconomic responses to a "fog of innovation" shock derived from forecaster disagreement in high-R&D industries present a different profile from the other measures. The shock elicits a contraction in real activity, with both industrial production and employment falling. Concurrently, the price level (CPI) increases, indicating an inflationary pressure. This co-movement of downward output and upward prices is characteristic of a *negative aggregate supply shock*.

The financial market response is negative, with the S&P 500 falling, suggesting

that uncertainty stemming from disagreement is considered a source of risk and discounted by equity investors after the first positive impulse response. There is also a slight decline in the federal funds rate, followed by a positive response in the longer horizon.

Overall, the evidence indicates that innovation uncertainty sourced from forecasters' disagreement functions as a potent negative demand shock, and it is tightening financial conditions, depressing asset prices, and prompting a noticeable policy response, and displays features of a negative demand shock. This result highlights the fact that uncertainty raised from disagreement among forecasters causes a more cautious response in the real economy and investors, unliek the ex-post median forecast error.

Note that, unlike the other measures, disagreement can be measured immediately (since it does not require information on the realized value of the forecast for its computation, just the forecasts themselves) suggesting that the R&D disagreement measure (alongside the aggregate disagreement measure) could be usefully used for forecasting purposes, especially since both of them point towards future negative shocks that could be of importance to investors.

Finally, as far as understanding the fog of innovation is concerned, the fact that R&D disagreement does not account for the behavior of R&D uncertainty shocks measured using median forecast errors indicates that this behavior is neither accounted for by bias nor by noise/disagreement. This indicates that the behavior of R&D uncertainty shocks has to do with unpredictability itself, the error itself, rather than the direction of the error (bias) or the fact that there is noise (disagreement). Indeed, the noise appears to have a distinct and negative effect. As for mean forecast errors, they appear to amalgamate the negative impact of disagreement shocks in the short run with the positive impact of the median fog of innovation shock in the medium term, possibly due to the fact that the mean-based measure is more susceptible to influence by outliers.

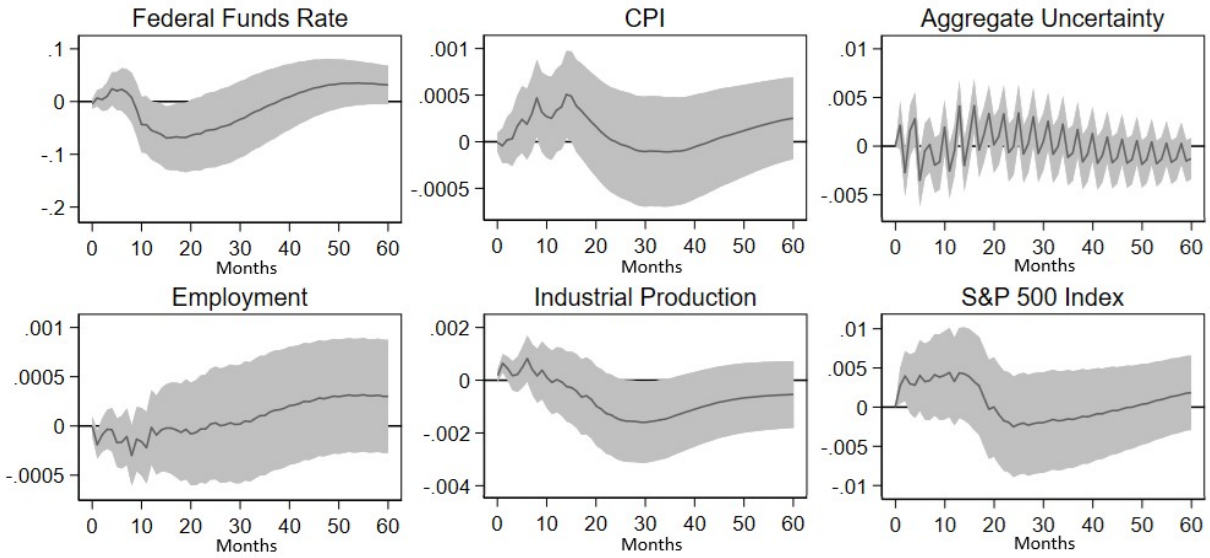


Figure 12 – Impulse response from fog of innovation shocks, measured as the average disagreement in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2019m12.

5.4 Robustness

In Appendix B, we examine the impact of aggregate uncertainty and the fog of innovation with an alternative ordering of the variables, where we switch the order of the uncertainty variables in the VAR. This specification allows the impact of R&D-based uncertainty to precede that of aggregate uncertainty, rather than the other way around. Results are broadly robust. First of all, all four measures of aggregate uncertainty behave like a negative demand shock. In contrast, the median fog of innovation behaves more like a positive supply shock; R&D disagreement behaves like a negative shock; median fog of innovation behaves first like the latter and later like the former, suggesting it is driven by both due to outliers; and R&D bias has

little aggregate impact.

In addition, in Appendix C we report results using the entire sample from 1981m7 to 2025m5. Overall we find that our key findings are robust: aggregate uncertainty has a *negative* impact on macroeconomic activity, whereas the median fog of innovation has a smaller but *positive* impact. Results after 2020 are a bit different, particularly concerning the stock market impact of aggregate uncertainty, suggesting that the extraordinary stabilization measures taken since 2020 and/or the rise of supply shock constraints since then may have affected the structural relationships between these macroeconomic indicators. However, results concerning the fog of innovation measures are robust to extending the time period, suggesting that structural relationships among macroeconomic variables as they related to the fog of innovation remain unchanged.

Finally, in Appendix D, we report the entire sample from 1981m7 to 2025m5 with the alternative ordering. Results are similar to using the entire sample with the benchmark variable ordering.

6 Conclusion

6.1 Macroeconomic Implications

This paper posits R&D as a potential source of economically significant uncertainty. First we use microeconomic data to underline that firm-level R&D is related to greater uncertainty about future firm outcomes using several different measures. Then, we develop macroeconomic indicators of aggregate uncertainty and of uncertainty stemming from R&D, and study their impact on macroeconomic outcomes. While aggregate uncertainty shocks have a significant negative impact on the macroeconomy, R&D-based uncertainty – the median fog of innovation – turns out to have a positive impact, albeit smaller and less persistent, suggesting that R&D-based uncertainty is more relevant for financial market conditions than for aggregate output, at least at business-cycle frequencies. Thus, while aggregate uncertainty behaves like a negative demand shock, the fog of innovation can act more like a positive supply

shock.

This could be because uncertainty stemming from R&D entails considerable upside opportunity in case innovation is successful, whereas the downside risk can be mitigated by simply not adopting whatever the outcome of the R&D is. Alternatively, the findings could be explained by the fact that R&D-based uncertainty is related to upward bias in expectations, at least at the microeconomic level. However, we would expect that such bias would relate to a macroeconomic upturn followed by a downturn once expectations are not realized, so we favor the first interpretation of R&D as a form of uncertainty that provides opportunities and risks that, at least at the macroeconomic level, can be mitigated in case of negative outcomes. In addition, we find that R&D bias does not account for these dynamics.

Furthermore, we find that R&D-based *disagreement* acts more like a negative aggregate shock. We conclude that the unforecastability of R&D is related to the possibility of discoveries with upside potential, whereas disagreement is a distinct and damaging influence on the overall economy. To answer our question "does uncertainty from R&D cloud the horizon?" at the microeconomic level the answer is "yes", but at the macroeconomic level the uncertainty and the attendant disagreement cloud the horizon in distinctly different ways.

The broader point is that there are different forms of economic uncertainty that are relevant for macroeconomic outcomes and which may have different impact. In our case the difference is quite stark, with one form of uncertainty behaving like a negative demand shock and another like a positive supply shock. Further unpacking of alterantive sources of macro-relevant uncertainty merits future research both for purposes of analysis and of forecasting.

Furthermore we find that some structural relationships between aggregate variables appear to have changed since the beginning of 2020. This suggests that the extraordinary stabilization measures taken since 2020 and/or the rise of supply shock constraints since then may have caused a structural break in the Fed's reaction function or in other key features of macroeconomic management, a topic which is beyond the scope of this paper but which is of independent interest.

6.2 Implications for Innovation Policy and Firm Strategy

Our paper shows that uncertainty is an intrinsic by-product of innovation. This finding has several implications.

First, policies that penalize uncertainty, such as short-term performance benchmarks or overly-strict disclosure rules, could have the unintended consequence of suppressing innovation. This suggests that resources devoted to R&D should be treated as patient capital, with different policies and disclosure requirements. Internal governance systems should explicitly recognize the "fog of innovation" phase of any R&D project.

Second, our paper finds that, at the firm level, the fog of innovation peaks after about a year, and then dissipates over three or four years. This finding is useful because it gives a specific horizon over which innovation activity could be evaluated – the length of the "fog of innovation" phase. Shorter-term assessments may ininterpret innovative activity as underperformance or as leading to unnecessary risk. This finding could be important for public grant management, sobsidies or other industrial policy programs related to innovation. Put another way, the evaluation of innovation policy should be aligned with the informational life cycle of R&D.

In addition, our finding that analysts are systematically over-optimistic in high-R&D periods suggests that managers play a key role in shaping how innovation uncertainty is interpreted by external evaluators. The implication is that firms engaged in R&D are not just managing innovation but also are managing *expectations* about their innovations. Thus, strategic communication about innovation is very important for firms, particularly at early stages.

Furthermore, analysts are not just over-optimistic but also less accurate in times of high R&D. This suggests that valuation models may systematically mis-price innovative firms. Such models should ideally find ways to explicitly account for informational uncertainty related to R&D activity. The same may be true for the development of other forms of intangible assets.

Finally, we find that innovation creates uncertainty, but also disagreement, and these appear to have different effects on the economy. Our finding that macroe-

conomic "fog of innovation" based on median forecast errors indicates that rising uncertainty around innovative sectors is not necessarily a sign of concern, rather it could simply reflect a period of increased experimentation. The unpredictability of such episodes is precisely because of the possibility of future gains, the specific forms of which remain to be fully uncovered. On the other hand, our R&D-based disagreement measure does behave as a negative shock, indicating that it is important to distinguish between different forms of uncertainty related to innovation. In particular, since aggregate disagreement and R&D-based disagreement can be measured month-to-month in real time, and since forecast errors are related to dynamics over several years, these measures could provide useful tools for policymakers relying on forecasts of the likely future path of the macroeconomy as it relates to innovation. Disagreement should be monitored separately from other forms of uncertainty, as it may signal coordination problems or conflicting narratives, about innovation and in general.

