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Rational inattention, misallocation, and the aggregate economy☆

Naveen Gondhi

Finance Department, INSEAD, Boulevard De Constance, Fontainebleau 77305, France

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A B S T R A C T

I study the effect of firm managers' information-processing constraints on production decisions, resource misallocation, and the aggregate economy. Managers have a finite information-processing capacity to reduce uncertainty about firm-specific and economy-wide shocks. The model implies that an increase in aggregate uncertainty leads to reallocation of capacity from learning about firm-specific shocks to learning about aggregate state, leading to higher misallocation of resources and lower output. In contrast, an increase in idiosyncratic uncertainty (through an opposite mechanism) has a non-monotonic effect on aggregate productivity. The model produces new implications regarding the co-movement of inputs and Labor-TFP sensitivity which I confirm empirically.

1. Introduction

Economic theory suggests that, in order to maximize output, scarce resources need to be deployed efficiently. Notably, recent work has documented substantial variation in the degree of resource misallocation over time.[1] However, available theories that attempt to explain this phenomenon often ignore the effect of information frictions on firms' decisions.[2] I argue that even if the firm manager can acquire capital in the market frictionlessly, he may not deploy the resources to the most efficient use if he cannot process all the information he has (attention constraint). In this paper, I propose a simple model of time-varying resource misallocation based only on the rational inattention of firm managers. Firm managers first

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E-mail address: naveen.gondhi@insead.edu

[1] See, for example, Hsieh and Klenow (2009), Gopinath et al. (2017), and Kehrig and Vincent (2017).

[2] For example, Midrigan and Xu (2014), Moll (2014), Buera et al. (2011), and Asker et al. (2014) study the role of financial frictions and capital adjustment costs in explaining this phenomenon. Notable exceptions are Bostanci and Ordonez (2020), and David et al. (2016), who examine the role of informational inefficiency of stock markets in explaining misallocation across countries.

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choose how much and what information to process and then make input decisions conditional on their expectations of the net present value (NPV) of the project (which is driven by future economic conditions). In particular, I assume that the net present value is driven by aggregate and firm-specific fundamentals, and I allow firm managers to acquire two types of information: data about the aggregate economy and information about their own firm. Importantly, information-processing ability is just like any other economic resource: It is in finite supply. As managers pay more attention to aggregate news, they devote less time to processing information about their own firm. I embed this feature in a tractable general equilibrium model and explore its testable implications.

The model builds on the standard RBC model with dispersed information (Angeletos and La'O (2009)). To this standard model, I add two features. First, firm managers have imperfect information not only about aggregate shocks but also about their firm-specific (idiosyncratic) shocks. Second, and most importantly, firm managers can either learn about aggregate and/or firm-specific shocks subject to a constraint on their information-processing capacity. The information-processing capacity of a firm manager is effectively a factor of production like labor and capital. One can interpret rise in information-processing capacity as rise in big data technologies, like artificial intelligence and machine learning, which are prediction algorithms. These technologies help managers predict the future demand for a firm's product (and help them forecast sales), which in turn assists them to make better production choices. My main insight is that when aggregate (idiosyncratic) uncertainty changes, it is critical to understand how this effects firm managers' attention choice and study the implications of this mechanism to production decisions, resource misallocation, and aggregate productivity.

My model delivers endogenous fluctuations in measured aggregate productivity (MAP) and output in response to movements in firms' information-processing constraint, aggregate, and idiosyncratic uncertainty.[3] In the model, measured aggregate productivity monotonically decreases with cross-sectional misallocation of resources. I identify two key forces that affect cross-sectional misallocation (and, hence, MAP). The first one is driven by imperfect information about idiosyncratic (firm-specific) shocks. In a perfect information benchmark, a high productive firm produces more and a low productive firm produces less. Any imperfect information about firm-specific shocks leads to cross-sectional misallocation of resources, which lowers measured aggregate productivity. The second one is driven by imperfect information about aggregate shocks and is given by the *belief dispersion across managers about aggregate shock*. As belief dispersion about aggregate shock increases, misallocation increases, which lowers productivity. The overall effect of an increase in aggregate (or idiosyncratic) uncertainty on measured aggregate productivity is a result of tension between these two forces.

Consider an increase in aggregate uncertainty. This induces managers to acquire less information about firm-specific shocks and more information about the state of the aggregate economy. As firms invest less time to learn about their idiosyncratic shocks, the input decisions of all firms are similar, and, hence, the degree of cross-sectional misallocation will be higher, which lowers aggregate productivity (first channel). Moreover, managers who learn more about aggregate shocks put less weight on their prior beliefs and more weight on their heterogeneous signals. This generates more dispersed beliefs and leads to a further drop in measured aggregate productivity (second channel). Through this second channel, my model can explain why belief dispersion rises endogenously when aggregate uncertainty is high, consistent with the data.[4] Both of these channels imply that an increase in aggregate uncertainty leads to an endogenous drop in measured aggregate productivity.[5] This result is consistent with past work (e.g., Bloom et al. (2018), and Basu and Bundick (2017)) that shows that increases in option-implied market volatility are followed by declines in output. My model proposes a different mechanism for this result and yields a new testable implication. My mechanism implies that the effect of aggregate uncertainty on measured productivity weakens as information-processing constraints rise. This implies that, as big data technologies like AI and machine learning evolve, the effect of aggregate uncertainty on the economy is weakened.

Conversely, a rise in idiosyncratic uncertainty induces managers to acquire more information about their own firm-specific shocks and less information about aggregate shocks. Learning more about firm-specific shocks leads to improved allocation of resources and a rise in aggregate productivity (first channel). However, learning less about aggregate shocks has a non-monotonic (hump-shaped) effect on dispersion of beliefs and, hence, on aggregate productivity (second channel). The net effect of idiosyncratic uncertainty is non-monotonic. For high levels of idiosyncratic uncertainty (relative to aggregate uncertainty), measured aggregate productivity increases with idiosyncratic uncertainty. For low levels of idiosyncratic uncertainty, measured aggregate productivity decreases with idiosyncratic uncertainty. Consistent with my model, Dew-Becker and Giglio (2020) find that idiosyncratic volatility is sometimes high in bad times, and sometimes high in good times.[6] I empirically test the key model prediction that the effect of idiosyncratic uncertainty on aggregate quantities is U-shaped.

My model delivers two key testable implications for real quantities. Note that learning about a shock allows managers to choose inputs that covary more with that shock. This simple mechanism gives the first testable implication: *The elasticity*

[3] As is standard in heterogeneous firm models, measured aggregate productivity can be different from aggregate productivity shock.

[4] Note that this channel is consistent with evidence in Bachmann et al. (2013) who argue that forecaster disagreement is high during recessions when aggregate uncertainty is high. My model provides a theoretical justification for why forecaster disagreement can be a good proxy for aggregate uncertainty.

[5] Note that this channel is also consistent with empirical evidence in Foster et al. (2000), who argue that reallocation of resources is a key factor driving aggregate productivity in the US economy.

[6] On the asset pricing side, there is mixed empirical evidence about the pricing of idiosyncratic volatility. Herskovic et al. (2016) argue that idiosyncratic volatility is priced negatively because of incomplete markets, and households face more labor income risk when idiosyncratic volatility increases. On the other hand, Driessen et al. (2009) show that an option trading strategy that replicates a payoff proportional to the rise in the average idiosyncratic volatility across firms earns high risk-adjusted returns; that is, idiosyncratic volatility is priced positively.

of a firm's input to its productivity shock increases with idiosyncratic uncertainty and decreases with aggregate uncertainty. For intuition, consider an increase in idiosyncratic uncertainty. As idiosyncratic uncertainty increases, firm managers shift their attention to learn more about their idiosyncratic shocks and, hence, the firm managers choice of inputs covary more with the idiosyncratic shock. Empirically, I estimate the response of employment growth to TFP and test this prediction. Using a measure of aggregate and idiosyncratic uncertainty (developed using option prices) by Dew-Becker and Giglio (2020), and the measure of TFP estimated as solow residual, I confirm that the elasticity of labor inputs to productivity shocks increases with idiosyncratic uncertainty and decreases with aggregate uncertainty.

The second testable implication is about "excess co-movement puzzle" documented in Christiano and Fitzgerald (1998), Rebelo (2005), Veldkamp and Wolfers (2007): Sectoral inputs (investment and labor) co-move highly with each other, even though the co-movement in sectoral productivity (TFP) is very weak. The second key testable implication of my model is that: *increases in idiosyncratic uncertainty lead to lower input co-movement across firms; an increase in aggregate uncertainty increases co-movement*. As idiosyncratic uncertainty increases, firm managers shift their attention to learn more about their idiosyncratic shocks and, hence, learn less about aggregate shocks. As all firms learn less about aggregate shocks, the co-movement of their inputs decreases. Using firm-level labor input data from COMPUSTAT, I show evidence supporting this prediction.

