# Information Quality Driven Business Cycles*

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January 30, 2022

**Abstract**

This paper introduces information quality to address puzzles in the endogenous uncertainty literature. The key idea is that even though information acquisition rises in a downturn, the quality of information acquired is lower, and hence, forecasts are inaccurate, and uncertainty remains high. To motivate the concept of information quality, I build a model with information search frictions. In the model, information quality depends on the data abundance and information search intensity. The model with information search frictions generates counter-cyclical information acquisition and uncertainty, and pro-cyclical information quality. This co-movement can rationalize facts that appear at odds with each other: on the one hand, information rigidities are documented to be lower in a downturn, and information acquisition is counter-cyclical, while on the other hand, measures of uncertainty are high, and forecasts remain inaccurate. Using the Survey of Professional Forecasters, I construct wedges and empirical evidence which documents that information quality declines in a downturn. Quantitatively, the model with information search frictions generates more amplification than a model with counter-cyclical information acquisition. This is due to the differences in the cyclicality of uncertainty dynamics generated by these models. In addition, lower information quality accounts for a significant portion of the decline in output and uncertainty fluctuations. The existence of information quality can also explain phenomena caused by behavioral biases, such as mistakes and expectational errors, when agents do not internalize fluctuations in information quality. Mistakes that occur due to information quality generates a substantial decline in output.

**JEL classification**: E32, E44, D84,

**Keywords**: Business Cycles, Information Acquisition, Uncertainty

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*I am indebted to my advisors Luminita Stevens, Pierre De Leo, and John Shea for their invaluable guidance and support. I am grateful to Yeow Hwee Chua, Thomas Drechsel, and Eugene Oue, and various participants at the University of Maryland Brownbag session for their useful feedback. All errors are my own.

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# 1 Introduction

Economic agents face uncertainty when making decisions, where uncertainty refers to the perceived variance of the hidden state. Uncertainty leads to suboptimal allocations compared to a perfect information environment. Chung and Veldkamp (2019) consider information as an input for reducing uncertainty. A natural agenda is to analyze the dynamics of information acquisition behavior over the business cycle. Several studies have documented that the incentive to acquire information increases in a downturn (e.g., Chiang (2021), Flynn and Sastry (2021)). Although information acquisition increases in a crisis, forecasts are inaccurate, and uncertainty remains high.[1]

To address this puzzle, this paper introduces information quality. The key idea is that even though information acquisition increases in a downturn, the quality of information acquired is lower, and hence, forecasts are inaccurate, and uncertainty remains high. This paper studies a model with information search frictions to motivate the concept of information quality. Information quality increases with the amount of mutual information generated from the model with search frictions, where mutual information is defined as the reduction in uncertainty. Mutual information depends on two key ingredients: the abundance of data and information search intensity. Data abundance is a function of the aggregate state of the economy. When the economy is in a boom, this generates more transactions and thus more data (see Farboodi and Veldkamp (2019)). A higher abundance of data generates more mutual information and less uncertainty in the economy. Mutual information also depends on information search intensity; that is, firms searching for more information leads to higher mutual information.

I define information acquisition behavior as information search intensity in the model. When an adverse shock occurs, data become scarce in the economy, and mutual information decreases on impact. As a result, the marginal benefit of searching for information increases, and furthermore, individuals need to search more to maintain the initial level of mutual information. Hence, information search intensity is counter-cyclical, consistent with empirical evidence of counter-cyclical information acquisition.

Next, I compare the level of mutual information between the model with information search frictions and a model without information search frictions (hereinafter denoted as the baseline model). I demonstrate that the level of mutual information in the model with information search frictions is lower than the baseline model due to information search costs. Subsequently, I introduce information quality as a model-based wedge between mutual information in these two models. When information quality is poorer, the difference in mutual information between the two models is larger.

Higher information search intensity in a downturn increases mutual information when

[1] Uncertainty is documented to be counter-cyclical (See Bloom (2009) and Bloom et al. (2018)).

information quality is unaccounted for. However, less data implies that information quality becomes poorer, reducing mutual information. The net effect is lower mutual information, which leads to higher uncertainty, inaccurate forecasts, and lower information quality in a downturn.

This co-movement can rationalize facts that appear at odds with each other: on the one hand, information acquisition is counter-cyclical, while on the other hand, measures of uncertainty are high and counter-cyclical, and forecasts remain inaccurate. In a model without information search frictions and information search intensity, information acquisition behavior is defined as the acquisition of mutual information. Because mutual information maps one-to-one with uncertainty; increases in mutual information and information acquisition lead to a fall in uncertainty. Hence, counter-cyclical information acquisition and uncertainty cannot co-exist.

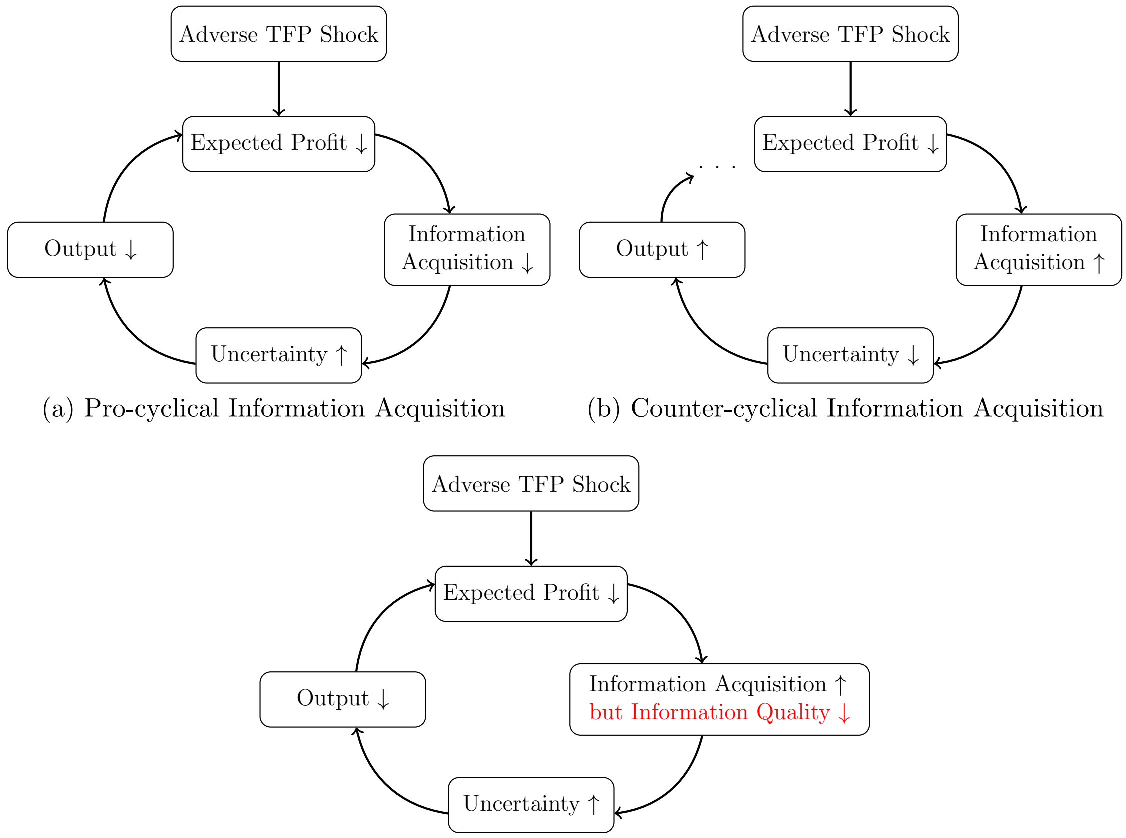
However, when I introduce information search intensity into the model with information search frictions, a disconnect occurs between mutual information and information acquisition when I define the latter as information search intensity. Hence, an increase in information acquisition or information search intensity does not necessarily imply an increase in mutual information, as mutual information depends on an additional ingredient, namely: the abundance of data. In this case, an increase in information acquisition or information search intensity is accompanied by a decline in mutual information due to data scarcity. As such, uncertainty rises in a downturn due to the mapping between mutual information and uncertainty.

Using the Survey of Professional Forecasters, I rely on the noisy information framework of Coibion and Gorodnichenko (2015) to construct measures of information quality. I demonstrate that a signal of the hidden state can be decomposed into realization and noise components. When information quality is perfect, the realization component accurately represents the hidden state of the economy. However, when information quality is poor, the realization component exhibits inaccuracies and deviates from the economy's actual hidden state. This generates expectational errors, which drive forecast errors. I then construct empirical-based wedges, which measure the absolute magnitude of expectational errors due to time-varying information quality. Finally, I document a decline in information quality during a crisis.

Next, I examine the implications of information quality. I demonstrate that the amplification and persistence of downturns in real business cycle models rely on pro-cyclical information acquisition. Consider an adverse productivity shock, which causes a decline in expected profits. As information acquisition is pro-cyclical, this leads to a decline in mutual information. Uncertainty rises due to the direct one-to-one mapping between mutual information and uncertainty. Output declindes because of the negative relationship between output and uncertainty, which further depresses expected profits.

This creates an amplification loop between output and uncertainty, which causes severe downturns.

However, relevant studies have documented empirically that information acquisition is counter-cyclical. Consider a model with counter-cyclical information acquisition and a negative productivity shock, which leads to a decline in expected profits. In this case, because information acquisition (defined as mutual information) is counter-cyclical, this leads to an increase in mutual information. The mapping between mutual information and uncertainty causes uncertainty to fall. This decline in uncertainty leads to an increase in output as well as dampens the effect of the adverse productivity shock. Hence, recessions will be short-lived and less severe.




(a) Pro-cyclical Information Acquisition

(b) Counter-cyclical Information Acquisition

(c) Counter-cyclical Information Acquisition with Information Quality

Figure 1: Business Cycle Dynamics

By introducing information quality and information search frictions, I can amplify recessions and generate counter-cyclical information acquisition simultaneously. Again, consider an adverse productivity shock that leads to a fall in expected profits. Information acquisition (defined as information search intensity) increases due to its counter-cyclical behavior. However, as information quality depends on data, data scarcity implies that the level of mutual information is lower and information quality declines, which causes uncertainty to increase. This implies a fall in output, creating an amplification loop between output and uncertainty.

