INFORMATION ACQUISITION AND THE FINANCE-UNCERTAINTY TRAP

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Abstract. Using novel measures of information acquisition, we document causal evidence of a feedback loop between firms' credit access and information acquisition. To examine the macroeconomic implications of this feedback loop, we develop a tractable general equilibrium framework with financial frictions and endogenous information acquisition. In line with the empirical evidence, the model predicts that a rise in information costs raises the level of uncertainty and reduces a firm's equity value, hampering its credit access. On the other hand, tightened credit constraints restrain activity of high-productivity firms, leading to misallocation that reduces aggregate productivity and firm profits, and discouraging information acquisition. This feedback loop creates a finance-uncertainty trap that substantially amplifies and prolongs business cycle fluctuations.

I. Introduction

Firms often need to make investment and hiring decisions under uncertainty. Acquiring information (for example, through collecting and analyzing data) helps reduce the level of uncertainty, enabling a firm to make more informed decisions and thus raising its expected profits. When financing constraints are tightened, however, a firm may not want to acquire information to reduce uncertainty, because limited credit access would restrain the operation scale of high-productivity firms, limiting the benefits of information acquisition. With less information and more uncertainty, firms would be more prone to making mistakes, reducing their expected profitability and, as a consequence, lenders would be less willing to extend

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credit. Thus, interactions between information acquisition and credit access can lead to a self-reinforcing loop, which we call a "finance-uncertainty trap," that can potentially deepen recessions.

Empirical evidence of this feedback loop, however, has been scant for two reasons. One is the lack of a good measurement of information acquisition. Unlike physical capital, information (or knowledge capital in general) is often an intangible asset, which is hard to measure explicitly. A second challenge stems from the difficulties of identifying the causal effects, since both information acquisition and credit access are endogenous and both respond to changes in firm-specific or aggregate economic conditions.

In this paper, we confront these empirical challenges and document causal evidence of a two-way feedback loop between firms' credit access and information acquisition. We further examine the economic mechanism of the feedback loop and its quantitative importance for business cycles within a general equilibrium framework that features heterogeneous firms making decisions on information acquisition before production, subject to credit constraints. Based on both our empirical evidence and the theoretical model, we argue that the finance-uncertainty trap plays a quantitatively important role in amplifying and propagating business cycle shocks.

To examine the empirical relations between information acquisition and credit access, we construct a novel measure of firm-level information acquisition using online job postings data from Lightcast. We identify information-related jobs using the Lightcast Occupation Taxonomy (LOT), such as business analysts, data scientists, and financial strategists, that are directly associated with acquiring, processing, or analyzing information critical to firms' decision making. The share of such job postings relative to a firm's total job postings is our proxy for the intensity of the firm's information acquisition efforts. We validate this input-based measure of information acquisition by showing that it is negatively correlated with the size of forecast errors in managerial guidance on quarterly earnings from the Institutional Brokers' Estimate System (IBES) database.

Using our measure of information acquisition, along with firm-level balance sheet data from Compustat, we document evidence that firms' information acquisition efforts and their credit conditions are tightly linked. Informed firms (i.e., those with a high share of information-related job postings) make smaller forecast errors and they also face easier credit access than uninformed firms. When credit conditions are tightened, firms (especially those with high leverage) reduce information gathering efforts, resulting in larger forecast errors in the managers' earnings guidance.

The observed links between information acquisition and credit access do not necessarily reflect causal relations, because the two variables are both endogenous to changes in the underlying economic conditions. A main empirical contribution of our paper is to document causal evidence of a two-way feedback loop between firm-level information acquisition and credit access.

To establish the causal effects of credit constraints on information acquisition, we exploit the variations in firm-level borrowing capacity caused by exogenous oil supply news shocks (constructed by Känzig (2021)). Such news shocks affect the future cash flows and the borrowing capacity of firms exposed to oil price risks, whereas they are orthogonal to the firms' current fundamental conditions. We find that an oil supply news shock that predicts declines in future oil prices significantly reduces information acquisition efforts by firms with greater exposures to the shock, resulting in a lower share of information-related job postings and larger forecast errors in managers' earnings guidance. We further show that oil supply news shocks drive changes in information acquisition efforts through the financial friction channel. These findings highlight the critical role of credit conditions in shaping firms' incentives to gather information, a key driver of the finance-uncertainty trap.

To establish the causal effects from the other direction (i.e., the effects of information acquisition on credit access and firm performance), we exploit exogenous variations in the quality of external information sources provided by the financial news media. Specifically, we follow the method of Hu (2024) and construct an exogenous shock to financial news production, driven by declines in news media's advertising revenues. Such a media shock reduces the supply of public information about a firm's financial conditions, raising the firm's costs of information acquisition. We find that an exogenous decline in a firm's media coverage reduces the firm's issuance of equity and long-term debt and increases its implied cost of capital. These effects reflect tightened access to external financing. Furthermore, such negative effects of a media shock on firms' external financing work through an information channel because the shock reduces the precision of earnings forecasts, which in turn reduces the firm's expected profitability, and therefore restricts the firms' credit access. These findings highlight the importance of information acquisition costs for firms' credit access, another key driver of the finance-uncertainty trap.

Motivated by our empirical evidence, we develop a dynamic general equilibrium model featuring financial frictions and endogenous information acquisition. Using the calibrated model, we show that the interactions between information frictions and financial frictions give rise to a finance-uncertainty trap that substantially amplifies business cycle fluctuations.

Firms in our model produce a homogeneous good using capital and labor, subject to idiosyncratic productivity shocks. Each firm observes a noisy signal of its idiosyncratic productivity, and the precision of the signal can be improved at a cost. Based on the signal received, firms form expectations about their profitability and choose the size of operation.

Firms rely on external financing for their working capital, with the borrowing capacity constrained by a fraction of the expected equity value (Jermann and Quadrini, 2012; Liu and Wang, 2014; Lian and Ma, 2021). Under perfect competition in the factor markets, only firms with sufficiently high productivity expect to make profits and choose to operate. Thus, improving the precision of the productivity signals offers an option value for a firm. If the firm learns that its productivity is likely high, then it expands production; otherwise, it remains inactive. The firm's information acquisition decision reflects a tradeoff between the cost and the benefit of acquiring information. In an equilibrium, there exists an endogenous threshold of information cost such that those firms with costs below that threshold choose to acquire information.

A two-way feedback between information acquisition and credit access emerges from our model. A shock that raises the cost of acquiring information discourages learning, reducing a firm's expected profits, which in turn tightens the credit constraints, further reducing profits and the gains from information acquisition. On the other hand, a shock that tightens credit constraints limits the scale of production for high-productivity firms, depressing factor prices, and enabling a subset of low-productivity firms to stay active in production. This results in misallocation that lowers aggregate productivity, reducing the expected profits and the benefits of acquiring information. This two-way feedback loop, which is in line with our empirical evidence, creates a finance-uncertainty trap that amplifies business cycle fluctuations.

We quantify the impact of endogenous information acquisition and credit constraints in propagating aggregate shocks with our calibrated model. In taking the model to the data, we match several key moments in the data related to firms' information production and forecasts. Under our calibration, the interactions between information frictions and financial frictions substantially amplify and prolong the effects of aggregate shocks over the business cycles.

I.1. **Related literature.** Our work contributes to the literature both empirically and theoretically. On the empirical side, we document evidence of a two-way feedback between information frictions and financial frictions, using novel measures of firm-level information acquisition based on job postings and earnings forecasts data. On the theory side, we develop a dynamic general equilibrium model calibrated to the micro-level data and study the quantitative importance of the finance-uncertainty trap.

Financial frictions can amplify the macroeconomic effects of uncertainty shocks. For example, Christiano et al. (2014) estimate a DSGE model with a financial accelerator mechanism and find that cross-sectional idiosyncratic uncertainty shocks (i.e., risk shocks) are quantitatively important for driving business cycle fluctuations. Gilchrist et al. (2014) argue that the impact of idiosyncratic uncertainty shocks on investment works mainly through changes in credit spreads. Arellano et al. (2019) show that financial frictions limit firms' ability to insure against idiosyncratic shocks, such that firms respond to an increase in uncertainty by pulling back hiring in order to reduce risks. In a recent study closely related to our work, Alfaro et al. (2024) present empirical evidence that, following an uncertainty shock, financially constrained firms reduce investment spending more than unconstrained firms. They present a general equilibrium model featuring a finance-uncertainty multiplier, through which financial frictions amplify the adverse effects of uncertainty shocks.[1] In our model, financial frictions also amplify uncertainty by hampering information acquisition. What is new is that uncertainty in our model is not an exogenous source of variations; instead, it is driven by firms' active efforts in acquiring information.

Information frictions are a key driver of firm-level uncertainty in our model. The importance of information frictions for business cycles has been extensively studied in the literature, building on the seminal contributions of Lucas (1972) and Sims (2003)[2]. For example, Van Nieuwerburgh and Veldkamp (2006) argue that noise that impedes learning slows recovery and makes booms more gradual than downturns. Veldkamp (2011) shows that information acquisition is procyclical: firms invest less in information production in recessions when payoffs are lower, resulting in higher uncertainty. Benhabib et al. (2016) highlight a static two-way feedback between procyclical information acquisition and aggregate TFP, arising from strategic complementarity in information acquisition and production in the Dixit–Stiglitz-type of monopolistic competition economy. Fajgelbaum et al. (2017) model "information cycles," where firms' costly experimentation declines in downturns, reinforcing output drops. Existing studies have also shown that information frictions can affect asset prices (Veldkamp, 2005; Kelly and Ljungqvist, 2012), corporate financing and investment (Sufi, 2009; Derrien and Kecskés, 2013; Guo et al., 2024; Charoenwong et al., 2024), business cycle comovements (Veldkamp and Wolfers, 2007), and public finance (Cornaggia et al., 2018, 2023). These studies illustrate how uncertainty can emerge endogenously from optimal information acquisition decisions, a feature that our model shares.

In a closely related study, Straub and Ulbricht (2024) develop a model of endogenous uncertainty, where an adverse financial shock could impair investors' ability to learn about

[1]Some other recent studies also emphasize the role of financial frictions in amplifying the impact of uncertainty shocks (Dong, 2023; Wang, 2023; Dong et al., 2025). There is a large and growing strand of literature on the macroeconomic effects of uncertainty shocks. Examples include Bloom (2009), Fernández-Villaverde et al. (2011), Jurado et al. (2015), Baker et al. (2016), Leduc and Liu (2016), Basu and Bundick (2017), Bloom et al. (2018), Berger et al. (2020), Firooz et al. (2025), among many others. For recent surveys of the uncertainty literature, see Bloom (2014) and Fernández-Villaverde and Guerrón-Quintana (2020).

[2]See Veldkamp (2011) and Maćkowiak et al. (2023) for recent reviews of the literature.

firm-level fundamentals, and the resulting increases in uncertainty reinforce financial distress. In their model, investors' learning about firm-level information is passive (i.e. "learning-by-doing"), and financial distress prevents firms from undertaking specialized projects that can better reveal their quality; hence, it reduces the *supply* of information on firms' quality to potential lenders and raises the level of uncertainty. In our model, firms choose conscientiously whether or not to acquire information by weighing the benefits and the costs of obtaining better information about their productivity. Thus, learning is active and it is driven by firms' *demand* for information. Those firms that face tighter credit constraints invest less in information acquisition, which in return raises the level of uncertainty, reducing the expected firm value and creditors' willingness to lend. More importantly, we present causal evidence of the two-way feedback between financial frictions and information frictions, lending empirical support to our model's key predictions.

II. Empirical Evidence

In this section, we document evidence of two-way causal relations between information frictions and financial frictions using firm-level data.

II.1. **Data and measurements.** We construct a measure of firm-level information frictions using online job postings data from Lightcast. Lightcast collects job postings information from over 40,000 online job boards and company websites, converting it into a systematic, machine-readable format, starting from 2010. The dataset covers nearly the entire universe of online job postings in the U.S., accounting for approximately 60–70% of all job openings in that country. We identify information-related jobs using the LOT, which encompasses over 1,800 occupation types, each accompanied by a detailed occupation description. From this taxonomy, we select 100 occupations that are most closely associated with information acquisition. We then classify job postings corresponding to these occupation types as information-related jobs.[3] The share of information-related jobs in all job postings provides an input-based measure of firm-level information production. A larger share of information-related jobs reflects a firm's greater efforts in gather information. We merge the Lightcast data with Compustat to obtain a sample that spans from 2010:Q1 to 2023:Q4, covering about 1,630 firms per quarter on average.

Figure 1 plots the aggregate time series of the share of information-related job postings. The share of firms that posted information-related jobs (i.e., the extensive margin, shown in Panel (A)) has been rising over time, with the notable exception of the COVID period when the share dropped sharply. Among those firms that posted information-related jobs, the average share of information-related jobs in all job postings (i.e., the intensive margin,

[3]The detailed list of information related occupations is provided by Table C.1 in the Appendix.

shown in Panel (B)) has declined over time. Reflecting these offsetting trends, the average share of information-related jobs (averaged across all firms, shown in Panel (C)) has been roughly stationary. During the COVID period when uncertainty surged, the share of firms posting information-related jobs plunged, while the average intensity of those job postings did not change much, such that the average share of information jobs among all firms declined.

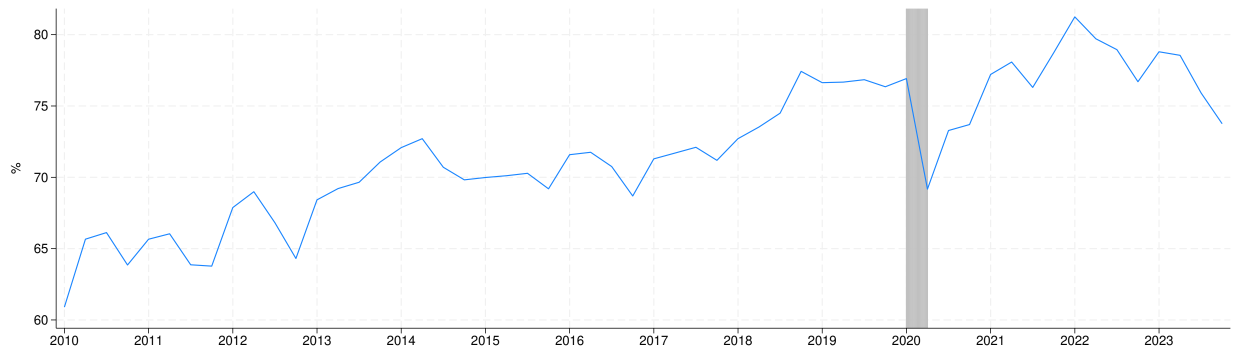
To validate our input-based measure of information acquisition using online job postings data, we construct a firm-level outcome-based measure of information acquisition using the size of forecast errors in firm managers' guidance on quarterly earnings in the IBES database. The IBES database covers over 6,000 North American companies, dating back to 1994. We measure the size of the forecast errors by the absolute value of the differences between a firm's realized quarterly earnings per share (EPS) and the firm manager's one-quarter-ahead forecasts. A larger forecast error partly reflects the outcome of lower information gathering efforts.[4] Figure 2 shows the aggregate time series of the managerial forecast errors over the sample period from 1995:Q2 to 2023:Q4. The forecast errors increased sharply in the 2008-2009 global financial crisis and again during the COVID period, coinciding with sharp increases in the earnings forecast error dispersion, reflecting heightened uncertainty during those periods.

The size of managerial forecast errors is negatively correlated with the share of information-related job postings, as shown in the summary statistics in Table 1. In particular, managers in informed firms (i.e., those with a share of information-related jobs above the median) make smaller forecasting mistakes than uninformed firms (with the average size of the forecast errors of 0.25% vs. 0.32%).[5] On average, informed firms have a much higher share of information-related job postings than do uninformed firms (14.55% vs. 2.37%). Uninformed firms also face tighter financing constraints measured by the Linn-Weagley (LW) index than informed firms.[6] These patterns suggest that managers in firms with more active information gathering make smaller mistakes in their earnings forecasts and thus face less uncertainty.

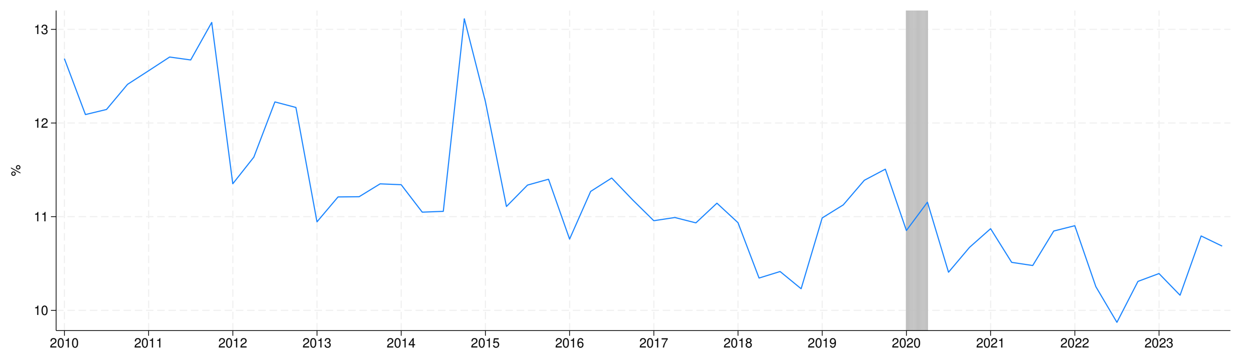
[4]Managers of publicly listed firms issue quarterly guidance for the companies' future performance, which can serve as a quantitative measure of the firms' own expectations regarding their future fundamentals. The IBES database provides detailed information on such managerial expectations for various metrics (such as EPS) extracted from press releases and corporate event transcripts. We provide some details on the construction of the IBES variables in Appendix C.2.

[5]The size of the forecast error is computed as the absolute deviation between 1-quarter-ahead managerial guidance on earning per share (EPS) and realized EPS, normalized by the beginning-of-period stock price.

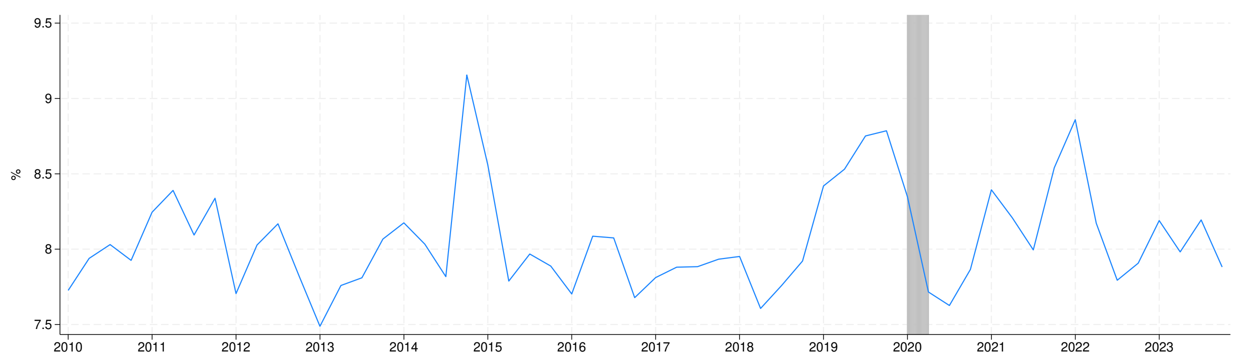
[6]Linn and Weagley (2024) use a random forecast model trained on textual analysis-based measures from Hoberg and Maksimovic (2015) to classify firms' financial constraints using accounting variables, with broader coverage of publicly traded firms than that in the original study of Hoberg and Maksimovic (2015). A higher value of the Linn-Weagley index means tighter financial constraints.