Finally, economists have long puzzled over why there are such astounding differences in the degree of resource misallocation across countries. For example, resource misallocation in India and China is much higher than in the United States. My model provides one natural explanation for these productivity differences, which relies on variations in management practices. In my model, we can interpret information-processing capacity of the manager as the proxy for managerial ability; that is, higher information-processing capacity corresponds to the ability of the manager to identify positive NPV projects and allocate more resources to them. In management education, we teach students that good management practices involve decisions that are data driven, and the better managers are the ones capable of leveraging data and making it an essential part of their decision-making process. In a recent study, Bloom et al. (2013) find that management practices in India are worse than those in the United States and they emphasize that informational barriers are the primary factor explaining this result.

Related Literature

My paper is related to several strands of literature. The first strand is the large body of literature on endogenous learning/inattention. Sims (2003), Mackowiak and Wiederholt (2009), Peng and Xiong (2006), Mondria (2010), Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010), Goldstein and Yang (2015), Maćkowiak and Wiederholt (2015), Kacperczyk et al. (2018), Banerjee et al. (2018), Farboodi et al. (2018), and Glasserman and Mamaysky (2019) provide excellent applications of this friction.[7] In a closely related paper, Kacperczyk et al. (2016) study the information-acquisition problem of a fund manager who can learn about several assets and show that fund managers optimally choose to process information about aggregate shocks in recessions and idiosyncratic shocks in booms. In contrast, I study the implications of endogenous learning (of managers) for firms' real decisions. Using survey data, Coibion et al. (2018) document pervasive inattention on the part of firms to different macroeconomic variables. The mechanism illustrated by my model echoes Gennaioli et al. (2016) and Alti and Tetlock (2014), who emphasize the importance of accounting for firm managers' expectations to explain the production inputs. Although it is common to most inattention models that agents prefer to learn about shocks with higher prior uncertainty, the implications of this channel in the context of firm managers' learning are non-trivial and are the main contribution of this paper.

A small, growing body of literature examines the effect of data on firm dynamics (Begenau et al. (2018)) and aggregate economy (Farboodi and Veldkamp (2021)). In these theories, firms accumulate a stock of usable knowledge that enhances productivity or facilitates prediction. My framework complements these ideas and uses rational inattention to think about how information-processing constraint interacts with aggregate and idiosyncratic uncertainty.

An obvious hurdle in testing models with learning is that we cannot directly observe the variables included in the firm managers' information set. There are two broad approaches to overcome this. The first one uses surveys to elicit beliefs of agents and test the models directly (see, for example, Coibion and Gorodnichenko (2015), and Bordalo et al. (2020)). The second approach tests the model indirectly: link the information choices to observable patterns in data. I follow this second approach and test the implications of my model.

Close to my paper, Mäkinen and Ohl (2015) and Benhabib et al. (2016a) study information acquisition in an RBC model. Mäkinen and Ohl (2015) model learning about aggregate economy, whereas Benhabib et al. (2016a) model learning about firm-specific (idiosyncratic) shocks. In contrast, I assume that firm managers can learn about both aggregate and idiosyncratic shocks, and their prior uncertainty is time-varying (exogenous), which leads to time-varying incentives to learn about these shocks.

Second, my paper relates to a vast theoretical debate that studies the mechanisms through which uncertainty shocks impact the aggregate economy. See Bloom (2014) for an extensive survey. Many models such as Bloom et al. (2018) and Vavra (2014) assume that firms draw exogenous idiosyncratic shocks with time-varying volatility in order to generate time variation in dispersion of outcomes. On the other side of the debate, papers such as Bachmann et al. (2011), Ilut et al.

[7] Empirical papers testing this friction include Kacperczyk et al. (2014), Huang et al. (2019), and Maćkowiak et al. (2009), among others.

(2018), and Baley and Blanco (2019) propose a varied set of mechanisms such as learning, ambiguity aversion, incomplete information, and customer search to generate variation in dispersion through the responsiveness channel. Berger and Vavra (2019) argue that significant time variation in responsiveness is necessary for the model to quantitatively match the empirical behavior of prices. My paper integrates these two literatures and studies the effect of exogenous uncertainty shocks on managers' incentive to learn. My tractable model delivers an endogenous response of measured productivity to changes in uncertainty that operate through changes in attention (and hence, responsiveness) and the degree of resource misallocation.

Representative agent models have explored the role of aggregate consumption growth volatility for explaining a host of asset-pricing stylized facts. Bansal et al. (2014) find that the market price of aggregate volatility risk is negative. Campbell et al. (2017) also analyze the role of uncertainty in an extended version of the ICAPM. While there is consistent evidence that aggregate volatility has a negative price of risk, there is mixed evidence on whether idiosyncratic volatility is priced positively or negatively. Driessen et al. (2009) show that an option trading strategy that replicates a payoff proportional to the rise in the average idiosyncratic volatility across firms earns high risk-adjusted returns; that is, idiosyncratic volatility is priced positively. On the other hand, Herskovic et al. (2016) argue that idiosyncratic volatility is priced negatively because of incomplete markets, and households face more labor income risk when idiosyncratic volatility increases.[8] Recently, Dew-Becker and Giglio (2020) examine the forecasting power of idiosyncratic uncertainty (constructed using options data) for aggregate output and find mixed evidence. The data appears to show that idiosyncratic uncertainty is sometimes high in bad times and sometimes high in good times. In my model, I show that the effect of idiosyncratic volatility is non-monotonic (U shaped), which can reconcile this mixed empirical evidence on the effect of idiosyncratic uncertainty.

Third, my paper also relates to the growing body of literature on the aggregate implications of misallocated resources, for example, Hsieh and Klenow (2009), David et al. (2016) and David and Venkateswaran (2019). As in my paper, David et al. (2016) study resource misallocation in an economy with imperfect (and exogenous) information. In addition to endogenizing the information acquisition decision, my model studies how fluctuations in uncertainty lead to endogenous fluctuations in measured aggregate productivity. Also related is David et al. (2018), who argue that cross-sectional dispersion in marginal products may not only reflect true misallocation, but also risk-adjusted capital allocation.

Fourth, my work complements the recent literature in macroeconomics that analyzes the role of information frictions on economic growth, which includes Van Nieuwerburgh and Veldkamp (2006), Lorenzoni (2009), Angeletos and La'O (2009), Straub and Ulbricht (2017), Hassan and Mertens (2015, 2017), Angeletos et al. (2018), and Benhabib et al. (2016b). Benhabib et al. (2016b) demonstrate that sentiment shocks can generate business cycle fluctuations. Through the informational role of prices, Sockin and Xiong (2015) argue that supply shocks can have an amplified effect on asset prices. Hassan and Mertens (2017) argue that small correlated mistakes about future productivity will get amplified through the stock market and lead to volatile asset prices and economic aggregates.

My paper is related to a growing body of literature that studies how idiosyncratic noise shocks in agents' information sets influence their actions, while a fully informed rational expectations (FIRE) agent would disregard such shocks. Andrade et al. (2022) analyze the data from a large panel of French firms and show how managers erroneously revise their aggregate inflation expectations in response to industry-level (idiosyncratic) variation in prices that has no bearing on the macroeconomy. Dessaint et al. (2019) show that firms significantly reduce their investment in response to non-fundamental drops in the stock price of their product-market peers, suggesting that managers have limited ability to filter out the noise in the stock prices when using them as signals about profitability of their investment opportunities. For households, D'Acunto et al. (2021) document that they rely on the price changes of goods in their grocery bundles when forming expectations about aggregate inflation. Similarly, Kuchler and Zafar (2019) show that individuals extrapolate from local house-price changes in their counties to form expectations about aggregate real estate inflation. My paper shows that agents attention to each variable depends on the economic environment and the uncertainty they face.

Economists have long been interested in how endogenizing information sets affect outcomes in coordination games such as "beauty contests" and "global games". Hellwig and Veldkamp (2009) consider a general beauty contest with information choice. Afrouzi (2020) develops a model that explains how imperfect oligopolistic competition affects firms' information acquisition and expectations. They find that firms have an incentive to pay direct attention to the mistakes of their competitors, even at the expense of paying less attention to the fundamental shocks. In tracking their competitors' beliefs, firms ignore aggregate shocks, and, as a result, their beliefs about aggregate variables are more inaccurate and noisy. Coibion et al. (2018) provide consistent evidence on the relationship between firms' number of competitors and their expectations. In my model, I refrain from these interesting effects and instead focus on the continuum of firms with monopolistic competition. In my model, input choice of firms is a beauty contest game: The optimal input choice of a firm is a function of an exogenous fundamental and the average output, and hence, firms do not have incentive to learn about the idiosyncratic mistakes of other firms.

[8] This literature goes back to Mankiw (1986) and Constantinides and Duffie (1996).

2. Model

In this section, I build a general equilibrium RBC model to investigate the link between uncertainty shocks, firm managers' attention choice, and their input decisions. In order to focus on the particular role of learning, I work with a simple framework in which rational inattention is the only friction.