More broadly, the implication is that there are contexts where disagreement could be more damaging than uncertainty. At the firm level, and among policymakers, this suggests that a goal in times of uncertainty is to develop tools and institutions to reduce interpretive divergence. In the context of innovation, this suggests that a policy akin to forward guidance should be adopted, including likely timelines and milestones used to make decisions, as well as increased transparency about uncertain elements rather than promotional optimism.

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A Proofs

Proof of Proposition 1. The solution b^* solves the following first order condition:

$$b^* = \frac{1}{2c}\frac{\tau'(b^*)}{\tau(b^*)^2},$$

which is positive as $\tau'(\cdot) > 0$. Furthermore

$$\frac{\partial b^*}{\partial c} = -\frac{1}{2c^2}\frac{\tau'(b^*)}{\tau(b^*)^2} + \frac{1}{2c}\frac{\tau''(b^*)\tau(b^*)^2 - 2\tau(b^*)\tau'(b^*)}{\tau(b^*)^4}\frac{\partial b^*}{\partial c}$$

Rearranging,

$$\frac{\partial b^*}{\partial c} = -\frac{1}{2c^2}\frac{\tau'(b^*)}{\tau(b^*)^2} + \frac{1}{2c}\frac{\tau''(b^*)\tau(b^*)^2 - 2\tau(b^*)\tau'(b^*)}{\tau(b^*)^4}\frac{\partial b^*}{\partial c}$$

or

$$\frac{\partial b^*}{\partial c} = -\frac{1}{2c^2}\frac{\tau'(b^*)}{\tau(b^*)^2} \div \left[1 - \frac{1}{2c}\frac{\tau''(b^*)\tau(b^*)^2 - 2\tau(b^*)\tau'(b^*)}{\tau(b^*)^4}\right] < 0$$

This expression is negative because $\tau''(b^*)\tau(b^*)^2 < 0$ and $2\tau(b^*)\tau'(b^*) > 0$, so the expression in the square brackets is positive, and the expression outside is negative. ■

Proof of Proposition 2. Condition 1 implies that $\tau(b) = vb^\alpha$ for some $v > 0$.[6] Notice that $\pi(b) = c \times v \times b^\alpha$, so in what follows without loss of generality we set $v = 1$.

[6]Constant elasticity α of τ in b implies that

$$\alpha = \frac{d\tau}{db}\frac{b}{\tau}$$

The optimal bias solves:

$$\begin{aligned} b &= \frac{1}{2c}\frac{\alpha b^{\alpha-1}}{b^{2\alpha}} \\ \Rightarrow \quad b^* &= \left(\frac{1}{2c}\alpha\right)^{\frac{1}{2+\alpha}} \end{aligned}$$

Inserting this expression into the form of π yields that

$$\pi\left(b^*\right) = c^{1-\frac{\alpha}{2+\alpha}}\left(\frac{1}{2}\alpha\right)^{\frac{\alpha}{2+\alpha}}$$

Then

$$\left.\frac{d\pi\left(b\right)}{dc}\right|_{b=b^*} = \left(1-\frac{\alpha}{2+\alpha}\right)c^{-\frac{\alpha}{2+\alpha}}\left(\frac{1}{2}\alpha\right)^{\frac{\alpha}{2+\alpha}} > 0$$

so that greater certainty yields greater precision. Thus more uncertainty yields lower precision and thus greater variance among forecasts. ■

B Alternative variable ordering

In this Appendix we want to examine if switching the order of aggregate uncertainty and R&D uncertainty has any impact on our results. Aside from providing robustness to our results, this identification strategy addresses a fundamental question: do

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Rearranging and integrating we have that

$$\int \frac{\alpha}{b}db = \int \frac{1}{\tau}d\tau$$

or

$$\alpha \ln b + c = \ln \tau$$

Rearranging

$$\begin{aligned} \tau &= e^{\alpha \ln b + c} \\ \tau &= \left(e^{\ln b}\right)^{\alpha} e^{c} \\ &\Rightarrow \quad \tau\left(b\right) = vb^{\alpha} \end{aligned}$$

where $v \equiv e^{c}$.

uncertainty shocks originating in the innovation sector spill over to create general economic uncertainty, or is innovation volatility largely contained within the R&D sector as before?

In our SVAR ordering, we place idiosyncratic R&D uncertainty before aggregate uncertainty, allowing R&D uncertainty shocks to affect aggregate uncertainty contemporaneously while assuming aggregate uncertainty affects R&D uncertainty only with a lag. After this step, the ordering between macro and micro uncertainty primarily affects only the timing of contemporaneous responses and does not alter the nature of the identified shock. The variables are ordered exactly as below.

$$\begin{bmatrix} \log(\text{S\&P 500 Index}) \\ \textit{Fog of innovation} \\ \text{Aggregate Uncertainty} \\ \text{Federal Funds Rate} \\ \log(\text{Wages}) \\ \log(\text{CPI}) \\ \text{Weekly Working Hours} \\ \log(\text{Employment}) \\ \log(\text{Industrial Production}) \end{bmatrix}$$

We continue to use 12 monthly lags and identify structural shocks by a recursive (Cholesky) decomposition and the results below are for the time-line before 2020.

B.1 Aggregate Uncertainty shocks

B.1.1 Median forecast errors

Following a one-standard-deviation aggregate uncertainty shock, industrial production declines persistently, accompanied by reductions in employment and equity prices. The Federal Reserve responds accommodatively by lowering interest rates and the CPI falls gradually. The orthogonalization procedure proves empirically relevant where aggregate uncertainty shocks have no contemporaneous effect on id-

iosyncratic R&D uncertainty (as evidenced by the near-zero response in Figure $B1$), confirming that our residual effectively captures the R&D-specific component. This allows us to cleanly test whether the fog of innovation transmits to the broader economy entirely independently from aggregate uncertainty.

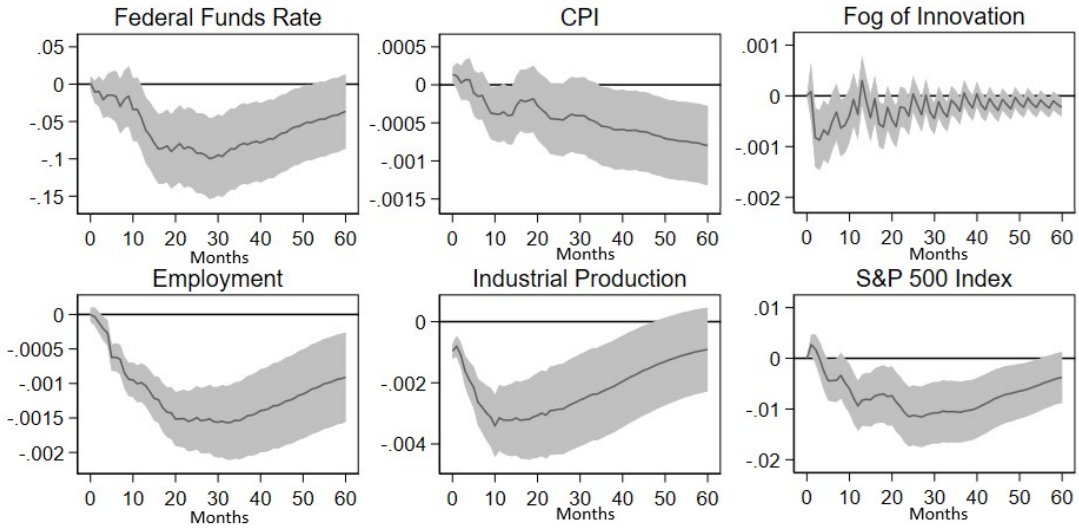


Figure $B1$ – Impulse response from aggregate uncertainty shocks measured using the median forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is the proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.1.2 Mean forecast errors

See Figure $B2$. Following a one-standard deviation uncertainty shock, industrial production declines persistently, accompanied by modest reductions in employment and equity prices. The CPI falls gradually, indicating deflationary pressures. The fog of innovation also decreases, suggesting that accommodative policy can dampen R&D specific uncertainty. The orthogonalization procedure proves empirically relevant because the monetary policy shock has no contemporaneous effect on fog of innovation,

confirming that the residual cleanly captures the R&D specific component.

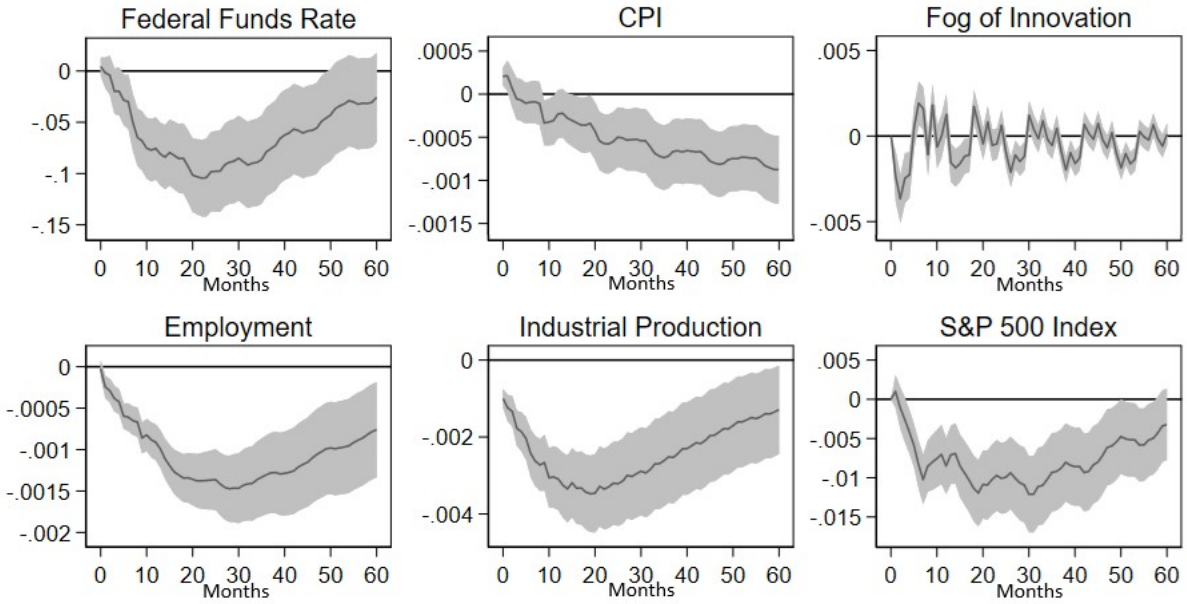


Figure $B2$ – Impulse response from aggregate uncertainty shocks measured using the mean forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.1.3 Median bias

Based on the results presented in Figure $B3$, the macroeconomic responses to a bias shock reveal a pattern consistent with a contractionary aggregate demand shock accompanied by a pronounced reduction in innovation-specific uncertainty.