(A) The share of firms that posted information-related jobs



(B) The average share of information jobs among firms that posted information-related jobs



(C) The average share of information-related jobs among all firms

FIGURE 1. Aggregate time series of information-related job posting

Notes: This figure shows the aggregate time series of the extensive margin, the intensive margin, and the average share of information-related job postings from the Lightcast-Compustat merged sample from 2010:Q1 to 2023:Q4. For each quarter, the extensive margin (panel (A)) is the share of firms that posted information-related jobs; the intensive margin (panel (B)) is the share of information-related jobs in all job postings averaged across firms that posted information-related jobs; the average share (panel (C)) is the share of information-related job postings to all job postings averaged across all firms.

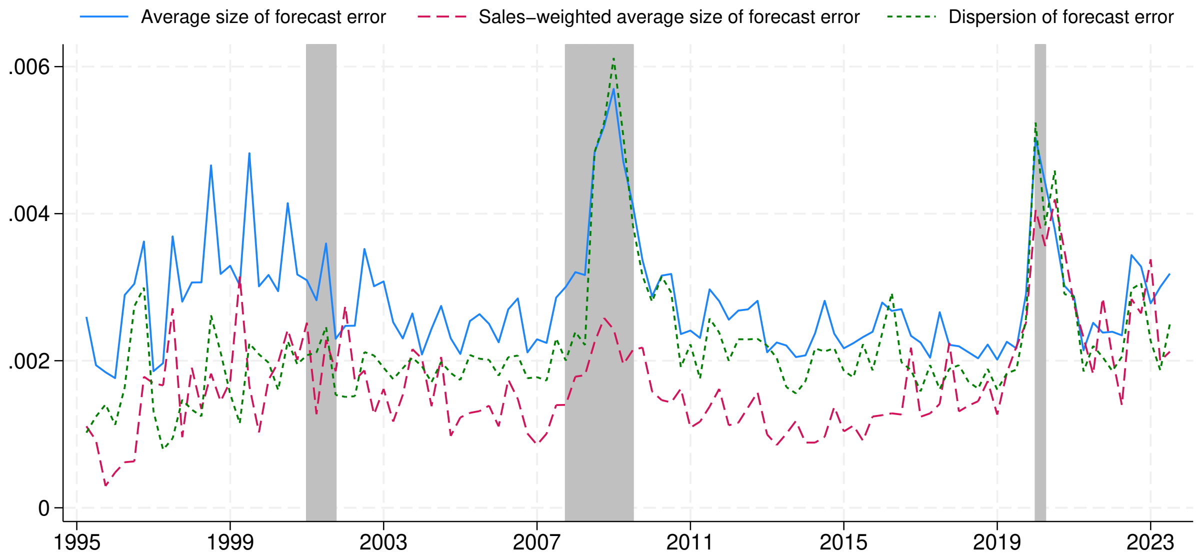


FIGURE 2. Aggregate time series of managerial forecast errors

Notes: This figure presents the time series of the average size of firm earnings' forecast errors (blue solid line), the sales-weighted forecast errors (red long-dashed line), and the forecast error dispersion (green short-dashed line). All time series are constructed from the merged IBES-Compustat sample spanning the periods from 1995:Q2 to 2023:Q4. For each quarter, the average forecast error is calculated as the simple mean of the absolute forecast errors; the sales-weighted average is the average absolute forecast errors weighted by each firm's share of total sales; the forecast error dispersion is measured by the interquartile range of forecast errors of individual firm managers. Firm-level forecast errors are computed as the difference between managers' one-quarter-ahead forecasts of the earnings per share (EPS) and the realized EPS, normalized by the firms' beginning-of-period stock prices. In the calculations of both the simple and sales-weighted averages, we exclude the observations with absolute forecast errors above the 99th percentile to mitigate the impact of extreme values.

They also suggest that firms' information production is positively correlated with easing of credit access.

II.2. **Correlations between credit conditions and information acquisition.** We begin with some evidence that changes in credit conditions are associated with changes in firm-level information acquisition. We measure aggregate credit conditions using the Adjusted National Financial Conditions Index (ANFCI) constructed by the Federal Reserve Bank

Table 1. Summary statistics

	Full Sample		Uninformed Firms		Informed Firms	
Variable	Mean	SD	Mean	SD	Mean	SD
Share of Info Job Postings (%)	8.41	9.46	2.37	2.31	14.55	10.00
Size of Forecast Errors $\times 100$	0.28	1.17	0.32	1.45	0.25	0.80
LW Index	0.13	0.58	0.19	0.60	0.06	0.55
Log Asset (1m)	7.41	1.48	7.26	1.45	7.55	1.50
Log Sale (1m)	5.92	1.50	5.87	1.52	5.97	1.48
Log Capital (1m)	5.31	1.91	5.40	2.00	5.23	1.81
Workers (1000)	26.51	133.48	33.73	170.20	19.18	79.92
Capital Growth (%)	3.33	13.91	2.88	12.97	3.77	14.75
Market Value Growth (%)	2.31	18.39	1.85	18.54	2.77	18.22
ROA (%)	1.21	2.79	1.28	2.74	1.13	2.83
Debt/Asset	0.20	0.20	0.20	0.22	0.20	0.19

Note: This table reports the summary statistics of the Lightcast-IBES-Compustat merged sample, which covers the period from 2010:Q1 to 2019:Q4. Informed firms are those with shares of information-related job postings above the median share. The degree of financial constraints is measured by the Linn-Weagley (LW) index from Linn and Weagley (2024).

of Chicago.[7] We estimate the dynamic effects of changes in financial conditions on firm-level information acquisition measured by the share of information-related job postings. In particular, we estimate a panel-data version of the local projections of Jordà (2005), with the following empirical specification

$$\begin{aligned} \Delta^k InfoJob_{j,t+k} &= \beta_{0,k} + \beta_{1,k}\Delta InfoJob_{j,t-1} + \beta_{2,k} ANFCI_t \times High\_Lev_{j,t-1} \\ &+ \beta_{3,k} High\_Lev_{j,t-1} + \Phi_{j,t-1} + \gamma_t + \eta_j + \varepsilon_{j,t+k}, \end{aligned} \tag{1}$$

where $k = 0, 1, 2, ...$ denotes the projection horizon. The dependent variable $\Delta^k InfoJob_{j,t+k} \equiv InfoJob_{j,t+k} - InfoJob_{j,t-1}$ is the cumulative change in firm j's share of information-related job postings from the pre-shock quarter $(t-1)$ to k quarters after the shock. The term $High\_Lev_{j,t-1}$ is a dummy variable indicating high leverage, and it equals 1 if firm j's debt-to-asset ratio (i.e., leverage) exceeds the median level in quarter $t-1$, and 0 otherwise. The regression includes controls for lagged growth of the information-related job share ($\Delta InfoJob_{j,t-1} \equiv InfoJob_{j,t-1} - InfoJob_{j,t-2}$), lagged firm-level controls ($\Phi_{j,t-1}$) including the firm size (measured by the logarithm of book assets) and profitability (measured by returns on assets, i.e., ROA). We also include controls for time fixed effects (γ_t) and firm fixed effects (η_j). The term $\varepsilon_{j,t+k}$ denotes the regression residual.

[7] The ANFCI isolates financial conditions that are uncorrelated with prevailing macroeconomic conditions. A positive value of ANFCI indicates tightening of financial conditions.

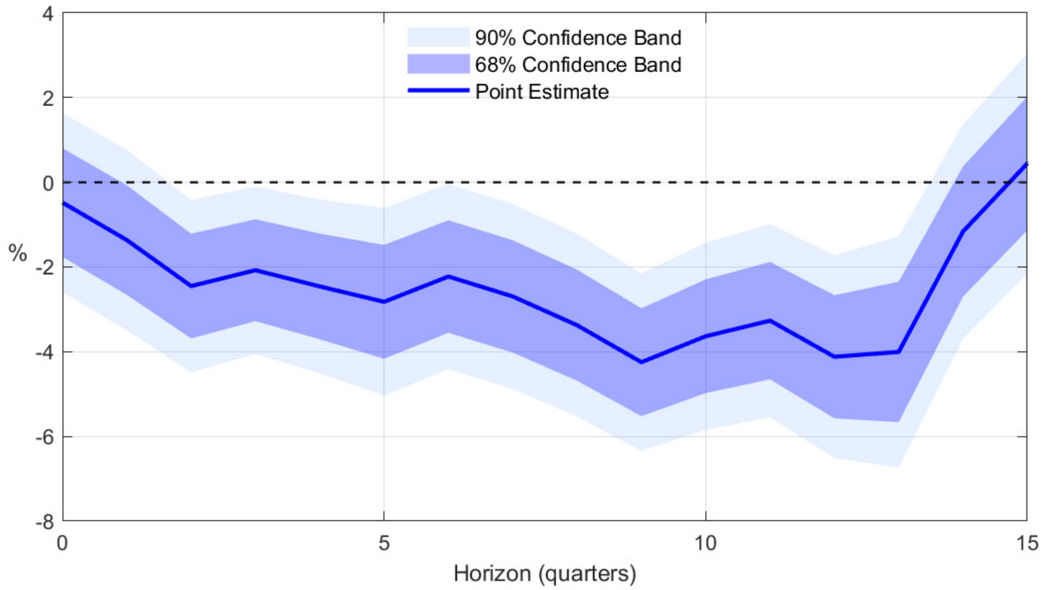


Figure 3. Impulse response of the share of information-related job postings to a one-standard-deviation tightening of aggregate financial conditions

Notes: This figure shows the impulse response of information-related job posting share to a one-standard-deviation increase in the adjusted aggregate financial condition index (ANFCI).

The coefficient of interest, $\beta_{2,k}$, captures the marginal effect of tightening aggregate credit conditions on firms with high leverage, i.e., those with greater exposures to changes in aggregate credit conditions. Figure 3 displays the estimated values of $\beta_{2,k}$ for $k = 0, 1, \ldots, 15$, which can be interpreted as the impulse responses of information-related job postings to a tightening of credit conditions. The figure shows that tightened credit conditions lead to persistent declines in the share of information-related job postings for firms with relatively high leverage. For instance, for a firm with above-median leverage ratio, a one-standard-deviation tightening of credit conditions reduces the share of information-related job postings by an additional 30 percent at the one-year horizon (i.e., $k = 4$) relative to its mean level.[8] The effects remain significant at the 90% confidence level for about 3 years, suggesting

[8]The standard deviation of ANFCI is normalized to 1, and the mean of the information-related job share is 8.41%. Thus, the estimated value of $\beta_{2,4} = -2.5$ implies that, for a firm with its leverage ratio above the median level, a one-standard-deviation increase in ANFCI reduces the share of information-related job posting by an additional 2.5 percentage point, which is equivalent to a decline of approximately 2.5 / 8.41 $\approx 30\%$ relative to the mean level of the information-related job share.

that tighter credit conditions are associated with persistent declines in firms' information acquisition efforts.[9]

II.3. **Causal effects of credit shocks on information acquisition.** The observed correlations between credit conditions and information acquisition do not necessarily reflect causal effects. For example, such correlations might reflect endogenous responses of both credit conditions and information production to changes in unobserved factors, such as managers' insider knowledge of the firm or firm-specific productivity shocks.

To identify the causal effects of changes in credit conditions on information acquisition, we exploit exogenous variations in firm-level credit capacity driven by, for example, oil supply news shocks. For a firm exposed to oil price risks, a news shock to oil supply that raises the expected future oil prices would boost the firm's future cash flows without affecting the firms' current fundamentals.

We use the oil supply news shock constructed by Känzig (2021). We measure firm $j's$ exposure to oil supply news shocks in a given quarter t (denoted by $OilExp_{j,t}$) using the rolling-window correlations of the firm's daily stock returns with oil price returns in the preceding 252 trading days.[10] This measure of exposures captures the heterogeneity in how oil price movements affect firms' cash flows in the past, and it is orthogonal to oil supply news shocks that affect expectations of future oil prices. A positive $OilExp_{j,t}$ implies that an increase in oil prices can boost the firm's profitability, enhancing its debt repayment ability and thus expanding its borrowing capacity.

We estimate the effects of oil supply news shocks on firm performance and information acquisition based on the regression

$$y_{j,t} = \beta_0 + \beta_1 \cdot y_{j,t-1} + \beta_2 \cdot OilExp_{j,t} + \beta_3 \cdot OilExp_{j,t} \times OilNews_t + \Phi_{j,t} + \gamma_t + \eta_j + \varepsilon_{j,t}, \quad (2)$$

where $y_{j,t}$ is the dependent variable that indicates firm performance measured by the logged price-to-earnings ratio ($\log(PE_{jt})$) or information acquisition efforts measured by the share of information-related job postings ($\log(IJS_{jt})$) or, alternatively, the size of the managers' forecast errors in the earnings guidance ($\log(FE^F_{jt})$). The term $OilNews_t$ denotes the oil supply news shock, with a positive value predicting a decline in future oil prices. The coefficient of interest β_3 captures the impacts of oil supply news shocks on firms that are more exposed to oil price risks. $\Phi_{j,t}$ denotes a set of firm-level controls, including the asset size, ROA, in addition to the lagged dependent variable. γ_t and η_j are time fixed effects and firm fixed effects, respectively.

[9]Tightened aggregate credit conditions lead to persistent declines in firms' information acquisition intensity, not only for firms with high leverage, but also for all firms on average, as we show in Appendix A.1.

[10]We measure the oil returns by daily log growth rates of spot oil prices.

Table 2. Oil Supply News Shock and Firm Information Acquisition

	OLS			2SLS		
Variable	$\log(PE_{jt})$	$\log(FE^F_{jt})$	$\log(IJS_{j,t})$	LW_{jt}	$\log(FE^F_{jt})$	$\log(IJS_{jt})$
	(1)	(2)	(3)	(4)	(5)	(6)
$OilExp_{j,t}$	-0.000	0.693	-0.208**	0.038	0.470	-0.136
	(0.071)	(0.512)	(0.100)	(0.106)	(0.534)	(0.103)
$OilExp_{j,t} \times OilNews_t$	-0.068***	0.401*	-0.129*	0.069**		
	(0.024)	(0.227)	(0.073)	(0.034)		
$\widehat{LW}_{jt}$					5.821*	-1.875*
					(3.292)	(1.060)
Observations	14,178	15,404	5,531	13,888	15,404	5,531
R-squared	0.749	0.030	0.347	0.033	0.030	0.347
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results of the regression (2). The dependent variables in the OLS regression include (1) the log of price-to-earnings ratio ($\log(PE_{jt})$), (2) the log of absolute managerial earnings forecast error ($\log(FE^F)$) from IBES; and (3) the log of information acquisition related job posting share ($IJS_{jt} \equiv 1 + 100 \cdot InfoJobPosting_{jt}/TotalJobPosting_{jt}$). $OilExp_{j,t}$ is the firm-level exposure to oil price shocks, measured as the one-year rolling-window correlation of stock returns with daily oil price returns. $OilNews_t$ is the oil supply news shock from Känzig (2021). LW_{jt} denotes the Linn-Weagley index measuring the tightness of firm-level credit constraints, and $\widehat{LW}_{jt}$ denotes the predicted firm-level financial constraint obtained from the first-stage regression (Column 4). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) to (3) of the Table 2 report the OLS results. According to Column (1), a positive oil supply news shock (which predicts a decline in future oil prices) significantly reduces the P/E ratio for firms exposed to oil price risks, suggesting that expected decline in oil prices erode expected cash flows (by more than the decline in current earnings). The erosion in expected cash flows potentially impairs a firm's ability of debt repayment, reducing its current capacity for credit access. Column (2) shows that the oil supply news shock raises the forecast errors in the managerial earning guidance, indicating diminished information precision of exposed firms. Column (3) shows that exposed firms also disproportionately reduce their information job postings following the oil supply news shock. The estimated effects of the oil supply news shock on information acquisition efforts are economically important. For a firm with no exposure to oil price risks to one with an exposure of 0.15 (i.e., a one-standard-deviation increase in exposures), a one-standard-deviation increase in oil supply news reduces the share of information-related job postings by 2% and increases the absolute managerial forecast error by approximately 6%.[11]

We further examine the extent to which oil supply news shocks could drive changes in firms' information acquisition efforts through the channel of financial frictions. For this purpose, we use the two-stage least squares approach of Bertrand and Mullainathan (2001). In the first stage, we regress the LW index on the same set of explanatory variables used in the specification (2). This regression helps isolate the effects of oil supply news shock on an exposed firm's financial constraints (measured by the LW index). The estimated coefficient on the interaction term in Column (4) shows that an oil supply news shock that predicts future declines in oil prices raises the LW index, implying a tightening of credit constraints for firms exposed to oil price risks. The estimated effects are statistically significant (at the 90% confidence level) and also economically important. The point estimate (0.069) implies that, for a firm positively exposed to oil price risks (i.e., with $OilExp_{j,t} = 1$), a one-standard-deviation news shock to oil supply triggers a 46% increase in the LW index from its average level.[12]

In the second stage, we regress each of our two measures of information acquisition (i.e., managerial forecast errors and the share of information-related job postings) on the predicted LW index (denoted by $\widehat{LW}_{jt}$) from the first-stage regression. The coefficient on the predicted LW index captures the effects of oil supply news shocks on firm information acquisition through the credit constraint channel. As shown in Columns (5) and (6) of Table 2, the estimated channeling effects are positive and statistically significant at the 90% level for both measures of information acquisition. The channeling effects are also economically important. According to the point estimates, through the credit constraint channel, a one-standard-deviation positive news shock to oil supply leads to a 40% increase in the managerial forecast errors and a 13% decrease in the share of information-related job postings for firms exposed to oil price risks.[13]

[11] In our sample, the standard deviation of oil supply news shock is normalized to 1.

[12] The standard deviation of the oil supply news shock is normalized to 1. The LW index has a mean value of 0.15 in this sample. Thus, for a firm with an exposure of 1, a one-standard-deviation increase in the oil supply news shock raises the LW index by 0.069, corresponding to a $0.069/0.15 \approx 46\%$ increase in the LW index relative to its mean.

[13] The first-stage regression shows that a one-standard-deviation positive oil supply news shock raises the LW index by 0.069 units (see Column (4) of the table). The estimated coefficients shown in Columns (5) and (6) suggest that the 0.069 increase in the LW index in turn leads to a $0.069 \times 5.821 \approx 40\%$ increase in the absolute value of managerial forecast errors and a $0.069 \times 1.875 \approx 13\%$ decline in the share of information-related job postings.

Our results are robust to replacing the firm-level exposures by the industry-level exposures at SIC 4-digit level (see Appendix A.2). One possible concern is that oil supply news shocks may coincide with higher uncertainty about future oil prices (Alfaro et al., 2024), which would incentivize firms with high exposures to oil price risks to acquire more information in order to reduce uncertainty. To mitigate this concern, we add an additional interaction term between oil supply news shock and the absolute value of a firm's exposure to oil price risks. This absolute value of the exposure measure captures the effects of oil price uncertainty. Our baseline results remain robust, as shown in Appendix A.2[14].