2.1. Setup

There are three time periods, $t \in \{0, 1, 2\}$. A continuum of firms of fixed measure one, indexed by i, produces intermediate goods using only labor according to

$$Y_i = AZ_iN_i^{\alpha} \qquad \alpha \leq 1, \tag{1}$$

where N_i denotes labor employed by the firm. Each firm's productivity is a product of two separate random variables: an aggregate component (A) and an idiosyncratic component (Z_i). From now on, I use small letters to refer to natural logarithm of capital letter variables. I assume z_i is independent across firms, $z_i \sim \mathcal{N}\left(-\frac{1}{2\tau_z}, \frac{1}{\tau_z}\right)$ and $a \sim \mathcal{N}\left(-\frac{1}{2\tau_a}, \frac{1}{\tau_a}\right)$ and these variables are independent. I define uncertainty as the prior variance of innovations, $\sigma_a^2\left(\text{defined as } \frac{1}{\tau_a}\right)$ and $\sigma_z^2\left(\text{defined as } \frac{1}{\tau_z}\right)$. I assume that firms learn in advance that the distribution of shocks in the next period is changing. This captures the notion of uncertainty that firms face about future business conditions. The intermediate goods are bundled to produce the single final good using a aggregator, $Y = \int Y_i di$.[9] The time line of the economy is given by: Time 0: Managers allocate their attention knowing the uncertainty they face, that is, the information set at time 0 is $\mathcal{I}^0 = \{\tau_a, \tau_z\}$.

Time 1: Managers receive signals s_{ia}, s_{iz} about aggregate and idiosyncratic shocks, respectively, and make labor hiring decisions. Workers go the respective firms, and wages adjust so that the labor market clears. At this point, workers and firm managers have the same information regarding TFP shocks. Denote their information set $\mathcal{I}_i^1$.

Time 2: Production occurs. All information is revealed. Commodities markets open, and prices clear these markets. Consumption takes place.

Households: There is a representative household, consisting of a consumer and a continuum of workers with preferences as follows:

$$\mathcal{U} = \left[U(C) - \int_i \frac{N_i^{1+\nu}}{1+\nu} di\right],$$

where $i \in [0, 1]$ indexes firm i, $U(C) = \frac{C^{1-\gamma}-1}{1-\gamma}$, and C represents consumption of final good at time 2, N_i is the labor effort of the worker who works for firm i, $\gamma > 0$ parametrizes the coefficient of relative risk aversion and also the income elasticity of labor supply, and ν parametrizes the Frisch elasticity of labor supply. Assume that all idiosyncratic risk is insurable and the representative household owns all the firms in the economy and its budget constraint is given by

$$\int PC_i di \leq \int \pi_i di + \int W_i N_i di,$$

where P denotes the price of good, π_i denotes the profits from firm i, and W_i denotes the wage of firm i workers.

Firms: The firm i's realized profit at time 2 is given by $\pi_i = PY_i - W_iN_i$. At time 1, each firm's objective is to maximize the representative household's valuation of its profits:

$$E\left[U'(C)\pi_i | \mathcal{I}_i^1\right]. \tag{2}$$

Market clearing: The representative household consumes the total output produced in the economy, $C = Y$. In the labor market, wages adjust to equate labor demanded and supplied. In the product market, prices adjust to equate demand and supply of goods.

Information sets: I make the following assumption about available signals.

Assumption 1. The private signals available to firm manager i are of the following form:

$$s_{ia} = a + \nu_{ia} \qquad\qquad s_{iz} = z_i + \nu_{iz}, \tag{3}$$

where $\nu_{ia} \sim \mathcal{N}\left(0, \frac{1}{\tau_{a,i}^s}\right)$ and $\nu_{iz} \sim \mathcal{N}\left(0, \frac{1}{\tau_{z,i}^s}\right)$ are purely idiosyncratic shocks, and they are by-product of rational inattention.

This assumption formalizes the idea that paying attention to the aggregate conditions and paying attention to the idiosyncratic conditions are separate activities. For example, attending to the current state of monetary policy is a separate activity from attending to the firm-specific productivity.

At time 0, I assume that firm managers have access to a variety of information sources and has to decide what to pay attention to, subject to an information flow constraint. Processing information is modeled as receiving noisy signals about

[9] For simplicity, I assume perfect substitutability across goods. All the results will go through with finite elasticity of substitution across goods.

the fundamentals. Firm managers' choose the precision of their signals, $\tau^s_{a,i}$ and $\tau^s_{z,i}$, subject to a learning constraint. In general, I assume that the learning constraint is given by $C(\tau^s_{a,i}, \tau_a) + C(\tau^s_{z,i}, \tau_z) \le \kappa$.

Formulating a problem with information choice requires a learning technology (i.e., cost function C). Which learning technology is appropriate depends on the type of data that agents are acquiring. Hellwig et al. (2012) argue that rational inattention is a useful way to describe more subjective evaluations, such as learning about the future productivity. Hence, in the baseline model, I assume that the cost function C is given by the mutual information between signals and the fundamental. For the assumed signal structure, this constraint reduces to

$$\underbrace{\frac{1}{2}\log_2\left[\frac{\tau^s_{a,i}+\tau_a}{\tau_a}\right]}_{\equiv\kappa_{a,i}} + \underbrace{\frac{1}{2}\log_2\left[\frac{\tau^s_{z,i}+\tau_z}{\tau_z}\right]}_{\equiv\kappa_{z,i}} \le \kappa \quad \text{and} \quad \tau^s_{a,i}, \tau^s_{z,i} \ge 0 \tag{4}$$

Note that the cost function in this case depends on the ratio between prior and posterior uncertainty. In Eq. (4), $\kappa_{a,i}$ denotes the information flow allotted to learning aggregate conditions, and $\kappa_{z,i}$ denotes the information flow allotted to learning idiosyncratic conditions. The other constraint I impose on agents' learning is that the chosen signal precisions are always non-negative.

2.1.1. Discussion about model setup

To keep the model tractable, I have made several stylized assumptions in the baseline setup. First, I assume that markets and equilibrium prices don't aggregate agents' information. In Online Appendix A.5, I relax this assumption and allow firm managers to trade and learn from stock markets. Although this model delivers several new insights, the main results in the baseline model continue to hold in this setup. Last but not least, similar insights hold when other (e.g. labor) markets aggregate firm managers' information.

Second, I assumed that the learning constraint is driven by the mutual information (4). In Online Appendix A.3, I relax this assumption and work with general cost function $C\left(\tau^s_{a,i}, \tau_a\right)$. I show that for any general cost function (under some conditions), the predictions of the model hold. These results show that what is relevant for our analysis is the assumption of substitutability/reallocation of attention.

Third, I assume that the firm manager has a fixed "channel capacity" for processing information, and the manager cannot increase/decrease the capacity conditional on the uncertainty he/she faces. This implies that capacity κ is a fixed input in a given period. One simple justification of this assumption is that changing the capacity (just like changing physical capital) takes time, and the manager cannot change it in a given period after the uncertainty is realized. In Online Appendix A.1, I relax this assumption and assume that the attention is costly and agents can choose their overall attention subject to a cost function $C(\kappa)$. I show that, with convex cost function, the results will be qualitatively robust.

Fourth, I only allow firm managers to choose one input (labor). The model will remain similar if firms have to choose both capital and labor, as long as both inputs can be adjusted freely every period (solved in Online Appendix A.8). With adjustment costs, the model becomes intractable.

Fifth, I assume that there is no information spillover from one firm to the other firm at time 1. One way to rationalize this is to assume that there a continuum of islands, which define the boundaries of local labor markets and information sets: Information is symmetric within the island and asymmetric across islands. This is similar to the setup in Angeletos and La'O (2009).

Sixth, I assume pure form rational inattention in which "*Information is available in a wide variety of forms*" and agents can choose the information structure flexibly. In reality, however, some information is only available in a particular form. For example, most managers might learn about aggregate shocks by following popular press i.e., public source of information. In this case, one can incorporate this assumption by adding a constraint to our baseline model by specifying the available signals. In Online Appendix A.2, I consider such an extension. I show that all the implications of the baseline model hold in such an extension.

Seventh, the baseline model assumes rational expectations, that is, all agents hold correct beliefs about the law of motion of the economy. In Online Appendix A.6, I abandon rational expectations and solve the model assuming that agents engage in k-level thinking, that is, restrict how far they go in terms of higher-order thinking. I show that, with k-level thinking alone, the model does not make the same predictions as the baseline model. Moreover, with k-level thinking and rational inattention, the model does make the same predictions as the baseline model under some additional assumptions.

2.2. Equilibrium

Definition 1. An equilibrium consists of an employment strategy $N(\mathcal{I}^1_i)$, a wage function $W\left(\mathcal{I}^1_i\right)$, an aggregate output function $Y(a, \tau_a, \tau_z)$, and signal precisions $\{\tau^s_{a,i}, \tau^s_{z,i}\}\left(\mathcal{I}^0\right)\forall i$, such that the following are true:

(i) Time 0: Firms choose attention allocation to maximize the net present value of future cashflows, subject to an information-processing constraint.
(ii) Time 1: Representative household and all firms are at their respective optima, at choosing employment strategies, conditional on their information set $\mathcal{I}^1_i$.

(iii) Time 2: Commodity prices are determined such that the respective markets clear.