Following the aggregate forecast bias shock, the Federal Funds Rate declines persistently, indicating a significant accommodative monetary policy response. This easing is aligned with a concurrent, gradual decline in the CPI, suggesting the shock introduces deflationary pressure.

The most distinctive feature is the response of the Fog of Innovation, which falls

sharply and substantially. This indicates that a correction to common forecast bias acts as a powerful clarifier, significantly reducing the level of uncertainty specifically related to R&D and innovation prospects.

Real activity contracts modestly but persistently, with industrial production showing a clearer negative response than employment. The S&P 500 also declines, reflecting a negative reassessment of equity valuations in this environment.

Overall, the evidence suggests that a median forecast bias shock functions as a negative demand shock, prompting policy easing and lower prices, while simultaneously resolving a substantial portion of innovation-related uncertainty. The shock appears to propagate through expectations and aggregate demand channels, with a more pronounced effect on investment and pricing (CPI and equities) than on the industrial production and labor market in the short to medium term.

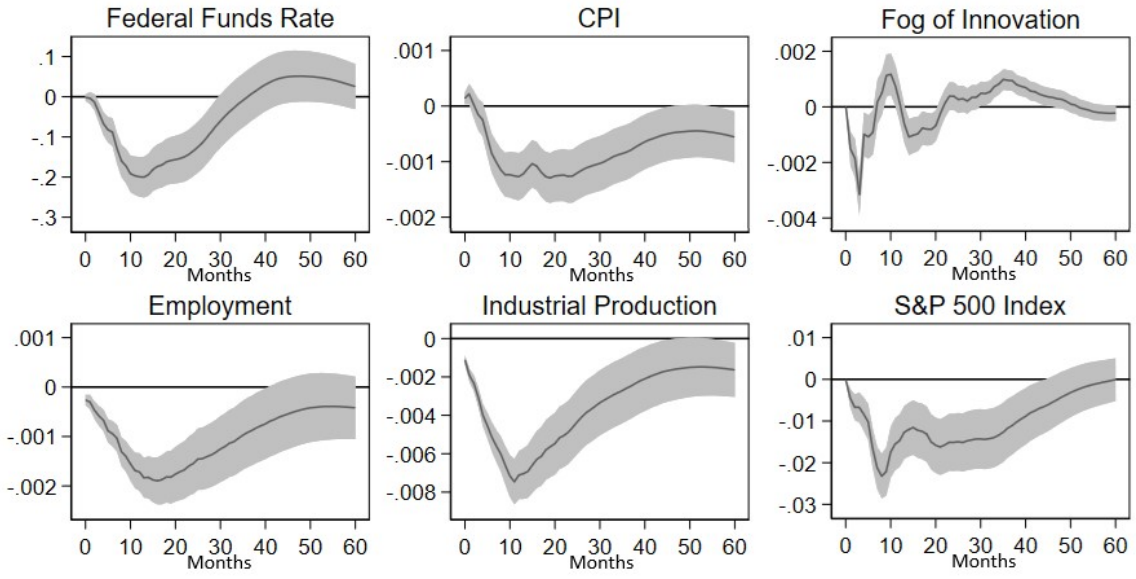


Figure $B3$ – Impulse response from aggregate uncertainty shocks measured using aggregate bias. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.1.4 Disagreement

Based on the results presented in Figure $B4$, the macroeconomic responses to a disagreement shock again reveal a pattern defined by a negative demand shock.

Following the disagreement shock, the Fog of Innovation collapses in 3 months but approaches zero and fluctuates around zero to the end of 5 years. Concurrently, the shock begins a standard negative aggregate demand response, whereas the Federal Funds Rate and CPI fall persistently after an initial positive response, indicating a monetary policy to offset weakening demand and a deflationary pressure.

The real side effects are clear but modest in magnitude compared to the evaporation of uncertainty. Both industrial production and employment decline persistently, while the S&P 500 also falls, reflecting a downward reassessment of equity valuations in this environment. Overall, the evidence suggests that a disagreement shock functions as a negative demand shock.

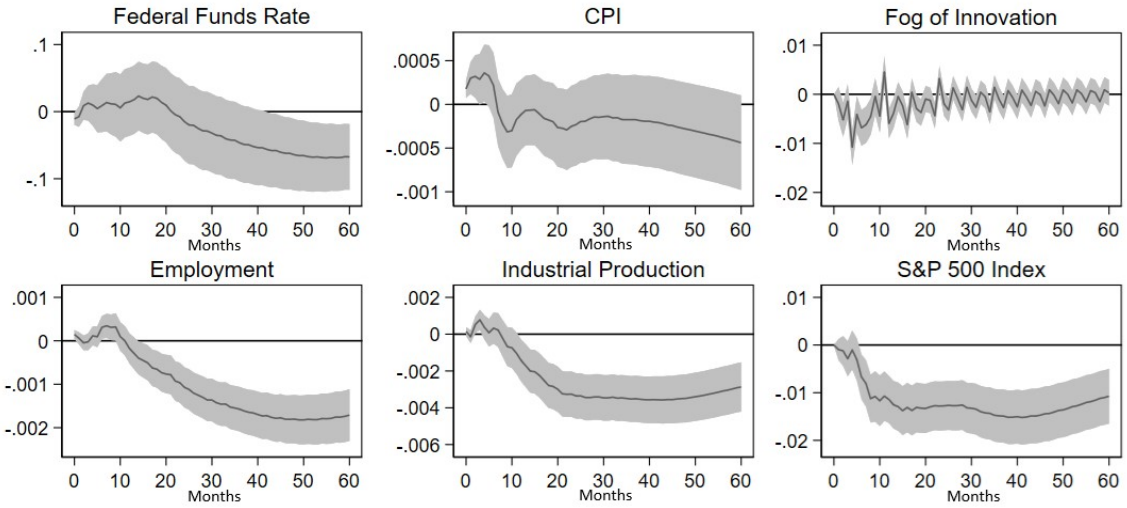


Figure $B4$ – Impulse response from aggregate uncertainty shocks measured using aggregate disagreement. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2019m12.

B.2 "Fog of Innovation" shocks

B.2.1 Median forecast error

Our analysis reveals that R&D uncertainty shocks continue to have a macroeconomic effect with similar properties to our benchmark specification. Following a one-standard-deviation R&D uncertainty shock, industrial production reacts positively to the shock, peaking within 20 months. Employment follows a similar though more persistent pattern. The stock market rises over about a year after which it tapers off gradually. Finally, R&D uncertainty exerts downward pressure on prices. All of this is consistent with the fog of innovation acting as a positive supply shock, as before.

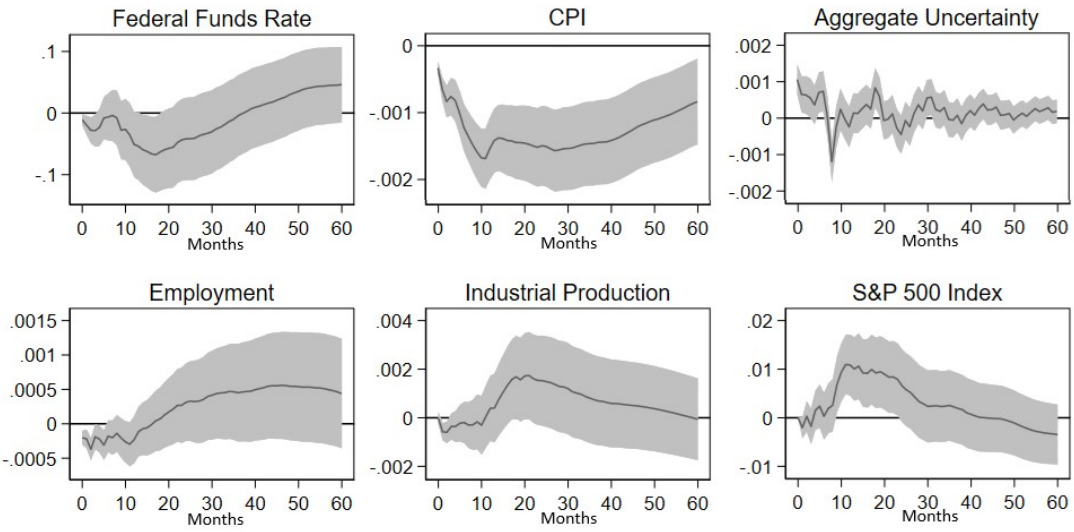


Figure $B5$ – Impulse response from fog of innovation shocks, measured as the median forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.2.2 Mean forecast error

The analysis of R&D uncertainty shock from the mean forecast error displays industrial production and employment decline modestly for 10 months and then start to recover persistently, which leads it to grow positively after 20 months. The stock market shows a short-run negative reaction followed by a positive long-run response. Concurrently, the Federal Reserve responds with a persistent easing of policy for over the first half of the timeline, as indicated by the falling Federal Funds Rate.

Consistent with the benchmark finding, the shock exerts clear downward pressure on the price level, with the CPI declining for 30 months and starts to increase gradually in the longer horizon.

Overall, this R&D uncertainty shock acts as a mild contractionary force on real activity at first while simultaneously easing financial conditions and reducing inflation. Later, however, things are different. The combination of falling output and prices suggests the shock operates through a channel that dampens aggregate demand at first and is redeemed as a modest positive supply shock later, as in the benchmark specification.