II.4. **Causal effects of information acquisition on credit access and firm performance.** We now examine the other direction of the feedback loop between firm information acquisition and credit access: How does a firm's information acquisition affect its credit access and profitability? Our hypothesis is that an increase in the cost of acquiring information reduces firms' incentives to gather information, raising the level of uncertainty, resulting in lower expected profits and tighter credit constraints. However, information acquisition and the ability to access credit are both endogenous. For example, a good manager can provide good forecasts of the firm's earnings and also help the firm raise external finance. To establish the causal effects requires an exogenous source of variations that directly impacts on firms' information acquisition costs.

For our purpose, we use the exogenous shocks to financial news production constructed by Hu (2024), who examines how advertising revenue shocks—the primary cash-flow source for media outlets—affect news production and corporate outcomes. He finds that a decline in media advertising revenues significantly reduces both the quality and the quantity of news provided by the financial news media. Thus, a negative financial news shock (through changes in advertising revenues) can act as an exogenous shock that raises the costs for firms to stay informed of their business prospect.

To estimate the impacts of financial news shocks on firm performance and external financing, we estimate the empirical specification

$$y_{j,t} = \beta_0 + \beta_1 \Delta FinNews_{j,t-1} + \Phi_{j,t} + \gamma_t + \eta_j + \varepsilon_{j,t}, \tag{3}$$

where $y_{j,t}$ is the dependent variable, including quarterly changes in the issuance of shock-term debt by firm j ($\Delta Debt^{ST}_{jt}$), changes in the firm's issuance of long-term debt ($\Delta Debt^{LT}_{jt}$), changes in the issuance of equity ($\Delta Equity_{jt}$), and the log of the implied costs of capital ($\log(CoC_{jt})$) constructed by Lee et al. (2021). An increase in the issuance of long-term debt or equity (relative to the issuance of short-term debt) and a decline in the cost of

[14]In Appendix A.2, we also show that our baseline results are not driven by firms from certain industries such as mining or information service.

capital would indicate a firm's improved access to external credit. The main independent variable is the financial news shock ($\Delta FinNews_{j,t-1}$) to firm j constructed by Hu (2024). The regression controls for firm characteristics ($\Phi_{j,t}$), firm fixed effects (η_j), and time-fixed effects (γ_t). The term $\varepsilon_{j,t}$ denotes the regression residuals.

TABLE 3. Impacts of Financial News Shock on Firm External Financing

Panel A: OLS					
Variables	$\Delta Debt^{ST}_{jt}$	$\Delta Debt^{LT}_{jt}$	$\Delta Equity_{jt}$	$\log(CoC_{jt})$	
	(1)	(2)	(3)	(4)	
$\Delta FinNews_{j,t-1}$	0.000	0.002***	0.002***	-0.003***	
	(0.000)	(0.000)	(0.000)	(0.001)	
Observations	76,763	152,264	152,264	119,642	
R-squared	0.026	0.017	0.009	0.739	
Firm-level Controls	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	
Panel B: 2SLS					
Variables	FE^F_{jt}	$\Delta Debt^{ST}_{jt}$	$\Delta Debt^{LT}_{jt}$	$\Delta Equity_{jt}$	$\log(CoC_{jt})$
	(1)	(2)	(3)	(4)	(5)
$\Delta FinNews_{j,t-1}$	-0.027*				
	(0.016)				
$\widehat{FE}^F_{jt}$		-0.010	-0.087***	-0.069***	0.095***
		(0.007)	(0.010)	(0.006)	(0.031)
Observations	23,496	76,763	152,264	152,264	119,642
R-squared	0.007	0.026	0.017	0.009	0.739
Firm-level Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results of the regression. The dependent variables are (1) $\Delta Debt^{ST}_{jt}$: short-term debt issuance (measured as the quarter-to-quarter change in short term debt, or Compustat item dlcch, scaled by asset), (2) $\Delta Debt^{LT}_{jt}$: long-term debt issuance (measured as the quarter-to-quarter change in long term debt, or Compustat item dltis-dltr, scaled by asset), (3) $\Delta Equity_{jt}$: equity issues (measure as the quarter-to-quarter change in equity issuance, or Compustat item sstk, scaled by asset), and (4) $\log(CoC_{jt})$: the logarithm of the implied cost of capital constructed by Lee et al. (2021). The independent variable $\Delta FinNews_{j,t-1}$ is the the financial news shock to firm j constructed by Hu (2024). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 (Panel A) shows the estimation results. An increase in media news production boosts both equity issuance and long-term debt issuance (the two variables are both scaled by total assets) and reduces the implied cost of capital, with no effects on the issuance of short-term debt. The point estimates suggest that a one-standard-deviation increase in financial news production raises the ratio of long-term debt issuance to total asset by 65%, increases the ratio of equity issuance to total asset by 28%, and reduces the cost of capital by 0.16%, relative to their mean levels.[15] These outcomes are in line with Hu (2024) and also align well with our hypothesis that increased costs of information production reduce firms' incentives to acquire information, impairing credit access and firm performance. [16]

We further examine the channeling effects of financial news media shocks on firm performance and credit access through the information friction channel using a two-stage least squares approach. In the first stage, we regress the forecast errors of managerial earnings guidance on the same set of explanatory variables used in our baseline OLS regression (3). According to Column (1) in Panel B of Table 3, a positive shock to financial news production significantly reduces managers' forecast errors.

In the second stage, we regress measures of external credit access on the predicted managerial forecast errors from the first stage (denoted by $\widehat{FE}^F_{j,t}$). The second-stage regression coefficient captures the effects of financial news production shock on firms' credit access through the information channel. The estimated coefficients shown in Columns (2) - (5) in Panel B suggest that a one-standard-deviation increase in financial news production reduces forecast errors by 1.4%, which, in turn, increases the ratio of long-term debt issuance to total asset by 75%, raises the ratio of equity issuance to total asset by 26%, and lowers the cost of capital by 0.13%.[17] The shock has no significant effects on short-term debt issuance. These findings are consistent with the pecking-order theory (Myers and Majluf, 1984). After an

[15]In our sample, the standard deviation of firm-level news production shock is 0.52, the average ratio of newly issued long-term debt to total asset is 0.0016, and the average ratio of equity issuance to total asset is 0.0037. Therefore, a one-standard-deviation increase in financial news production raises the ratio of long-term debt issuance to total asset by 0.52×0.002, which is a $0.52 \times 0.002 / 0.0016 \approx 65\%$ increase relative to the average level, boosts the ratio of equity issuance to total asset by 0.52×0.002, which is a $0.52 \times 0.002 / 0.0037 \approx 28\%$ increase relative to the average level, and lowers the cost of capital by $0.52 \times 0.003 \approx 0.16\%$.

[16]Consistent with our theory, the effects are stronger for smaller firms (See Appendix A.3)

[17]In our sample, the standard deviation of firm-level news production shock is 0.52, the average ratio of long-term debt issuance to total asset is 0.0016, and the average ratio of equity issuance to total asset is 0.0037. A one-standard-deviation increase in financial news production changes forecast error by $0.52 \times -0.027 \approx -1.4\%$. This, in turn, increases the ratio of long-term debt issuance to total asset by $-0.087 \times -1.4\% \approx 0.0012$, which is an increase of $0.0012/0.0016 \approx 75\%$ relative to the average level. It also raises the ratio of equity issuance to total asset by $-0.069 \times -1.4\% \approx 0.00097$, equivalent to an increase of $0.00097/0.0037 \approx$

improvement in informational environment (e.g., an increase in news production), firms face a lower degree of information friction and should change the composition of their financing to use more of those which were previously too costly: equity first, then long-term debt, followed by lower risk short-term debt.[18]

III. The Model

We present a tractable general equilibrium model featuring heterogeneous firms facing financial and information frictions. Consistent with the empirical evidence documented in the previous section, the model highlights the interactions between financial frictions and information acquisition decisions. In the model, firms face idiosyncratic costs of information acquisition, such that they possess imperfect information about their productivity. Firms also face credit constraints for financing working capital, which restrict the production scale of high-productivity firms. These two sources of frictions distort firm decisions, resulting in misallocation of resources.

III.1. **Household.** The economy is populated by a continuum of identical and infinitely-lived households. The representative household has the GHH preferences (Greenwood et al., 1988)

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t \log\left(C_t - \theta\frac{N_t^{1+\gamma_N}}{1+\gamma_N}\right), \tag{4}$$

where $\beta \in (0,1)$ denotes the subjective discount factor, C_t denotes consumption, N_t denotes hours worked, $\theta > 0$ is the utility weight for leisure, $\gamma_N > 0$ is the inverse Frisch elasticity of labor supply, and $\mathbb{E}$ is the unconditional expectation operator.

The household chooses consumption C_t, labor supply N_t, and the end-of-period capital stock K_{t+1} to maximize the utility (4), subject to the sequence of budget constraints

$$C_t + K_{t+1} = W_t N_t + R_t K_t + D_t + (1-\delta)K_t, \tag{5}$$

taking as given the wage rate W_t, the capital rental rate R_t, and the dividend income from firms D_t. The parameter $\delta \in (0,1)$ denotes the capital depreciation rate.

The household's optimizing decisions lead to the labor supply equation

$$W_t = \theta N_t^{\gamma_N}, \tag{6}$$

and the intertemporal Euler equation

$$1 = \mathbb{E}_t M_{t+1}(1-\delta+R_{t+1}), \tag{7}$$

26% relative to the average level. Through the information channel, the news media shocks also reduces the cost of capital by $0.095 \times 1.4\% \approx 0.13\%$.

[18]We obtained similar results when we use variations in analysts' forecast errors (instead of financial news coverage) as a proxy for changes in firms' information acquisition costs. See Appendix A.4.

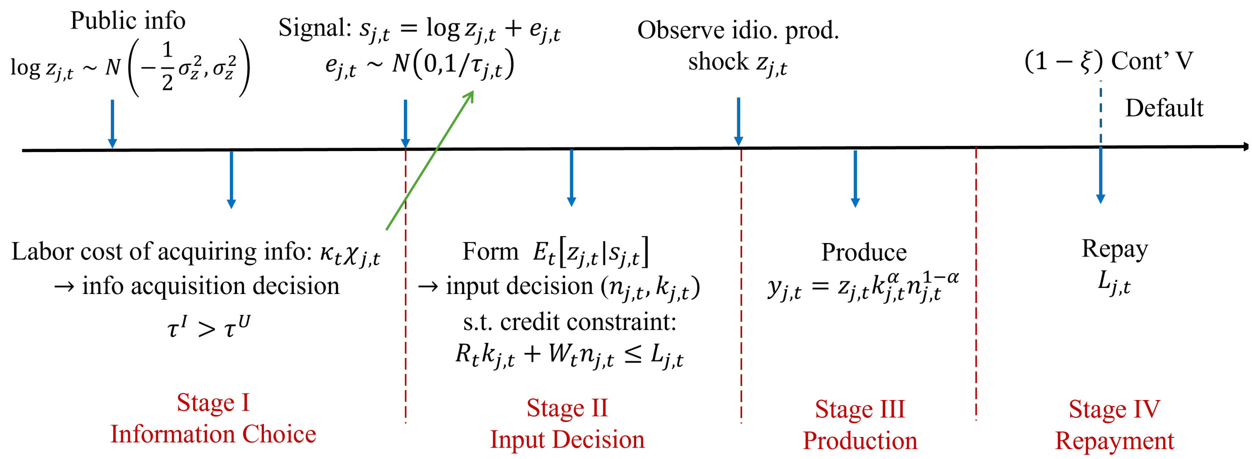


FIGURE 4. Timeline of events and decisions

where M_{t+1} is the stochastic discount factor given by

$$M_{t+1} = \beta \frac{C_t - \frac{N_t^{1+\gamma_N}}{1+\gamma_N}}{C_{t+1} - \frac{N_{t+1}^{1+\gamma_N}}{1+\gamma_N}}. \tag{8}$$

III.2. **Firm.** There is a continuum of firms indexed by $j \in [0, 1]$. Each firm operates a constant returns production technology that transforms capital and labor inputs into final consumption goods. The production function is given by

$$y_{j,t} = z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}, \tag{9}$$

where $z_{j,t}$ is the idiosyncratic productivity shock, $n_{j,t}$ denotes the labor input, $k_{j,t}$ denotes the capital input and $\alpha \in (0, 1)$ is the share of capital input. The productivity $z_{j,t}$ is independently and identically distributed across firms and over time, following the log-normal distribution

$$\log z_{j,t} \sim \mathcal{N}\left(-\frac{1}{2}\sigma_z^2, \sigma_z^2\right), \tag{10}$$

with a mean of 1 and a variance of $\exp(\sigma_z^2) - 1$.

III.2.1. *Timeline of events.* Timing is critical for the incorporation of financial frictions and information frictions within the model economy. Figure 4 depicts the timing of events within a period.

Within each period, there are four stages. In stage I, each firm observes the aggregate shocks and an idiosyncratic information acquisition cost $\chi_{j,t}$, which is a random variable that is independently and identically distributed (i.i.d.) across firms and over time, with the cumulative distribution function $F(\cdot)$. Each firm faces also an idiosyncratic productivity shock denoted by $z_{j,t}$. Although the distribution of $z_{j,t}$ is public information, individual firms do not observe their realizations at this stage. A firm can observe a noisy private signal $s_{j,t}$ about its productivity, such that

$$s_{j,t} = \log z_{j,t} + e_{j,t}, \quad e_{j,t} \sim N(0, 1/\tau_{j,t}), \tag{11}$$

where $\tau_{j,t}$ denotes the signal precision. After observing the signal, each firm decides whether or not to acquire information. To acquire information, firm j needs to hire $\kappa_t \chi_{j,t}$ units of information-related workers at the competitive wage rate W_t. The term κ_t denotes an exogenous aggregate information cost shock, which follows the stationary stochastic process

$$\log \kappa_t = (1 - \rho_\kappa) \log \kappa + \rho_\kappa \log \kappa_{t-1} + \sigma_\kappa \varepsilon_{\kappa t}, \tag{12}$$

where κ is the mean level of the information cost shock, $\rho_\kappa \in (0, 1)$ and σ_κ are, respectively, the persistence and the standard deviation of the shock, and $\varepsilon_{\kappa t}$ is the innovation that follows the standard normal distribution.

If a firm pays the information cost, then it receives a private signal with a high precision (i.e., $\tau_{j,t} = \tau^I$). In this case, the firm is "informed". Without paying the fixed cost, the private signal would have a low precision (i.e., $\tau_{j,t} = \tau^U < \tau^I$), in which case the firm is "uninformed."[19]

In stage II, each firm observes the realization of the signals $s_{j,t}$ and makes production decisions conditional on the perceived productivity. The firm hires $n_{j,t}$ units of production workers at the wage rate W_t and rents $k_{j,t}$ units of capital at the rental rate R_t. To finance its working capital (i.e., the payments to the input factors), the firm relies on external debt (or loans, denoted by $L_{j,t}$).

In stage III, each firm observes its own idiosyncratic productivity shocks $z_{j,t}$ and produces $y_{j,t}$ units of output according to the constant-returns production function (9).

In stage IV, a firm can choose to repay the loans $L_{j,t}$ or to default. If the firm repays the debt $L_{j,t}$, then it pays dividends $d_{j,t}$ to the household and enters the next period. Otherwise, if it defaults, a fraction $\xi_t \in (0, 1)$ of the firm's continuation value would be seized by the lender. With this type of imperfect contract enforcement, the ex ante borrowing limit for a firm would be ξ_t fraction of its expected continuation value (Kiyotaki and Moore, 1997). We assume that ξ_t follows the stationary stochastic process

$$\log \xi_t = (1 - \rho_\xi) \log \xi + \rho_\xi \log \xi_{t-1} + \sigma_\xi \varepsilon_{\xi t}, \tag{13}$$

[19]For tractability, we assume that firms make information choices without financial constraints, thereby eliminating the channel through which a firm must allocate limited borrowing capacity between production and information acquisition. Incorporating this additional channel would further strengthen our model's mechanism.

where ξ is the mean level of the information cost shock, $\rho_\xi \in (0,1)$ and σ_ξ are, respectively, the persistence and the standard deviation of the shock, and $\varepsilon_{\xi t}$ is the innovation that follows the standard normal distribution.

After the debt repayment decisions, the economy transitions to period $t+1$, and the same sequence of events repeats.

III.2.2. *Information structure.* Upon observing signal $s_{j,t}$, firm j updates its belief using Bayes' Law. Given prior distribution (10) and signal structure (11), firm j forms the following posterior distribution of $z_{j,t}$:

$$\log z_{j,t} \mid s_{j,t} \sim \mathcal{N}\left(\frac{\sigma_z^{-2}\mu_z + \tau_{j,t}s_{j,t}}{\sigma_z^{-2} + \tau_{j,t}}, \frac{1}{\sigma_z^{-2} + \tau_{j,t}}\right), \tag{14}$$

where the posterior mean is a weighted average of the prior mean $\mu_z = -\frac{1}{2}\sigma_z^2$ and signal realization $s_{j,t}$. A firm assigns a greater weight on its signal if the signal precision $\tau_{j,t} \in \{\tau^I, \tau^U\}$ is higher. The signal precision depends on the firm's information choices: an informed firm receives more precise private signals than an uninformed one (i.e., $\tau^I > \tau^U$).

Conditional on the signal $s_{j,t}$, firm j's expectations (or forecasts) of its productivity $z_{j,t}$ is given by

$$\mu_{j,t} \equiv \mathbb{E}\left[z_{j,t} \mid s_{j,t}\right] = \exp\left(\frac{\tau_{j,t}}{\sigma_z^{-2} + \tau_{j,t}} s_{j,t}\right). \tag{15}$$

The forecast $\mu_{j,t}$ follows a log-normal distribution, with $\log \mu_{j,t} \sim \mathcal{N}\left(-\frac{1}{2}(\sigma_\mu^I)^2, (\sigma_\mu^I)^2\right)$ for informed firms, and $\log \mu_{j,t} \sim \mathcal{N}\left(-\frac{1}{2}(\sigma_\mu^U)^2, (\sigma_\mu^U)^2\right)$ for uninformed firms, where $(\sigma_\mu^I)^2 = \frac{\tau^I}{\sigma_z^{-2}+\tau^I}\sigma_z^2 > (\sigma_\mu^U)^2 = \frac{\tau^U}{\sigma_z^{-2}+\tau^U}\sigma_z^2$. The conditional forecasts of productivity $(\mu_{j,t})$ by informed firms have a larger dispersion than those by uninformed firms (i.e., $\sigma_\mu^I > \sigma_\mu^U$), reflecting that the forecasts of informed firms are closer to the true productivity $z_{j,t}$.[20] We denote the cumulative distribution functions of the forecasts $\mu_{j,t}$ by G^I and G^U for informed firms and uninformed firms, respectively.

We solve the firm's optimization problems backward. We begin by deriving the firm's credit constraint based on its default decision at the end of a period. Next, we examine the firm's optimal production decision given its borrowing capacity and available information sets. Finally, we analyze the optimal information choice at the beginning of the period.