I solve the model backwards. In Section 2.2.1, I characterize the equilibrium at $t = 1$ for given attention choice decisions made at $t = 0$. In Section 2.2.2, I solve for managers' optimal attention allocation decisions.

2.2.1. Equilibrium at time 1

Lemma 1. *Given $\mathcal{I}_i^1$, the equilibrium at time 1 is pinned down by the following condition:*

$$\underbrace{\alpha E_i\left[U'(C)AZ_i\right]N_i^{\alpha-1}}_{\substack{\text{Marginal utility}\\\text{of Consumption}}\times\substack{\text{Marginal Product}\\\text{of Labor}}} = \underbrace{N_i^{\nu}}_{\text{Marginal Dis-utility}}. \tag{5}$$

Condition (5) equates the private cost and benefit of effort for each firm. The right-hand side is simply the marginal dis-utility of an extra unit of labor, and the left-hand side is the product of marginal utility of consuming extra unit of the good i and the marginal product of labor. Note that aggregate revenue equals aggregate output, which implies

$$Y = \int_i Y_i di = A\int Z_i\left(\alpha E_i\left[C^{-\gamma}AZ_i\right]\right)^{\frac{\alpha}{\nu+1-\alpha}}di. \tag{6}$$

I next conjecture that the logarithm of equilibrium labor chosen, n_i, is linear in the firm's information set $\mathcal{I}_i^1 = \{s_{ia}, s_{iz}\}$, and aggregate output y is linear in aggregate state a, and I verify that there is always a unique log-linear equilibrium.

Proposition 1. *At time 1, there is a unique log-linear symmetric equilibrium:*

1. *Employment chosen by firm i (conditional on $\mathcal{I}_i^1$) is given by*

$$n_i = \log N_i = \varphi_0 + \varphi_a s_{ia} + \varphi_z s_{iz}. \tag{7}$$

2. *Aggregate output is log-linear in aggregate state variable a:*

$$y = \log Y = \psi_0 + \psi_a a. \tag{8}$$

Moreover, $\varphi_z = \frac{1}{\nu+1-\alpha}\left(\frac{\tau_z^s}{\tau_z^s+\tau_z}\right)$ and all other coefficients are reported in the appendix.

Proposition 1 shows that each firm's input decision is a log-linear function of its private signals, while the aggregate output is a log-linear function of the aggregate state variable. Proposition 1 also implies that, φ_z, the elasticity of input choice to idiosyncratic shock increases with τ_z^s, the signal precision of idiosyncratic shock. I will use this property to derive unique empirical implications of my mechanism in Section 3.2.

2.2.2. Endogenous attention allocation (time 0)

Until now, I have solved for the firms' optimal input decisions given their signals, that is, solved for time 1 equilibrium. In this subsection, I will endogenize their signals, that is, solve their time 0 problem. It is easy to show that information flow constraint (4) is always binding (Blackwell (1953)). This implies that, firms face a trade-off: attending more carefully to aggregate conditions requires attending less carefully to idiosyncratic conditions. This substitutability in learning is a crucial assumption and drives many results in this paper.

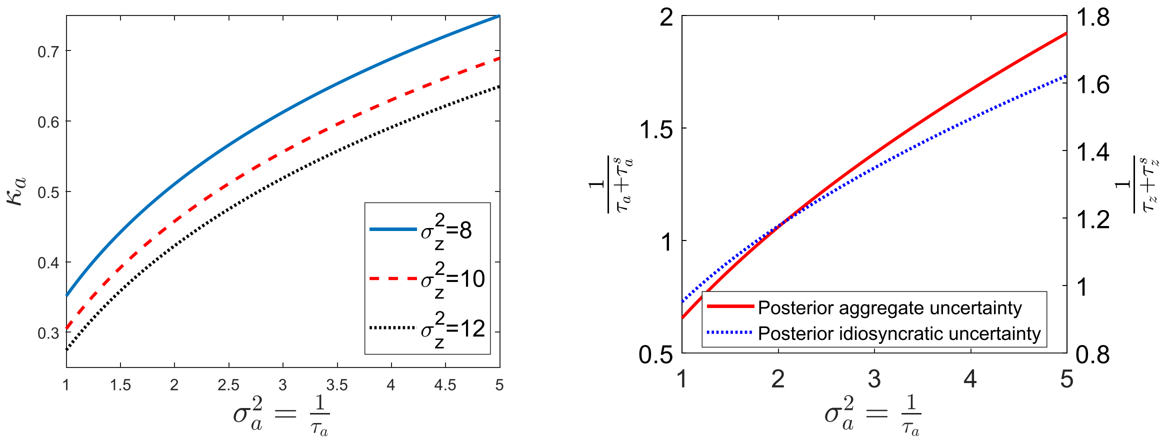
I now solve the firm manager's information acquisition problem (i.e., time 0 problem). Substituting the optimal labor hiring (7) into the firm manager's objective function (2), the net present value can be rewritten as $E_i\left[U'(C)\pi_i\right] \propto \left[E_i[X_i]\right]^{1+\delta}$, where $X_i \equiv C^{-\gamma}AZ_i$ and $\delta \equiv \frac{\alpha}{\nu+1-\alpha}$. This implies that managers want to forecast Z_i (idiosyncratic shock), A (aggregate shock) and aggregate consumption (also driven by aggregate shock). The information choice problem of the firm manager is to choose attention allocated to aggregate and idiosyncratic conditions (i.e., κ_{ai} and κ_{zi}) by maximizing the expected payoff (NPV) subject to an information-processing constraint, that is,

$$\max_{\kappa_{ai},\kappa_{zi}} E\left[\left[E_i[X_i]\right]^{1+\delta}|\mathcal{I}^0\right] \tag{9}$$

subject to assumption (1) and learning constraint (4). The outer expectation operator in (9) is the expectation under the information set $\mathcal{I}^0$, whereas the inner expectation is under the information set $\mathcal{I}_i^1$. The solution to this problem is given below.

Proposition 2. *Suppose all other managers devote attention κ_a to aggregate conditions. The optimal attention paid by manager i to aggregate conditions, $\kappa_{a,i}^*$ is a solution of*

$$\underbrace{2^{2\kappa_{a,i}}}_{\substack{\text{Attention to}\\\text{aggregate shock}}} = 2^{\kappa}\underbrace{\sqrt{\frac{\tau_z}{\tau_a}}}_{\text{Relative Uncertainty}}\underbrace{\frac{\left(2^{2\kappa_a}\right)}{\left(1+\left(2^{2\kappa_a}-1\right)(\gamma\delta+1)\right)}(|\gamma-1|)}_{\text{Relative Importance}}. \tag{10}$$



(a) Aggregate attention (b) Posterior aggregate uncertainty

Fig. 1. Equilibrium attention paid to aggregate conditions. Panel (a) plots the attention paid (κ_a) as a function of prior aggregate uncertainty and idiosyncratic uncertainty in an economy with endogenous learning. Panel (b) plots posterior aggregate uncertainty ($\frac{1}{\tau_a+\tau_a^s}$) and posterior idiosyncratic uncertainty ($\frac{1}{\tau_z+\tau_z^s}$) as a function of prior aggregate uncertainty in an economy with endogenous learning. Other parameter values are set to $\gamma = 3$, $\nu = 3$, $\kappa = 2$, and $\alpha = 0.7$, $\sigma_z^2 = 10$.

If the solution of the equation above is greater than κ, *then* $\kappa_{a,i}^* = \kappa$. *If the solution of equation above is negative, then* $\kappa_{a,i}^* = 0$.

Eq. (10) determines the attention paid to aggregate conditions by firm manager i. The right-hand side of Eq. (10) has two factors: 1. Relative uncertainty 2. Relative importance. First, when aggregate conditions are more variable than idiosyncratic conditions, agents pay more attention to aggregate conditions. Relative importance is an endogenous object and depends on the equilibrium attention by other agents. I will solve for a symmetric equilibrium in which all managers pay the same attention to aggregate conditions, that is, $\kappa_{a,i}^* = \kappa_a \forall i$.

Lemma 2. *Attention allocation exhibits substitutability across managers, that is, as other managers pay more attention, manager i pays less attention. This implies that there exists a unique, symmetric equilibrium for attention allocation.*

Fig. 1 panel (a) illustrates the equilibrium attention paid to the aggregate conditions, κ_a, as a function of aggregate uncertainty. The various lines correspond to different values of idiosyncratic uncertainty, levels as indicated in the legend. As aggregate uncertainty increases (as we move along the x axis), agents pay more attention to aggregate conditions and less attention to idiosyncratic conditions. As idiosyncratic uncertainty increases, agents pay less attention to aggregate conditions and more attention to firm-specific conditions. The following theorem shows the results formally.