Quantitatively, the model with information search frictions generates impulse responses that yield 29% more amplification than the model with counter-cyclical information acquisition. In addition, a one standard deviation productivity shock generates a decline in information quality of 3.9 percentage points. This causes a 1.17% fall in output. Moreover, time-varying information quality explains approximately 85% of fluctuations in uncertainty.

In this study, I also consider behavioral errors or "mistakes" as an extension. In the model with information search frictions, economic agents internalize that information quality is time-varying. When agents do not internalize fluctuations in information quality, this generates behavioral errors or "mistakes". I find that behavioral errors generate a substantial decline of 0.47 percentage points in output. Moreover, the cost of mistakes increases as the elasticity of substitution increases.

**Related Literature.** This study contributes to four strands of the literature. First, it is related to the cyclical behavior of information acquisition. In this strand of literature, it has been widely documented that information acquisition is counter-cyclical. Flynn and Sastry (2021) uses data from US public firms' regulatory filings and financial statements to document that firms' attention to macroeconomic conditions increases during downturns. Chiang (2021) uses Google traffic data to document higher search intensity in recessions. In addition, these studies built theoretical models that generate counter-cyclical attention to macroeconomic conditions (see also Mäkinen and Ohl (2015)).

In these models, counter-cyclical information acquisition generates more volatile macroeconomic moments (e.g., aggregate output), which they define as uncertainty. However, this differs from the definition of uncertainty used by Bloom (2009). Bloom (2009) defines uncertainty as the *actual* volatility of exogenous shocks, which drives the *perceived* volatility of shocks and the actual volatility of aggregates. In turn, each firm's behavior is affected by perceived volatility rather than actual volatility. If uncertainty is defined as the perceived volatility of shocks, then counter-cyclical information acquisition implies pro-cyclical uncertainty in these theoretical models. By introducing search frictions and defining information acquisition behavior as information search intensity, this paper addresses this puzzle by generating the joint behavior of counter-cyclical information acquisition and uncertainty.

Moreover, these models generate counter-cyclical information acquisition by relying on different mechanisms. Flynn and Sastry (2021) assume that firms are owned by risk-averse households, which pay more attention to macroeconomic conditions when aggregate consumption is low. Mäkinen and Ohl (2015) demonstrate that by learning from prices, fluctuations in prices affect the incentive to acquire information. Furthermore, Chiang (2021) considers a strategic approach to acquiring information, in which reacting more to an event generates higher volatility, and each agent faces more uncertainty regarding the aggregate actions of others. My work is complementary to these mechanisms as I demonstrate that scarcity in data (e.g., Farboodi and Veldkamp (2019) can generate counter-cyclical information acquisition.

Second, this paper is related to the endogenous uncertainty literature and how these models generate the amplification and persistence of downturns. In Van Nieuwerburgh and Veldkamp (2006) and Saijo (2006), since the noise to signal ratio is counter-cyclical, learning and information acquisition are pro-cyclical. This generates asymmetric and severe recessions. Fajgelbaum et al. (2017) find that firms acquire more information by investing more in good times. Although their mechanism relies on "learning by doing", it is analogous to pro-cyclical information acquisition.

Evidently, the amplification and persistence of downturns in endogenous uncertainty models rely on pro-cyclical information acquisition. I demonstrate that if information acquisition is counter-cyclical, recessions will be short-lived and adverse shocks will be dampened. Thus, I contribute to this strand of literature by documenting that information quality is necessary for generating severe downturns.

Third, this paper is related to the literature on information rigidity and its macroeconomic implications. Coibion and Gorodnichenko (2015) consider consensus forecasts to find the presence of information rigidities relative to the full information rational expectations (FIRE) benchmark. Furthermore, Bordalo et al. (2020) consider forecasts at the individual level to find overreaction in macroeconomic expectations. I rely on the noisy information framework of Coibion and Gorodnichenko (2015) to construct a proxy for information quality. In particular, I include a wedge in the noisy information model that can be interpreted as information quality, which gives rise to alternative interpretations of the regressions in Coibion and Gorodnichenko (2015).

Lastly, this paper is related to the literature on expectational and behavioral errors such as "mistakes". Various applications of behavioral and expectational errors exist in macroeconomics. Chahrour and Jurado (2021) provide an empirical approach for recovering expectational errors which are orthogonal to fundamentals. Chahrour et al. (2021) demonstrate that expectational errors generated from such an empirical approach can resolve exchange rate puzzles. Lian (2021) applies this framework to study macroeconomic consumption and show the model generates higher marginal propensity when consumers anticipate future mistakes. This paper contributes to this strand of the literature by applying the concept of expectational errors and "mistakes" to endogenous uncertainty models. Moreover, I provide a potential explanation for this phenomenon, namely time-varying information quality.

**Layout.** The remainder of the paper is organized as follows. Section 2 provides an overview of a basic model and its intuition. Section 3 documents empirical evidence of lower information quality during downturns. Section 4 explains the parametrization, calibration and estimation strategy and presents the estimation results. Section 5 studies the quantitative implications of time-varying information quality. Section 6 concludes.

# 2 Basic Model

In this section, I first build a partial equilibrium information acquisition model without information search frictions. I denote this as the baseline model. This generates pro-cyclical information acquisition. Then, I introduce information search frictions in the model to illustrate the mechanisms behind counter-cyclical information acquisition behavior.

## 2.1 Firms

### 2.1.1 Final Goods Producers

There are competitive firms which produce final goods under perfect information, with the aggregate production function:

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

where $\epsilon > 1$.

The profit maximizing input satisfies

$$Y_{i,t} = P_{i,t}^{-\epsilon} Y_t \tag{2}$$

### 2.1.2 Intermediate Goods Producers

There is a continuum of firms with a measure of 1, that produces intermediate goods. Each firm $i$ is a monopolist of good $i$ with production function:

$$Y_{i,t} = Z_t K_{i,t}^{\alpha} N_{i,t}^{1-\alpha} \tag{3}$$

Firm $i$ produces $Y_{i,t}$ to maximize its profit under uncertainty about aggregate productivity $Z_t$. Aggregate productivity evolves according to the following process:

$$\log Z_t = z_t = \rho_z z_{t-1} + u_t \tag{4}$$

where $u_t \sim N(0, \frac{1}{\tau_z})$. Each firm cannot observe $z_t$ directly. Instead, it observes a signal of $z_t$, given by:

$$s^z_{i,t} = f(z_t, \underbrace{\chi^{emp}_t}_{\substack{\text{Noise due to} \\ \text{Information Quality}}}, \underbrace{v_{i,t}}_{\substack{\text{Noise due to} \\ \text{all other sources}}}) \tag{5}$$

where the signal contains the actual realization of $z_t$, noise due to time-varying information quality $\chi^{emp}_{i,t}$, and noise due to all other sources $v_{i,t}$. Denote uncertainty as $Var(z_t|s^z_{i,t})$, which is the perceived variance of $z_t$ after observing the signal $s^z_{i,t}$. The presence of noise leads to uncertainty. Each firm can acquire information by increasing the precision of the signal and reducing the variance of noise and subsequently, uncertainty about $z_t$.

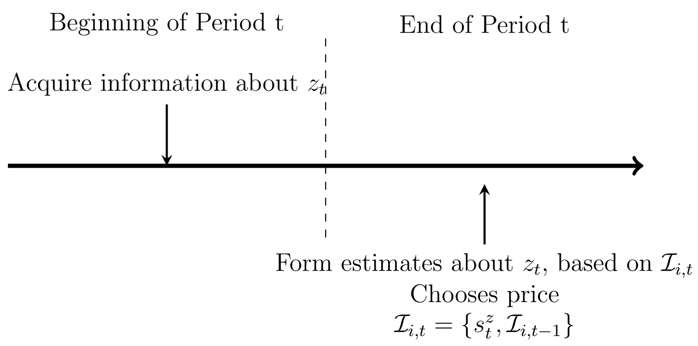



Figure 2: Timeline of Events

**Timeline of Events.** Figure 2 shows the timeline of events in the economy. At the beginning of each period, each agent observes their beginning-of-period capital stock $K_t$. In addition, aggregate technology $Z_t$ realizes. However, all agents cannot observe the actual value of $Z_t$. The problem facing the intermediate goods firm consists of three stages:

1. *Information Acquisition Choice.* Each firm $i$ chooses its precision of the signal .
2. *Pricing Choice.* Based on the precision of the signal chosen in the first stage, each firm receives a signat $s^z_{i,t}$. Based on the signal $s^z_{i,t}$, firms form estimates about $z_t$ based on information set at time $t$, $\mathcal{I}_{i,t} = \{s^z_{i,t}, \mathcal{I}_{i,t-1}\}$. Each firm chooses its price based on its beliefs.
3. *Production Choice.* $z_t$ is realized and known, firms choose labor and capital.

At the end of each period, the markets clear. I solve the firm's problem by backward induction. In stage 3, each firm's cost minimization under perfect information implies:

$$W_t N_{i,t} + R_t K_{i,t} = \frac{1}{Z_t}\Big(\frac{W_t}{1-\alpha}\Big)^{1-\alpha}\Big(\frac{R_t}{\alpha}\Big)^{\alpha} Y_{i,t} \tag{6}$$

Denote $C(W_t, R_t) = \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_t}{\alpha}\right)^{\alpha}$. In stage 2, each firm's pricing choice occurs under imperfect information. Each firm's information set in period $t$ is given by $\mathcal{I}_{i,t} = \{s^z_{i,t}, \mathcal{I}_{i,t-1}\}$, which depends on the signal received, and its information set in period $t-1$. Each firm's profit-maximization problem is given by:

$$\max_{P_{i,t}} \left[\bigg(P_{i,t} - C(W_t, R_t)\bigg) P_{i,t}^{-\epsilon} Y_t | \mathcal{I}_{i,t}\right] \tag{7}$$

The optimal price of firm $i$ is given by:

$$P_{i,t} = \frac{\epsilon}{\epsilon - 1} C(W_t, R_t) \mathbb{E}_{i,t}\left(\frac{1}{A_t}\right) \tag{8}$$

The optimal price consists of the constant monopolistic markup and expected real marginal costs. As shown in Appendix A, after summing both sides of Eq. (8), I obtain the following expression for aggregate output:

$$Y_t = \left(\int_0^1 \mathbb{E}_{i,t}\Big(\frac{1}{A_t}\Big)^{1-\epsilon} \mathrm{di}\right)^{\frac{1}{\epsilon-1}} K_t^{\alpha} N_t^{1-\alpha} \tag{9}$$

By using the information structure described in figure 2, Eq. (9) can be rewritten as:

$$Y_t = \exp\Big(\tilde{z} - \frac{Var(z_t | s^z_{i,t})}{2}\Big) K_t^{\alpha} N_t^{1-\alpha} \tag{10}$$

where $\tilde{z} = \mathbb{E}_{i,t}(z_t | \mathcal{I}_{i,t})$ is the conditional expectation of $z_t$ after observing the signal $s^z_{i,t}$. Eq. (10) shows that output is decreasing in uncertainty $Var(z_t | s^z_{i,t})$. When firms make their pricing decisions under uncertainty, they deviate from the approach of first-best optimal pricing under full information. As uncertainty increases, deviations from this approach increase, and as such, uncertainty is counter-cyclical.