[20]To see this, consider the extreme case with $\tau^U \to 0$, such that uninformed firms do not learn anything from the productivity signals. In this case, the conditional forecast $\mu_{j,t}$ by uninformed firms would become degenerate, collapsing to the unconditional expectations of $z_{j,t}$, with zero dispersion (i.e., $(\sigma_\mu^U)^2 = \frac{\tau^U}{\sigma_z^{-2}+\tau^U}\sigma_z^2 = 0$). A more precise signal leads to a larger dispersion of the conditional forecast, such that the forecast is closer to the true productivity process.

III.2.3. *Production decision.* Based on its private information $\{s_{j,t}\}$ and public information, a firm forms expectation on its individual productivity, denoted as $\mu_{j,t} = \mathbb{E}[z_{j,t} \mid s_{j,t}]$, and choose production inputs $k_{j,t}$ and $n_{j,t}$ accordingly to maximize the expected value.

The firm's optimization problem can be formulated as follows:

$$V_t(\mu_{j,t}) = \max_{n_{j,t},k_{j,t}} \mu_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha} + L_{j,t} - R_t k_{j,t} - W_t n_{j,t} + \max\{-L_{j,t} + \mathbb{E}_t M_{t+1} V_{j,t+1}, (1-\xi_t)\mathbb{E}_t M_{t+1} V_{j,t+1}\}$$

subject to the working capital constraint

$$R_t k_{j,t} + W_t n_{j,t} \leq L_{j,t}. \tag{16}$$

In this model, contract enforcement is imperfect, creating an incentive for firms to default on their loans. To rule out default in equilibrium, the incentive compatibility constraint requires an upper bound on the total amount of loans granted to the firm, such that

$$L_{j,t} \leq \xi_t \mathbb{E}_t M_{t+1} V_{j,t+1} \equiv \xi_t P_t, \tag{17}$$

where $P_t \equiv \mathbb{E}_t M_{t+1} V_{j,t+1}$ denotes the firm's ex-dividend stock price, i.e., the continuation value. Since firms are ex ante identical and the productivity shocks are i.i.d. across firms and over time, we conjecture (and later verify) that the stock market value P_t is identical for all firms. An increase in either the default punishment ξ_t or the stock value P_t would reduce the incentive to default, thereby enhancing a firm's borrowing capacity.

After imposing the incentive-compatibility constraint (17), we can rewrite the firm's optimizing problem as

$$V_t(\mu_{j,t}) = \max_{n_{j,t},k_{j,t}} \mu_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha} - R_t k_{j,t} - W_t n_{j,t} + P_t. \tag{18}$$

The optimal choices of labor and capital inputs are described by the first-order conditions

$$\alpha \mu_{j,t} k_{j,t}^{\alpha-1} n_{j,t}^{1-\alpha} = (1+\omega_{j,t}) R_t, \tag{19}$$

$$(1-\alpha)\,\mu_{j,t} k_{j,t}^{\alpha} n_{j,t}^{-\alpha} = (1+\omega_{j,t}) W_t, \tag{20}$$

where $\omega_{j,t}$ is the Lagrangian multiplier of the borrowing constraint (16). Using the factor demand functions, we obtain the firm's expected profit (or dividend flow, denoted by $d_{j,t}$) conditional on its private signal, and it is given by

$$\mathbb{E}[d_{j,t} \mid s_{j,t}] = \left\{ \mu_{j,t} \left[\frac{(1-\alpha) R_t}{\alpha W_t} \right]^{1-\alpha} - \frac{1}{\alpha} R_t \right\} k_{j,t} \tag{21}$$

A firm would choose to be active in production if and only if its expected productivity $\mu_{j,t}$ is sufficiently high such that $\mathbb{E}[d_{j,t} \mid s_{j,t}] \geq 0$. It follows that there exists a threshold level of the expected productivity μ_t^* such that a firm chooses to engage in production subject to binding credit constraints if and only if $\mu_{j,t} \geq \mu_t^*$. Conversely, if the expected productivity is below this threshold, the firm would remain inactive. At the threshold level of the expected productivity, the firm expects zero profit, rendering it indifferent between producing and remaining inactive. This indifference condition establishes the threshold level of the expected productivity

$$\mu_t^* \equiv \left(\frac{R_t}{\alpha}\right)^{\alpha}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}. \tag{22}$$

The expected productivity threshold increases with the factor prices R_t and W_t, such that an increase in the marginal cost of production would turn some active firms with expected productivity close to the threshold into inactive ones.

If $\mu_{j,t} \geq \mu_t^*$, then the firm produces as much as possible, until it reaches the borrowing capacity. Conversely, if $\mu_{j,t} < \mu_t^*$, the firm rents no capital, hires no workers, and does not engage in production. The optimal factor demand functions can be summarized by

$$k_{j,t} = \begin{cases} \frac{\alpha}{R_t}\xi_t P_t, & \mu_{j,t} \geq \mu_t^* \\ 0, & \mu_{j,t} < \mu_t^* \end{cases} \tag{23}$$

and

$$n_{j,t} = \begin{cases} \frac{1-\alpha}{W_t}\xi_t P_t, & \mu_{j,t} \geq \mu_t^* \\ 0, & \mu_{j,t} < \mu_t^* \end{cases} \tag{24}$$

After the realization of idiosyncratic productivity $z_{j,t}$, the realized output from production is

$$y_{j,t} = \begin{cases} \frac{z_{j,t}}{\mu_t^*}\xi_t P_t, & \mu_{j,t} \geq \mu_t^* \\ 0, & \mu_{j,t} < \mu_t^*. \end{cases} \tag{25}$$

Accordingly, the realized profit is

$$d_{j,t} = \begin{cases} \left(\frac{z_{j,t}}{\mu_t^*} - 1\right)\xi_t P_t & \mu_{j,t} \geq \mu_t^* \\ 0, & \mu_{j,t} < \mu_t^*. \end{cases} \tag{26}$$

Firm j's expected value function conditional on its signal is

$$V_t(\mu_{j,t}) = \max\left(\frac{\mu_{j,t}}{\mu_t^*} - 1, 0\right)\xi_t P_t + P_t. \tag{27}$$

III.2.4. *Information choice.* At the beginning of a period, the signal $s_{j,t}$ and, consequently, the expected productivity $\mu_{j,t}$ have not yet been realized. A firm's decision regarding information acquisition influences the precision of $s_{j,t}$ and, therefore, the distribution of $\mu_{j,t}$. We define a dummy variable $\mathcal{I}_{j,t}$, which takes the value of 1 if firm j acquires information and 0 if it does not. Conditional on $\mathcal{I}_{j,t}$, firm j's expected value prior to drawing signal $s_{j,t}$ is

$$\overline{V}_t(\mathcal{I}_{j,t}) = \begin{cases} \xi_t \pi^I(\mu_t^*)P_t + P_t, & \mathcal{I}_{j,t} = 1 \\ \xi_t \pi^U(\mu_t^*)P_t + P_t, & \mathcal{I}_{j,t} = 0 \end{cases}$$

where $\pi^I(\mu_t^*)$ and $\pi^U(\mu_t^*)$ are the expected profit rates prior to the signal realization, which are given by

$$\pi^I(\mu_t^*) = \mathbb{E}\left[\max\left(\frac{\mu_{j,t}}{\mu_t^*} - 1, 0\right) \mid \mathcal{I}_{j,t} = 1\right],$$

and

$$\pi^U(\mu_t^*) = \mathbb{E}\left[\max\left(\frac{\mu_{j,t}}{\mu_t^*} - 1, 0\right) \mid \mathcal{I}_{j,t} = 0\right].$$

Lemma III.1. *Informed firms have higher expected profits than uninformed firms. That is,* $\pi^I(\mu_t^*) > \pi^U(\mu_t^*)$.

Proof. By the information structure, $\log \mu_{j,t}|_{\mathcal{I}_{j,t}=1} \sim \mathcal{N}(-\frac{1}{2}(\sigma_\mu^I)^2, (\sigma_\mu^I)^2)$ and $\log \mu_{j,t}|_{\mathcal{I}_{j,t}=0} \sim \mathcal{N}(-\frac{1}{2}(\sigma_\mu^U)^2, (\sigma_\mu^U)^2)$, with $(\sigma_\mu^I)^2 = \frac{\tau^I}{\sigma_z^{-2}+\tau^I}\sigma_z^2 > (\sigma_\mu^U)^2 = \frac{\tau^U}{\sigma_z^{-2}+\tau^U}\sigma_z^2$. Since $\mathbb{E}[\mu_{j,t} \mid \mathcal{I}_{j,t} = 1] = \mathbb{E}[\mu_{j,t} \mid \mathcal{I}_{j,t} = 0] = 1$ and $Var(\mu_{j,t} \mid \mathcal{I}_{j,t} = 1) = \exp((\sigma_\mu^I)^2) - 1 > Var(\mu_{j,t} \mid \mathcal{I}_{j,t} = 0) = \exp((\sigma_\mu^U)^2) - 1$, the expected productivity $(\mu_{j,t})$ of informed firms is a mean-preserving spread of that of uninformed firms. Since the expected profit function $\max\left(\frac{\mu_{j,t}}{\mu_t^*} - 1, 0\right)$ is convex in $\mu_{j,t}$, it follows from the Jensen's inequality that $\pi^I(\mu_t^*) > \pi^U(\mu_t^*)$. □

As signal precision improves, the signal approaches the true productivity to be realized. This enables firms to exploit the signal's option value in production decisions: they expand output when the signal is high or remain inactive when the signal is low. In contrast, with less precise signals—or in the extreme case where the signal is entirely uninformative—firms disregard the signal and rely on the common prior expectation to make production decision. Given the convex payoff structure associated with productivity, this lack of flexibility translates into a lower ex-ante expected profit compared to scenarios with precise signals.

A firm makes its optimal information choice by balancing the marginal benefits and costs of acquiring information. The costs involve hiring $\kappa_t\chi_{j,t}$ units of information-related workers at the competitive wage rate W_t. Thus, firm j faces the binary information choice problem

$$\max\left\{\left[1 + \xi_t\pi^I(\mu_t^*)\right] P_t - W_t\kappa_t\chi_{j,t}, \left[1 + \xi_t\pi^U(\mu_t^*)\right] P_t\right\}. \tag{28}$$

where the first (second) term represents the expected net profit with (without) information acquisition. There exists a threshold level of the idiosyncratic information acquisition cost, denoted by χ_t^*, such that a firm acquires information if and only if $\chi_{j,t} \leq \chi_t^*$. This threshold is pinned down by the indifference condition of information acquisition such that

$$W_t\kappa_t\chi_t^* = \left[\pi^I(\mu_t^*) - \pi^U(\mu_t^*)\right] \xi_t P_t. \tag{29}$$

The threshold χ_t^* increases with the relative payoffs from information acquisition $(\pi^I(\mu_t^*) - \pi^U(\mu_t^*))$ and the expected stock market value (P_t). An increase in the stock market value allows the firm to expand its borrowing capacity and thus increases the scale of production.

Since informed firms have higher expected profit than uninformed firms (i.e., $\pi^I(\mu_t^*) > \pi^U(\mu_t^*)$), the benefits of information acquisition increase as well, raising the threshold of information costs and inducing more firms to acquire information.

III.2.5. *Stock market value.* Lastly, we can establish the dynamic pricing equation of firms' stock market value P_t. At the beginning of a period, conditional on the realization of individual information cost $\chi_{j,t}$, the firm value is

$$\overline{V}_t(\chi_{j,t}) = \begin{cases} -W_t\kappa_t\chi_{j,t} + \left[1 + \xi_t\pi^I(\mu_t^*)\right] P_t, & \text{if} \quad \chi_{j,t} \leq \chi_t^*, \\ \left[1 + \xi_t\pi^U(\mu_t^*)\right] P_t, & \text{otherwise.} \end{cases} \tag{30}$$

Therefore, the stock market value is

$$P_t = \mathbb{E}_t M_{t+1} \int_{\chi_{j,t+1}} \overline{V}_{t+1}(\chi_{j,t+1}) dF(\chi_{j,t+1}) = \mathbb{E}_t M_{t+1}(\pi_{t+1}\xi P_{t+1} + P_{t+1}) \tag{31}$$

where $\mathbb{E}_t$ is the expectation operator based on period-t information, and π_{t+1} represents the average profit rate, given by

$$\pi_{t+1} = \pi^U(\mu_{t+1}^*) + \left[\int_0^{\chi_{t+1}^*} \left(1 - \frac{\chi_{j,t+1}}{\chi_{t+1}^*}\right) dF(\chi_{j,t+1})\right] \left[\pi^I(\mu_{t+1}^*) - \pi^U(\mu_{t+1}^*)\right]. \tag{32}$$

The average profit π_{t+1} increases with the future information acquisition threshold χ_{t+1}^*, highlighting an important dynamic feedback channel due to endogenous borrowing capacity. As more firms acquire information in the future, reflected by a rise in χ_{t+1}^*, their expected profitability also increases. This raises the current stock value through the asset pricing equation (31), which, in turn, relaxes the current borrowing constraint and encourages more current information acquisition, as indicated by equation (29).

Eq. (31) also verifies our conjecture that the continuation value $\mathbb{E}_t M_{t+1} V_{j,t+1}$ is identical for all firms.

III.3. **Equilibrium.** A competitive equilibrium consists of sequences of prices $\{W_t, R_t\}$, household allocations $\{C_t, K_t, N_t\}$, and firm allocations $\{k_{j,t}(\mu_{j,t}), n_{j,t}(\mu_{j,t}), y_{j,t}(\mu_{j,t}), \mathcal{I}_{j,t}(\chi_{j,t})\}$ such that, taking the prices as given, the allocations for each type of agents solve their optimization problems and all markets clear.

III.3.1. *Aggregate productivity and allocation efficiency.* Define aggregate output, capital and productive labor (distinguished from labor allocated to information acquisition) as $Y_t \equiv \int_0^1 y_{j,t} dj$, $K_t \equiv \int_0^1 k_{j,t} dj$ and $N_t^P \equiv \int_0^1 n_{j,t} dj$.

Proposition 1. The aggregate production function is given by

$$Y_t = A_t K_t^\alpha (N_t^P)^{1-\alpha}, \tag{33}$$

where A_t denotes the endogenous total factor productivity (TFP) and is given by

$$A_t = \frac{F(\chi_t^*)[1 - G^I(\mu_t^*)]A_t^I + [1 - F(\chi_t^*)]\,[1 - G^U(\mu_t^*)]A_t^U}{\underbrace{F(\chi_t^*)[1 - G^I(\mu_t^*)]}_{\textit{Mass: active informed firms}} + \underbrace{[1 - F(\chi_t^*)][1 - G^U(\mu_t^*)]}_{\textit{Mass: active uninformed firms}}}. \tag{34}$$

Here, A_t^I and A_t^U are the aggregate expected productivity of active informed and uninformed firms, respectively, and they are given by

$$A_t^I = \mathbb{E}\left[\mu_{j,t} \mid \mu_{j,t} \geq \mu_t^*, \mathcal{I}_{jt} = 1\right], \quad A_t^U = \mathbb{E}\left[\mu_{j,t} \mid \mu_{j,t} \geq \mu_t^*, \mathcal{I}_{j,t} = 0\right]. \tag{35}$$

Proof. See Appendix B.1. □

The constant-returns-to-scale production technology facilitates the derivation of a tractable aggregate production function. Idiosyncratic information costs divide firms into informed and uninformed groups: firms with low information costs ($\chi_{j,t} \leq \chi_t^*$) acquire information, whereas those with high information costs ($\chi_{j,t} > \chi_t^*$) remain uninformed. Among both informed and uninformed firms, credit constraints further categorize firms into active and inactive groups: firms with high expected productivity ($\mu_{j,t} \geq \mu_t^*$) choose to operate, while those with low productivity expectations ($\mu_{j,t} < \mu_t^*$) choose to suspend production. Consequently, the total factor productivity, A_t, is a weighted average of the productivity of active informed firms, A_t^I, and active uninformed firms, A_t^U, with weights determined by their respective shares among active firms.

Proposition 2. Informed firms on average have higher productivity than uninformed firms, such that $A_t^I > A_t^U$. Furthermore, aggregate TFP A_t increases with both information acquisition threshold χ_t^* and expected productivity threshold μ_t^*.

Proof. See Appendix B.2. □

Allocation efficiency is influenced by both information frictions and financial frictions. In the absence of these frictions, due to the constant-returns-to-scale production technology, all resources would be allocated to the most productive firm, which is the one with the highest realized productivity $z_{j,t}$. However, the presence of these frictions causes market allocations to deviate from the optimal outcome.

With information frictions, firms make production decisions based on expected productivity $\mu_{j,t}$ rather than true productivity $z_{j,t}$. If expected productivity underestimates true productivity levels, firms will underproduce; conversely, if it overestimates, firms will overproduce. Both scenarios result in inefficiencies. As the information acquisition threshold χ_t^* increases, more firms opt to acquire information, leading to more accurate productivity forecasts. This reduces the deviation of their production decisions from full-information levels, thereby improving allocation efficiency.

Financial frictions further distort resource allocation by limiting production scales. Firms with high productivity expectations on average have higher realized productivity than those with low expectations. However, credit constraints limit the production scale of high-productivity firms, leading to resource misallocation. As indicated by equation (22), tightened credit constraints depress factor prices by restraining high-productivity firms from expanding, lowering the productivity threshold and enabling a subset of low-productivity firms to stay active. This in turn reduces aggregate TFP.

III.3.2. *Factor prices.* By Equation (19) and (20), the wage rate and the capital rental rate are respectively given by

$$W_t = (1-\alpha)\,\mu_t^* K_t^{\alpha} (N_t^P)^{-\alpha}, \tag{36}$$

$$R_t = \alpha \mu_t^* K_t^{\alpha-1} (N_t^P)^{1-\alpha}. \tag{37}$$

Thus, the factor prices reflect the marginal products of the input factors of the firms with expected productivity at the threshold level (i.e., μ_t^*).

III.3.3. *Labor market clearing condition.* Labor market clearing implies that

$$N_t = N_t^P + N_t^I, \tag{38}$$

where N_t is the labor supply. The term N_t^P is the aggregate demand for production workers given by

$$N_t^P = \underbrace{\left\{F(\chi_t^*)\left[1-G^I(\mu_t^*)\right] + \left[1-F(\chi_t^*)\right]\left[1-G^U(\mu_t^*)\right]\right\}}_{\textit{mass of active firms}} \times \underbrace{\frac{1-\alpha}{W_t}\xi_t P_t}_{\textit{productive labor per active firm}} \tag{39}$$

and N_t^I is the aggregate demand for information workers given by

$$N_t^I = \kappa_t \int_0^{\chi_t^*} \chi_{j,t} dF(\chi_{j,t}). \tag{40}$$

III.3.4. *Equilibrium system.* In summary, the equilibrium system can be characterized by the aggregate variables $\{Y_t, N_t, N_t^P, N_t^I, C_t, K_t, P_t, W_t, R_t, \chi_t^*, \mu_t^*\}$, which are determined by equations (6), (7), (29), (31), (33), (36), (37), (38), (39), (40), along the aggregate resource constraint

$$C_t + K_{t+1} = (1-\delta)K_t + Y_t. \tag{41}$$

III.4. **Mechanism.** The key mechanism of this model lies in the two-way feedback between information acquisition and borrowing constraints. This feedback mechanism amplifies the impact of exogenous shocks, particularly shocks to information costs or to the borrowing capacity.