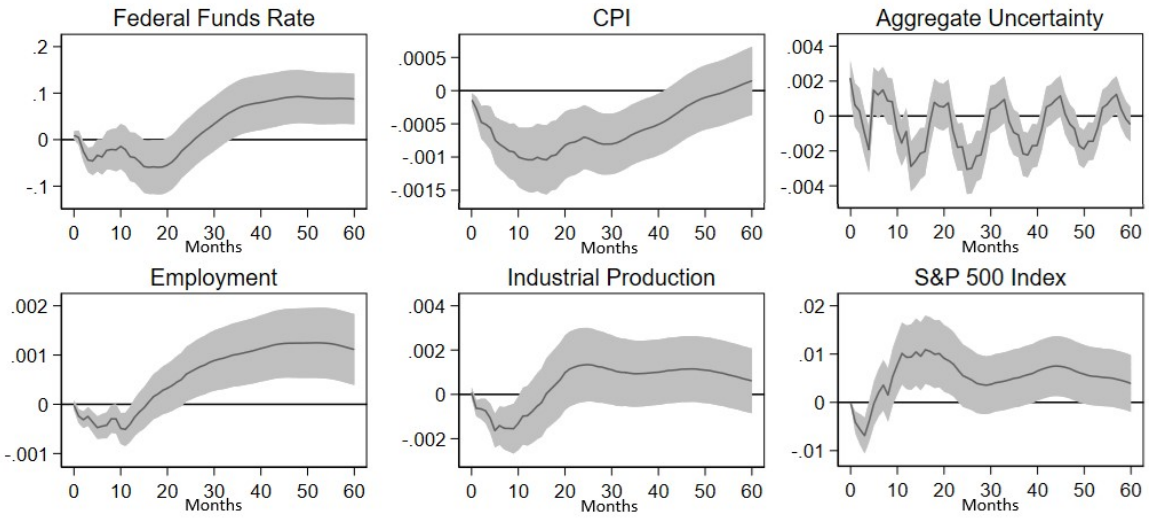


Figure *B*6– Impulse response from fog of innovation shocks, measured as the mean forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.2.3 Median bias

Based on the results presented in Figure *B*7, the macroeconomic responses to a median forecast bias shock reveal an asymmetric impact, whereas employment is affected positively by the median forecast bias shock; industrial production responds modestly negative.

The shock elicits a negligible and transient monetary policy response, with the Federal Funds Rate showing negative movement for the first 10 months after the shock. The Consumer Price Index (CPI) is essentially unchanged because its very small magnitude, indicating very small deflationary consequences for the overall economy. Similarly, the responses of industrial production and the S&P 500 are negative and short-lived. This is similar to the benchmark specification.

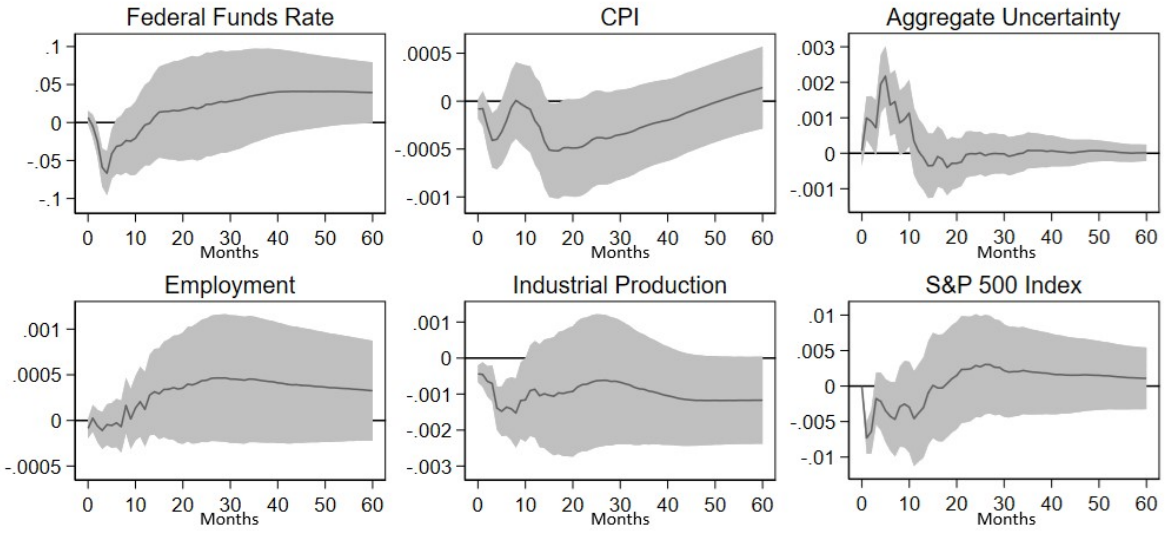


Figure *B*7 – Impulse responses from estimation of benchmark VAR, measured as the median bias in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

B.2.4 Disagreement

Our analysis reveals that the disagreement shock over R&D oriented firms produces a distinct macroeconomic profile, contrasting with the positive supply-side effects associated with the mean and median forecast shocks. Following the shock, indus-

trial production declines modestly but persistently and move to the negative side around 10 months after the shock and remain negative despite the gradual increreasing responsr after 30 months, indicating a contraction in real economic activity. Meanwhile, employment, the other indicator of the real economy shows a positive response floowed by the muted response for around 20 months. This is accompanied by a sustained easing of monetary policy, as evidenced by the persistently falling Federal Funds Rate for 20 months which starts to gradually increase again after that. The upward path in the CPI signifies consistent inflationary pressure which gets muted after 20 months.

Equity markets also respond positively first to after the shock but this reponse gets muted after 25 months, with the S&P 500 fluctuating reaction. Overall, this disagreement across forecasters' shock functions primarily as a modest negative supply shock. It triggers a contraction in output, tha tprompts an inflationary response. There is a positive asset market response, likely due to the accommodative federal funds response.

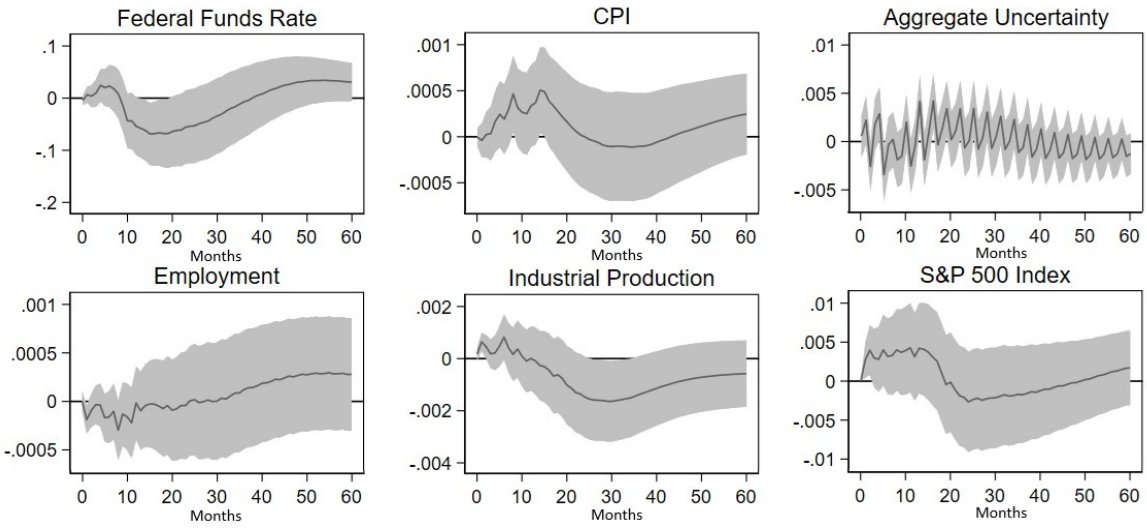


Figure *B*8 – Impulse responses from estimation of benchmark VAR, measured as the average disagreement in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2019m12.

C Robustness: VAR including recent data

In the main text we estimate the structural VAR over the pre-2020 sample, in order to keep the analysis comparable with earlier work and to focus on a period in which the forecast and macro series are relatively homogeneous, unaffected by possible structural changes due to the impact of COVID and the attendant policy response. As a robustness check, this appendix reports results from re-estimating the same nine-variable VAR using all available monthly data through 2025. Throughout this appendix we keep the specification and the identification strategy unchanged from the benchmark regressions.

C.1 Aggregate Uncertainty Shocks

C.1.1 Median forecast error

Figure $C1$ reports impulse responses to a one-standard error deviation innovation in the aggregate uncertainty shock. Over the extended sample, the responses of real activity (industrial production and employment) remain negative but are less persistent than in the pre-2020 sample. The stock market now rises instead of falling as in the pre-2020 sample, possibly due to the unprecedented policy response to COVID in the post-2020 era.

The responses of inflation and the policy rate are also modest. The federal funds rate has a sharp negative response to the positive aggregate uncertainty shock, supporting the idea of monetary easing criteria; however, this reaction becomes gradually positive on the longer horizon. CPI responds gradually and the impact is positive.

Overall, the full-sample SVAR confirms that aggregate uncertainty has a negative macroeconomic impact. However, this time it has some features associated with supply shocks, such as a higher inflation, as well as a higher stock market. This is consistent with the fact that macroeconomic uncertainty has been very high since 2020, but that the exact sources of uncertainty have been related to supply-side issues such as global supply chain problems during the pandemic and more recent fragmentation of supply chains due to geopolitical tensions. The dynamics are more consistent with a negative supply shock than a negative demand shock.