In stage 1, firms acquire information to reduce the level of uncertainty in the signal. In order to maximize expected profits in stage 1, it is useful to firm $i$'s realized profits after stage 3. This is given by:

$$\Pi_{i,t} = \left(P_{i,t} - \frac{1}{A_t}C(W_t, R_t)\right)Y_{i,t} = \frac{1}{\epsilon}Y_t\frac{\mathbb{E}_{i,t}(\frac{1}{A_t})^{1-\epsilon}}{\int_0^1 \mathbb{E}_{i,t}(\frac{1}{A_t})^{1-\epsilon}\mathrm{d}i} \tag{11}$$

After taking expectations of Eq. (11) over all possible signal realizations, firm $i$'s expected profit is given by:

$$\Pi_{i,t}^{E} = \frac{1}{\epsilon}Y_t\frac{\exp\left\{(\epsilon-1)(\tilde{z} - \frac{Var(z_t|s_{i,t}^z)}{2}\right\}}{\exp\left\{(\epsilon-1)(\tilde{z} - \frac{Var(z_t|s_{-i,t}^z)}{2}\right\}} \tag{12}$$

Eq. (12) shows that expected profits are increasing in $Y_t$ and decreasing in uncertainty. This implies that when the economy is in a boom, a firm's expected profits are higher. In addition, as the precision of the signal improves and uncertainty falls, this reduces the occurrence of mispricing. Hence, this also leads to an increase in expected profits. Since expected profits depend only on the aggregate state, I now drop $i$ subscripts for each firm's information acquisition choice.[2] I now introduce the differences between the baseline model and the model with search frictions, which occurs in stage 1.

## 2.2 Firm's Information Acquisition Problem in the Baseline Model

I now describe the firm's problem in stage 1 for the baseline model. Each firm increases their expected profits by acquiring more information. I define information as outlined in Shannon (1948):

$$I(z_t; s_{i,t}^z) = \log_2\left(\frac{Var(z_t)}{Var(z_t|s_{i,t}^z)}\right) \tag{13}$$

where $I(z_t; s_{i,t}^z)$ represents mutual information. Mutual information is a measure of uncertainty reduction. As firms acquire more information, this means that each firm chooses a lower value of $Var(z_t|s_{i,t}^z)$, which implies a larger amount of mutual information and a greater reduction in uncertainty. When the signal is not informative at all, $Var(z_t|s_{i,t}^z)$ equals the unconditional variance of $z_t$, $Var(z_t)$. In this case, mutual information equals zero, and there is no uncertainty reduction.

In addition to choosing $I(z_t; s_{i,t}^z)$ to maximize expected profits, each firm faces information processing costs, $\theta_I I(z_t; s_{i,t}^z)$, where $\theta_I$ is the unit cost of processing information. Hence, each firm faces a trade-off between choosing mutual information $I(z_t; s_{i,t}^z)$ to in-

[2]The only source of heterogeneity that each firm faces are idiosyncratic noise $v_{i,t}$ of the signal. Therefore, pricing and production choices remain heterogenous as they depend on the signals received.

crease expected profits and incurring information processing costs. Each firm's maximization problem is thus given by:

$$\max_{I_t} \Pi_t^E - \underbrace{\theta_I I(z_t; s_t^z)}_{\text{Information Processing Costs}} \tag{14}$$

In the baseline model, I define information acquisition as the quantity of mutual information, $I(z_t; s_{i,t}^z)$. Higher uncertainty, or a lower reduction in uncertainty, implies that less information is acquired. Hence, in the baseline model, there is a one to one inverse mapping between information acquisition and the level of uncertainty.

I will now show that the maximization problem in Eq. (14) generates counter-cyclical uncertainty and pro-cyclical information acquisition. The first order condition of the maximization problem in Eq. (14) is given by:

$$\frac{\partial \Pi_t^E}{\partial I(z_t; s_t^z)} = \theta_I \tag{15}$$

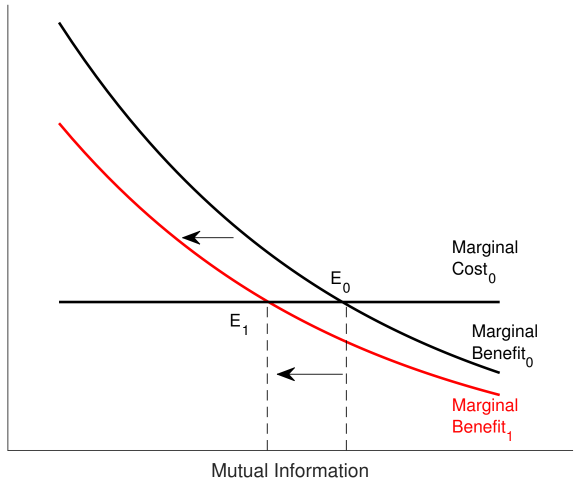
Eq. (15) equates the marginal benefit to the marginal cost of acquiring information. As shown in Figure 3, the marginal benefit of acquiring information is decreasing in $I_{i,t}$, and as such, expected profits are concave in $I_{i,t}$. This is due to the convex costs of posting a suboptimal price that differs from the first-best price under full information. In contrast, the marginal cost of acquiring information is equal to the unit cost of processing information. The initial equilibrium of mutual information, or information acquisition, is given by the interaction of the marginal cost and marginal benefit curves at $E_0$.

Consider a negative shock to $z_t$. This decreases the expected profits of each firm. As expected profits fall, each firm's expected marginal product of inputs fall. As a result, the marginal benefit of acquiring information decreases. This leads to a leftward shift of the marginal benefit curve. As such, the equilibrium mutual information decreases from $E_0$ to $E_1$.

A decline in mutual information implies counter-cyclical uncertainty and pro-cyclical information acquisition. This is due to the inverse mapping between uncertainty and information acquisition, in which the information acquired is defined in the baseline model to be mutual information. However, empirical evidence, such as presented by Flynn and Sastry (2021), shows counter-cyclical information acquisition behavior. Moreover, in the context in which information acquired is defined as mutual information, counter-cyclical information acquisition and uncertainty cannot co-exist.[3]

[3]Counter-cyclical information acquisition and uncertainty cannot co-exist in a framework where uncertainty is endogenously determined. However, they can co-exist under exogenous fluctuations of uncertainty.

Figure 3: Pro-cyclical Information Acquisition and Counter-cyclical Uncertainty




*Notes*: This figure plots the marginal benefit and marginal cost of acquiring $I(z_t; s^z_{i,t})$ and shows how their responses to a negative TFP shock.

## 2.3 Model with Search Frictions

In order to reconcile the co-existence of counter-cyclical information acquisition and uncertainty, I introduce search frictions in the firm's information acquisition problem. In the baseline model, firms maximize their payoffs by choosing mutual information. In contrast, in the model with search frictions, firms maximize their payoffs by searching for information and choosing information search intensity $S_t$. Their total benefit of searching for information is determined by their expected profits, $\Pi^E_t$, which is identical to that in the baseline model. However, in this case, when searching for information, they incur total costs $\kappa(S_t, I_t)$, given by:

$$\kappa(S_t, I_t) = \underbrace{\theta_I I(z_t; s^z_{i,t})}_{\text{Information Processing Costs}} + \underbrace{\theta_S S_t}_{\text{Information Search Costs}} \tag{16}$$

Eq. (16) shows that in the model that includes search frictions, in addition to information processing costs, each firm incurs information search costs with a unit cost of $\theta_S$. Search costs represent the idea that in order to obtain information, individuals will exert effort to search for it via the internet, or acquire data containing the information they require. Firms solve the following maximization problem:

$$\max_{I_t, S_t} \Pi^E_t - \kappa(S_t, I_t) \tag{17}$$

subject to

$$\underbrace{I(z_t; s_{i,t}^z)}_{\substack{\text{Yield of search intensity} \\ \text{in terms of entropy reduction} \\ \text{(or Mutual Information)}}} = \underbrace{D_t(z_t)}_{\substack{\text{Supply of Information} \\ \text{or "Data" (Farboodi} \\ \text{and Veldkamp (2021)}}} \cdot \underbrace{S_t^{\alpha_S}}_{\text{Demand for Information}} \tag{18}$$

Eq. (18) shows that as each firm chooses their search intensity, this generates a yield of search intensity in terms of mutual information or entropy reduction. The yield of search intensity is increasing in search intensity. In other words, as individuals search more for information, they obtain more mutual information and reduce uncertainty. I denote the behavior of searching for information as the "demand for information".

I also assume $\alpha_S$ to be less than 1, which implies decreasing returns to search intensity. Consider an individual who searches for information about "coronavirus" on the internet. This will generate numerous articles containing information. Since the person has no prior knowledge about the term "coronavirus", they will be able to obtain information (as measured in mutual information) about the subject. As they move on to the next article, however, this may repeat information from the previous article. Hence, the marginal gain of mutual information from reading an additional article decreases. As a result, this intuitively illustrates that the yield of a search can exhibit decreasing returns in search intensity.

The yield of search intensity also depends on the "supply of information". This depends on data, as modeled by Farboodi and Veldkamp (2019). According to Farboodi and Veldkamp (2019), data is modeled as a by-product of output. The idea proposed by Farboodi and Veldkamp (2019) is that as output increases, this leads to higher transactions in the economy, which in turn increases the amount of data points.