Table 4 summarizes the model's key equilibrium conditions, alongside two counterfactual scenarios: exogenous information and exogenous borrowing constraints. Eq.a in the table represents the labor market clearing condition (38), capturing the general equilibrium interaction between the information choice cutoff χ_t^* and the production cutoff μ_t^*. Since $1 - G^I(\mu_t^*) > 1 - G^U(\mu_t^*)$, that is, informed firms are more likely to operate, a general equilibrium complementarity exists between the two cutoffs. An increase in χ_t^* raises the labor demand for both goods production and information acquisition, driving up equilibrium wages and, consequently, the production cutoff μ_t^*.

Eq.b in Table 4 describes the equilibrium trade-off for information acquisition, derived from combining the indifference condition (29), the labor market clearing condition (38), and aggregate demand for production workers in Eq. (39). The left-hand side represents the marginal cost of acquiring information (in labor units), and the right-hand side represents the marginal benefit, also in labor units. Investing in information acquisition turns a firm from uninformed to informed, yielding a net profit gain (per worker) of $\frac{\pi^I(\mu_t^*)-\pi^U(\mu_t^*)}{1-\alpha}$, which, multiplied by the number of production workers per active firm, yields the marginal benefit of information acquisition.[21] In the case of exogenous information, we assume a constant threshold for information choices, such that the mass of informed firms is fixed at $\bar{\chi}$.

Eq.c in Table 4 presents the borrowing constraint. It is endogenously determined by the firm's incentive of repayment, with the borrowing capacity given by a fraction ξ_t of the firm's stock market value. The stock market value itself is determined recursively by the dynamic asset pricing equation. In the case with exogenous borrowing constraints, the borrowing capacity is assumed to be a constant at $\bar{L}$.

[21]The term $N_t - \kappa_t \int_0^{\chi_t^*} \chi_{j,t} dF(\chi_{j,t})$ measures total production labor, and $F(\chi_t^*)\left[1 - G^I(\mu_t^*)\right] + \left[1 - F(\chi_t^*)\right]\left[1 - G^U(\mu_t^*)\right]$ measures the number of active firms. The ratio of these two terms thus measures the production labor per active firm.

TABLE 4. A summary of the key mechanism

Labor market clearing condition (Eq.a)	
$N_t = \left\{F(\chi_t^*)\left[1 - G^I(\mu_t^*)\right] + \left[1 - F(\chi_t^*)\right]\left[1 - G^U(\mu_t^*)\right]\right\} \frac{1-\alpha}{W_t} L_t + \kappa_t \int_0^{\chi_t^*} \chi_{j,t} dF(\chi_{j,t})$	
Endogenous Information (Eq.b)	Exogenous Information
$\kappa_t \chi_t^* = \frac{\pi^I(\mu_t^*) - \pi^U(\mu_t^*)}{1-\alpha} \frac{N_t - \kappa_t \int_0^{\chi_t^*} \chi_{j,t} dF(\chi_{j,t})}{F(\chi_t^*)[1-G^I(\mu_t^*)] + [1-F(\chi_t^*)][1-G^U(\mu_t^*)]}$	$\chi_t^* = \bar{\chi}$
Endogenous Borrowing Constraint (Eq.c)	Exogenous Borrowing Constraint
$L_t = \xi_t P_t$ $P_t = \mathbb{E}_t M_{t+1}\left[\pi_{t+1}(\mu_{t+1}^*, \chi_{t+1}^*) L_{t+1} + P_{t+1}\right]$	$L_t = \bar{L}$

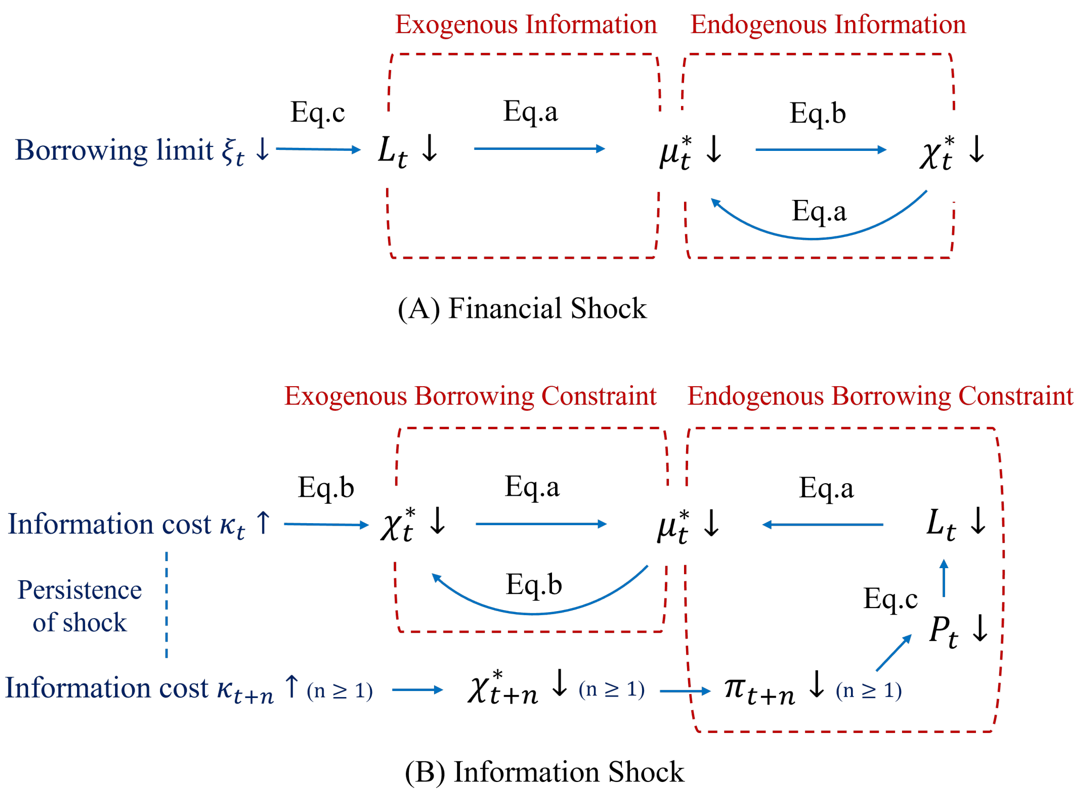


FIGURE 5. Graphical illustration of two-way feedback mechanism

To illustrate the amplification effect of the two-way feedback mechanism, we analyze two exogenous shocks: one to the aggregate information cost κ_t and the other to the borrowing limit ξ_t. Figure 5 provides graphical illustrations.

Panel (A) shows that when the borrowing capacity shrinks, active firms scale back production, weakening demand for production factors. This pushes down factor prices and lowers the production threshold μ_t^*, as described by Eq.a in Table 4. This effect arises even without endogenous information acquisition (the left box). When firms can endogenously make information choices, deteriorated credit access further discourages equilibrium information acquisition (the right box). According to Eq.b in Table 4, a lower productivity cutoff μ_t^* diminishes the production scale of individual firms by both suppressing total labor supply (via reduced wages) and increasing the number of active firms. Since some low productivity firms turn from inactive to active in production, aggregate TFP falls. Consequently, active firms experience smaller profit gains from information production, reducing the mass of informed firms (as the information choice cutoff χ_t^* falls). The decline in information production raises firm-level uncertainty and further curtails production and information acquisition, pushing the production cutoff μ_t^* even lower. Thus, endogenous information acquisition amplifies the initial macroeconomic and reallocation effects triggered by an exogenous tightening of credit conditions.

Panel (B) of Figure 5 illustrates the propagation mechanism of an information shock that raises the cost of information acquisition (κ_t), where endogenous borrowing constraints operate through a dynamic channel. An increase in information acquisition cost directly reduces the mass of informed firms, raising the level of uncertainty and turning some unproductive firms from inactive to active in production, as indicated by a lower production cutoff μ_t^* (Eq.a in Table 4). This reallocation lowers aggregate TFP, reducing the gains from information production, and thus further discouraging information acquisition (Eq.b in Table 4). This effect works independently of endogenous borrowing constraints. When borrowing capacity is endogenously tied to a firm's stock market value, an additional dynamic feedback loop arises through the forward-looking asset-pricing equation (Eq.c in Table 4). If the information shock persists over multiple periods, reduced future information acquisition undermines future profitability, which depresses the current stock price. As a result, firms are able to borrow less today, enabling more unproductive firms to enter production and further lowering production cutoffs. This amplifies the initial impact of the information shock.

III.5. **Steady state.** The steady-state equilibrium can be characterized by the two key thresholds: the information choice cutoff χ^* and the production cutoff μ^*, which can be solved analytically from the two equilibrium conditions

$$\kappa\chi^* = \frac{\pi^I(\mu^*) - \pi^U(\mu^*)}{1-\alpha} \frac{N(\mu^*) - \kappa \int^{\chi_t^*} \chi_j F(\chi_j)}{F(\chi^*)\left[1 - G^I(\mu^*)\right] + \left[1 - F(\chi^*)\right]\left[1 - G^U(\mu^*)\right]} \tag{42}$$

$$\left(\frac{1}{\beta} - 1\right)\frac{1}{\xi} = \pi^U(\mu^*) + \left[\int_0^{\chi^*} \left(1 - \frac{\chi_j}{\chi^*}\right) dF(\chi)\right]\left[\pi^I(\mu^*) - \pi^U(\mu^*)\right] \tag{43}$$

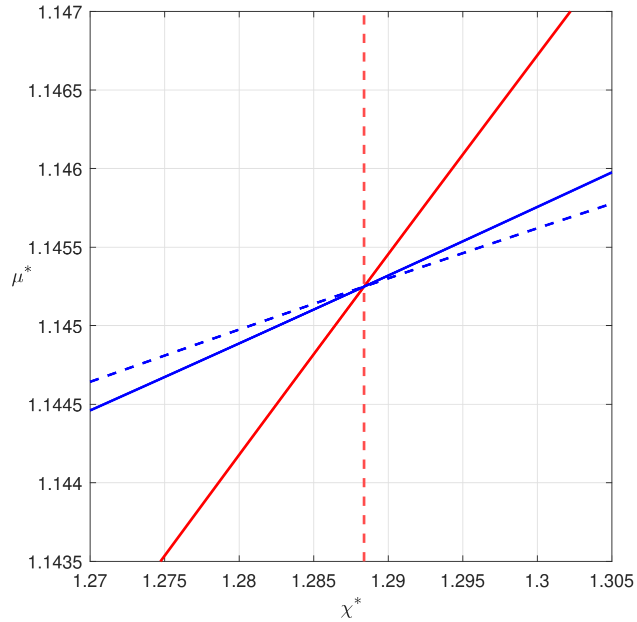


FIGURE 6. Two-way feedback effect in the steady-state equilibrium

Notes: The red solid line and blue solid line plot Eq. (42) and (43), respectively. The dashed red line is the counterpart of Equation (42) under exogenous information, where χ^* is fixed. The dashed blue line is the counterpart of Equation (43) under exogenous borrowing constraints, where borrowing capacity is fixed. Parameter values are set based on Table 5.

where

$$N(\mu^*) = \left[\frac{1-\alpha}{\theta} \left(\frac{\alpha}{1/\beta - 1 + \delta} \right)^{\frac{\alpha}{1-\alpha}} \right]^{\frac{1}{\gamma_N}} (\mu^*)^{\frac{1}{(1-\alpha)\gamma_N}}$$

Equation (42) is the steady-state version of Eq.a in Table 4. Equation (43) corresponds to Eq.c in Table 4 evaluated at steady state, where we have imposed the average profit equation (32). These two equations reflect the two-way interactions between information friction and credit constraints and they pin down the two steady-state equilibrium variables: the information cutoff χ^* and the production cutoff μ^*.

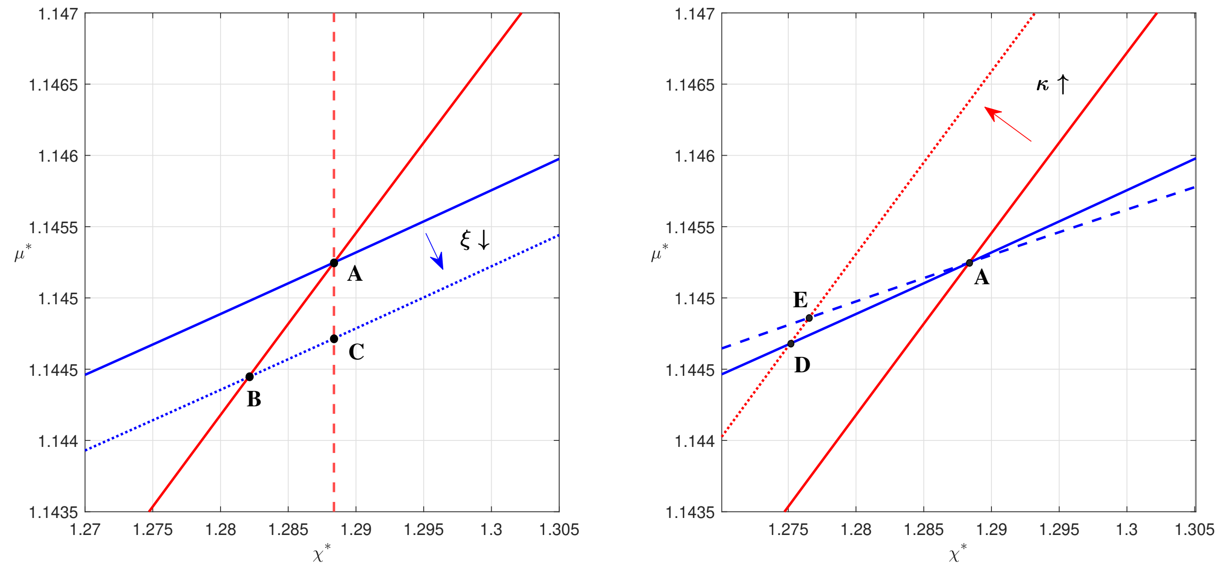
Figure 6 plots Equation (42) (red solid line) and Equation (43) (blue solid line). For comparison, we also depict an exogenous-information counterpart of Equation (42) (the vertical red dashed line), where the information cutoff χ^* is fixed at $\bar{\chi}$, independent of the production cutoff μ^*. Additionally, we include the counterpart of Equation (43) under an exogenous borrowing constraint with the borrowing capacity fixed at $\bar{L}$ (blue dashed line), which is notably flatter than the original curve. Under an endogenous borrowing constraint, an increase in steady-state information production (i.e., an increase in χ^*) boosts profitability and the firms' stock market value, thereby expanding the borrowing capacity. This, in turn, intensifies the competition for production factors, raising the factor prices and pushing some low-productivity firms out of the set of active firms. This reallocation improves aggregate TFP, amplifying the initial increase in the production cutoff and resulting in a steeper relation between μ^* and χ^* than that in the case with a fixed borrowing capacity.

Figure 7 illustrates the comparative statics. Panel (A) depicts the effects of a permanent tightening of the borrowing constraints, represented by a reduction in the loan-to-value ratio ξ. The blue solid line denotes the initial position of Equation (43). The tighter borrowing constraints reduce the production scale for active firms, lowering demand for production factors. The decline in factor prices enable some low-productivity firms to become active in production and thereby lowering the production cutoff μ^* for a given information choice cutoff χ^*. As a result, Equation (43) shifts downward from the blue solid line to the blue dotted line. Points A denotes the initial equilibrium, while B and C indicate the new steady states under the baseline model and the counterfactual with exogenous information, respectively. When firms are allowed to make endogenous information choices, fewer firms choose to acquire information. This lowers the information cutoff χ^*, which further depresses the production cutoff μ^* due to the deteriorated productivity of operating firms.

Panel (B) of Figure 7 shows the impact of higher information acquisition costs. As firms become less willing to acquire information, Equation (42) shifts upward, from the red solid line to the red dotted line. Points D and E represent the new steady states under the baseline model and the counterfactual with exogenous borrowing constraints, respectively. When borrowing limits are endogenously tied to stock values, reduced borrowing capacity further weakens the equilibrium selection effect, lowering the production cutoff μ^*. This reduces labor hiring per active firm, making information acquisition less profitable and further decreasing the information cutoff χ^*. As a result, under endogenous borrowing constraints, the steady state features both lower average productivity (lower μ^*) and fewer informed firms (lower χ^*).

III.6. **Dynamics.** To examine the model's transmission mechanism, we solve the dynamic model and compute impulse responses based on calibrated parameters.

III.6.1. *Calibration.* Table 5 displays the parameter calibration. The first set of parameters $\{\beta, \alpha, \delta, \gamma_N, \theta\}$ are calibrated following the business cycle literature. We set the subject discount factor to $\beta = 0.99$, which corresponds to an annualized risk-free rate of 4 percent since one period in our model corresponds to one quarter. We set the cost share of capital to $\alpha = 0.34$, the capital depreciation rate to $\delta = 0.025$, and the inverse Frisch elasticity to $\gamma_N = 0.2$. We calibrate the relative utility weight on leisure, θ, such that model-implied steady-state labor hours is one-third of the total time endowment. We calibrate the average



(A) Reducing borrowing capacity

(B) Increasing information acquisition cost

Figure 7. Comparative statics

Notes: Panel (A) and (B) plot the steady-state effect of reducing borrowing capacity and increasing information production cost, respectively. In panel (A), the solid blue line and dotted blue line plot the original and new position of Equation (43), the solid red line plots Equation (42), and the dashed red line plots the case of exogenous information, where χ^* is fixed at the original steady-state level. Point A and B mark the new steady states under exogenous information and endogenous information, respectively. In panel (B), the solid red line and dotted red line plot the the original and new position of Equation (42), the solid blue line plots Equation (43), and the dashed red line plots the case of exogenous borrowing constraint, where the borrowing capacity is fixed at the original steady-state level. Point C and D represent the new steady states under exogenous borrowing constraint and endogenous borrowing constraint, respectively. Parameter values are set based on the calibration in Table 5.

loan-to-value ratio to $\xi = 0.35$, matching the average ratio of working capital to market equity in the Compustat data.

The second set of parameters $\{\sigma_z^2, \tau^I, \tau^U, \kappa, \eta, \chi_m\}$ characterize information frictions. This set of parameters includes σ_z^2, which governs the volatility of firms' priors about their productivity; τ^I and τ^U, that measure the precisions of the signals for informed and uninformed firms, respectively; κ, which measures aggregate costs of information aggregation; and η and χ_m, the shape and the scale parameters of the Pareto-distribution of the idiosyncratic information cost with the c.d.f. $F(\chi_{j,t}) = 1 - (\chi_{j,t}/\chi_m)^{-\eta}$. These parameters jointly shape the cost, benefit, and equilibrium outcome of firms' endogenous information acquisition.