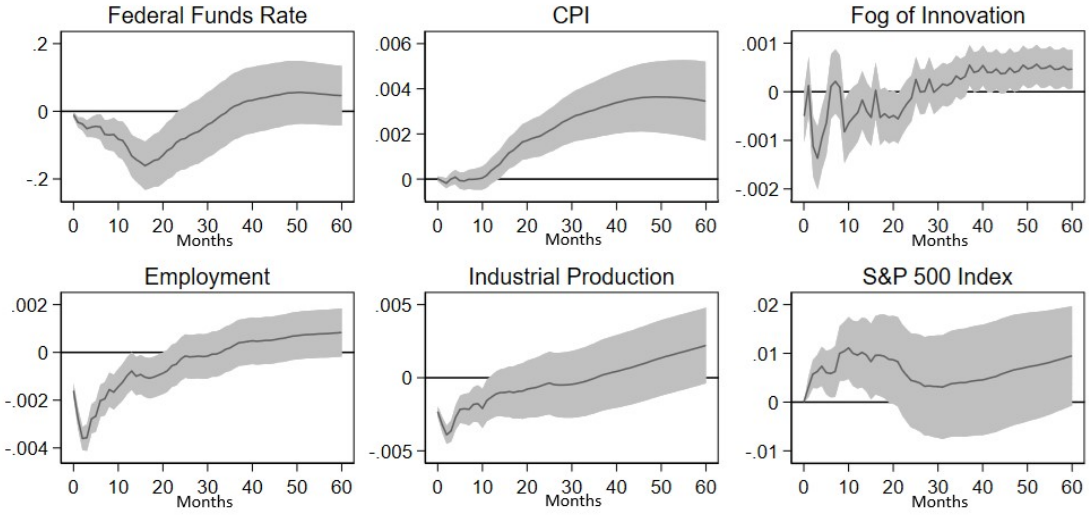


Figure $C1$ – Impulse response from aggregate uncertainty shocks measured using the median forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

C.1.2 Mean forecast error

Figure $C2$ reports impulse responses to a one-standard-deviation innovation in the mean of aggregate uncertainty shock over the full sample.

Following the shock, real activity contracts modestly, whereas industrial production and employment both decline, though the responses are not strongly persistent. Notably, the stock market falls steadily, similar to the negative reaction found in the post-2020 subsample but with a smaller magnitude.

The response to inflation is positive, contrasting with the negative response found in the post-2020 subsample. The CPI declines very slightly at first, indicating weak deflationary pressure, following with a inflationary response after a year. The federal funds rate also shows a negative movement.

Overall, the full-sample evidence confirms that an aggregate uncertainty shock retains a negative impact on real activity and equity valuations. However, its deflationary implication is limited, but its inflationary response is aligned with a supply-side contraction rather than with the demand side, because the real economy shows a negative response. This suggests that the character of uncertainty shocks can vary across time depending on the underlying economic structure and the nature of the shocks dominating the sample. Again, we think that the mean forecast error is likely to be affected by outliers, so we expect its behavior to be more noisy that uncertainty measured using median forecast errors. Nonetheless, this measure of aggregate uncertainty remains largely consistent with a negative macroeconomic shock.

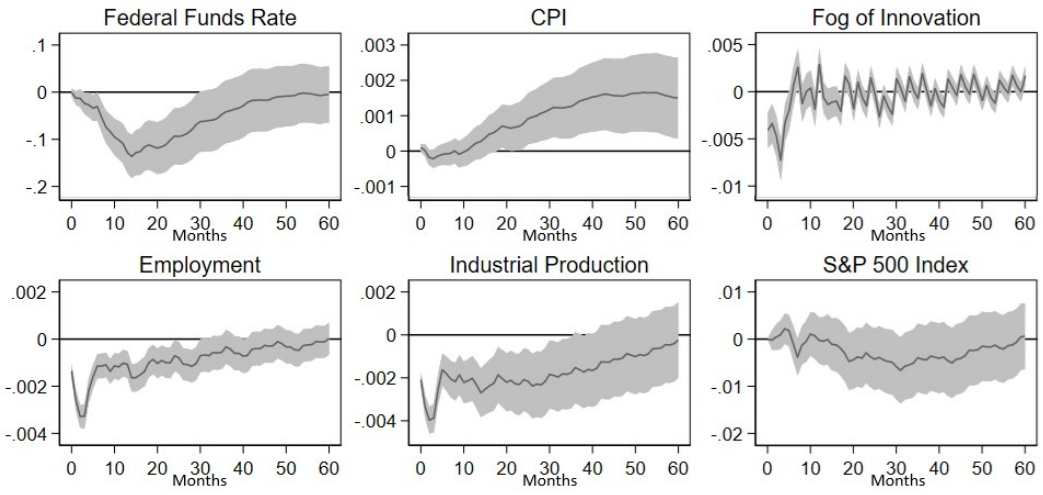


Figure $C2$ – Impulse response from aggregate uncertainty shocks measured using the mean forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

C.1.3 Median bias

Figure $C3$ reports the impulse responses to a one-standard-deviation shock in the aggregate median bias over the full sample.

Following the shock, real activity contracts sharply and persistently. Following the shock, both industrial production and employment declined steadily. The stock market also falls in a pronounced and sustained manner, reflecting a broad-based reassessment of economic prospects.

The policy response is strongly accommodative. The federal funds rate declines substantially and persistently, indicating aggressive monetary easing to counteract the contractionary impulse. The CPI falls gradually, confirming clear deflationary pressure.

Notably, the fog of innovation, the measure of R&D-specific uncertainty, also declines after the shock, suggesting that a correction to common forecast bias simultaneously creates a portion of innovation-related uncertainty for high R&D industries.

Overall, the full-sample evidence indicates that an aggregate median bias shock acts as a negative demand disturbance with depressing output, employment, and equity prices, and acts as a negative demand shock.

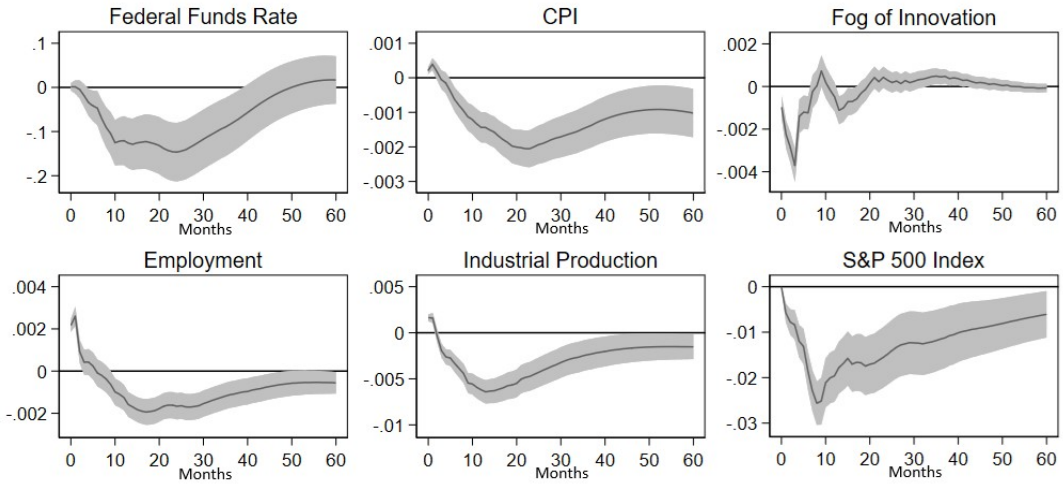


Figure $C3$ – Impulse response from aggregate uncertainty shocks measured using aggregate bias. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

C.1.4 Disagreement

Figure $C4$ reports impulse responses to a one-standard-deviation innovation in the disagreement forecast shock over the full sample.

Following the shock, real activity contracts modestly but persistently; industrial production and employment both decline gradually. The stock market falls steadily and strongly, indicating a negative reassessment of equity valuations.

The policy response is not consistent. Although the federal funds rate increases as an immediate response in the first 30 months, it declines persistently in the longer horizon, reflecting a sustained monetary easing to counteract the shock's contractionary effects. The CPI also falls, even if it is a modest decline, confirming deflationary pressure.

Notably, the fog of innovation falls steadily over the first 5 months, suggesting that heightened disagreement ultimately forces a convergence of forecasts and reduces innovation-related uncertainty in the short-run.

Overall, the full sample shows that a disagreement shock operates as a contractionary demand shock. It reduces output, lowers prices, and resolves a portion of innovation uncertainty, while depressing equity markets. The pattern aligns with a scenario in which greater aggregate uncertainty signals deteriorating economic prospects, and by generating uncertainty, makes the future more foggy.

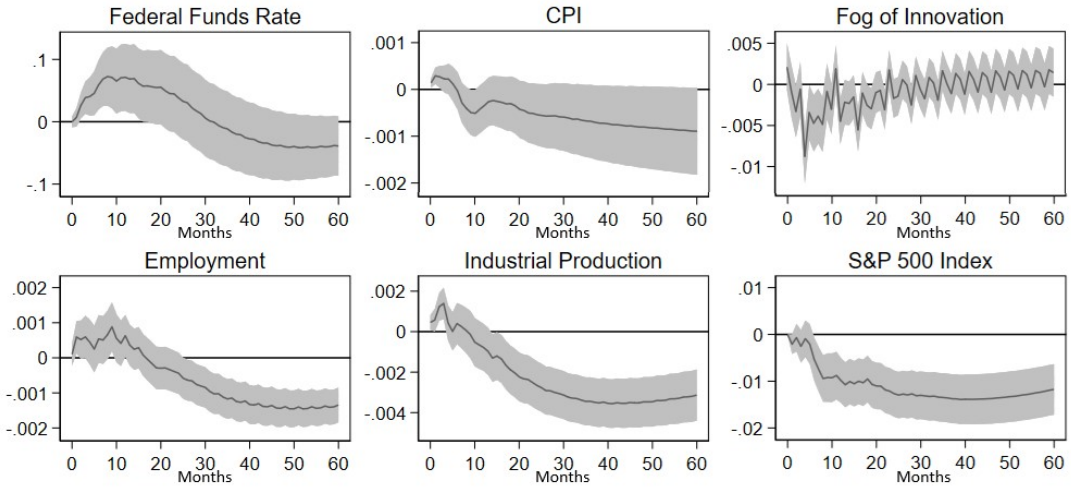


Figure $C4$ – Impulse response from aggregate uncertainty shocks measured using aggregate disagreement. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

C.2 "Fog of innovation" shocks

C.2.1 Median forecast errors

Figure $C5$ presents the corresponding responses to a one-standard deviation innovation in R&D uncertainty from forecasts using firms in high-R&D industries. The main observation from this estimation is that R&D uncertainty continues to display features more consistent with a positive supply shock.

A shock to R&D uncertainty generates a smaller but positive movement in industrial production and employment. The response of CPI is likewise negative, as before.

Equity prices display a positive response to R&D uncertainty shocks at short horizons. This pattern is consistent with the interpretation in the main text, reflecting "innovation news" with upside potential, and that these idiosyncratic innovation shocks do not aggregate into large macro-wide risk. At the same time, the lack of precisely estimated negative responses supports our central conclusion: even when we extend the data to 2025, R&D-based uncertainty shocks do not resemble conventional aggregate uncertainty shocks in their macroeconomic impact and they behave more like a small positive supply shock. In this sense, the response of R&D-based uncertainty is more consistent across samples than the impact of aggregate uncertainty.