Proposition 3. *In a symmetric interior equilibrium, attention paid to aggregate shock satisfies*

$$1 + \left(2^{2\kappa_a} - 1\right)(\gamma\delta + 1) = (\gamma - 1)2^{\kappa}\sqrt{\frac{\tau_z}{\tau_a}}. \tag{11}$$

This implies that attention paid to aggregate conditions

- *increases with aggregate uncertainty, that is,* $\frac{\partial \kappa_a}{\partial \tau_a} \leq 0$,
- *decreases with idiosyncratic uncertainty, that is,* $\frac{\partial \kappa_a}{\partial \tau_z} \geq 0$ *and*
- *increases with risk aversion, that is,* $\frac{\partial \kappa_a}{\partial \gamma} \leq 0$.

Proposition 3 tells us that firm managers want to learn more about any shock that has a high prior payoff variance. Information is most valuable about the most uncertain outcomes. The more risk averse the households are, the more worried about the aggregate consumption she is, and, hence, it is more attractive to allocate attention to aggregate shocks.

Recessions: If recessions are periods of high risk aversion and high aggregate uncertainty relative to idiosyncratic uncertainty, the model's prediction is that firm managers' pay more attention to aggregate shocks in recessions.[10] I will use this result later to argue why output endogenously falls during recessions in this model even without a negative first-moment shock.

[10] Kacperczyk et al. (2016) model recessions similarly. Even though both aggregate and idiosyncratic uncertainty rises in crises, the relative increase in aggregate uncertainty is higher (See Figure OA1 in online appendix).

2.3. Discussion of the main channel

In the baseline model, I interpret prior variance ($\frac{1}{\tau_a}$) as aggregate uncertainty. This is similar to the modeling choice in Bloom et al. (2018), where conditional variance fluctuates one-to-one with the variance of productivity shocks. In models with inattention, where managers learn from signals and can lower their posterior uncertainty, it might seem natural to refer to the posterior variance as uncertainty. Hence, it is important to study how posterior uncertainty changes with prior aggregate uncertainty. In my model, posterior uncertainty is an endogenous variable, which will reflect some combination of exogenous uncertainty shocks and firms' optimal allocation responses to those shocks.

Fig. 1 panel (b) illustrates the posterior uncertainties faced by the agents as prior aggregate uncertainty changes. As prior aggregate uncertainty increases, managers pay more attention to aggregate shocks. However, as the solid line in panel (b) indicates, the posterior aggregate uncertainty faced by the manager also rises. This implies that the main results will be the same even if an econometrician measures uncertainty as posterior variance. Moreover, as prior aggregate uncertainty increases, agents pay less attention to idiosyncratic shocks, and, hence, posterior idiosyncratic uncertainty (dotted line in the figure) also increases. This will lead to positive correlation in measurement of aggregate and idiosyncratic uncertainty. This might partially explain why aggregate and idiosyncratic uncertainty move together in the data. Similarly, we can show that, as prior idiosyncratic uncertainty increases, both posterior idiosyncratic and aggregate uncertainties rise.

The following section explains the model's key implications. Although it is common to most learning models that agents prefer to lean against uncertainty, I argue that the implications of this mechanism in the context of firm managers making real decisions are novel, surprising and economically significant.

3. Implications of endogenous learning

3.1. Aggregate implications

In this subsection, I study the aggregate implications of uncertainty shocks and endogenous learning. Note that aggregate output in the economy is log-linear and is given in Eq. 8. The aggregate labor defined as $N = \left(\int_i N_i^{1+\nu} di\right)^{\frac{1}{1+\nu}}$ is also log-linear in aggregate state variables. Given this, I can now define the measured aggregate productivity.

Definition 2. I define *measured aggregate productivity (MAP)* in the economy as $A^* \equiv \frac{Y}{N^\alpha}$.

This implies the log of measured aggregate productivity $a^* = y - \alpha n$. This is how an econometrician with aggregate data (Y, N) computes aggregate productivity in this economy.

Proposition 4. *Log of measured aggregate productivity ($a^* \equiv y - \alpha n$) is given by*

$$a^* = a + \underbrace{\frac{\delta\left(1 - 2^{-2\kappa_z}\right)}{2\tau_z}}_{\substack{\text{Effect of} \\ \text{Idiosyncratic uncertainty}}} - \underbrace{\frac{\delta}{2\tau_a}\left(\frac{(\gamma - 1)^2\left(2^{2\kappa_a} - 1\right)}{\left(2^{2\kappa_a}(\gamma\delta + 1) - \gamma\delta\right)^2}\right)}_{\substack{\text{Effect of} \\ \text{Aggregate uncertainty}}} \tag{12}$$

$$\equiv a + h_z(\tau_z, \kappa_z) + h_a(\tau_a, \kappa_a), \tag{13}$$

where κ_a and κ_z denote the attention allocated to aggregate and idiosyncratic conditions.

Corollary 1. *The following results hold:*

1. *Keeping the uncertainty faced by managers fixed, measured aggregate productivity increases with attention allocated to idiosyncratic shocks i.e.,* $\frac{\partial a^*}{\partial \kappa_z} > 0$.
2. *Keeping the uncertainty faced by managers fixed, measured aggregate productivity is U-shaped in attention allocated to aggregate shocks.*

Expression (12) is at the heart of the core mechanism and reveal a sharp connection between the attention allocation to aggregate and idiosyncratic conditions and the measured productivity. Note from Eq. (12) that measured productivity has three terms: exogenous aggregate TFP shock a, endogenous components from idiosyncratic uncertainty and aggregate uncertainty. The second term in Eq. (12) is driven by imperfect information about idiosyncratic (firm-specific) shocks and is the product of idiosyncratic uncertainty ($\sigma_z^2 \equiv 1/\tau_z$) and the weight managers place on idiosyncratic signals ($r_z \equiv 1 - 2^{-2\kappa_z}$). Economically, this term captures the effect of cross-sectional misallocation of resources across firms due to imperfect information about idiosyncratic shocks. As managers learn more about their idiosyncratic productivity shocks (i.e, as κ_z increases), resources are allocated more efficiently, leading to higher measured aggregate productivity.

The third term in Eq. (12) captures the effect of aggregate uncertainty. Economically, the term denotes the dispersion of beliefs across managers about the aggregate shock. As dispersion of beliefs increases, misallocation increases and measured aggregate productivity decreases. Mathematically, measured aggregate productivity is a concave function of individual firm managers' beliefs.[11] Because of Jensen's inequality, more dispersion lowers the average, and, hence, the measured aggregate productivity decreases with dispersion of beliefs about aggregate state. Corollary 1 shows that MAP is U-shaped in κ_a i.e., dispersion of beliefs about aggregate shocks is hump-shaped in attention allocated to aggregate shocks. Intuitively, as attention to aggregate shocks increases from zero, dispersion in beliefs initially increases because Bayesian agents puts less weight on prior and more weight on the heterogeneous signals received. However, as attention keeps increasing, eventually beliefs converge because they will be close to the true fundamental.

Next, I analyze how uncertainty affects measured aggregate productivity. Taking derivative of Eq. (13), I get

$$\frac{da^*}{d\tau_a} = \underbrace{\frac{\partial h_a}{\partial \tau_a}}_{\text{direct effect}} + \underbrace{\frac{\partial h_a}{\partial \kappa_a}\frac{\partial \kappa_a}{\partial \tau_a} + \frac{\partial h_z}{\partial \kappa_z}\frac{\partial \kappa_z}{\partial \tau_a}}_{\text{Effect of endogenous learning}} . \tag{14}$$

Change in aggregate uncertainty has two effects on aggregate productivity. The first one is the direct effect, which captures the effect of uncertainty keeping attention fixed, that is, the effect in benchmark economy. The second effect captures the effect of endogenous learning. First, let's analyze the benchmark economy where attention is exogenous, that is, κ_a and κ_z are constants. In this economy, it is obvious from Eq. (12) that an increase in aggregate (idiosyncratic) uncertainty decreases (increases) measured aggregate productivity. This captures the direct effect term in Eq. (14). In an economy with endogenous attention allocation, κ_z and κ_a are endogenous objects (because of learning), and these depend on the uncertainty that the managers face. The net effects of aggregate and idiosyncratic uncertainty on measured aggregate productivity are summarized below.