We calibrate σ_z^2 by targeting the observed volatility of idiosyncratic profitability, measured by the realized log dispersion in markup (defined as the sales/cost ratio) of Compustat firms.[22] To calibrate the signal precision parameters τ^I and τ^U, we target two moments in the data: (1) the average posterior uncertainty, measured by the dispersion of log forecast errors in markups, and (2) the gains of forecast precision from information acquisition, measured as the ratio of posterior uncertainties between informed and uninformed firms, where we classify a firm as informed in a given quarter if its share of information-related job postings is above the median in the same quarter based on the Lightcast data. For the parameters characterizing information costs, we normalize the scale parameter of the idiosyncratic information cost distsribution to $\chi_m = 1$ and we calibrate the shape parameter η along with the mean of the aggregate information cost parameter κ by targeting two moments in the Lightcast data: the share of informed firms, which is 50% by definition, and the average share of information-related job postings.[23] Table 6 summarizes the targeted moments.

The third set of parameters characterize the stochastic processes of the exogenous shocks. These parameters include $\{\rho_\kappa,\ \sigma_\kappa,\ \rho_\xi,\ \sigma_\xi\}$. We estimate the persistence of the information acquisition cost ρ_κ to 0.98 to match the persistence of the firm-level financial news coverage.[24] We set the persistence of the financial shock as $\rho_\xi = 0.97$, based on the estimation of Jermann and Quadrini (2012). The standard deviations of both shocks are normalized to 0.01.

III.6.2. *Macroeconomic effects of financial shocks.* Our firm-level evidence suggests that a shock that tightens firms' credit constraints discourages information acquisition. We now use our calibrated model to examine the economic mechanism and the quantitative importance of a financial shock for the aggregate economy.

For this purpose, we consider two types of financial shocks, one is a direct shock to the loan-to-value (LTV) ratio ξ_t, and the other is an aggregate TFP news shock that affects expected future cash flows, in line with the oil news shock that we studied in the empirical

[22]In the model, an active firm's sales are $\frac{z_{j,t}}{\mu_t^*}\xi_t P_t$ and its cost is $\xi_t P_t$, implying a log markup of $\log z_{j,t} - \log \mu_t^*$. Calibration details are in Appendix D.

[23]The average share of information-related job posting is computed as the average of quarterly ratio of information-related job postings to total job postings.

[24]To obtain the persistence of the firm-level financial news coverage, we estimate the following panel regression

$$\log(FinNews_{j,t}) = \beta_0 + \beta_1 \cdot \log(FinNews_{j,t-1}) + \phi_t + \eta_j + \varepsilon_{j,t}$$

where $\log(FinNews_{j,t})$ represents the log of financial news coverage on firm j in year t. ϕ_t and η_j are time fixed and firm fixed effect respectively. We obtain an estimate of $\beta_1 = 0.91$ at the annual frequency, equivalent to 0.98 at the quarterly frequency.

Table 5. Calibrated Parameters

	Parameter Description	Value
β	Subjective discount factor	0.99
α	Capital share	0.34
δ	Capital depreciation rate	0.025
γ_N	Inverse Frisch elasticity	0.2
θ	Utility weight on leisure	3.253
ξ	Loan to value ratio	0.35
σ_z^2	Dispersion of firm-level TFP shock	0.1354
$\frac{1}{\tau^I+\sigma_z^{-2}}$	Posterior uncertainty: informed	$0.35\sigma_z^2$
$\frac{1}{\tau^U+\sigma_z^{-2}}$	Posterior uncertainty: uninformed	$0.71\sigma_z^2$
κ	Aggregate information cost	$0.141N_{ss}$
η	Shape of individual information cost	2.33
χ_m	Level of individual information cost	1
σ_κ	Volatility of information shock	1%
ρ_κ	Persistence of information shock	0.98
σ_ξ	Volatility of financial shock	1%
ρ_ξ	Persistence of financial shock	0.97

Table 6. Targeted Moments

Moments	Data	Model
SD of log markup	0.30	0.30
SD of log forecast error in markup / SD of log markup	0.91	0.90
SD of log forecast error in markup: informed / uninformed	0.70	0.70
Share of informed firms	0.50	0.50
Average share of information-related jobs	0.07	0.07

Notes: This table presents targeted moments. Markup equals sales over cost expenditure. Expected markup equals expected sales over cost expenditure, derived from IBES managerial earning guidance data. Log forecast error is defined as $\log(\textit{markup}) - \log(\textit{markup forecast})$. Computation details are in Appendix D.

section. Conditional on a financial shock, we simulate the calibrated model based on third-order approximations of the equilibrium conditions around the deterministic steady-state.[25]

[25] We adopt the methodology of Fernández-Villaverde et al. (2011) and Leduc and Liu (2016) to compute impulse responses. Specifically, the model is first simulated over a large number of periods to compute the ergodic mean of each variable. It is then simulated using the ergodic means as a starting point. Impulse responses to aggregate shocks are calculated as the difference between the simulated path with the shock and the baseline path without shocks. This approach helps capture potential nonlinear effects of the shock.

Figure 8 displays the impulse response functions (IRFs) to a 1% reduction in the LTV, both in the baseline calibrated economy (blue solid line) and a counterfactual economy with the share of informed firms fixed at the steady state level (red dashed line). The LTV shock that tightens firms' borrowing constraints reduces the production scale of active firms, depressing factor prices, and allowing some low-productivity firms to turn active. The resulting misallocation reduces aggregate TFP, triggering a recession with synchronized declines in output, consumption, investment, and labor hours, as shown in the Figure. The resulting decline in the stock price further tightens the borrowing constraints for active firms, deepening the recession. This financial accelerator mechanism operates even in the absence of information frictions (i.e., the counterfactual with a fixed share of informed firms), in line with the literature (Liu and Wang, 2014). With endogenous information production as in our baseline model, the LTV shock reduces expected profits, discouraging information production and resulting in a lower share of informed firms (see the middle panel of the Figure). With less information, firms on average make more errors in forecasting productivity and thus face higher levels of uncertainty. This in turn reduces the expected profits and the stock price. The declines in the stock price further tighten the firms' borrowing constraints, creating a feedback loop that throws the economy into a "finance-uncertainty trap."

The information channel is quantitatively important for amplifying and prolonging the macroeconomic effects of the financial shock. Figure 8 shows that, compared to the counterfactual with no endogenous variations in information acquisition, the baseline model generates a substantially deeper and longer recession. For example, following a one-percent reduction in the LTV ratio, the maximum decline in aggregate output in the baseline economy is about 28% more than that in the counterfactual, and output also stays below the steady-state level for a much longer duration.

The second financial shock that we consider is a TFP news shock.[26] With forward-looking credit constraints, our model features a novel intertemporal channel of information acquisition: a news shock that raises expected future profits incentivizes information acquisition today. Through this intertemporal channel, a news shock has immediate impacts on the aggregate economy. The mechanism echoes our empirical findings that oil supply news shocks drive changes in information acquisition and firm performance through financial frictions (see Section II.3).

We examine the impacts of a news shock that raises the expected four-quarter-ahead aggregate TFP by 1%.[27] Figure 9 displays the IRFs in the baseline economy with endogenous

[26]Chen and Song (2013) and Görtz et al. (2022) provide theory and evidence showing financial frictions as a transmission mechanism for news shocks to translate into aggregate TFP fluctuations.

[27]We do not include aggregate TFP shocks in the baseline model for ease of exposition. To incorporate a TFP news shock, we assume that firm-level productivity includes an exogenous aggregate component

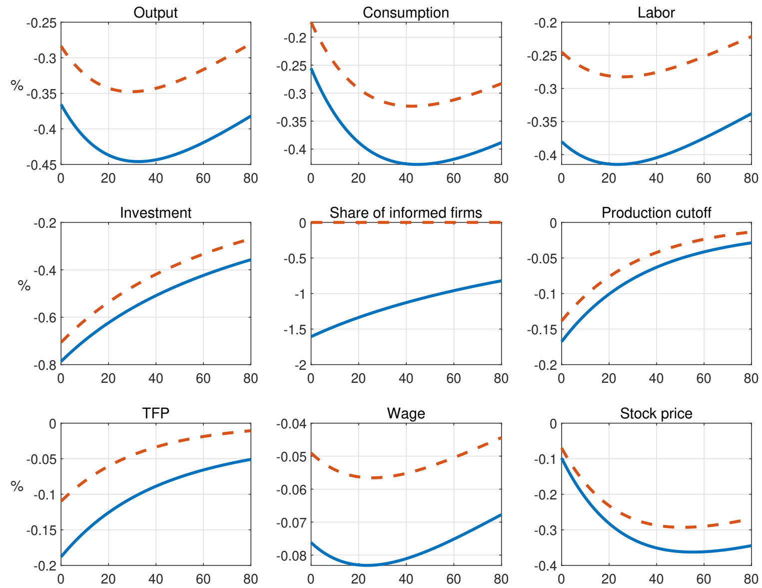


FIGURE 8. Impulse response to financial shocks: Baseline model vs. counterfactual with exogenous information

Notes: This figure shows the IRFs to a negative 1% shock to loan-to-value ratio ξ_t in the calibrated model (blue solid lines) and in the counterfactual model where the information choice cutoff χ_t^* is fixed at its steady-state level (red dashed lines). The horizontal axis shows the periods (quarters) since the impact of the shock. The vertical axis shows the percent deviations of each variable from its steady-state level. Parameters are calibrated according to Table 5.

information acquisition (blue solid lines) and and a counterfactual one where the share of informed firms is fixed at the steady state level (red dashed line). The news shock immediately raises the forward-looking stock prices, relaxing the borrowing constraints faced by active firms. The resulting increases in factor demand push up worker wages and capital rents and thus raising the productivity threshold μ_t^*. Since some low-productivity firms become inactive, the endogenous component of aggregate TFP rises, raising current-period output before the productivity news is materialized. With endogenous information acquisition, the increased expected profitability raises the share of informed firms, amplifying the positive effect of the news shock through the finance-information feedback loop. The amplification is also quantitatively large. Compared to the counterfactual economy with a fixed share of

(denoted by Z_t) such that the production function (9) is replaced by $y_{j,t} = Z_t z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}$, where aggregate TFP follows the stationary stochastic process:

$$\log(Z_t) = \rho_Z \log(Z_{t-1}) + \sigma_Z \varepsilon_{Z,t-4} \tag{44}$$

where $\varepsilon_{Z,t-4}$ denotes the news shocks that increase the four-quarter ahead TFP, ρ_Z denotes the persistence of the TFP shock, and σ_Z denotes the standard deviation of the news shock. We follow the literature and set the persistence to $\rho_z = 0.95$ (Smets and Wouters, 2007) and we normalize the size of the shock to $\sigma_Z = 0.01$.

informed firms, aggregate output in the baseline economy increases by about 30% more in the impact period (i.e., period 0) of the news shock.[28]

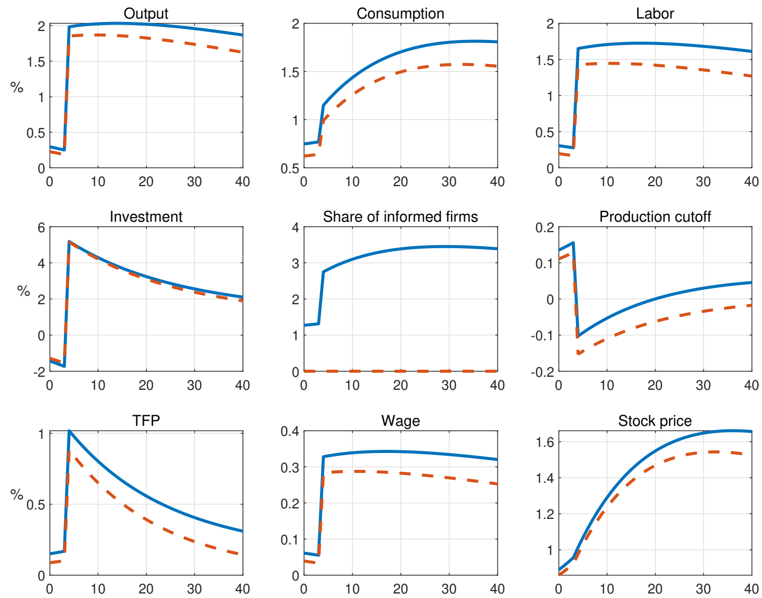


FIGURE 9. Impulse response to TFP news shocks: Benchmark model vs. counterfactual with exogenous information

Notes: This figure shows the IRFs to a news shock that raises four-quarter-ahead aggregate TFP by 1% in the calibrated model (blue solid lines) and in the counterfactual model where the information choice cutoff χ_t^* is fixed at its steady-state level (red dashed lines). The horizontal axis shows the periods (quarters). The vertical axis shows the percent deviations of each variable from its steady-state level. The persistence of TFP process is set at 0.95. Other parameters are calibrated according to Table 5.

III.6.3. *Macroeconomic effects of information shocks.* Our empirical evidence also suggests that a shock that raises the cost of information production (e.g., a negative financial news media shock) hampers firms' credit access. We now use our calibrated model to examine the macroeconomic impacts of a shock to information acquisition costs and the quantitative importance of the credit-constraint channel for propagating the information shock.

Figure 10 displays the IRFs to an information shock that raises the aggregate cost of information production in the baseline model (blue solid line) and also in the counterfactual with the firms' borrowing limit fixed at its steady-state value (red dashed line). The rise in the information costs discourages information acquisition, reducing the share of informed firms and raising the level of uncertainty. Facing higher uncertainty, active firms scale back production, lowering factor demand and factor prices. The declines in factor prices

[28]The news shock raises period-0 output by 0.295% in the baseline model and by 0.227% in the counterfactual, implying an amplification of (0.295%-0.227%)/0.227% ≈ 30% through the information channel.

in turn allow some low-productivity firms to turn from inactive to active in production, exacerbating the misallocation of resources and resulting in a decline in aggregate TFP. By depressing TFP, the shock generates a recession with synchronized declines in aggregate output, consumption, investment, and labor hours.

Endogenous credit constraint propagates and amplifies the impacts of information shocks. In the baseline model with an endogenous borrowing capacity, the information shock reduces the expected profitability and firms' equity value, further tightening credit constraints for active firms. Relative to the counterfactual with a fixed borrowing capacity, the endogenous responses of the borrowing limit in our baseline model exacerbates the decline in aggregate TFP, further deepening the recession.

The credit-constraint channel is quantitatively important, as illustrated by the differences between the blue solid lines and the red dashed lines in Figure 10. For example, the maximum decline in aggregate output induced by the information shock in the baseline model is about 38% larger than that in the counterfactual economy with a fixed borrowing capacity. The recessionary effects of the shock are also more persistent in the baseline economy.

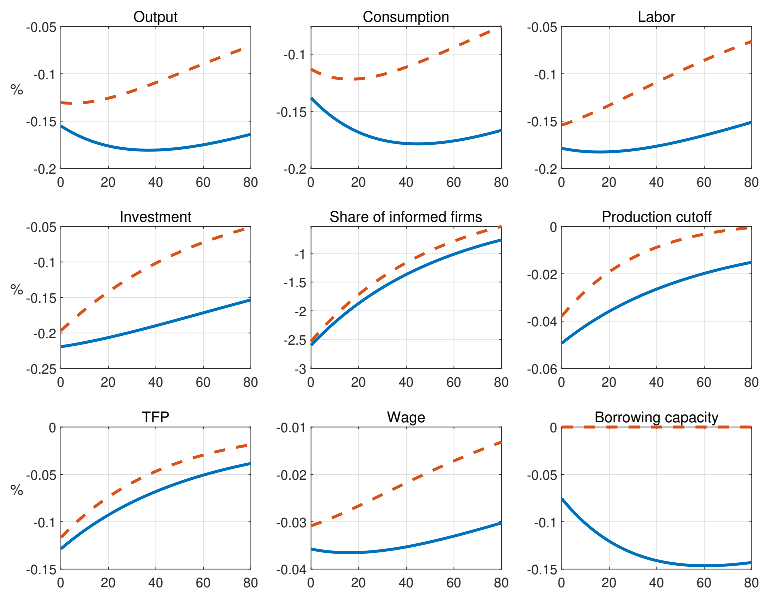


FIGURE 10. Impulse response to information shocks: Benchmark model vs. counterfactual with fixed borrowing capacity

Notes: This figure shows the IRFs to a 1% positive shock to the aggregate information cost κ in the calibrated model (blue solid lines) and in the counterfactual model where the borrowing capacity is fixed at its steady-state level(red dashed lines). The horizontal axis shows the periods (quarters) since the impact of the shock. The vertical axis shows the percent deviations of each variable from its steady-state level. Parameters are calibrated according to Table 5.

IV. Conclusions

We have documented empirical evidence on the two-way feedback between information acquisition and financial frictions. Our evidence suggests that a shock that tightens a firm's borrowing capacity discourages information acquisition efforts; and conversely, a shock that raises a firm's cost of information production hampers the firm's access to external credit. We develop a tractable dynamic general equilibrium model where firms face incomplete information and credit constraints and show that the interactions between information acquisition and financial frictions create a finance-uncertainty trap. An increase in the costs of acquiring information discourages learning and raises the level of uncertainty, reducing the firm's expected profits and further hampering the firm's credit access. A tightening of credit constraints, on the other hand, limits the scale of production by high-productivity firms, reallocating resources to lower-productivity firms. The resulting misallocation reduces aggregate productivity, lowering firms' stock market value and the benefits of information acquisition. Our calibrated model suggests that this finance-uncertainty trap plays a quantitatively important role in amplifying and propagating business cycle shocks.

In our model, the presence of incomplete information and financial frictions renders the competitive equilibrium allocations sub-optimal and appropriate policy interventions can potentially improve welfare. For example, one could use our framework to evaluate the macroeconomic and welfare implications of targeted credit supports during downturns (such as the Paycheck Protection Program loans implemented during the Covid period). Such policy would allow active, high-productivity firms to maintain credit access in a recession, alleviating the misallocation associated with credit constraints. Furthermore, such policy could also encourage active firms' information production, reducing the level of uncertainty, and enabling the economy to escape from the finance-uncertainty trap. Similarly, policies that encourage information dissemination, for example, through countercyclical subsidies to financial news production, could reduce the level of uncertainty, mitigating the declines in firm value, and thereby alleviating the recessionary effects of the finance-uncertainty trap. In light of our finding that the finance-uncertainty trap plays a quantitatively important role in the transmission of business cycle shocks, studying the macro and welfare implications of these policies is an important and promising avenue for future research.

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Appendix

Appendix A. Additional Empirical Results

A.1. **Average response to the changes in aggregate credit condition.** In the main text, we document evidence that changes in aggregate financial conditions reduce information-related hiring for firms with high leverage relative to the median level. Here, we further examine the *average* effects of changes in aggregate credit conditions on firms' information acquisition intensity.

We estimate the local projections specification

$$\begin{aligned} \Delta^k InfoJob_{j,t+k} &= \beta_{0,k} + \beta_{1,k}\Delta InfoJob_{j,t-1} + \beta_{2,k}ANFCI_t \\ &+ \Phi_{j,t} + \Omega_t + \eta_j + \varepsilon_{j,t,k}, \quad k = 0, 1, 2, ... \end{aligned} \tag{A.1}$$

The variables in this regression are the same as in the baseline regression (1), except for the vector of macroeconomic control variables denoted by Ω_t, which includes real GDP growth and inflation.[29] The coefficient of interest is $\beta_{2,k}$, which captures the average responses of information acquisition intensity to changes in credit conditions.