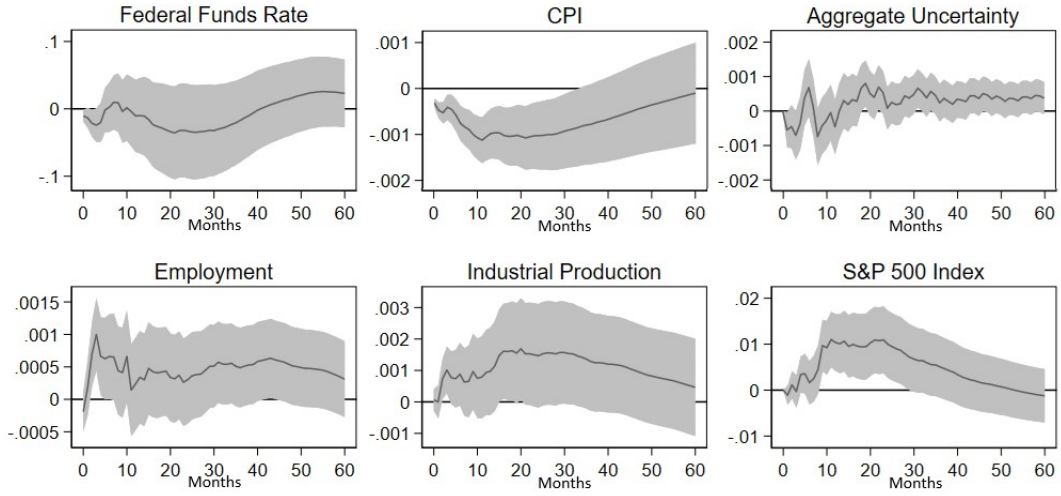


Figure $C5$ – Impulse response from fog of innovation shocks, measured as the median forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

C.2.2 Mean forecast errors

Based on Figure $C6$, the estimated responses to a one-standard-deviation "fog of innovation" shock, derived from orthogonal mean forecast shocks, are as follows.

The shock creates a slight negative response as soon as uncertainty occurs, followed by a positive response in the long run in the real economy, meaning industrial production and employment are responding positively to the shock.

Consistent with a positive supply-side disturbance, the Consumer Price Index exhibits a clear and sustained negative response.

Financial markets respond positively: equity prices drop on impact on the shock, but then rise, with the positive effect enduring throughout the horizon. Furthermore, the results display that R&D-related uncertainty (fog of innovation) has weaker and

less persistent macroeconomic consequences than general uncertainty.

Again, the measure of fog of innovation based on the mean forecast error looks like a negative demand shock at first and a weak positive supply shock later. However, aside from the impact on prices, its macroeconomic impact is weak and inconsistent as before.

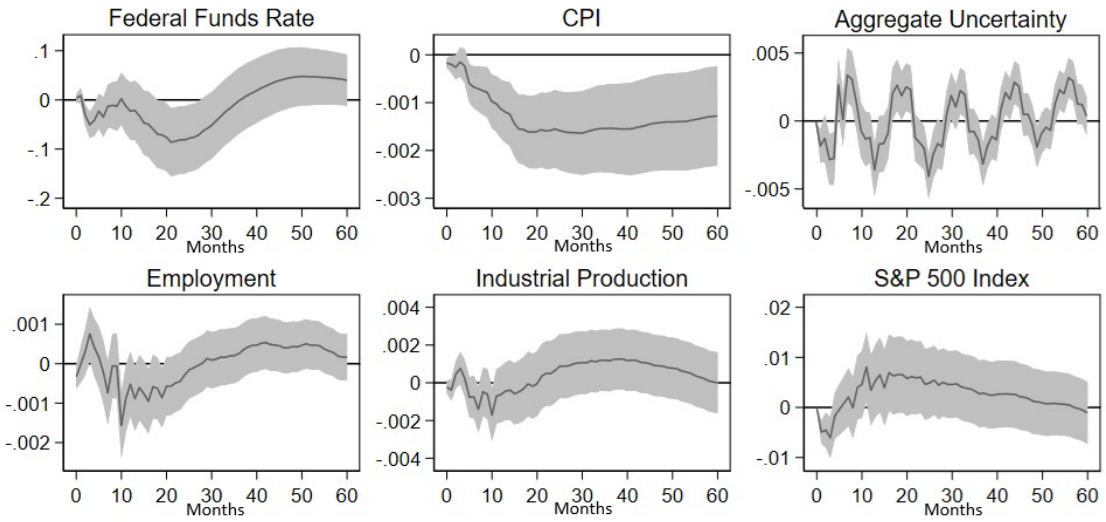


Figure $C6$ – Impulse response from fog of innovation shocks, measured as the mean forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard erorr confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

C.2.3 Median Bias

Based on Figure $C7$, the impulse responses to a one-standard-deviation "fog of innovation" shock, derived from orthogonal median bias shocks, present the following key dynamics.

The response in the real economy is muted. Employment displays a very slight and transient negative effect before returning to near zero. Industrial production

shows a similar pattern of a negligible initial decline followed by a gradual reversion.

The shock elicits a modest, muteed response in the Federal Funds Rate, drawing towards the negative side. The Consumer Price Index shows a clear and sustained negative response. Financial markets also respond similarly, with a slight negative response in the S&P 500, which fluctuates around zero on the longer horizon. Aggregate uncertainty, after a possible initial spike, declines steadily over time.

Overall, the macroeconomic consequences of this R&D-related uncertainty shock are weak and less persistent than those of conventional aggregate uncertainty. The pattern, is very short-lived suggesting that bias shocks have little in the way of aggregate implications, except for the negative impact on prices and the FFR which could be due to the short-term association with aggregate uncertainty, which is a negative demand shock.

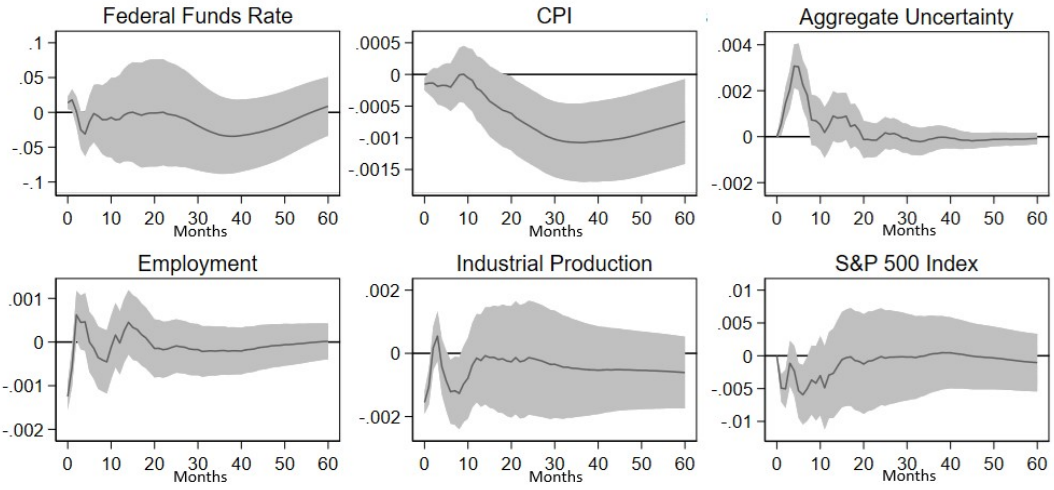


Figure *C*7 – Impulse response from fog of innovation shocks, measured as the median bias in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

C.2.4 Disagreement

Based on Figure $C8$, the impulse responses to a one-standard-deviation shock capturing orthogonal disagreement among R&D-oriented firms reveal a pattern that s somewhat different from the pre-2020 results.

The effects on real activity (industrial production) are initially positive, followed by a longer negative response. Employment grows modestly on impact before stabilizing at a slightly higher level. The Consumer Price Index shows a small but positive and gradually increasing response, indicating mild inflationary pressures. Over the medium term disagreement continues to behave like a negative supply shock, with rising prices and lower industrial production, but the short run responses are harder to interpret.

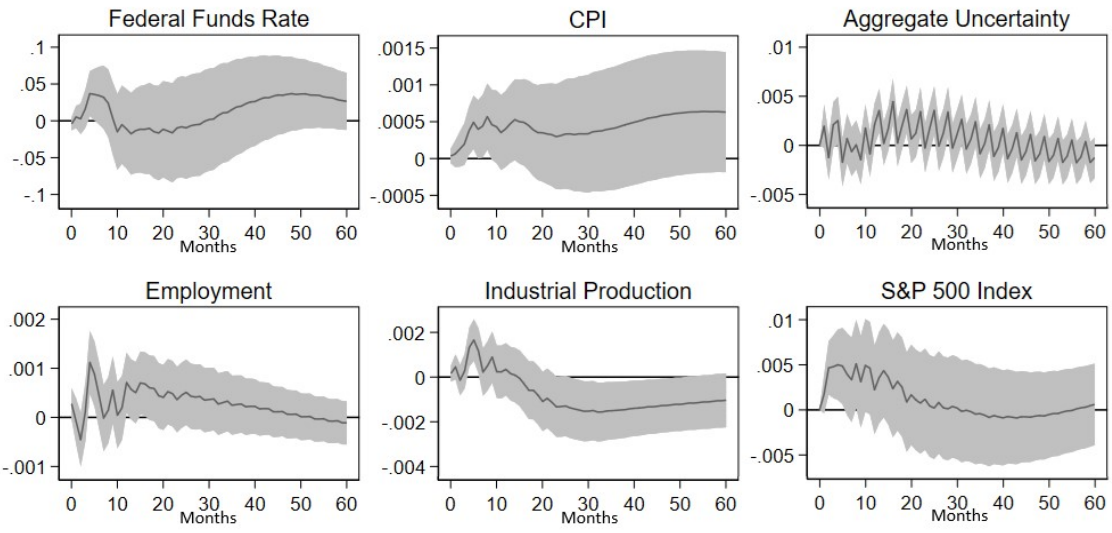


Figure $C8$ – Impulse response from fog of innovation shocks, measured as the aggregate disagreement in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

D Full sample with alternative variable ordering

This section tests whether reversing the order of R&D and aggregate uncertainty alters our findings, while this test will be run over the entire sample from 1981 to 2025. This step will address whether R&D uncertainty spills over into the broader economy or remains contained within the innovation sector.