In the model with search frictions, I assume that data depends on $z_t$, since output $Y_t$ is highly correlated with $z_t$ in the absence of other real frictions. As data becomes more abundant in the economy, this implies that there is more available information for firms to mine and search. Hence, the yield from searches increases in the amount of data in the economy.

In addition, data in the economy exhibits increasing returns to scale in productivity.[4] As output is expressed Farboodi and Veldkamp (2019) in terms of productivity after each firm's profit maximization problem, it can be shown that output is convex in $z_t$. This captures the idea of network structures in the form of a "yeoman farmer" model, in which the economy consists of sectors which provide and sell goods or services, and also purchase goods or services supplied by other sectors. Increasing returns of data and

[4]The results of the model do not hinge on the increasing returns of data to productivity, or the decreasing returns to search intensity.

output to $z_t$ rationalizes with a "chain" network as in Woodford (2021). Consider an economy with $N$ sectors, in which there is a shutdown in one of the sectors. Then, in a network structure, the other $N-1$ sectors will be worse off. However, in the case in which there is a shutdown in $K$ of the sectors in a "chain" network, then the other $N-1$ sectors will be more than $K$ times worse off (in terms of output) as compared with the event of a shutdown in one of the sectors. The increasing returns of data to $z_t$ is consistent with non-linear effects of this network structure.

### 2.3.1 Counter-Cyclical Information Search and Uncertainty

In the model with search frictions, I define the behavior of information acquisition as information search intensity, instead of the quantity of mutual information. Due to this definition, an increase in information acquisition or information search intensity ($S_{i,t}$) does not necessarily mean a decline in uncertainty. In other words, unlike the baseline model, there is now a disconnect between information acquisition or information search intensity ($S_{i,t}$) and mutual information ($I_{i,t}$), in which mutual information is a direct measure of uncertainty reduction. This is because mutual information does not solely depend on search intensity; it also depends on the supply of information and abundance of data in the economy.

$$\frac{\partial \Pi_t^E}{\partial I(z_t; s_t^z)} = \theta_I + \theta_S z_t^{-1} S_t^{1-\alpha_S} \tag{19}$$

Eq. (19) shows the first order conditions when firms choose information search intensity. The left and right hand side of Eq. (19) denotes the marginal benefit and marginal cost of information search intensity respectively. Consider a fall in $z_t$. This leads to two different effects on the marginal benefit of information search intensity, and an additional effect on the marginal cost of search intensity. The first effect of a fall in $z_t$ on the marginal benefit of search intensity is identical to its counterpart in the baseline model. A fall in $z_t$ reduces expected profits. This, in turn, causes a decrease in expected marginal product of inputs and hence, a fall in the marginal benefit of information acquisition or information search intensity. I denote this as the expected profit effect.

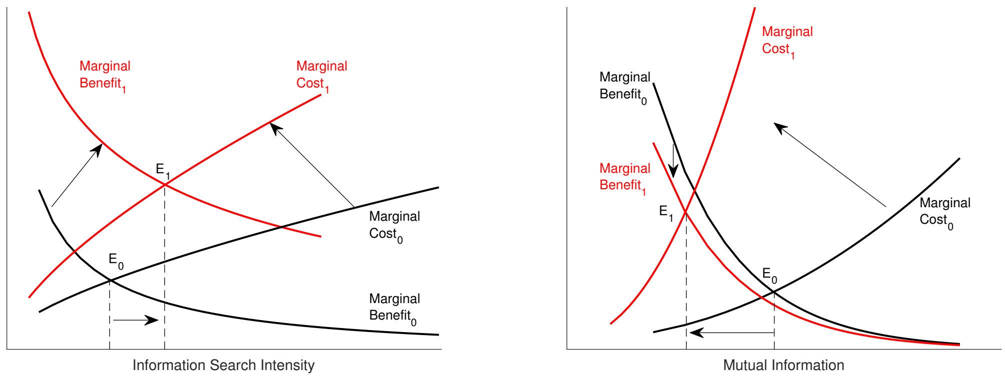
A fall in $z_t$ also affects the abundance of data, which in turn affects the level of mutual information in the economy. The marginal benefit of information search intensity is decreasing in the level of mutual information due to convex costs of mispricing. As such, this leads to a rise in the marginal benefit of information search intensity. Intuitively, when a decline in $z_t$ leads to less mutual information and higher uncertainty, firms incentivized to search more in order for the quantity of mutual information to return to its original level. I denote this as the mutual information effect.

The marginal cost of information search intensity is also affected by $z_t$. As $z_t$ falls, the marginal cost of information search intensity rises. This is because each individual needs to search more to obtain a given unit of mutual information. I denote this as the marginal cost effect. In summary, there are three different effects shown in Eq. (19), two of which affect the marginal benefit of information search intensity (expected profit and mutual information effects), and one of which affects the marginal cost of information search intensity (marginal cost effect).

The overall effect of a fall in $z_t$ on information search intensity depends on the relative changes in marginal benefit and marginal cost of information search intensity. A decrease in the marginal benefit of information search intensity due to the expected profits effect implies a higher level of information search intensity in a downturn. In addition, an increase in the marginal cost of information search intensity also leads to an increase in information search intensity in a crisis. Taken together, these two effects (expected profit and marginal cost effects) imply pro-cyclical information search intensity.

However, the marginal benefit of information search intensity can rise if it is dominated by the effects of a fall in the abundance of data (the mutual information effect). This leads to counter-cyclical information search intensity, all else being equal. If the rise in information search intensity due to the mutual information effect dominates the pro-cyclical force caused by the expected profits and the marginal cost effects, then information search intensity *can* be counter-cyclical.

Figure 4: Effect of a Negative Shock to $z_t$ on Search Intensity and Mutual Information




(a) Counter-cyclical Search Intensity (b) Counter-cyclical Uncertainty

*Notes*: This figure presents the impact of a negative shock to $z_t$ to information search intensity and mutual information.

Figure 4 (a) plots the scenario in which information search intensity rises in response to an adverse total factor productivity (TFP) shock. When the mutual information effect dominates the expected profit effect, the marginal benefit of search intensity shifts to the right. Due to the marginal cost effect, the marginal cost curve shifts upward. In this case, information search intensity rises from $E_0$ to $E_1$ in response to a fall in $z_t$.

Figure 4 (b) plots the dynamics of mutual information in response to a TFP shock. Since mutual information is plotted on the horizontal axis, the mutual information effect does not shift the marginal benefit curve.[5] As such, the expected profit effect shifts the marginal benefit curve downward. In addition, the marginal cost effect shifts the marginal cost curve upward. Taken together, this implies that mutual information falls unambiguously, which implies counter-cyclical uncertainty.

## 2.4 Information Quality

Denote $I_t^*$ and $\hat{I}_t$ as mutual information acquired in the baseline model and the model with search frictions respectively:

Baseline Model:

$$I_t^* = \arg\max_{I} \mathbb{E}[\pi_t] - \theta_I I(z_t; s_{i,t}^z) \tag{20}$$

Model with Search Frictions:

$$\hat{I}_t = \arg\max_{I,S} \mathbb{E}[\pi_t] - \theta_I I(z_t; s_{i,t}^z) - \theta_S S_t \tag{21}$$

subject to

$$I(z_t; s_{i,t}^z) = D_t(z_t) \cdot S_t^{\alpha_S} \tag{22}$$

$I_t^*$ represents the first best mutual information acquired, relative to the model with search frictions which generates $\hat{I}_t$.

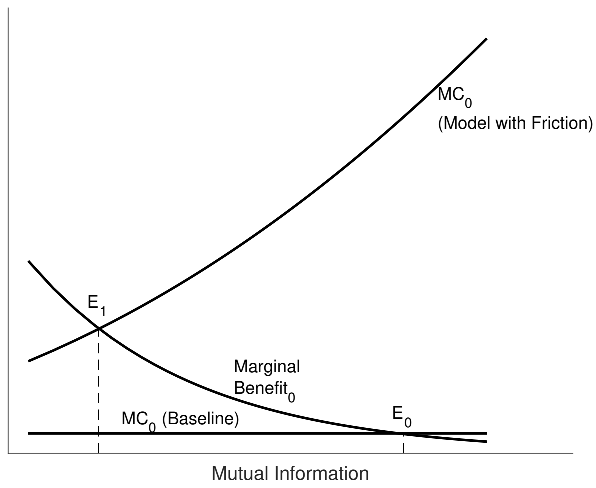
Figure 5 illustrates that whenever search cost $\theta_S$ is greater than zero, the marginal cost of search intensity in the model with search frictions is strictly greater than that of the baseline model. The level of mutual information in the model with search frictions, $\hat{I}_t$ ($E_0$), is less than the efficient level of mutual information in the baseline model ($E_1$), as long as search costs $\theta_S$ is greater than zero. Hence, $\hat{I}_t$ is inefficient relative to $I_t^*$ in the baseline model.

Next, in order to introduce the concept of information quality, I augment a wedge $\chi_t^{\text{model}}$ between $\hat{I}_t$ and $I_t^*$, such that $\chi_t^{\text{model}}$ satisfies

$$\hat{I}_t = \chi_t^{\text{model}} I_t^* \tag{23}$$

[5]The mutual information effect leads to a *movement* along the marginal benefit curve instead, since mutual information is plotted on the horizontal axis.

Figure 5: Information Quality and the Importance of $\theta_s$




*Notes*: This figure plots the marginal benefit and marginal cost of acquiring $I(z_t; s^z_{i,t})$ for both the baseline model and the model with search frictions.

The wedge $\chi_t^{\text{model}}$ is a measure of information quality. As $I_t^*$ denote the first best mutual information acquired, this implies that in the baseline model, information quality is perfect. In contrast, the level of mutual information in the model with search frictions is inefficient. Therefore, information quality is imperfect, and $\chi_t^{\text{model}}$ is less than one.

**Interpretation of Information Quality.** Consider a scenario in which a firm forms forecasts about annual GDP growth. Suppose that the actual value of GDP growth is 2%. Each firm hires five analysts that obtain information about annual GDP growth and form their forecasts based on signals provided by these analysts. Assume also that they obtain information from the same source.[6] Each analyst then produces a signal about annual GDP growth. Under the baseline model, this generates the following signals:

$$A_1 = \{1.85, 1.95, 2.00, 2.05, 2.15\}$$

From the signals $A_1$, because of the presence of uncertainty in the baseline model, the baseline model generates different signals from different analysts even though information quality is perfect. Even though uncertainty exists, the signals in $A_1$ revolve around the actual value of GDP growth of 2%. This phenomenon is due to perfect information quality, in which the information source accurately represents the actual hidden state with an average value of 2%. However, residual uncertainty may exist due to different interpretations of information by different analysts.