Proposition 5. *The following results hold with endogenous learning:*

1. *As aggregate uncertainty increases, the measured aggregate productivity decreases. The effect is stronger in an economy with endogenous learning than in the benchmark economy. Moreover, as the information-processing capacity increases, the effect of aggregate uncertainty on measured productivity decreases.*
2. *Measured aggregate productivity is non-monotonic (U-shaped) in idiosyncratic uncertainty. When idiosyncratic uncertainty is high relative to aggregate uncertainty, measured aggregate productivity increases with idiosyncratic uncertainty. When aggregate uncertainty is high relative to idiosyncratic uncertainty, measured aggregate productivity decreases with idiosyncratic uncertainty. In the benchmark economy, measured aggregate productivity always increases with idiosyncratic uncertainty.*
3. *As information-processing capabilities (κ) increase, measured aggregate productivity increases.*

Aggregate uncertainty shock: Increase in aggregate uncertainty negatively affects measured aggregate productivity, holding other aggregate state variables constant. First, from Eqs. (12) and (14), the direct effect of increases in aggregate uncertainty is to lower measured aggregate productivity. However, as aggregate uncertainty increases, firms learn less about idiosyncratic shocks (κ_z decreases) and more about aggregate shocks (κ_a increases). Decrease in learning about idiosyncratic shocks lead to inefficient allocation of resources across firms and lowers aggregate productivity, that is, h_z decreases (first indirect effect). The third term in Eq. (13) captures the dispersion of beliefs about the aggregate shock, which also decreases with higher aggregate uncertainty. This is because, as aggregate uncertainty increases, agents learn more about aggregate shocks and get more dispersed private signals. For a fixed capacity allocated to aggregate shocks (κ_a), increasing the aggregate uncertainty leads to higher dispersion of beliefs. A Bayesian agent puts less weight on prior and more weight on the heterogeneous signals received, and this increases the dispersion of beliefs across firm managers and lowers measured aggregate productivity. However, as capacity allocated (κ_a) increases, the dispersion of beliefs has a hump shaped effect (Corollary 1). Proposition 5 shows that the net effect on belief dispersion is always negative (Second indirect effect). Hence, my model rationalizes why belief dispersion rises endogenously when aggregate uncertainty is high, consistent with the data. This implies that all the terms in Eq. (14) have the same sign (negative) and, hence, the overall effect of aggregate uncertainty on measured aggregate productivity is negative and stronger than in the benchmark economy. Finally, as information-processing capacity increases, the effect of aggregate uncertainty on measured productivity decreases. This suggests that, even when exposed to the same aggregate uncertainty shock, economy with better information-processing managers will be more resilient.

Idiosyncratic uncertainty shock: Changes in idiosyncratic uncertainty has a non-monotonic effect on measured aggregate productivity. From Eq. (12), the direct effect (keeping κ_a and κ_z fixed) of increases in idiosyncratic uncertainty is to increase measured aggregate productivity. However, as idiosyncratic uncertainty increases, firms learn more about idiosyncratic shocks (κ_z increases) and less about aggregate shocks (κ_a decreases). As firms learn more about their idiosyncratic shocks, the information friction shrinks: Resources are allocated more efficiently, which leads to higher productivity (first indirect channel). However, learning less about aggregate shocks has a non-monotonic (hump-shaped) effect on measured aggregate productivity. It turns out that the net effect is non-monotonic and positive only when idiosyncratic uncertainty is high relative to aggregate uncertainty.

Information-processing capability: As κ increases, agents devote more attention to both idiosyncratic and aggregate shocks. More attention to idiosyncratic shocks has a positive effect on aggregate productivity, and more attention to ag-

[11] This is because the logarithm of measured aggregate productivity is the arithmetic mean of the logarithm of individual firms' beliefs.

gregate shocks has a non-monotonic effect on aggregate productivity. However, Proposition 5 implies that the net effect is always positive.

In my model, we can interpret the information-processing capacity of the manager as the proxy for managerial ability, that is, higher information-processing capacity corresponds to the ability of the manager to identify positive NPV projects and allocate more resources to them. In a recent study, Bloom et al. (2013) find that management practices in India are worse than those in the United States, and they emphasize that informational barriers are the primary factor in explaining this result. Hence, my model can potentially explain why resource misallocation is worse in India and China compared to the United States.

Recessions: As noted earlier, recessions are periods of high risk aversion and high aggregate uncertainty relative to idiosyncratic uncertainty.[12] In the model, both of these effects lead firm managers to learn more about aggregate shocks and less about idiosyncratic shocks. This implies that the misallocation in the economy rises and, hence, measured productivity falls.

Discussion of results

My model implies that an increase in aggregate uncertainty leads to drop in measured productivity. In the empirical literature, there is consensus that aggregate uncertainty (macro-volatility) is counter-cyclical and leads to rise in discount rates. The channel in my model operates through higher dispersion of beliefs when aggregate uncertainty is high, which is consistent with the empirical observation during crises episodes. On the other hand, there is mixed evidence on whether idiosyncratic uncertainty is counter-cyclical or not. Recently, Dew-Becker and Giglio (2020) examine the forecasting power of idiosyncratic uncertainty (constructed using options data) for aggregate output. The data appears to show that idiosyncratic uncertainty is sometimes high in bad times, and sometimes high in good times. The existing theoretical models (e.g., Christiano et al. (2014),and Bloom et al. (2018)) predict that cross-sectional uncertainty should be clearly countercyclical and should be more tightly related to aggregate output, inconsistent with the data. In my paper, I highlight a novel channel that shows that the effect of idiosyncratic uncertainty is non-monotonic, which can potentially reconcile this mixed empirical evidence on the effect of idiosyncratic uncertainty. In Section 4.3, I provide evidence for the key model implication: The effect of idiosyncratic uncertainty is U-shaped.

Dew-Becker and Giglio (2020) document that there was surprisingly little variation in idiosyncratic uncertainty from 1980 to 1995. After 1995, idiosyncratic uncertainty moves much more (although still less than market uncertainty, in proportional terms), with three distinct increases, during the tech boom, the financial crisis, and the coronavirus epidemic. During the tech boom, idiosyncratic uncertainty is much higher than aggregate uncertainty and hence my model (Proposition 5, Statement 2) predicts that it is good times. During the financial crisis, idiosyncratic uncertainty increases but it is lower than the increase in aggregate uncertainty. Proposition 5 (Statement 2) states that, when aggregate uncertainty is high relative to idiosyncratic uncertainty, measured aggregate productivity decreases with rise in idiosyncratic uncertainty. Hence, during such episodes, increase in idiosyncratic uncertainty is bad news.

Eisfeldt and Rampini (2006) show that capital reallocation decreases during bad times, whereas the misallocation of inputs increases during downturns, implying that the benefit of reallocation seems high in bad times.[13] One potential explanation is the counter-cyclical information quality on investment opportunities. During economic downturns, uncertainty at both the aggregate and idiosyncratic level rises sharply with aggregate uncertainty increasing more than idiosyncratic uncertainty. This implies that, during these episodes, firm managers pay more attention to aggregate shocks and less attention to idiosyncratic shocks. This implies that, capital misallocation rises endogenously and the benefit of reallocation rises (because of increased idiosyncratic uncertainty). Hence, my model can provide one potential explanation for the capital reallocation puzzle.

3.2. Empirical predictions

Benchmark economy: Since endogenous learning (inattention) is the main friction, the benchmark economy is the one in which learning is exogenous, that is, one in which attention allocations κ_a and κ_z are constant and independent of uncertainty faced by the agents. I will refer to this specification as the benchmark economy and come up with predictions that will help us to distinguish this benchmark economy from an economy with endogenous learning.

In the model, firm managers choose production inputs (labor choice) to maximize the value of the firm conditional on their information set. Note that the optimal labor input chosen by the firm is given by

$$n_i = \varphi_0 + \varphi_a s_{ia} + \varphi_z s_{iz}. \tag{15}$$

In the above equation, there are 2 endogenous objects φ_a and φ_z. My testable predictions highlight the effect of each of these equilibrium objects separately.

The first prediction is about the elasticity of firm's inputs (n_i) to its idiosyncratic productivity. Note from Eq. (15) that the elasticity of firm's inputs to its idiosyncratic signal is given by φ_z. Moreover, Proposition 1 implies that $\varphi_z \propto \frac{\tau_z^s}{\tau_z^s+\tau_z} =$

[12] see Figure OA1 in online appendix.

[13] Kehrig and Vincent (2017) shows that, at the establishment level, the benefits of capital reallocation are counter-cyclical.

$1-2^{-2\kappa_z}$, that is, the loading of the manager's input choice on his idiosyncratic signal depends on the attention allocated to it. As managers learn more about idiosyncratic shocks, they put more weight on the idiosyncratic signal received.

Proposition 3 teaches us that increased aggregate uncertainty prompts attention reallocation toward aggregate risk. This implies that average attention devoted to aggregate shocks should increase and the attention devoted to idiosyncratic shocks should decrease. This in turn implies that a manager's input decision covaries more with the aggregate shock and less with the firm-specific shock. This reallocation argument leads us to the first testable prediction.