D.1 Aggregate Uncertainty Shocks

D.1.1 Median forecast errors

The results in Figure $D1$ confirm that in the extended-sample SVAR with reverse order, the aggregate uncertainty shocks negatively impact real activity, though the effects on industrial production and employment are slightly smaller than in the pre-2020 period which is a similar results to the original benchmark VAR. In the whole sample estiamtion we have a positive stock market response, and a modestly positive impact on inflation (CPI). The federal funds rate response in the first 30 months is negative, while in the longer horizon starts to become positive gradually. This pattern, characterized by weaker output and higher prices, resembles the effects of a negative supply-side shock. These results are consistent with the nature of post-2020 uncertainty and the original order.

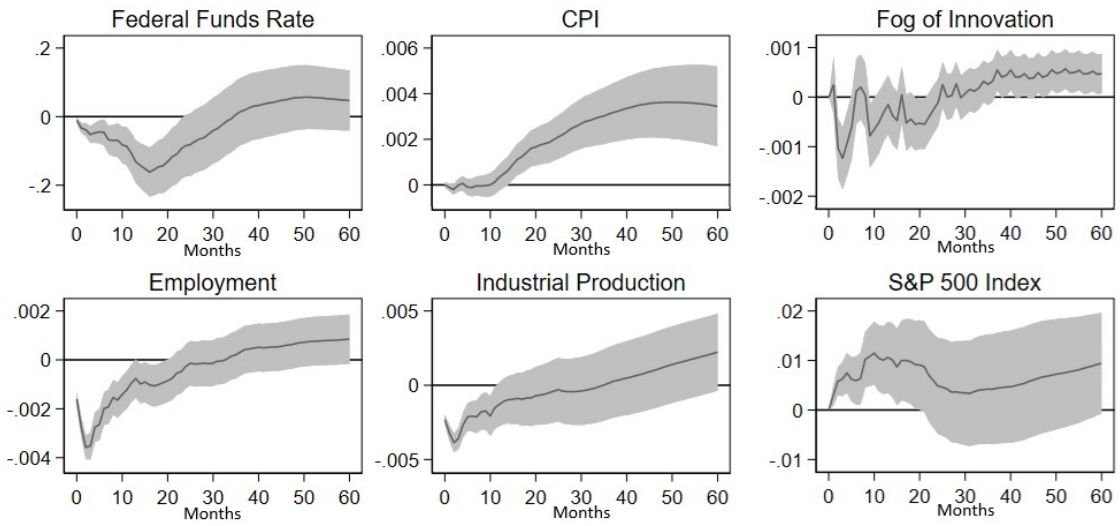


Figure $D1$ – Impulse response from aggregate uncertainty shocks measured using the median forecast error. The shock is one standard standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is the proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

D.1.2 Mean forecast errors

The results in the Figure $D2$ confirm that in the extended-sample SVAR with reverse ordering, aggregate uncertainty shocks negatively impact real activity. This is reflected in the consistently negative mean forecast errors for employment and Industrial Production throughout the forecast horizon. However, the effects appear less persistent than in the pre-2020 period, a finding similar to the original benchmark VAR.

In the full sample estimation, we observe a slightly negative stock market response. There is also a modestly positive impact on inflation (CPI), as seen in their error paths moving from negative toward zero or slightly positive territory. The fed-

eral funds rate; however, reacts negatively and sharply to the shock, while it starts a gradual return after 20 months. This pattern admits the effects of a supply-side shock. These results are consistent with the nature of post-2020 uncertainty and align with the findings from the original ordering.

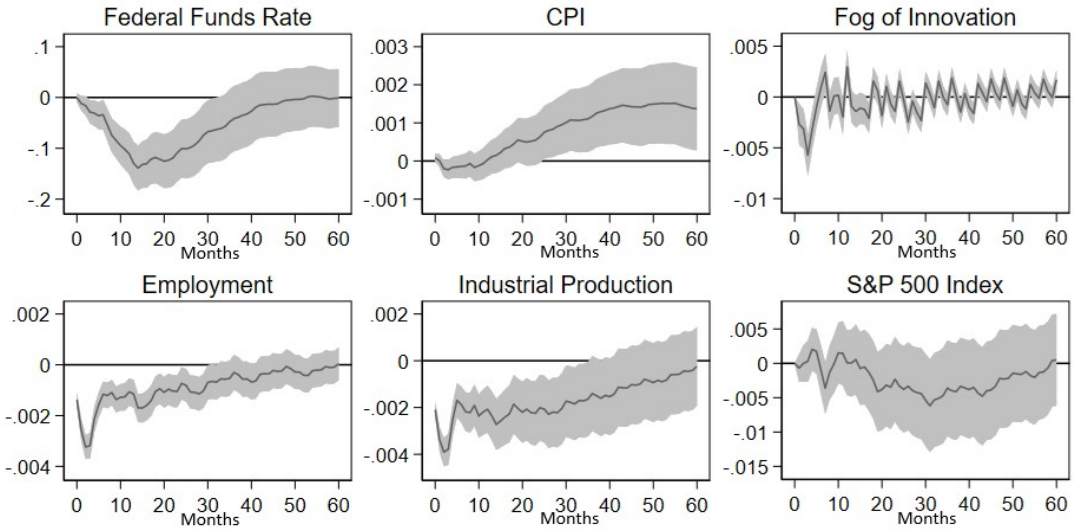


Figure $D2$ – Impulse response from aggregate uncertainty shocks measured using the mean forecast error. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

D.1.3 Median bias

The median forecast bias results support and refine the interpretation of uncertainty shocks in the extended sample. The shock from median bias to employment and Industrial Production confirms a negative response, suggesting the shock's impact is recognized with a lag in forecasts, after which the negative bias persists.

The response pattern for prices and interest rates are also clearly negative. The

Federal Funds Rate exhibits a negative response after the median bias shock. Likewise, CPI shows a persistent negative reaction after the shock. This combination aligns with the characterization of a negative demand-side shock.

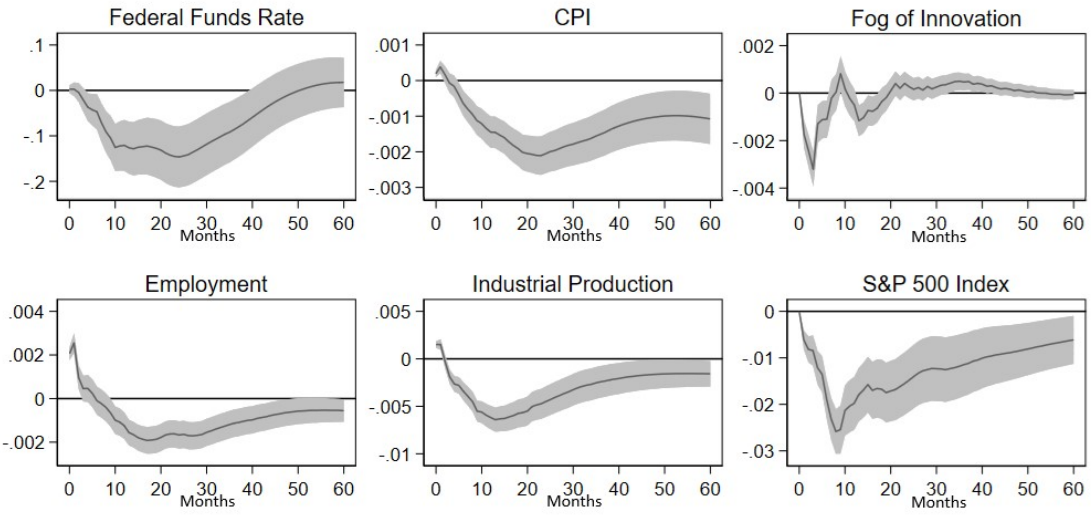


Figure $D3$ – Impulse response from aggregate uncertainty shocks measured using aggregate bias. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

D.1.4 Disagreement

The aggregate disagreement shock reveals significant dispersion in the real economic variables. All indicators of the real economy, including employment and Industrial Production, show a steadily decreasing reaction after the shock is observed.

Aggregate disagreement shock is impacting the Federal Funds Rate index positively first, which follows with a negative impact on the longer horizon. CPI also adapt an deflationary response after the shock, indicating the occurrence of the negative demand shock. S&P 500 response to the disagreement shock is present but

slightly more mutednegative which aligns with the incentive reaction to the growing uncertainty. This pattern, where disagreement causes a negative response to the real activity and policy variables, and relatively lowers the inflation, further supports the characterization of the shock as a negative demand shock but one that creates ambiguity about the policy response.

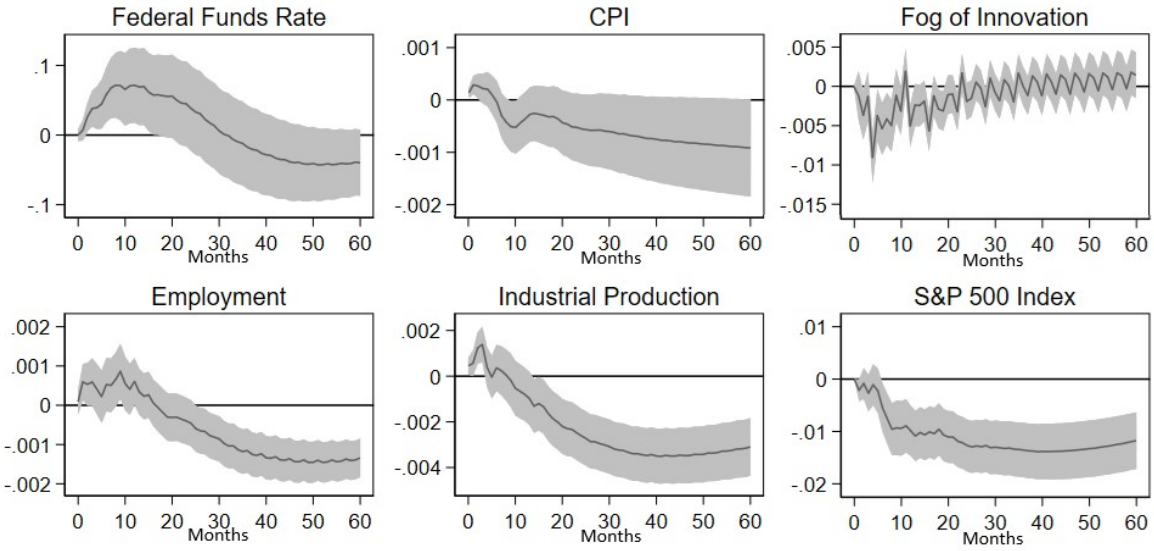


Figure $D4$ – Impulse response from aggregate uncertainty shocks measured using aggregate disagreement. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

D.2 "Fog of innovation" shocks

D.2.1 Median forecast errors

A shock to R&D uncertainty continues to resemble a modest positive supply shock – see Figure $D5$. It generates a small, positive response in industrial production and

employment, while reducing inflation (CPI). Equity prices fall after a rise in the short run, consistent with the "innovation news" interpretation; these firm-specific shocks signal upside potential without aggregating into broad economic risk. Crucially, the absence of strong negative responses confirms that R&D uncertainty does not act like a traditional aggregate uncertainty shock. Even in the extended sample, its macroeconomic impact remains distinct and more akin to a beneficial supply-side disturbance.