[6] This simplifies the illustration of information quality.

Now consider the model with search frictions, which generates imperfect information quality. Suppose that information quality from the information source is low. This generates the following signals:

$$A_2 = \{0.85, 0.95, 1.00, 1.05, 1.15\}$$

$A_2$ generates the same dispersion in noise as $A_1$. However, because information quality is imperfect, the information source does not accurately represent the true hidden state. This means that conditional on residual uncertainty in the baseline model, imperfect information quality generates an average signal (1%) that is not truly representative of the hidden state, instead of generating an average signal of 2% from the information source. If economic agents internalize time-varying information quality, this generates higher uncertainty compared to the baseline model.[7] Hence, this shows why $\hat{I}_t$ is lesser than $I_t^*$.

It is also worthwhile to point out that mutual information acquired in the model with search frictions can be interpreted in a search and matching framework as in models with labor search (Mortensen and Pissarides (1994)) or customer capital search frictions (Gourio and Rudanko (2014)). In these models, agents search for a match with one another. In my model, firms search for a match with information (with quantity $I_t^*$). If the match is successful, the firm will then acquire mutual information $I_t^*$. If a firm fails in finding a match with information (with quantity $I_t^*$), then they receive zero mutual information. In this framework, the probability of finding a match will be given by $\chi_t^{\text{model}}$.

### 2.4.1 Lower Information Quality in Downturns

Consider a fall in $z_t$. In the baseline model, $I_t^*$ falls as the marginal benefit of acquiring mutual information decreases. This is evident in figure 3. The marginal benefit of acquiring mutual information declines in the model with search frictions, identical to the baseline model. This leads to a lower level of $\hat{I}_t$.

In addition, the model with search frictions generates an increase in the marginal cost of acquiring mutual information. This is evident in the right panel of figure 4. This leads to a further decline in $\hat{I}_t$. Since the decrease in $\hat{I}_t$ is larger than that of $I_t^*$, the measure of information quality $\chi_t^{\text{model}}$ falls in response to a decrease in $z_t$.[8]

[7] It is possible that firms do not internalize the time-varying nature of information quality. In this case, they generate behavioral errors or mistakes. This is discussed in Section 5.

[8] While marginal cost is constant in the baseline model and it is increasing in the model with search frictions, for a given decline in the marginal benefit, $\hat{I}_t$ can decline by less than that of $I_t^*$ due to the decline in marginal benefit. However, in the calibrated model (and for all of the parameter space), the rise in marginal cost is sufficiently large so that the decrease in $\hat{I}_t$ is larger than that of $I_t^*$. As such, information quality $\chi_t^{\text{model}}$ falls.

In the model with search frictions, an increase in search intensity during a crisis increases mutual information when mutual information is unadjusted for quality.[9] This generates pro-cyclical uncertainty. However, in this case, mutual information is contaminated with lower quality, consistent with a decrease in $\chi_t^{\text{model}}$. After adjusting for quality, mutual information $\hat{I}_t$ decreases during a crisis, leading to counter-cyclical uncertainty.

### 2.5 Key Takeaways from the Basic Model

Traditional information acquisition models generate counter-cyclical uncertainty and pro-cyclical information acquisition. By introducing information search frictions, I generate the joint behavior of counter-cyclical uncertainty and information acquisition. Information search costs generates imperfect information quality, which decreases in quality in a recession. The model with search frictions then demonstrates that uncertainty rises after accounting for a decrease in information quality during a crisis.

## 3 Empirical Evidence

In this section, I rely on the framework in Coibion and Gorodnichenko (2015) and construct a measure of information quality. I then explore the cyclicality of information quality and show that information quality declines in a downturn. I also show how the framework in Coibion and Gorodnichenko (2015) relates to the model discussed in the earlier section.

### 3.1 Data

The key insights of this analysis require expectations data. I use the Survey of Professional Forecasters (SPF) run by the Federal Reserve Bank of Philadelphia. The survey is conducted with around 40 professional forecasters surveyed in each quarter. Forecasts for the current and subsequent four quarters for several macroeconomic outcomes such as GDP, price indices, consumption, investment, and unemployment are reported in the dataset.

### 3.2 Methodology

I follow Coibion and Gorodnichenko (2015) and present the noisy information model.[10]

[9] The data component, $D(\bar{z})$, is fixed when mutual information is unadjusted for quality.

[10] The model in this paper can also resemble the sticky information model as in Coibion and Gorodnichenko (2015). See Appendix for more details.

### A: Noisy Information Model in Coibion and Gorodnichenko (2015)

The noisy information model in Coibion and Gorodnichenko (2015) resembles the baseline model in the theoretical section. In this model, agents continuously update their information sets but never acquire full information about the state. This resembles a signal extraction problem, in which agents receive a signal $s_{i,t}^{z,A}$ of a hidden state $z_t$, where

$$s_{i,t}^{z,A} = z_t + v_{i,t} \tag{24}$$

where $v_{i,t}$ is a random variable that is normally distributed with mean zero and i.i.d across time and agents. Each agent $i$ uses the Kalman Filter to generate forecasts of $z_t$ conditional of observing the signal $s_{i,t}^{z,A}$

$$F_{i,t}z_t = Gs_{i,t}^{z,A} + (1-G)F_{i,t-1}z_t \tag{25}$$

where $F_{i,t}$ is the forecast of $z_t$ of agent $i$ at time $t$ and G is the Kalman gain which represents the relative weight of the informativeness of the signal $s_{i,t}^{z}$, as compared to past information. Coibion and Gorodnichenko (2015) then averages Eq. (25) across agents at arrive at

$$z_{j,t+h} - F_t z_{j,t+h} = \underbrace{\frac{1-G}{G}}_{\beta_1}(F_t z_{j,t+h} - F_{t-1}z_{j,t+h}) + v_{j,t+h,t}^{A} \tag{26}$$

where $z_{j,t+h} - F_t z_{j,t+h}$ denote forecast errors which measures the difference between its realization and its forecast of $z_{j,t+h}$ at time $t$ for macroeconomic variable $j$, $F_t z_{j,t+h} - F_{t-1}z_{j,t+h}$ denote forecast revisions, which measure how forecasters update their forecasts between $t-1$ and $t$ for macroeconomic variable $j$, and $v_{j,t+h,t}^{A}$ is an expectational error, which denotes the proportion of forecast errors that cannot be explained by forecast revisions. Under full information rational expectations, $\beta_1$ should be equal to zero as forecast errors should be unpredictable. However, Coibion and Gorodnichenko (2015) find evidence of information rigidity, in which the Kalman gain $G$ is less than one and $\beta_1$ is greater than zero. Moreover, they run the regression in Eq. (26) across various macroeconomic variables $j$ in each quarter $t$ and extract time-varying coefficient $\beta_{1,t}$. They find that the measure of information rigidity declines in a downturn. This implies that forecasters update their information sets more in a recession, which points to countercyclical information acquisition.

### B: Noisy Information Model with Information Quality

In order to extract measures of information quality, I rely on the following signal structure:

$$s_{i,t}^{z,B} = \chi_t^{\text{emp}} z_t + v_{i,t} \tag{27}$$

I account for information quality in Model B by introducing a wedge $\chi_t^{\text{emp}}$.[11] The interpretation of the wedge is related to information quality and expectational errors. If information quality is perfect, then the information source produces signals (conditional on individual noise $v_{i,t}$) that accurately represent the true hidden state, and correspondingly, expectational errors equal zero. Hence, perfect information quality implies that forecasts should not exhibit any expectational errors. In this case, $\chi_t^{\text{emp}}$ equals one. When information quality is low, the source of information produces signals (conditional on individual noise $v_{i,t}$) that do not accurately represent the true hidden state. Correspondingly, expectational errors are large in absolute terms. Hence, lower information quality generates a wedge $\chi_t^{\text{emp}}$ that deviates away from one.

The wedge produces the signal $s_{i,t}^{z,B}$ such that by observing the signal $s_{i,t}^{z,B}$, forecast revisions in Model B maps directly into forecasts without any expectational errors that are present in Model A.[12] Hence, the wedge $\chi_t^{\text{emp}}$ accounts for expectational errors due to information quality.

Each agent $i$ then uses the Kalman Filter to generate forecasts of $z_t$ conditional of observing the signal $s_{i,t}^{z,B}$

$$F_{i,t} z_t = G s_{i,t}^{z,B} + (1 - G) F_{i,t-1} z_t \tag{28}$$

This leads to the following reduced form regression

$$z_{j,t+h} - F_t z_{j,t+h} = \underbrace{\frac{1 - G\chi^{\text{emp}}}{G\chi^{\text{emp}}}}_{\beta_2} F_t z_{j,t+h} - \underbrace{\frac{1 - G}{G\chi^{\text{emp}}}}_{\beta_3} F_{t-1} z_{j,t+h} + v_{j,t+h,t}^B \tag{29}$$

In Model A, Coibion and Gorodnichenko (2015) imposes the restriction that $\beta_2 = \beta_3$. In Model B, I allow $\beta_2$ to be different from $\beta_3$, so as to extract a measure of information quality. In other words, accounting for information quality implies a test of the difference between $\beta_2$ and $\beta_3$. Coibion and Gorodnichenko (2015) finds that $\beta_2$ is not statistically different from $\beta_3$, which implies that $\chi^{\text{emp}}$ averages to one across time.

[11] I also consider an alternative scenario with an additive wedge, instead of a multiplicative wedge. See Appendix for more details.

[12] Model B implies that expectational errors are equal to zero on average across various macroeconomic variables. However, expectational errors are still present for each macroeconomic variable.