Prediction 1: *The elasticity of a firm's inputs to its (idiosyncratic) productivity shock decreases with aggregate uncertainty and increases with idiosyncratic uncertainty.*

This prediction doesn't hold in the benchmark economy in which attention allocation is an exogenous constant. In such an economy, the elasticity of a firm's inputs to its (idiosyncratic) productivity shock is constant. Moreover, note that labor choice can be rewritten as

$$n_i = \varphi_0 + \varphi_a s_{ia} + \varphi_z s_{iz} = \varphi_0 + \varphi_a a + \varphi_z z_i + \varphi_a \nu_{ia} + \varphi_z \nu_{iz}. \tag{16}$$

By definition, idiosyncratic TFP shocks (z_i) and noise in signals (ν_{ia} and ν_{iz}) are uncorrelated across firms, which then implies that the covariance (co-movement) of inputs across firms is given by

$$\mathrm{Cov}\left(n_i, n_j\right) = \underbrace{\frac{1}{\tau_a}}_{\text{Aggregate uncertainty}} \times \underbrace{\varphi_a^2}_{\text{Endogenous object}}. \tag{17}$$

Eq. (17) implies that the forces causing production inputs to co-vary are aggregate uncertainty and an endogenous object φ_a (elasticity of labor choice to aggregate shock). The following proposition provides a characterization of how covariance of inputs changes with aggregate and idiosyncratic uncertainty.[14]

Proposition 6. *In an economy with endogenous learning, covariance of inputs decreases with idiosyncratic uncertainty and increases with aggregate uncertainty. In the benchmark economy, covariance of inputs does not change with idiosyncratic uncertainty.*

Proposition 6 states that, with endogenous learning, covariance of inputs decreases with idiosyncratic uncertainty. As idiosyncratic uncertainty increases, firms allocate less capacity to learn about aggregate shocks, and this decreases the elasticity of labor choice to aggregate signal (φ_a). As all firms learn less about aggregate shocks, covariance of their inputs decreases. This is not true in the benchmark economy. In the benchmark economy, as idiosyncratic uncertainty increases, covariance of inputs does not change. This is evident from Eq. (17), which depends on aggregate uncertainty and aggregate signal precision and is independent of idiosyncratic uncertainty.

On the other hand, as aggregate uncertainty increases, firms learn more about aggregate shocks and φ_a increases. This implies covariance of inputs increases with aggregate uncertainty. This result holds even without endogenous learning (i.e., in benchmark economy), as can be seen from expression (17).

Fig. 2 plots the covariance of inputs versus idiosyncratic uncertainty (left plot) and aggregate uncertainty (right plot) in the benchmark economy (dotted line) and in an economy with endogenous learning (solid line). In the left plot, note that the covariance of inputs does not change with idiosyncratic uncertainty in the benchmark economy and decreases with idiosyncratic uncertainty in an economy with endogenous learning. This leads us to my second testable prediction.

Prediction 2: *Covariance of inputs across firms decreases with idiosyncratic uncertainty.*

Both the predictions directly follows from optimal attention allocation decisions switching over the business cycle and does not hold in the benchmark economy. In the next section, I test these predictions.

4. Empirical evidence on the learning mechanism

An obvious hurdle in testing models with endogenous learning is that we cannot directly observe the variables included in firm managers' information set. One approach to overcome this would be to test the model indirectly: link the information choice (solved in the previous sections) to observable patterns in data. In this section, I follow this approach and provide evidence supporting predictions 1 and 2 of the model. I also provide evidence for the aggregate implication of the model: the effect of idiosyncratic uncertainty is U-shaped.

4.1. Data

Our sample includes all firms in the COMPUSTAT (North America) Fundamentals Annual Files listed on the NYSE/AMEX/NASDAQ exchanges, excluding financial firms (SIC 6000 - 6999) and public utilities (SIC 4900 - 4999). The key variables for our analysis are the number of employees (EMP), investment and the capital stock, given by the investment

[14] In section Online Appendix A.5, I introduce stock market into the analysis and argue that managers learning from stock price can generate excess covariance of inputs. Here, I shutdown that channel and focus on the implications of endogenous learning.

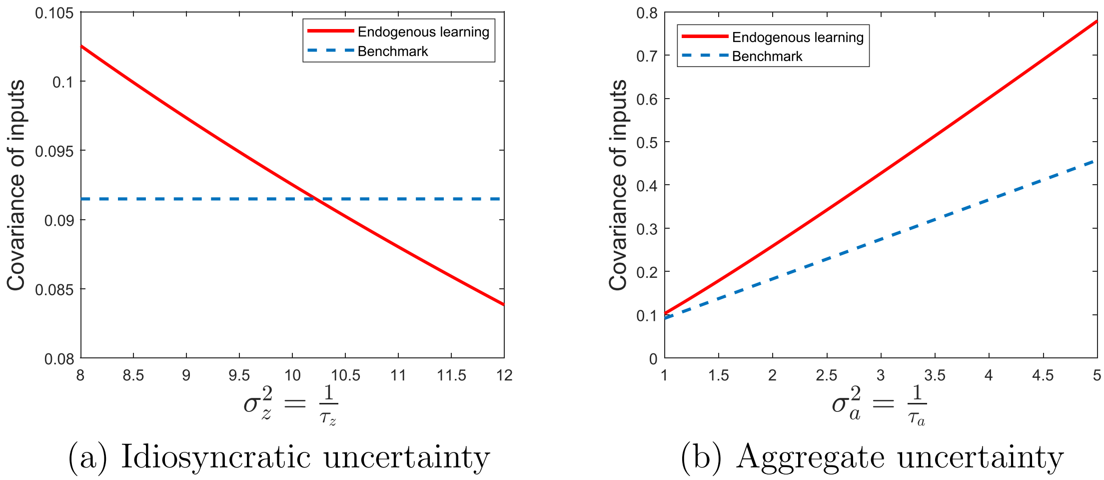


Fig. 2. lot of covariance in inputs. This figure plots the covariance of inputs as a function of aggregate uncertainty (left) and idiosyncratic uncertainty (right) in an economy with endogenous learning (solid line) and the benchmark economy (dotted lines).

(CAPX), and stock of property, plant and equipment (PPENT). Data on labor expenses is very sparse in COMPUSTAT, I therefore construct it as the product of employees (EMP) and aggregate yearly average wage index from the US Social Security Administration. The growth rate in labor expenses is used to define the positive and negative employment adjustment. This is the key dependent variable in the analysis. A comparison of the COMPUSTAT variable for staff expenses (XLR) with our series on labor expenses suggests that our approximation is reasonable, delivering an unbiased estimate for labor expenses.

Measuring uncertainty: Time series of aggregate uncertainty and idiosyncratic uncertainty is from stock options on S&P 500 and individual firms. Aggregate uncertainty is S&P 500 option-implied volatility. Idiosyncratic uncertainty is just the average firm-level option-implied conditional variance minus market-implied conditional variance. Importantly, these measures of uncertainty are forward-looking by construction. These variables are quite similar to the measure proposed in Dew-Becker and Giglio (2020). These implied volatilities are derived from an endogenous outcome - stock returns - rather than a fundamental shock, like TFP. Nevertheless, they represent the most common measure of uncertainty studied in the literature, and they have the attractive feature that they give a measure of uncertainty based on actual investments people have made, in addition to being forward-looking. For robustness, I repeat my analyses using other measures of uncertainty proposed in the literature (Bloom et al. (2018)), and the results are similar.

TFP: I estimate firm-level productivity (TFP) as the solow residual measured as follows:

$$z_{i,t} = y_{i,t} - \beta_k k_{i,t} - \beta_l l_{i,t} \tag{18}$$

where $y_{i,t}$ denotes the log of value added, $k_{i,t}$ denotes the log of capital, $l_{i,t}$ denotes the log of labor, β_k and β_l denote the capital and labor share of production respectively.

The key variables for this estimation are the beginning of period capital stock (PPENT), the stock of labor (EMP) and the value added. Value added is constructed as the difference of sales and materials. While sales (SALE) are directly available in COMPUSTAT, I construct materials as total expenses minus labor expenses. Total expenses is sales (SALE) minus the sum of operating income after depreciation (OIADP) and depreciation (DP).

When measuring the productivity level ($z_{i,t}$), I estimate β_l as labor share of total value added in the corporate sector. This is given by the total compensation paid to labor as a fraction of total value added.[15] Measuring capital costs presents an empirical challenge since most of the physical capital stock is owned by firms rather than leased. I assume that firms have constant-returns-to-scale production and hence, $\beta_k = 1 - \beta_l$.

Controls: Hayashi (1982) argues that Q is the sufficient statistic for firm's investment decision, and, hence I use it as a control. Even though my main dependent variable is about labor expenses, one might argue that the same mechanism holds for labor expenses. Tobin's q (Q) is measured as (AT+(PRCC*CSHO)-CEQ)/AT, where PRCC is the annual price close (fiscal year end), CSHO is common shares outstanding, AT is total assets and CEQ is common equity. A large body of research starting with Fazzari et al. (1987) suggests that firms facing financial constraints should exhibit higher sensitivity of investment to cash flows. In order to control for this, I use cash flow scaled with beginning of period capital stock (PPENT) as a control. Cash flow is defined as the sum of income before extraordinary items (IB) and depreciation and amortization (DP).

[15] This is similar to the measure in Karabarbounis and Neiman (2014). The advantage of this approach is that they estimate labor share at the yearly level. Moreover, they employ better data from Bureau of Economic Analysis (BEA) in estimating labor share.

Table 1
Summary statistics This table shows the summary statistics of all the variables. For each firm i and year t, $n_{i,t}$ denotes the growth in labor expenses, $z_{i,t}$ denotes the solow residual measured as in Eq. (18), $t_{i,t}$ denotes the innovation in solow residual measured as in Eq. (21), $\sigma_{z,t}$ and $\sigma_{a,t}$ denotes the idiosyncratic and aggregate uncertainty respectively. I include the sample average, median, 25th, and 75th percentiles, and standard deviations of all the variables of interest, as well as the control variables. Refer to variable definitions for more information on each variable.