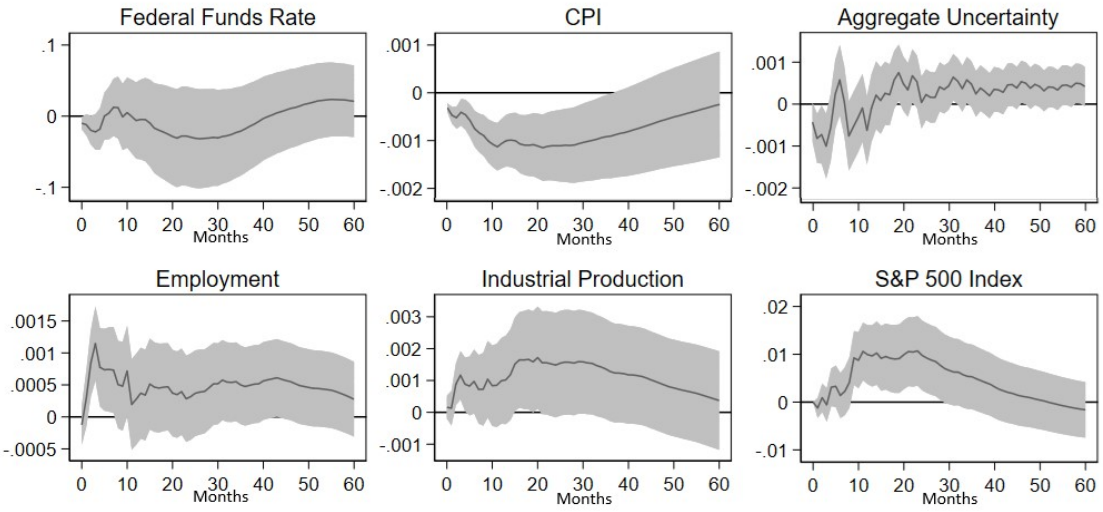


Figure $D5$ – Impulse response from fog of innovation shocks, measured as the median forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

D.2.2 Mean forecast errors

A shock to R&D uncertainty measured using mean forecast errors continues to have a mixed impact. Initially, it looks like a positive supply shock, with employment

and industrial production going up slightly at first, dropping, and then rising again later. However, the stock market declines initially, eventually rising and tapering off gradually. This is consistent with the mean-based measure being possibly influenced by outliers, which leads to unclear results.

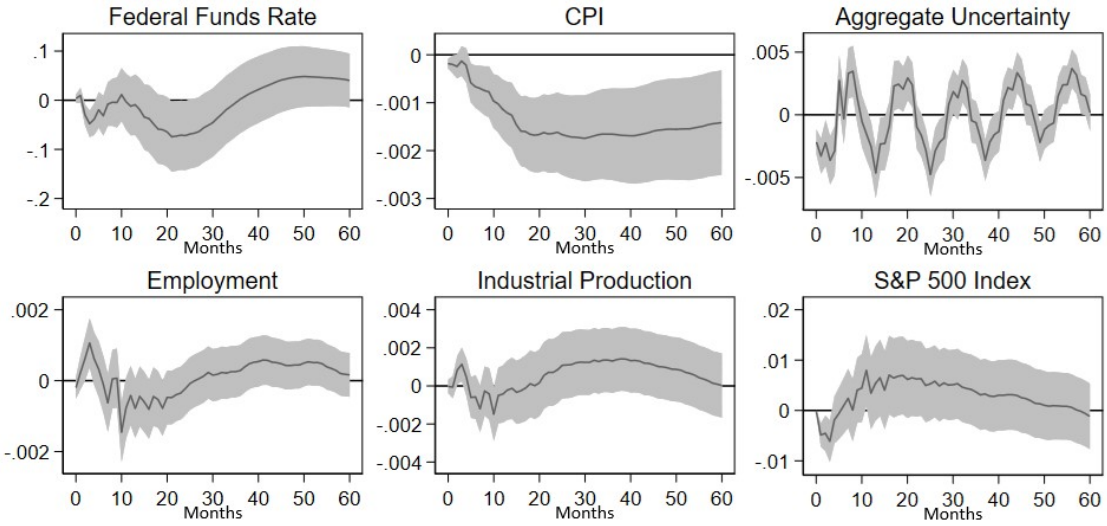


Figure *D*6 – Impulse response from fog of innovation shocks, measured as the mean forecast error in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

D.2.3 Median bias

A shock to the median bias in R&D continues to resemble the results in the aggregate uncertainty shock, but in a very smaller magnitude. The initial response of industrial production and employment is negative but short-lived. The CPI declines gradually over several years before reverting. The monetary policy response is nuted. Overall, this shock can be recognized as a modest and very short-lived negative demand shock – it contributes to aggregate uncertainty, but does not account for the aggregate

impact of the median forecast error "fog of innovation" shock, so that bias is not the main factor accounting for the behavior of R&D uncertainty. All of this is consistent with the other estimation approaches.

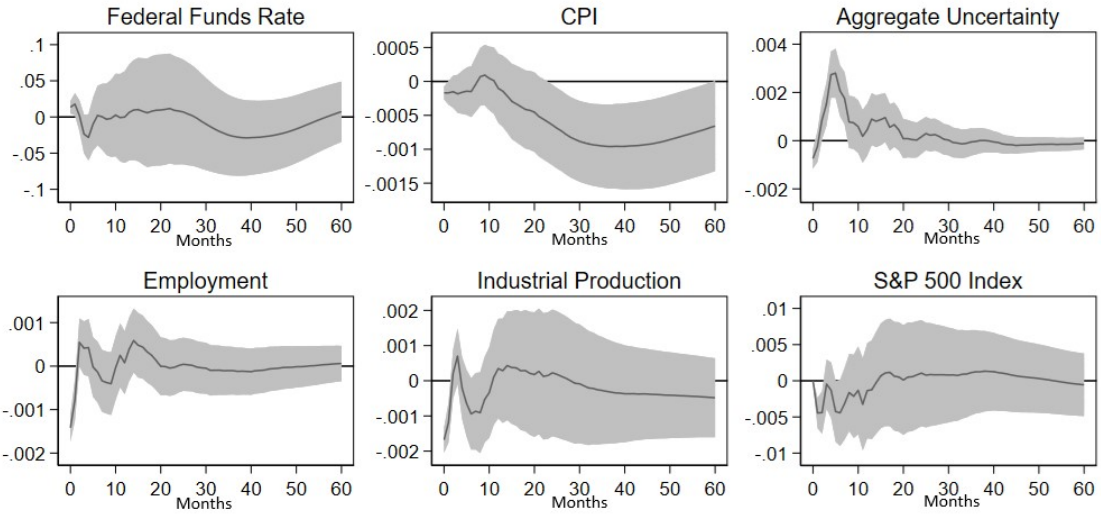


Figure $D7$ – Impulse response from fog of innovation shocks, measured as the median bias in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands.The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m1 to 2025m5.

D.2.4 Disagreement

A shock to R&D disagreement in this case leads to an initial increaes followed by a slow decline in industrial output and share prices. The responses of most variables except for the federal funds rate is mostly muted compared to the benchmark specification. Again, we conclude that structural relationships since 2020 may have changed.

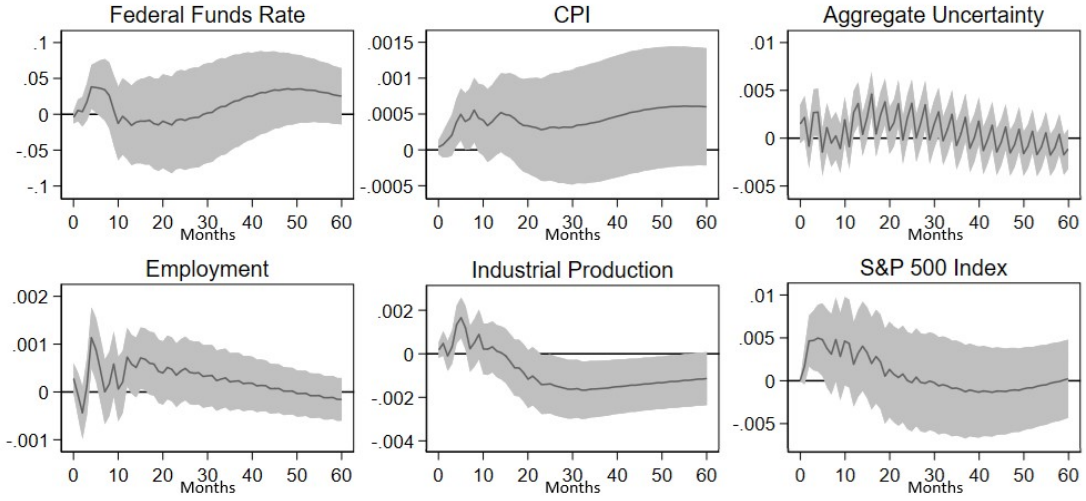


Figure *D*8 – Impulse response from fog of innovation shocks, measured as the average disagreement in R&D intensive industries. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long-run trends. The sample period is 1982m1 to 2025m5.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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