The regression equation in Model B relates to the regression equation in Model A in the following way:

$$z_{t+h} - F_t z_{t+h} = \underbrace{(\beta_2 - \beta_3) F_t z_{t+h}}_{\substack{\text{Accounting for} \\ \text{Inaccurate Information}}} + \beta_3 \underbrace{(F_t z_{t+h} - F_{t-1} z_{t+h})}_{\substack{\text{Information} \\ \text{Acquisition (CG)}}} + v^B_{t+h,t} \tag{30}$$

When restricting $\beta_2 = \beta_3$, this generates expectational errors $v^A_{t+h,t}$. However, $v^A_{t+h,t}$ can be decomposed into a component that is driven by inaccurate information and expectational errors $v^B_{t+h,t}$. In other words, the concept of information quality explains a proportion of expectational errors, that were originally derived in Coibion and Gorodnichenko (2015).

In my analysis of time-varying information quality, I run the regression in Eq. (29) across various macroeconomic variables $j$ in each quarter $t$. Since there are two unknowns $G_t$ and $\chi^{\text{emp}}_t$, and two corresponding coefficients $\beta_{2,t}$ and $\beta_{3,t}$, Eq. (29) is exactly identified. I consider the following measure of information quality:

$$|\beta_{2,t} - \beta_{3,t}| = |\frac{1}{\chi^{\text{emp}}_t} - 1| \tag{31}$$

Figure 6: Plot of Information Quality Measure

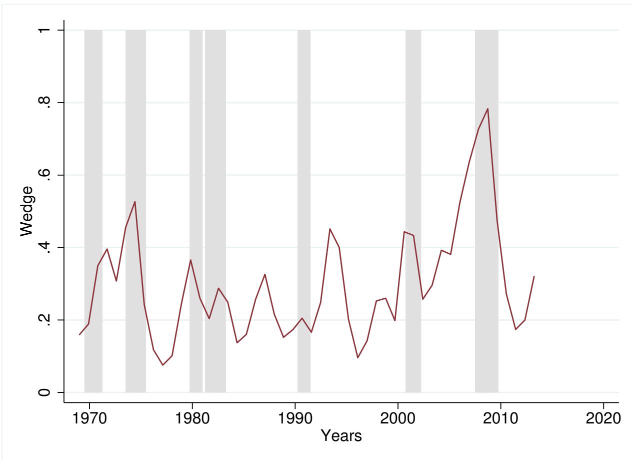



Figure 6 plots the relevant measure over time. I find that the magnitudes in deviations of $\beta_2$ to $\beta_3$ tend to be higher in recessions (shaded grey areas, dated by NBER). This supports the theoretical prediction that information quality declines in downturns.

## 3.3 Relationship between Model and Empirics

The noisy information framework in Coibion and Gorodnichenko (2015) can be applied to the theoretical models presented in the earlier section.

**Signal Structure in the Baseline Model.**

The baseline model corresponds to the noisy information model in Coibion and Gorodnichenko (2015). Economic agents internalize that each signal consists of two components: the realization and noise components. The realization component consists of the actual value of $z_t$ while the noise component consists of noise resulting from uncertainty in the baseline model. Hence, the signal $s_{i,t}^z$ in the baseline model takes the following form:

$$s_{i,t}^z = f(z_t, 1, v_{i,t}) = \underbrace{z_t}_{\text{Realization Component}} + \underbrace{v_{i,t}}_{\text{Noise Component}} \tag{32}$$

Since information quality is perfect in the baseline model, noise, which is due to information quality, is constant, implying the absence of uncertainty generated from information quality. In this case, the signal in the baseline model is an additive sum of $z_t$ and noise $v_{i,t}$. When firms acquire information in the baseline model, this corresponds to a reduction in the variance of $v_{i,t}$.

In the baseline model, because information quality is perfect, the realization component of the signal equals the actual hidden state $z_t$ and accurately represents the true hidden state. The only source of uncertainty that agents in the baseline model face originates from $v_{i,t}$. In addition, because information acquired $I_t^*$ does not reduce all uncertainty about $z_t$, the noise component captures the residual uncertainty in the baseline model.Lower information rigidities in a downturn, documented by Coibion and Gorodnichenko (2015), implies a larger Kalman gain. This, in turn, is at odds with pro-cyclical information acquisition. The signal structure in the model with search frictions will be able to reconcile this puzzle.

**Signal Structure in the Model with Search Frictions.**

In the model with search frictions, information quality is imperfect. As such, the realization component equals $\chi_t^{\text{emp}} z_t$, in which $\chi_t^{\text{emp}}$ does not equal one. This demonstrates the idea that the realization component of the signal does not equal the actual hidden state $z_t$. Hence, this corroborates the empirical framework that the empirical wedge $\chi_t^{\text{emp}}$ captures expectational errors caused by imperfect information quality. Therefore, the signal structure in the model with search frictions satisfies

$$s^z_{i,t} = f(z_t, \chi^{\text{emp}}_t, v_{i,t}) = \underbrace{\chi^{\text{emp}}_t z_t}_{\text{Realization Component}} + \underbrace{v_{i,t}}_{\text{Noise Component}} \tag{33}$$

Where $\chi^{\text{emp}}_t$ is a random variable with its mean equal to one and increasing variance as information quality declines. In the model with search frictions, agents face two sources of uncertainty: uncertainty about noise $v_{i,t}$, and uncertainty about the realization component due to fluctuations in information quality $\chi^{\text{emp}}_t$. The reduction in the variance of $v_{i,t}$ corresponds to mutual information obtained in the model with search frictions that is unadjusted for information quality. Hence, the residual difference in mutual information is translated to uncertainty originating from noise due to information quality ($\chi^{\text{emp}}_t$) in the realization component.

In this scenario, an increase in quality-unadjusted mutual information corresponds to an increase in uncertainty reduction of $v_{i,t}$. Unlike the signal structure in the baseline model, this is consistent with lower information rigidities in a downturn as documented by Coibion and Gorodnichenko (2015). At the same time, information quality declines, and the variance of $\chi^{\text{emp}}_t$ increases in a recession. The net effect is an increase in uncertainty ($Var(z_t|s^z_{i,t})$. Hence, the signal structure of the model with search frictions can rationalize facts (counter-cyclical information rigidity and uncertainty) that appear at odds with each other.

The model implied wedge $\chi^{\text{model}}_t$ also maps directly to the empirical implied wedge $\chi^{\text{emp}}_t$ in the following way. As the variance of $\chi^{\text{emp}}_t$ increases and it deviates further away from one, mutual information decreases, and uncertainty increases in the model with search frictions. As such, information quality $\chi^{\text{model}}_t$ decreases as $\chi^{\text{emp}}_t$ deviates further away from one. In section 5, I will conduct a quantitative assessment of the empirical wedge by mapping it to the model implied wedge and computing its effects on the business cycle. In addition, I use the constructed empirical measure of information quality to validate its quantitative theoretical implications.

# 4 Model Calibration and Estimation

Next, I examine quantitative implications of information quality and consider a quantitative RBC model. This section discusses the calibration and estimation of the quantitative RBC model. I first discuss additional ingredients and the calibration and estimation strategy of the model.

## 4.1 Additional Ingredients

**Household.** In both the baseline model and the model with search frictions, I include a consumer who maximizes utility, consisting of consumption and labor:

$$\max_{C_t, N_t} \sum_{t=0}^{\infty} \beta^t [\log C_t - \phi \frac{N_t^{1+\eta}}{1+\eta}]$$

subject to

$$K_{t+1} = R_t K_t + W_t N_t - C_t + (1-\delta) K_t + I_t$$

The consumer rents capital and supply labor to firms at rental rate $R_t$ and wage rate $W_t$ respectively. The consumer then invests in capital in period $t+1$ and chooses consumption $C_t$ to maximize utility.

**Constant Gain Learning.**I introduce constant gain learning, which implies a constant speed of learning about the hidden state $z_t$ after observing the signal $s_{i,t}^z$. Posterior expectations (expectations after observing the signal at time $t$) is given by

$$\mathbb{E}(z_t|\mathcal{I}_{i,t}) = \bar{g} s_{i,t}^z + (1-\bar{g}) \mathbb{E}(z_t|\mathcal{I}_{i,t-1}) \tag{34}$$

Eq. (34) shows that posterior expectations are a weighted sum of the signal and prior expectations (expectations before observing the signal at time $t$), in which the weights are governed by the constant gain parameter $\bar{g}$. Under Bayesian learning, the speed of learning depends on the variance of noise or uncertainty in the economy. However, in order to compare different types of models featuring different uncertainty dynamics, I introduce the constant gain parameter $\bar{g}$ to control for the differences in the speed of learning.[13]

## 4.2 Calibration and Estimation Strategy

I split the parameters into three categories, $\Xi_1$, $\Xi_2$ and $\Xi_3$. The parameters in $\Xi_1$ are calibrated externally, while the parameters in $\Xi_2$ are calibrated internally to match data moments. The parameters in $\Xi_3$ are then estimated using Bayesian methods. $\Xi_1$ consists of the following parameters

$$\Xi_1 : \{\beta, \eta, \alpha, \delta, \epsilon\}$$

[13] I am interested in the dynamics and interactions between output and uncertainty. As for the differences due to the dynamics of learning, I leave that for future research.

The discount rate $\beta$ is set to 0.99. I assume an infinite elastic labor supply ($\eta = 0$). The capital income share $\alpha$ is set to 0.33. The depreciation rate $\delta$ is set to 0.025 at a quarterly frequency. Lastly, I set the elasticity of substitution $\epsilon$ to be 4, which implies an average markup of $\frac{4}{3}$. Next, $\Xi_2$ consists of the following parameters

$$\Xi_2 : \{\bar{g}, \theta_I\}$$

where $\bar{g}$ is the constant gain parameter. I use $\Xi_2$ to target the dynamics of uncertainty. In particular, $\Xi_2$ is jointly targeted to match two moments: the elasticity of output to uncertainty and the volatility of uncertainty. In models of time-varying uncertainty, real frictions, such as non-convex adjustment costs (Bloom (2009), Bloom et al. (2018)) or financial frictions (Arellano et al. (2019)), are required to generate sizable responses of output to uncertainty shocks. However, other than information frictions and information search frictions, real frictions are absent in this paper. As such, the elasticity of output to uncertainty will be much smaller in my framework.

Moreover, uncertainty measures are known to be highly volatile. For instance, in Bloom (2009), an uncertainty shock is measured to be a 100% increase in uncertainty. Even if the model generates reasonable output responses to uncertainty, if uncertainty does not fluctuate as much, its effects on output will be muted. Hence, higher volatility in uncertainty is required to generate realistic dynamics of output and uncertainty.