Figure A.1 shows the estimated values of $\beta_{2,k}$. It indicates that a one-standard-deviation tightening of credit condition reduces the share of information-related job postings by approximately 28% at the one-year horizon (i.e., $k = 4$).[30]

[29]To estimate the average effects of changes in credit conditions, we cannot include time fixed effects, which would absorb the effects of $ANFCI_t$.

[30]A one-standard-deviation credit tightening reduces the share of information-related job postings by 2.37% at the one-year horizon, which is equivalent to a 2.37%/8.41% $\approx$ 28% reduction from the average level (8.41% in our sample).

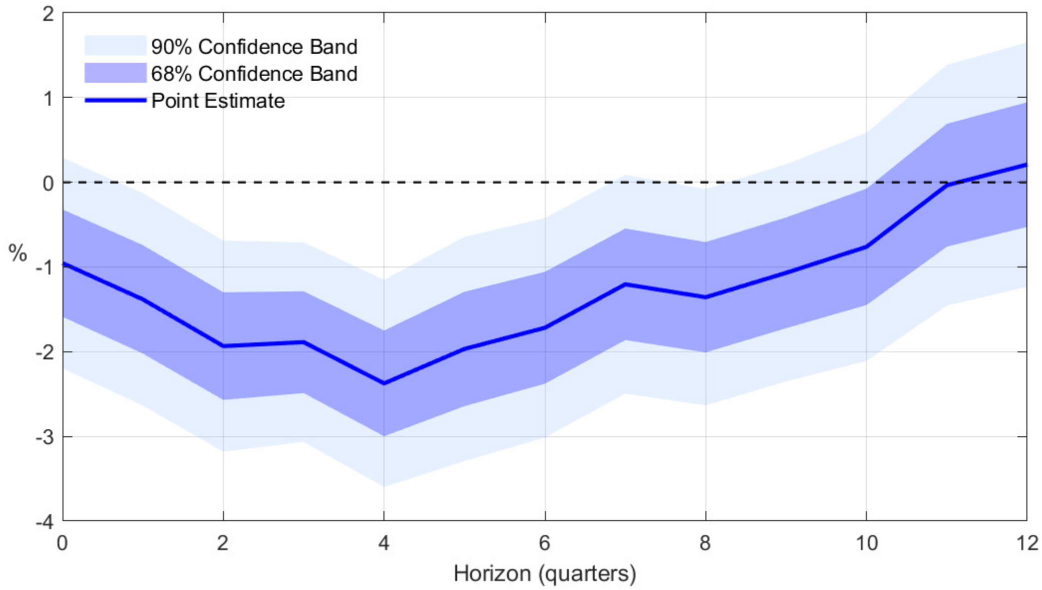

FIGURE A.1. Average response of the share of information-related job postings to a one-standard-deviation tightening of aggregate financial conditions

Notes: This figure shows the average response of information-related job posting share to a one-standard-deviation increase in the adjusted aggregate financial condition index (ANFCI).

A.2. **Robustness of the causal effects of credit shocks on information acquisition.** We conduct several robustness checks. First, we replace the baseline measure of firm-level exposures to oil price shocks by industry-level exposures ($OilExp_{s,t}$), i.e. the 252-trading-day rolling-window covariance of industry-level stock returns with oil price returns. We re-estimate the regression in Eq. (2). The results shown in Table A.1 (Column 1 for OLS and Column 4 for 2SLS) are consistent with the baseline results shown in Table 2.

TABLE A.1. Oil Supply News Shock and Firm Information Acquisition

Variable	(1) $\log(FE^F_{jt})$	(2) $\log(FE^F_{jt})$	(3) LW_{jt}	(4) $\log(FE^F_{jt})$	(5) $\log(FE^F_{jt})$
	OLS		2SLS		
$OilExp_{s,t}$	1.322**	1.319**	0.087	0.682	0.265
	(0.550)	(0.550)	(0.132)	(0.593)	(0.712)
$OilExp_{s,t} \cdot OilNews_t$	0.594***	0.978**	0.081**		
	(0.224)	(0.478)	(0.035)		
$\widehat{LW}_{jt}$				7.345***	12.101**
				(2.770)	(5.917)
$\lvert OilExp_{s,t}\rvert \cdot OilNews_t$		-0.516			-0.516
		(0.520)			(0.520)
Observations	18,951	18,951	17,081	18,951	18,951
R-squared	0.027	0.027	0.042	0.027	0.027
Firm Control	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results of the regression (2), where the exposure measure is replaced by that based on industry-level stock return covariance. The dependent variable is the log of absolute managerial earnings forecast error ($\log(FE^F)$) from IBES. $OilExp_{s,t}$ is measured as the one-year rolling-window covariance of SIC 4-digit industry-level stock returns with oil price returns. $OilNews_t$ is the positive oil supply news shock from Känzig (2021). LW_{jt} denotes the Linn-Weagley index measuring the tightness of firm-level credit constraints, and $\widehat{LW}_{jt}$ is the predicted value obtained from the OLS regression (Column 3). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

One potential concern is that oil news supply shocks may coincide with higher uncertainty about future oil price (Alfaro et al., 2024), which would incentivize firms with high exposures to oil price shocks (in the absolute value sense) to acquire more information in order to reduce uncertainty. To mitigate concerns about this alternative mechanism, we include interactions between oil supply news shocks and firm's absolute exposures to oil price as an additional control variable in the regression. According to the estimation results shown in Column (2) and (5), the coefficient of our interest, i.e. β_3, remains positive and statistically significant. Thus, our main results are robust after controlling for the potential confounding effects of oil price uncertainty.

We also estimate Eq.(2) using samples excluding firms from certain industries. For example, we remove mining and utility firms (with 2-digit NAICS code 21-22), who might be more exposed to oil price risk but less relevant for our study. Table A.2 shows that our results remain robust to using this sample. Our results are also robust to using a subsample excluding firms in the information-related service sector (with NAICS code 50-59), whose employment might be dominated by the info-related jobs (see Table A.3).

Table A.2. Oil Supply News Shock and Firm Information Acquisition (Excluding Mining and Utility Sectors)

	OLS			2SLS		
Variable	$\log(PE_{jt})$	$\log(FE^F_{jt})$	$\log(IJS_{j,t})$	LW_{jt}	$\log(FE^F_{jt})$	$\log(IJS_{jt})$
	(1)	(2)	(3)	(4)	(5)	(6)
$OilExp_{j,t}$	-0.000	0.693	-0.208**	0.038	0.470	-0.136
	(0.071)	(0.512)	(0.100)	(0.106)	(0.534)	(0.103)
$OilExp_{j,t} \times OilNews_t$	-0.068***	0.401*	-0.129*	0.069**		
	(0.024)	(0.227)	(0.073)	(0.034)		
$\widehat{LW}jt$					5.821*	-1.875*
					(3.292)	(1.060)
Observations	14,178	15,404	5,531	13,888	15,404	5,531
R-squared	0.749	0.030	0.347	0.033	0.030	0.347
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results a la Table 2, using a subsample excluding mining and utility firms. The dependent variables in the OLS regression include (1) the log of price-to-earnings ratio ($\log(PEjt)$), (2) the log of absolute managerial earnings forecast error ($\log(FE^F)$) from IBES; and (3) the log of information acquisition related job posting share ($IJS_{jt} \equiv 1 + 100 \cdot InfoJobPosting_{jt}/TotalJobPosting_{jt}$). $OilExp_{j,t}$ is the firm-level exposure to oil price shocks, measured as the one-year rolling-window correlation of stock returns with daily oil price returns. $OilNews_t$ is the oil supply news shock from Känzig (2021). LW_{jt} denotes the Linn-Weagley index measuring the tightness of firm-level credit constraints, and $\widehat{LW}_{jt}$ denotes the predicted firm-level financial constraint obtained from the first-stage regression (Column 4). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3. Oil Supply News Shock and Firm Information Acquisition (Excluding Information Service Related Firms)

	OLS			2SLS		
Variable	$\log(PE_{jt})$	$\log(FE^F_{jt})$	$\log(IJS_{j,t})$	LW_{jt}	$\log(FE^F_{jt})$	$\log(IJS_{jt})$
	(1)	(2)	(3)	(4)	(5)	(6)
$OilExp_{j,t}$	0.105	0.340	-0.211*	0.032	0.126	-0.141
	(0.078)	(0.562)	(0.111)	(0.123)	(0.576)	(0.111)
$OilExp_{j,t} \times OilNews_t$	-0.058**	0.476**	-0.156**	0.071*		
	(0.025)	(0.234)	(0.076)	(0.036)		
$\widehat{LW}jt$					6.744**	-2.210**
					(3.313)	(1.083)
Observations	11,034	11,882	4,237	10,730	11,882	4,237
R-squared	0.742	0.033	0.358	0.027	0.033	0.358
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results a la Table 2, using a subsample excluding information service related firms. The dependent variables in the OLS regression include (1) the log of price-to-earnings ratio ($\log(PEjt)$), (2) the log of absolute managerial earnings forecast error ($\log(FE^F)$) from IBES; and (3) the log of information acquisition related job posting share ($IJS_{jt} \equiv 1 + 100 \cdot InfoJobPosting_{jt}/TotalJobPosting_{jt}$). $OilExp_{j,t}$ is the firm-level exposure to oil price shocks, measured as the one-year rolling-window correlation of stock returns with daily oil price returns. $OilNews_t$ is the oil supply news shock from Känzig (2021). LW_{jt} denotes the Linn-Weagley index measuring the tightness of firm-level credit constraints, and $\widehat{LW}_{jt}$ denotes the predicted firm-level financial constraint obtained from the first-stage regression (Column 4). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.3. **Robustness of the casual effects of financial news shocks on firm credit access.** In the main text, we show that exogenous reductions in financial news production reduce information acquisition by firms and raise the cost of external financing.According our theory, the effects should be stronger for smaller firms, who are arguably more financially constrained and dependent on financial news coverage. Table A.4 confirmed that this is indeed the case when we repeat the estimation using a subsample of firms with asset size below the median.

TABLE A.4. Impacts of Financial News Shock on Firm External Financing (Small Firms)

Panel A: OLS					
Variables	$\Delta Debt^{ST}jt$	$\Delta Debt^{LT}jt$	$\Delta Equity_{jt}$	$\log(CoC_{jt})$	
	(1)	(2)	(3)	(4)	
$\Delta FinNews_{j,t-1}$	0.000	0.002***	0.003***	-0.005***	
	(0.000)	(0.000)	(0.000)	(0.002)	
Observations	32,276	64,016	64,016	41,310	
R-squared	0.039	0.020	0.012	0.690	
Firm-level Controls	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	

Panel B: 2SLS					
Variables	FE^F_{jt}	$\Delta Debt^{ST}jt$	$\Delta Debt^{LT}jt$	$\Delta Equity_{jt}$	$\log(CoC_{jt})$
	(1)	(2)	(3)	(4)	(5)
$\Delta FinNews_{j,t-1}$	-0.061**				
	(0.026)				
$\widehat{FE}^F_{jt}$		-0.007	-0.026***	-0.045***	0.076***
		(0.005)	(0.007)	(0.005)	(0.026)
Observations	8,219	32,276	64,016	64,016	41,310
R-squared	0.018	0.039	0.020	0.012	0.690
Firm-level Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results of the regression. The dependent variables are (1) $\Delta Debt^{ST}jt$: short-term debt issuance (measured as the quarter-to-quarter change in short term debt, or Compustat item dlcch, scaled by asset), (2) $\Delta Debt^{LT}jt$: long-term debt issuance (measured as the quarter-to-quarter change in long term debt, or Compustat item dltis-dltr, scaled by asset), (3) $\Delta Equity_{jt}$: equity issues (measure as the quarter-to-quarter change in equity issuance, or Compustat item sstk, scaled by asset), and (4) $\log(CoC_{jt})$: the logarithm of the implied cost of capital constructed by Lee et al. (2021). The independent variable $\Delta FinNews_{j,t-1}$ is the the financial news shock to firm j constructed by Hu (2024). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4. **Analyst forecast precision.** In the main text, we show that exogenous reductions in financial news production reduce information acquisition by firms and raise the cost of external financing. In this subsection, we consider an alternative source of variations in information friction based on the precisions of financial analysts' forecasts of firms' earnings per share available from IBES database. Since analysts and firm managers share a common pool of information sources (such as news coverage, policy changes, etc.), variations in analysts' forecast precision could capture changes in the quality of information accessible by firm managers.

For our purpose, we regress alternative measures of firm performance on the size (i.e., absolute value) of the average forecast errors by analysts, based on the empirical specification

$$y_{j,t} = \beta_0 + \beta_1 \log(FE^A_{j,t}) + \Phi_{j,t} + \gamma_t + \eta_j + \varepsilon_{j,t}. \tag{A.2}$$

where the dependent variable $y_{j,t}$ includes (1) the tightness of firm-level financial constraints measured by the Linn-Weagley (LW) index, denoted as LW_{jt}; (2) the growth rate of earnings before interest, taxes, depreciation, and amortization, denoted as $\Delta \log(EBITDA_{jt})$; (3) the log of the price-to-earnings (P/E) ratio, denoted $\log(PE_{jt})$; and (4) the log of return on assets ($\log(ROA_{jt})$). The key independent variable $FE^A_{j,t}$ is the average forecast error by *analysts* on firm j's EPS (scaled by the end-of-period stock share price). We control for firm-level characteristics, summarized by $\Phi_{j,t}$, as well as firm- and time- fixed effects.

Table A.5 summarizes the estimation results. The table shows that a lower precision of the analyst forecasts (i.e., a larger forecast error) is associated with an increase in the tightness of the firm's financing constraints (Column (1)) and reductions in firm valuation and profitability (Columns (2)-(4)). These correlations are statistically significant at the 90 or 95 percent confidence levels. They suggest that a deterioration in the information environment hampers firm performance and weakens its access to external credit.

Table A.5. Analyst's forecast error and firm performance

Variables	(1) LW_{jt}	(2) $\Delta\log(EBITDA_{jt})$	(3) $\log(PE_{jt})$	(4) $\log(ROA_{jt})$
$\log(FE^A_{j,t})$	0.007^{**}	-0.003^{***}	-0.089^{***}	-0.056^{***}
	(0.003)	(0.001)	(0.003)	(0.004)
Constant	0.067	0.238^{***}	1.592^{***}	-1.792^{***}
	(0.080)	(0.020)	(0.085)	(0.087)
Observations	79,154	73,783	71,001	71,904
R-squared	0.011	0.089	0.717	0.161
Firm Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of the regressions of firm performance on analysts' forecast errors. The dependent variables shown in the 4 columns include, respectively, (1) firm-level financial constraints (LW_{jt}) measured by the Linn-Weagley index; (2) changes in the log of EBITDA; (3) the log of the P/E ratio; and (4) the log of return on assets. The independent variable, $\log(FE^A_{j,t})$, is the log of the average analyst forecast errors on earnings per share, scaled by the end-of-period stock price, which we use as a proxy for information acquisition costs. All regressions include firm-level controls, firm fixed effects, and time fixed effects. Robust standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix B. Proofs

In this section we provide additional information on deriving the model.

B.1. **Proof of Proposition 1.**

Proof. By individual decision rules (23), (24), and (25), we can obtain the aggregate capital

$$K_t = \left\{F(\chi_t^*)[1 - G^I(\mu_t^*)] + [1 - F(\chi_t^*)][1 - G^U(\mu_t^*)]\right\} \frac{\alpha}{R_t}\xi_t P_t, \tag{B.1}$$

the aggregate productive labor

$$N_t^P = \left\{F(\chi_t^*)[1 - G^I(\mu_t^*)] + [1 - F(\chi_t^*)][1 - G^U(\mu_t^*)]\right\} \frac{1-\alpha}{W_t}\xi_t P_t \tag{B.2}$$

and the aggregate output

$$\begin{aligned} Y_t &= \{F(\chi_t^*)\mathbb{E}[z_{j,t} \times \mathbf{1}(\mu_{j,t} \geq \mu_t^*) \mid \mathcal{I}_{j,t} = 1] \\ &\quad + [1 - F(\chi_t^*)]\mathbb{E}[z_{j,t} \times \mathbf{1}(\mu_{j,t} \geq \mu_t^*) \mid \mathcal{I}_{j,t} = 0]\} \frac{1}{\mu_t^*}\xi_t P_t \\ &= \left\{F(\chi_t^*) \int_{\mu_t^*} \mu_{j,t} dG^I(\mu_{j,t}) + [1 - F(\chi_t^*)] \int_{\mu_t^*} \mu_{j,t} dG^U(\mu_{j,t})\right\} \frac{1}{\mu_t^*}\xi_t P_t. \end{aligned} \tag{B.3}$$

The last equality holds for the following reasons. Since $z_{j,t} = \mu_{j,t} + v_{j,t}$ and $\mathbb{E}\left[v_{j,t} \mid \mu_{j,t}\right] = 0$, it follows that

$$\begin{aligned} & \mathbb{E}\left[z_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mathcal{I}_{j,t} = 1\right] \\ = \;& \mathbb{E}\left[\mu_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mathcal{I}_{j,t} = 1\right] + \mathbb{E}\left[v_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mathcal{I}_{j,t} = 1\right] \\ = \;& \mathbb{E}\left[\mu_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mathcal{I}_{j,t} = 1\right] + \mathbb{E}\left\{\mathbb{E}\left[v_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mu_t^*\right] \mid \mathcal{I}_{j,t} = 1\right\} \\ = \;& \int_{\mu_t^*}^{+\infty} \mu_{j,t} dG^I\left(\mu_{j,t}\right) + \mathbb{E}\left\{\mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \underbrace{E\left[v_{j,t} \mid \mu_t^*\right]}_{=0} \mid \mathcal{I}_{j,t} = 1\right\} \\ = \;& \int_{\mu_t^*}^{+\infty} \mu_{j,t} dG^I\left(\mu_{j,t}\right). \end{aligned}$$

Similarly,

$$\mathbb{E}\left[z_{j,t} \times \mathbf{1}\left(\mu_{j,t} \geq \mu_t^*\right) \mid \mathcal{I}_{j,t} = 0\right] = \int_{\mu_t^*}^{+\infty} \mu_{j,t} dG^U\left(\mu_{j,t}\right). \tag{B.4}$$

By Equation (B.1), (B.1), (B.3), and production cutoff definition (22), we can obtain the aggregate production function

$$Y_t = A_t K_t^\alpha (N_t^P)^{1-\alpha}, \tag{B.5}$$

where A_t is the endogenous total factor productivity (TFP), given by

$$A_t = \frac{F(\chi_t^*)[1 - G^I(\mu_t^*)]A_t^I + [1 - F(\chi_t^*)]\left[1 - G^U(\mu_t^*)\right]A_t^U}{F(\chi_t^*)[1 - G^I(\mu_t^*)] + [1 - F(\chi_t^*)][1 - G^U(\mu_t^*)]}. \tag{B.6}$$

A_t^I and A_t^U are the aggregate TFP for informed firms and uninformed firms:

$$A_t^I = \mathbb{E}\left[\mu_{j,t} \mid \mu_{j,t} \geq \mu_t^*, \mathcal{I}_{j,t} = 1\right] = \frac{\int_{\mu_t^*}^{+\infty} \mu_{j,t} dG^I(\mu_{j,t})}{1 - G^I(\mu_t^*)}, \tag{B.7}$$

$$A_t^U = \mathbb{E}\left[\mu_{j,t} \mid \mu_{j,t} \geq \mu_t^*, \mathcal{I}_{j,t} = 0\right] = \frac{\int_{\mu_t^*}^{+\infty} \mu_{j,t} dG^U(\mu_{j,t})}{1 - G^U(\mu_t^*)}. \tag{B.8}$$

□

B.2. **Proof of Proposition 2.** We first prove that improvement in forecast precision enhances the endogenous allocation efficiency, i.e., $A_t^I > A_t^U$.