The introduction of the constant gain parameter $\bar{g}$ can rectify this problem. In my model, aggregate output depends on inputs and prices, which depend on posterior expectations at time $t$. Consider a shock to $u_t$. Then, deviations in expectations from the steady state are given by

$$\mathbb{E}(\Delta z_t | \mathcal{I}_{i,t}) = \bar{g} u_t \tag{35}$$

As the exogenous processes will be estimated using Bayesian techniques (discussed in the next part), fluctuations of posterior expectations $\mathbb{E}(\Delta z_t | \mathcal{I}_{i,t})$ are required to match the fluctuations of GDP growth data used in the Bayesian estimation process. When $\bar{g}$ falls and fluctuations in $\mathbb{E}(\Delta z_t | \mathcal{I}_{i,t})$ are held constant, this implies a rise in the estimated parameter $\sigma_z$. A higher value of $\sigma_z$ implies a smaller value of $\tau_z$. From Eq. (10), a smaller value of $\tau_z$ leads to a larger response of aggregate output $Y_t$ to residual uncertainty $\frac{1}{\tau_z + \tau_{v,i,t}}$ (uncertainty about $z_t$ after observing the signal). In addition, a larger value of $\sigma_z$ leads to higher prior uncertainty (uncertainty about $z_t$ before observing the signal). This causes larger fluctuations in information acquisition behavior, which translates into more sizable fluctuations in residual uncertainty.

Next, information processing cost $\theta_I$ jointly affects the elasticity of output to uncertainty and fluctuations in uncertainty. A lower value of $\theta_I$ implies that agents have a higher incentive to process information. This leads to a lower rigidity of information acquisition, which translates into higher volatility of uncertainty. Given fluctuations in $z_t$ and output $Y_t$, this translates into lower output responses to uncertainty.

Lastly, $\Xi_3$ consists of the following parameters

$$\Xi_3 : \{\alpha_S, \alpha_D, \theta_S, \rho_z, \sigma_z, \sigma_I\}$$

I assume that returns to data take the following functional form

$$D_t = z_t^{\alpha_D} \tag{36}$$

Due to limited evidence of the parameter restrictions governing Eq. (18), I use Bayesian techniques to estimate $\Xi_3$. I retrieve quarterly data for US GDP growth and Google average search shares of the top 20 major US media in the Business and Industrial category. All parameters that govern Eq. (18) relates to fluctuations in information search intensity. Hence, Google search shares sufficiently discipline these parameters. Given two different observables, I also introduce shocks to mutual information so that the dynamic system is identified. To conduct Bayesian estimation, I obtain 1,00,000 draws from a Markov Chain Monte Carlo algorithm, discard the first 25%, and use the remaining draws to compute posteriors.

Table 1: Parameters from Internal and External Calibration

| **A: Parameters Set Independently** | | | |
|---|---|---|---|
| Interpretation | Symbol | Value | Source |
| Household discount rate | $\beta$ | 0.99 | Standard Literature |
| Labor Supply Elasticity | $\eta$ | 0 | |
| Capital income share | $\alpha$ | 0.33 | |
| Depreciation | $\delta$ | 0.025 | |
| Elasticity of Substitution | $\epsilon$ | 4 | |
| **B: Internally Calibrated Parameters** | | | |
| Interpretation | Symbol | Value | Target (From Bloom (2009)) |
| Information Processing Cost | $\theta_I$ | 0.0118 | Elasticity of Output to Uncertainty |
| Constant Gain | $\bar{g}$ | 0.0126 | Volatility of Uncertainty |

Panels A and B of Table 1 show the externally and internally calibrated parameters, respectively. Table 2 shows the targetted moments. As in Bloom (2009), a 100% increase in uncertainty lead to a 2.5% drop in output. This implies a relatively small value of the elasticity of output to uncertainty. In addition, the standard deviation of uncertainty is

Table 2: Model and Data Moments

| **Targeted Moments** | **Model** | **Data** |
|---|---|---|
| Elasticity of Output to Uncertainty | 0.025 | 0.025 |
| Volatility of Uncertainty | 0.355 | 0.355 |

relatively large at 33.5%. Table 2 demonstrates that the model can perfectly match the elasticity of output to uncertainty and volatility of uncertainty. Moreover, the constant gain parameter $\bar{g}$ lies close to the range of estimates in Cole and Milani (2020).

Table 3: Parameters from Bayesian Estimation

| **C: Estimated Parameters (Posterior Mode)** | | |
|---|---|---|
| Interpretation | Symbol | Value |
| Returns to Search Intensity | $\alpha_S$ | 0.69 |
| Returns to "Data" | $\alpha_D$ | 2.94 |
| Search Cost | $\theta_S$ | 0.106 |
| Productivity Persistence | $\rho_z$ | 0.78 |
| Productivity volatility | $\sigma_z$ | 1.20 |
| Shock to information (volatility) | $\sigma_I$ | 2.98 |

Table 3 shows the estimated parameters $\Xi_3$ using Bayesian methods. As expected, with $\alpha_S$ less than one, the yield of information exhibits diminishing returns to search intensity. In addition, as $\alpha_D$ is greater than one, the yield of information exhibits increasing returns to "data".

The search cost $\theta_S$ determines whether information search intensity is counter-cyclical. A higher value of $\theta_S$ implies that the marginal cost of searching for information rises by more when there is a negative shock to $z_t$. A higher response of marginal cost will lead to pro-cyclical information search intensity instead of its counter-cyclical behavior. In the Bayesian estimation, I set the prior of $\theta_S$ such that it lies in the region where information search intensity is counter-cyclical. In this way, the posterior mode of $\theta_S$ turns out to be in the same parameter region. As a robustness exercise, I also set the prior of $\theta_S$ in the region where information search intensity is pro-cyclical. After estimating the model with data on Google search shares, which are documented to be counter-cyclical, the posterior mode of $\theta_S$ eventually lands in the parameter region that generates counter-cyclical information search intensity. This is because the Bayesian estimation depends on the mapping from the model to the observables. Suppose the model predicts pro-cyclical information search intensity, while Google search shares are counter-cyclical. In that case, this generates a low value of the likelihood function, as the model will require shocks at the extreme ends of its normal distribution.

# 5 Information Quality Driven Business Cycles

I now study the quantitative implications of information quality in business cycles. First, I show that the introduction of information quality can reconcile with the co-existence of counter-cyclical uncertainty and information acquisition. The model then generates lesser amplification without information quality. Second, I quantify the effects of a fall in information quality. Lastly, I show that information quality can generate phenomena caused by behavioral biases, such as mistakes, when agents do not internalize fluctuations in information quality. I then document a substantial decline in output due to mistakes.

## 5.1 Model with Information Quality Generates Amplification

This section studies the importance and business cycle implications of introducing information search frictions and information quality. I now compare between two models:

1. Model with information search frictions which generates counter-cyclical information acquisition and uncertainty, and pro-cyclical information quality.
2. Model with counter-cyclical information acquisition rule, which generates pro-cyclical uncertainty.

The setup and main intuitions of the first model are discussed in the earlier section. The second model does not incorporate information search frictions. Hence, it cannot replicate the co-existence of counter-cyclical uncertainty and information acquisition. Since the baseline model cannot generate counter-cyclical information acquisition, I assume a counter-cyclical information acquisition rule, given by

$$I_t^* = I^{ss} + \phi(Y_t - Y^{ss}) + \epsilon_t^I \tag{37}$$

where $\phi$ is restricted to be less than zero, and $\epsilon_t^I \sim N(0, \sigma_t^{I2})$. I use $\phi$ and $\sigma_t^I$ to jointly target the elasticity of output to uncertainty and volatility of uncertainty.

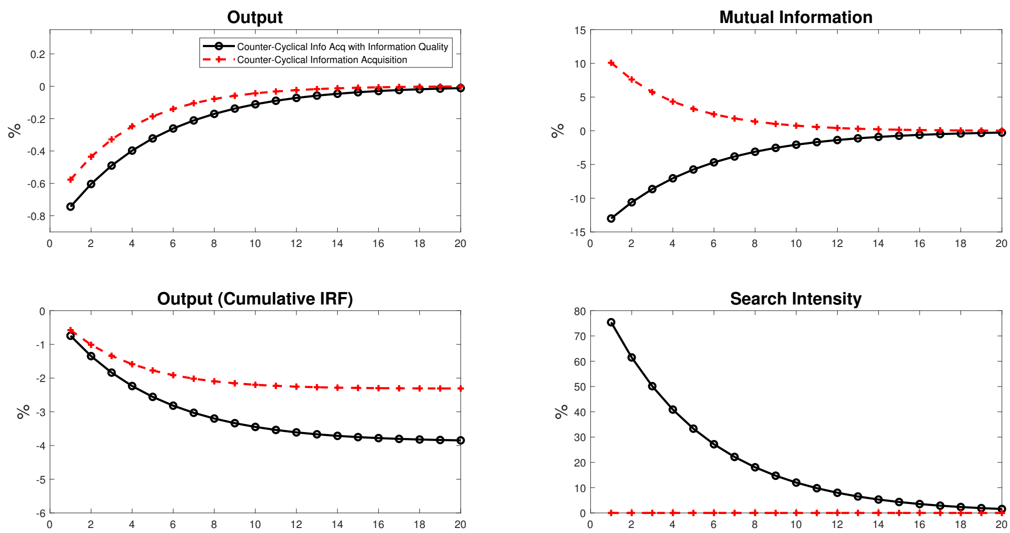
Figure 7 shows the impulse responses of aggregate variables to a one standard deviation decrease to $z_t$ for both models. Information search intensity increases by approximately 80% in response to the shock, demonstrating counter-cyclical information search intensity. At the same time, mutual information falls by 13% percent in response to the shock, which demonstrates counter-cyclical uncertainty. Hence, the model with information search frictions can generate counter-cyclical information acquisition and uncertainty.

In contrast, the model with the counter-cyclical information acquisition rule generates counter-cyclical mutual information, which implies pro-cyclical uncertainty. In the absence of information search frictions and information quality, information search intensity is irrelevant in this analysis.