Proof. Since $\log \mu_{j,t} \sim \mathcal{N}\left(-\frac{1}{2}(\sigma_\mu^I)^2, (\sigma_\mu^I)^2\right)$ for informed firms, and $\log \mu_j \sim \mathcal{N}\left(-\frac{1}{2}(\sigma_\mu^U)^2, (\sigma_\mu^U)^2\right)$ for uninformed firms, we can obtain that $A_t^I = A(\sigma_\mu^I, \mu_t^*)$ and $A_t^U = A(\sigma_\mu^U, \mu_t^*)$, where function $A(\sigma_\mu, \mu_t^*)$ is defined as

$$A(\sigma_\mu, \mu_t^*) = \frac{\Phi\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)}{1 - \Phi\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)},$$

where Φ is the c.d.f. of standard normal distribution.

Since $(\sigma_\mu^I)^2 = \frac{\tau^I}{\sigma_z^{-2} + \tau^I}\sigma_z^2 > (\sigma_\mu^U)^2 = \frac{\tau^U}{\sigma_z^{-2} + \tau^U}\sigma_z^2$, to prove $A_t^I > A_t^U$, we show that $\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu} > 0$.

$$\begin{aligned}
\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu} &\propto \frac{\phi\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)}{\Phi\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)}\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right) + \frac{\phi\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)}{1 - \Phi\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)}\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right) \\
&= \left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)\left[-\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)\right] \times \\
&\left\{\frac{\phi\left(-\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)\right)}{\Phi\left(-\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)\right)} \frac{1}{-\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)} - \frac{\phi\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)}{\Phi\left(\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}\right)} \frac{1}{\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu}}\right\},
\end{aligned}$$

where ϕ is the p.d.f. of the standard normal distribution.

To determine the sign of $\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu}$, we consider the following cases.

Case I: $\mu_t^* < \exp\left(-\frac{1}{2}\sigma_\mu^2\right) < \exp\left(\frac{1}{2}\sigma_\mu^2\right)$. In this case, $\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu} > -\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right) > 0$. For $x > 0$, $\frac{d}{dx}\left[\frac{\phi(x)}{\Phi(x)}\frac{1}{x}\right] < 0$. It follows that $\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu} > 0$.

Case II: $\exp\left(-\frac{1}{2}\sigma_\mu^2\right) < \mu_t^* < \exp\left(\frac{1}{2}\sigma_\mu^2\right)$. In this case, $\frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu} > 0 > -\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)$. We can directly obtain that $\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu} > 0$.

Case III: $\exp\left(-\frac{1}{2}\sigma_\mu^2\right) < \exp\left(\frac{1}{2}\sigma_\mu^2\right) < \mu_t^*$. In this case, $0 > \frac{1}{2}\sigma_\mu - \frac{\log \mu_t^*}{\sigma_\mu} > -\left(\frac{1}{2}\sigma_\mu + \frac{\log \mu_t^*}{\sigma_\mu}\right)$. For $x < 0$, $\frac{d}{dx}\left[\frac{\phi(x)}{\Phi(x)}\frac{1}{x}\right] < 0$. Therefore, $\frac{\partial A(\sigma_\mu, \mu_t^*)}{\partial \sigma_\mu} > 0$.

To sum up, we have shown that $\frac{\partial A(\sigma_\mu,\mu_t^*)}{\partial\sigma_\mu} > 0$ and $A_t^I > A_t^U$.

Next, we show that the aggregate TFP, A_t, increases with both the information cutoff χ_t^* and the production cutoff μ_t^*.

According to Equation (B.6), the aggregate total factor productivity (TFP), A_t, is computed as a weighted average of the TFP of informed firms, A_t^I, and uninformed firms, A_t^U, with the weights determined by the respective shares of informed and uninformed firms among active firms. As the information cutoff, χ_t^*, rises, a greater proportion of firms choose to acquire information, thereby increasing the share of informed firms among active firms, i.e., $\frac{F(\chi_t^*)[1-G^I(\mu_t^*)]}{F(\chi_t^*)[1-G^I(\mu_t^*)]+[1-F(\chi_t^*)][1-G^U(\mu_t^*)]}$. Given that informed firms have higher TFP ($A_t^I > A_t^U$), the increased weight of informed firms results in higher aggregate TFP. Therefore, A_t increases with χ_t^*.

Define a new cumulative distribution function for the expected productivity, $\mu_{j,t}$, as $\tilde{G}_t(\mu_{j,t}) = F(\chi_t^*)G^I(\mu_{j,t}) + [1-F(\chi_t^*)]G^U(\mu_{j,t})$. $\tilde{G}_t$ represents the c.d.f. of the expected productivity among active firms at period t. Then Equation (B.6) can be written as

$$A_t = \frac{F(\chi_t^*)\int_{\mu_t^*}^{+\infty}\mu_{j,t}dG^I(\mu_{j,t}) + [1-F(\chi_t^*)]\int_{\mu_t^*}^{+\infty}\mu_{j,t}dG^U(\mu_{j,t})}{F(\chi_t^*)[1-G^I(\mu_t^*)]+[1-F(\chi_t^*)][1-G^U(\mu_t^*)]} = \frac{\int_{\mu_t^*}^{+\infty}\mu_{j,t}d\tilde{G}_t(\mu_{j,t})}{1-\tilde{G}_t(\mu_t^*)}, \quad \text{(B.9)}$$

which implies that A_t increases with μ_t^*. □

Appendix C. Data Construction

We utilize data from Compustat, IBES, and Lightcast (formerly Burning Glass), which offer information on firms' balance sheets, earnings forecasts, and job postings, respectively. Below, we outline our sample construction procedures.

C.1. **Compustat Sample.** we employ the quarterly Compustat sample of US public firms, which spans from 1971Q1 to 2019Q4. Following the standard practice, We include firms incorporated in the US (Compustat fic = USA) that trade on major stock exchanges (NYSE, AMEX, and NASDAQ, Compustat exchg = 11, 12 or 14), for which the native currency is US dollars (Compustat curcd = USD). We exclude firm-quarter observations with obvious errors: missing or nonpositive values in reported revenue, employment, capital and total asset. We drop the following sectors: (1) agriculture, forestry, and fishing: $sic < 999$; (2) utilities: $4900 \leq sic \leq 4999$; (3) financial services: $6000 \leq sic \leq 6999$; (4) nonoperating establishments ($sic = 9995$) and industrial conglomerates ($sic = 9997$).

C.2. **IBES Sample.** We use managerial guidance and analyst forecasts from the IBES dataset.

C.2.1. *Managerial guidance.* For managerial guidance, we retrieve all quarterly earnings guidance from the IBES Guidance Detail file from 1994 to 2019. The sample starts in 1994 as this is the first year when the IBES systematically collected information on managerial guidance.

We focus on firms incorporated in the United States (IBES usfirm = 1) with their native currency in US dollars (IBES curr = USD). Following standard practice, we select earnings per share (EPS) as the primary forecast variable and use quarterly EPS forecasts, which target the EPS of a specific fiscal quarter. We include managerial guidance only if its announcement date falls within 0 to 93 days before the end of the targeted fiscal quarter. For firms with multiple guidance announcements for the same fiscal quarter, we retain only the earliest one within the quarter. For example, if Firm A issues guidance for the fiscal quarter ending December 31, 2018, on August 15, November 15, and December 15, we retain the November 15 announcement. The August 15 guidance is excluded as it occurs too far in advance, potentially reflecting uncertainty related to the fiscal quarter ending September 30, 2018.

Managerial guidance includes both point and range forecasts (with upper and lower bounds). For range forecasts, we calculate the midpoint between the upper and lower bounds as the final forecast value. The filtered guidance data is merged with quarterly Compustat data and beginning-of-quarter stock price data from CRSP. This process results in 36,529 observations spanning 1995Q2–2023Q4, averaging about 320 firms per quarter.

C.3. **Lightcast sample.** Lightcast's job posting data, available from 2010Q1, covers nearly all online job vacancies and includes the Lightcast Occupation Taxonomy (LOT) for each posting. While Lightcast includes both public and non-public companies, we focus on the sample of U.S. public firms.

C.3.1. *Identify information-related jobs.* With the help of large language models (Grok.com in our case), we are able to identify job postings related to information acquisition based on their Lightcast occupation taxonomy (LOT). To identify occupations related to information acquisition by firms—encompassing duties such as gathering data on market demand for products, production costs, aggregate economic conditions, and financial metrics—we employed an iterative prompting strategy utilizing the Grok large language model developed by xAI. Initially, without supplementary data, the model was queried with a prompt delineating the criteria for information acquisition roles, yielding illustrative examples including financial analysts, market research analysts, cost accountants, and economists.[31] Subsequently,

[31]The prompt given in this step is:"I am conducting research to identify jobs related to information acquisition within companies. These roles involve gathering data on factors influencing firms' profitability,

the model was furnished with a comprehensive taxonomy of occupations from the Lightcast database, comprising job titles and detailed duty descriptions, and instructed to select positions most aligned with the information acquisition framework based on textual analysis of the descriptions.[32] In a final refinement iteration, the model was directed to exclude less pertinent occupations from this subset, culminating in a curated list of 100 jobs deemed most relevant to the research objectives[33]. We label a job as information acquisition related if its LOT falls within the 100 categories listed in Table C.1.

C.3.2. *Identify firms which acquire information.* A firm is classified as an "informed" firm (corresponds to the firm which acquires information in the model) in a given quarter if its share of information-related job posting to total job posting exceeds the quarterly median level. By merging the firm-quarter Lightcast sample with the quarterly Compustat sample, we obtain 91,238 firm-quarter observations spanning from 2010Q1 to 2023Q4, average about 1630 firms per quarter.

C.4. **Compustat-IBES-Lightcast merged sample.** Finally, we merge the quarterly Compustat sample, IBES sample and Lightcast sample constructed in C.1, C.2 and C.3, obtaining 15,092 firm-quarter observations from 2010Q1 to 2023Q4, averaging about 270 firms per quarter.

Table C.1. Occupations Related to Information Acquisition

Business Analysis and Strategy		
• Business Analyst (General)	• Corporate Development Manager	• Economist
• Business Analysis Manager	• Chief Strategy Officer	• Survey Researcher
• Business Program Analyst	• Business / Management Consultant	• Talent Acquisition Director
• Strategic Planner / Analyst	• Management Consulting Partner	• Human Resources Analyst
• Corporate Development Analyst	• Economic Consulting Partner	• Human Resources Consultant
Operations and Supply Chain Management		

including but not limited to market demand for products, production costs, aggregate economic conditions, and financial conditions. Please provide some examples of jobs that meet these criteria."

[32]The prompt given in this step is:"I am providing a spreadsheet that lists specific job titles along with descriptions of their duties. Please review the entire list and identify all positions that are most closely related to information acquisition, as determined by their job descriptions."

[33]The prompt given in this step is: "I am providing a spreadsheet that lists 160 specific job titles along with descriptions of their duties. Please review the entire list and identify 100 positions that are most closely related to information acquisition, as determined by their job descriptions."

Table C.1. Occupations Related to Information Acquisition (Continued)

- Operations Analyst (General)
- Operations Research Analyst
- Demand Planner
- Logistician (General)
- Production Planner
- Supply Chain Specialist (General)
- Supply Planner
- Demand Planning Analyst
- Inventory Analyst
- Logistics Analyst
- Materials Analyst
- Supply Chain Analyst
- Supply Chain Planning Analyst
- Supply Chain Sourcing Analyst
- Demand Planning Manager
- Business Continuity Planner / Analyst
- Investment Operations Analyst
- Marketing Operations Analyst

Financial and Risk Management

- Financial Analyst (General)
- Investment / Portfolio Analyst
- Treasury Analyst
- Financial Quantitative Analyst
- Pricing Analyst
- Budget Analyst
- Accounting Analyst
- Pricing Manager
- Risk Analyst
- Risk Consultant
- Risk Manager
- Loss Control Consultant
- Director of Risk Management
- Chief Financial Officer
- Accounting Manager
- Financial Manager (General)
- Financial Planning Manager
- Mortgage Manager
- Revenue Manager
- Operational Risk Analyst
- Project Management Analyst
- Estimator

Data Analytics and Business Intelligence

- Business Intelligence Analyst
- Data Analyst
- Data Scientist
- GIS Analyst
- Data Analytics Manager
- Data Science Manager
- Data Manager
- Chief Data Officer
- Decision Support Analyst
- General ERP Analyst / Consultant
- Oracle Consultant / Analyst
- SAP Analyst / Admin

Marketing and Sales

- Brand Manager
- Content Marketing Manager
- Director of Digital Marketing
- Digital Marketing Manager
- Field Marketing Manager
- Marketing Analytics Manager
- Marketing Automation Manager
- Marketing Campaigns Manager
- Director of Marketing
- Marketing Manager (General)
- Director of Product Marketing
- Product Marketing Manager
- Digital Marketing Analyst
- Marketing Analyst (General)
- Trade Marketing Analyst
- Digital Marketing Specialist
- Marketing Analytics Specialist
- Marketing Specialist (General)
- Marketing Strategist
- Product Marketing Specialist
- Sales and Marketing Specialist
- Sales Representative (General)
- Director of Business Development
- District Sales Manager
- Area Sales Manager
- Sales Operations Manager
- E-Commerce Analyst (General)
- E-Commerce Specialist
- Analytics Product Manager
- Director of Product Development
- Director of Product Management
- Product Development Manager
- Product Line Manager

Appendix D. Calibration

We provide details on the construction of targeted moments in Table 6. These moments are constructed based on the pre-pandemic sample up to 2019:Q4.

D.1. **Standard deviation of log markup.** Markup is defined as:

$$markup \equiv \frac{sales\ per\ share}{costs\ per\ share} = \frac{sales\ per\ share}{sales\ per\ share - earnings\ per\ share}. \tag{D.1}$$

In the model, for a firm actively engaged in production, its sales per share and earnings per share are given by $\frac{z_{j,t}}{\mu_t^*}\xi_t P_t$ and $\left(\frac{z_{j,t}}{\mu_t^*} - 1\right)\xi_t P_t$, respectively. This implies that the cross-sectional standard deviation of $\log(markup)$ in the steady state is

$$SD(log\ markup) = SD(\log z_j - \log \mu^*) = SD(\log z_j), \tag{D.2}$$

which serves as a measure for the level of prior volatility in idiosyncratic fundamentals.

To compute $SD(log\ markup)$, we use the quarterly Compustat sample constructed in Appendix C.1. The model assumes an idiosyncratic productivity process which is i.i.d. across firms and across time, leading to i.i.d. distributed markups. However, in reality, markups exhibit serial correlation within firms due to the persistence of market power. In addition, they are also influenced by firm-specific factors and business cycle conditions. To isolate these factors, which are beyond the scope of our model, we regress each firm's log markup on its lagged value and include both firm and time fixed effects. The regression specification is as follows:

$$\log(markup_{j,t}) = \beta_0 + \beta_1 \log(markup_{j,t-1}) + \gamma_t + \eta_j + \varepsilon_{j,t}, \tag{D.3}$$

where γ_t and η_j represent time and firm fixed effects, respectively.

The standard deviation of the residual, $\varepsilon_{j,t}$, is then calculated as a proxy for $SD(log\ markup)$.

D.2. **SD of log forecast error in markup / SD of log markup.** Define the markup forecast as

$$markup\ forecast \equiv \frac{forecast\ of\ sales\ per\ share}{cost\ per\ share} = \frac{sales\ per\ share - EPS + EPS\ Forecast}{sales\ per\ share - EPS}.$$

Define log forecast error of markup as

$$logFE \equiv \log\left(markup\right) - \log\left(markup\ forecast\right).$$

In the model, a firm j's markup forecast at period t is $\frac{\mu_{j,t}}{\mu_t^*}$, implying that the log forecast error in markup is

$$\log\frac{z_{j,t}}{\mu_t^*} - \log\frac{\mu_{j,t}}{\mu_t^*} = \log z_{j,t} - \log \mu_{j,t}.$$

This serves as a proxy for the log-level forecast error of idiosyncratic fundamentals, and its standard deviation reflects the degree of posterior uncertainty.

Using Compustat-IBES merged sample constructed in Appendix C.2, we calculate realized markups, markup forecasts, and log forecast errors. To mute the potential impacts of serial correlations, firm-specific factors and business cycle conditions, we compute $SD(log\ markup)$ as the standard deviation of the residuals from regression (D.3). Similarly, $SD\left(log\ forecast\ error\right)$ is calculated as the standard deviation of residuals from the following regression:

$$logFE_{j,t} = \beta_0 + \beta_1 \log(markup_{j,t-1}) + \beta_2 forecast\_horizon_{j,t} + \gamma_t + \eta_j + \nu_{j,t}, \tag{D.4}$$

where $\log(markup_{j,t-1})$ controls potential behavioral biases in forecasting (e.g., extrapolation); $forecast\_horizon_{j,t}$, defined as the difference between the forecast announcement date and the target date, accounts for the effect of forecast horizon on forecast precision; γ_t and η_j represent time and firm fixed effects, respectively.

Finally, we measure the ratio of posterior uncertainty to prior uncertainty using

$$\frac{SD\left(log\ forecast\ error\right)}{SD(log\ markup)}.$$

D.3. **SD of log forecast error in markup: informed / uninformed.** Using the Compustat-IBES-Lightcast merged sample constructed in Appendix C.4, we re-estimate regressions (D.3) and (D.4) separately for informed and uninformed firms. For informed firms, we compute $SD\left(log\ forecast\ error \mid informed\right)$ and $SD\left(log\ markup \mid informed\right)$; for uninformed firms, we calculate $SD\left(log\ forecast\ error \mid uninformed\right)$ and $SD\left(log\ markup \mid uninformed\right)$, following the same method outlined in Appendix D.2.

To quantify the gain from information acquisition, we calculate the following ratio:

$$\frac{SD\left(log\ forecast\ error \mid informed\right)/SD\left(log\ markup \mid informed\right)}{SD\left(log\ forecast\ error \mid uninformed\right)/SD\left(log\ markup \mid uninformed\right)}.$$

This ratio adjusts the relative dispersion in log forecast errors by the relative dispersion in log markups, to control for the ex-ante difference in prior uncertainty between informed and uninformed firms.

D.4. **Share of informed firms.** We define a firm as "informed" in a given quarter if its share of information-relation job postings to total job postings exceeds the quarterly median level. By this definition, the share of informed firms is 50%.

D.5. **Share of information acquisition-related job postings.** Using the Lightcast-Compustat merged sample constructed in Appendix C.3, we calculate the total number of information-related job postings and overall job postings for each quarter. We then compute the quarterly share of information-related job postings and average this share across all quarters to proxy the steady-state level.