The model with information search frictions generates a larger decline of 0.75% in output than a decline of 0.57% in the model with the counter-cyclical information acquisition rule. Intuitively, this difference is a result of the cyclicality of uncertainty. Consider a negative shock to $z_t$. Firms obtain more mutual information and face less uncertainty in the model with the counter-cyclical information acquisition rule. This leads to a rise in expected profits as it is decreasing in uncertainty. The rise in expected profits dampens and counter-acts the negative TFP shock and dampens the amplification of a downturn.

In contrast, in the model with information search frictions, firms exhibit higher search intensity and lesser mutual information simultaneously. As a result, they face more uncertainty. Higher uncertainty leads to a fall in expected profits and output, further reducing the incentive to acquire mutual information. Mutual information declines even more, which further elevates uncertainty and depresses output. This leads to an amplification loop between output and uncertainty.

Figure 7: Impulse Response Functions (Comparing Models)




*Notes*: This figure plots the impulse responses of a one standard deviation shock (decrease) to $z_t$. Black line with connecting dots show the IRFs of the model with information search frictions. Red dotted line with crosses show the IRFs of the model with counter-cyclical information acquisition rule.

The mechanism emphasized here is evident from the impulse responses of mutual information. Due to the amplification loop between output and uncertainty, there is a larger decline in mutual information in the model with search frictions. In contrast, the model with the counter-cyclical information rule generates a smaller increase in mutual information.

The interaction and amplification loop between output and uncertainty also generates the persistence of recessions. The bottom left-hand panel of Figure 7 plots the cumulative impulse response of output. It demonstrates a substantial difference between the model with search frictions and the counter-cyclical information acquisition rule. Quantitatively, the model with search frictions generates 29 % more amplification than the model with the counter-cyclical information acquisition rule.

## 5.2 Quantitative Effects of Information Quality

Next, I study the quantitative effects of information quality. I compare between two models:

1. Model with information search frictions which generates time-varying information quality.
2. Model with fixed information quality.

The model with fixed information quality corresponds to a model in which data $D(z_t)$ is fixed. To isolate the effects of information quality, I take the difference between changes in output in both models due to a one standard deviation shock to $z_t$. In the model with information search frictions, the measure of information quality $\chi_t^{\text{model}}$ falls by 3.9 percentage points. In the model with search frictions, output decreases by 1.17% and uncertainty increases by 9.03%. In contrast, an increase in information search intensity in a downturn decreases uncertainty by 75.80% when information quality is not accounted for. This translates into a 0.43% rise in output due to increased mutual information. Hence, the net effect of information quality is a 1.17% decline in output.

In addition, fluctuations in information quality generate an 84.83% rise in uncertainty. Notably, the introduction of information quality generates contrasting dynamics of uncertainty in terms of cyclicality and magnitude, which implies that information quality is an important driver of uncertainty. Since the standard deviation of uncertainty in Bloom (2009) is 35.5%, the model with search frictions explains approximately 25 % of fluctuations in uncertainty. I view this result as complementary to Bloom et al. (2018), which document that uncertainty constitutes a significant portion of business cycle fluctuations. In my framework, I build on Bloom et al. (2018) by showing that origins of uncertainty can be due to information quality. Information quality can potentially also explain large spikes in uncertainty during downturns (Orlik and Veldkamp (2014)). This coincides with significant declines in information quality around recession periods shown in Figure 6 in the empirical section.

**Behavioral Errors or "Mistakes".** In the model with information search frictions, an assumption is that agents internalize that information quality is time-varying. In this scenario, they choose prices while internalizing the signal structure as:

$$s^z_{i,t} = \chi^{\text{emp}}_t z_t + v_{i,t} \tag{38}$$

where $\chi^{\text{emp}}_t$ is a time-varying measure of information quality. Suppose that agents do not internalize fluctuations in information quality, as in the empirical section. In this scenario, they internalize the signal structure as

$$s^z_{i,t} = \chi^{\text{emp}}_{ss} z_t + v_{i,t} \tag{39}$$

where $\chi^{\text{emp}}_{ss}$ is a measure of information quality at steady state. Even though agents internalize the signal structure given by Eq. (39), the actual signal structure is given by Eq. (38). As such, agents make behavioral errors, which I deem as "mistakes". A relevant exercise is to evaluate the quantitative effects of exhibiting behavioral errors.

Table 4: Quantitative Effects due to a 1 SD negative TFP shock

| **A: Quantitative Effects of Information Quality** | | | |
|---|---|---|---|
| | Type of Model | | |
| | Time-varying Information Quality | Fixed Information Quality | Difference |
| Information Quality | - 3.90% | - | - 3.90% |
| Output | - 0.75% | 0.43% | - 1.17% |
| Uncertainty | 9.03% | - 75.80% | 84.83% |
| **B: Quantitative Effects of Making Mistakes** | | | |
| | Type of Model | | |
| | Time-varying Information Quality | Time-Varying Information Quality with Mistakes | Difference |
| Output | - 0.75% | - 1.22% | - 0.47% |

*Notes*: This table shows the effects of a one standard deviation negative shock to $z_t$ on different variables in different models. Panel A shows the quantitative effects of information quality. Panel B shows the quantitative effects of making mistakes, when agents do not internalize that information quality is time-varying.

Panel B in Table 4 shows that downturns are more severe when agents' actions exhibit behavioral errors. A model that features time-varying information quality with behavioral errors generates a decline of 1.22% in output. The last column takes the difference in loss of output between a model with and without mistakes. Mistakes account for a decline of 0.47 percentage points in output. In addition, I document that the decline in output due to mistakes are related to the quantitative effects of information quality in the following way:

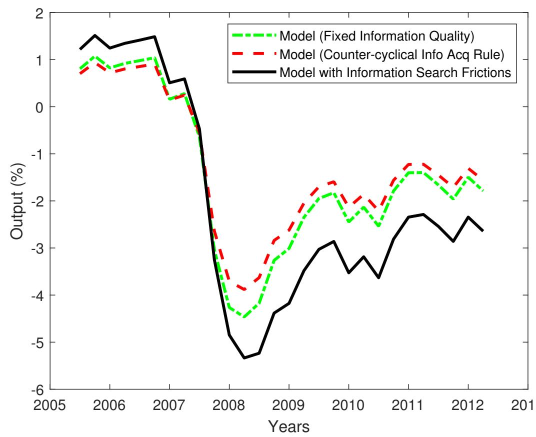
$$\Delta_{\text{Mistakes}} \approx \epsilon \cdot \Delta_{\text{IQ/Baseline}} \tag{40}$$

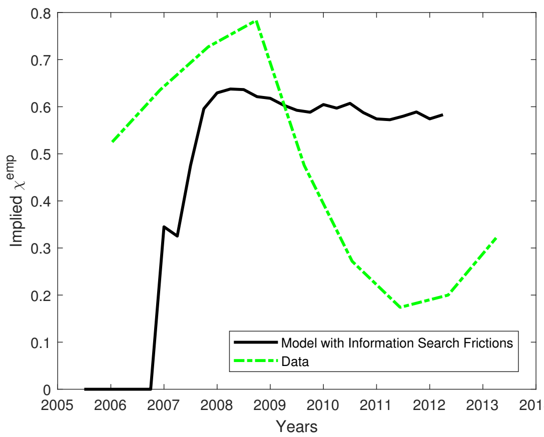
where $\Delta_{\text{IQ}}$ refers to the loss in output between the baseline model and the model with search frictions, $\epsilon$ is the elasticity of substitution, and $\Delta_{\text{Mistakes}}$ refers to the loss in output due to making mistakes. As the elasticity of substitution increases, firms hold lesser monopoly power and control over market demand. When a firm makes a mistake in pricing, consumers tend to substitute away to other firms more aggressively due to higher elasticity of substitution. As such, behavioral errors and mistakes are more costly when firms hold lesser market power.

## 5.3 Mapping to Empirical Evidence

Lastly, I conduct a quantitative exercise to evaluate the model's performance in matching the empirical estimates of information quality during the 2008 financial crisis. The empirical measure of information quality $\chi_t^{\text{emp}}$ reaches its highest value at approximately 0.8. The exercise in this section also seeks to interpret the quantitative importance of the empirical measure.

Figure 8: Dynamics during the 2008 Financial Crisis




*Notes*: This figure presents dynamics of output (left panel) and the empirical measure of information quality (right panel) during the 2008 financial crisis.

The right panel in Figure 8 shows that the model can generate a significant increase in $\chi_t^{\text{emp}}$ (approximately 0.6). Even though the model cannot generate values of $\chi_t^{\text{emp}}$ that matches the magnitude (approximately 0.8) given by the empirical measure of information quality, the model can explain a significant proportion of the fluctuations in the empirical measure during the 2008 financial crisis.

The left panel in Figure 8 plots deviations of output from the steady state during the 2008 financial crisis. The model with information search frictions generates a substantial decrease of about 5.5 % in output. In contrast, models with fixed information quality and the counter-cyclical information acquisition rule generate less pronounced downturns than the model with information search frictions. This is consistent with the quantitative results from Sections 4.1 and 4.2.

The quantitative cost of information quality can be measured by the difference between output generated by the model with fixed information quality and the model with information search frictions. This implies that a value of approximately 0.8 for the empirical measure of information quality corresponds to about one percentage point output loss. This points to evidence that fluctuations in information quality can be a crucial driver of business cycles and severe downturns.

# 6 Conclusion

This paper introduces information quality to address puzzles in endogenous uncertainty models. Information quality depends on the abundance of data and information search intensity. The model with information search frictions generates counter-cyclical information acquisition and uncertainty, and pro-cyclical quality.

This co-movement can rationalize facts that appear at odds with each other: on the one hand, information acquisition is counter-cyclical, while on the other hand, measures of uncertainty are high, and forecasts are inaccurate in recessions.

Quantitatively, the model with information search frictions amplifies business cycle dynamics due to the cyclicality of uncertainty dynamics. In addition, fluctuations in information quality account for a significant portion of the decline in output and rise in uncertainty. The existence of information quality can also explain phenomena caused by behavioral biases, such as mistakes, which can generate severe downturns. The notion of information quality can shed light on factors driving uncertainty and hence, business cycle dynamics.

Therefore, this paper emphasizes the importance of information as an input. The implications of information quality can be extended to other areas, such as the economic value of information and the efficient level of information driven by its supply and demand.

It would be interesting to study optimal economic policies that affect information along these margins. I leave these extensions for future research.

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