Variable	N	Mean	Std Dev	P25	P50	P75
$n_{i,t}$: **Labor growth**	63131	0.089	0.206	-0.015	0.061	0.158
$z_{i,t}$: **TFP**	63131	-0.353	0.401	-0.591	-0.368	-0.123
$\sigma_{z,t}$: **Idio. Uncert**	40	0.248	0.064	0.210	0.226	0.257
$\sigma_{a,t}$: **Agg. Uncert**	40	0.178	0.051	0.132	0.172	0.213
$z_{i,t} \times \sigma_{z,t}$: **TFP* Idio. Uncert**	63131	-0.087	0.100	-0.144	-0.088	-0.029
$z_{i,t} \times \sigma_{a,t}$: **TFP* Agg. Uncert**	63131	-0.062	0.074	-0.103	-0.060	-0.020
$t_{i,t}$: **TFP shock**	63131	0.016	0.253	-0.079	0.021	0.119
$t_{i,t} \times \sigma_{z,t}$: **TFP shock* Idio. Uncert**	63131	0.003	0.065	-0.019	0.005	0.028
$t_{i,t} \times \sigma_{a,t}$: **TFP shock* Agg. Uncert**	63131	0.002	0.048	-0.013	0.003	0.020
Cash flow/K	63131	0.544	1.721	0.172	0.351	0.676
Tobin Q	63118	1.633	1.123	1.025	1.302	1.835

4.2. Methodology

The first prediction of the model is that the elasticity of a firm's inputs to its (idiosyncratic) productivity shock decreases with aggregate uncertainty and increases with idiosyncratic uncertainty. To test this prediction, I estimate the following regression equation:

$$n_{it} = \beta_i + \alpha_t + \gamma_1 z_{i,t} + \gamma_2 z_{i,t} \times \sigma_{z,t} + \gamma_3 z_{i,t} \times \sigma_{a,t} + Controls + \epsilon_{i,t}, \tag{19}$$

where β_i and α_t denote firm and time-fixed effects; $\sigma_{z,t}$ and $\sigma_{a,t}$ denote idiosyncratic and aggregate uncertainty, respectively. Our model predicts that optimal input chosen by firm i is given by

$$\log(\text{Inputs}_i) = \varphi_0 + \varphi_a a + \varphi_z z_i + \varphi_a \nu_{ia} + \varphi_z \nu_{iz}, \tag{20}$$

where ν_{iz} and ν_{ia} denote the signal errors firm i receives. Note that having time-fixed effects in the regression equation will absorb the effect of aggregate shock (a) in Equation (20). One of the predictions of the model (using Equation (20) and Proposition 1) is that the elasticity of inputs to idiosyncratic TFP shock, $\varphi_z \propto \frac{\tau_z^s}{\tau_z^s + \tau_z} \equiv 1 - 2^{-2\kappa_z}$, increases as agents learn more about idiosyncratic shocks. This implies that in the regression Eq. (19), γ_2 (i.e., coefficient on $z_{i,t} \times \sigma_{z,t}$) is positive: If idiosyncratic uncertainty increases, firms learn more about idiosyncratic shocks, and, hence, the elasticity of firms inputs to its TFP shock should be higher. Next, the model also implies that γ_3 (i.e., coefficient on $z_{i,t} \times \sigma_{a,t}$) should be negative. If aggregate uncertainty is higher, firms learn more about aggregate shocks and less about idiosyncratic shocks, and, hence, the elasticity of firms' inputs to its TFP shock will be lower.

Regression results are reported in Table 2. Column 1 implies that higher productivity levels is associated with higher labor growth, as expected. Column 2 shows that γ_2 is in fact positive and significant. This implies that sensitivity of labor expenses to productivity is higher when idiosyncratic uncertainty increases. If idiosyncratic uncertainty increases, firms learn more about idiosyncratic shocks, and, hence, the elasticity of firms' inputs to TFP shock is higher. Column 3 shows that γ_3 is in fact negative and significant. This implies that sensitivity of labor expenses to productivity is lower when aggregate uncertainty increases. Finally, Column 4 considers the effect, controlling for Q and cash flow/K. The asymmetry between aggregate and idiosyncratic uncertainty is still manifested. From Column 4, note that one standard deviation increase in idiosyncratic uncertainty from its mean increases the sensitivity of labor input to productivity by $0.211 \times 0.064 = 0.014$, a 8.26% increase in the sensitivity.[16] Similarly, a one standard deviation increase in aggregate uncertainty from the mean decreases the sensitivity of labor input to productivity by $0.16 \times 0.051 = 0.009$, a 4.95% decrease in sensitivity.

As robustness, I define TFP shocks ($t_{j,t}$: innovations in TFP) as the residual from the first-order auto-regressive equation for firm-level TFP,

$$z_{j,t} = \mu + \rho z_{j,t-1} + t_{j,t}, \tag{21}$$

where $z_{j,t}$ is the level of TFP of firm j in year t, μ, ρ denote the regression coefficients. In the above specification, $t_{j,t}$ captures the residual the econometrician could not forecast, given time $t-1$ information. I assume that the firm manager is also trying to learn about this shock. I re-estimate regression Eq. (19) with this definition of fundamentals. The results

[16] The sensitivity of labor input to TFP shock when idiosyncratic uncertainty and aggregate uncertainty are at the respective means is $0.141 + 0.211 \times 0.248 - 0.16 \times 0.178 = 0.165$.

Table 2
TFP and firm level labor expense. This table presents the firm-level yearly regression:

$$n_{it} = \beta_i + \alpha_t + \gamma_1 z_{i,t} + \gamma_2 z_{i,t} \times \sigma_{z,t} + \gamma_3 z_{i,t} \times \sigma_{a,t} + Controls + \epsilon_{i,t}.$$

The dependent variable in the regressions is growth in labor expenses. TFP of a firm in a given year is the solow residual, $z_{i,t}$, defined in Eq. (18). $\sigma_{z,t}$ denotes the proxy for idiosyncratic uncertainty. $\sigma_{a,t}$ denotes the proxy for aggregate uncertainty. Standard errors (in parenthesis) are clustered by firm and year. The data is yearly and covers the period 1982 to 2019.

	$n_{i,t}$: Labor growth			
	(1)	(2)	(3)	(4)
TFP	0.184***	0.133***	0.147***	0.141***
	(0.008)	(0.020)	(0.020)	(0.019)
TFP× Idio. uncertainty		0.210***	0.301***	0.211**
		(0.067)	(0.093)	(0.085)
TFP× Agg. uncertainty			-0.200*	-0.160*
			(0.105)	(0.097)
Cash flow/K				0.002
				(0.001)
Tobin Q				0.023***
				(0.002)
Constant	0.155***	0.155***	0.155***	0.109***
	(0.003)	(0.002)	(0.002)	(0.005)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	62,832	62,832	62,832	62,819
R^2	0.256	0.256	0.256	0.264

are reported in table OA3 of the Online Appendix and are similar qualitatively. In sum, the data support Prediction 1 of the theory.[17]

Next, I focus on Prediction 2 of the model: covariance of inputs across firms decreases with idiosyncratic uncertainty.[18]

Construction of input covariance: Let $l_{i,t}$ and l_t denote the labor expense of firm i in year t and aggregate labor expense in year t, respectively. By definition $l_t = \sum l_{it}$. Denote growth in labor expense at firm level and aggregate level by n_{it} and n_t. Growth in labor expense at aggregate level can be rewritten as

$$n_t \equiv \frac{\Delta l_{t+1}}{l_t} = \sum_i \frac{\Delta l_{i,t+1}}{l_t} = \sum_i \frac{l_{i,t}}{l_t}\frac{\Delta l_{i,t+1}}{l_{i,t}} = \sum_i w_{it} n_{it},$$

where w_{it} denotes the share of labor expense of firm i in the aggregate labor expense.

Also, let $V\left([n_\tau]_{t-4}^{t+4}\right)$ denote the variance of $\{n_{t-4}, \ldots n_t, \ldots, n_{t+4}\}$. Using the definition of the variance for the above equation, we get

$$V\left([n_\tau]_{t-4}^{t+4}\right) = \underbrace{\sum_i V\left([w_{i,\tau} n_{i,\tau}]_{t-4}^{t+4}\right)}_{\text{Variance component}} + \underbrace{\sum_i \sum_{j\neq i} Cov\left([w_{i,\tau} n_{i,\tau}]_{t-4}^{t+4}, \left[w_{j,\tau} n_{j,\tau}\right]_{t-4}^{t+4}\right)}_{\text{Covariance (co-movement) component}}.$$

Using the above equation, I compute the covariance of inputs across firms (Cov_t) as the difference between $V\left([n_\tau]_{t-4}^{t+4}\right)$ and $\sum_i V\left(\left[w_{i,\tau} n_{i,\tau}\right]_{t-4}^{t+4}\right)$. Then, I regress it on aggregate and idiosyncratic uncertainty as follows:

$$Cov_t = b_0 + b_1 \sigma_{a,t} + b_2 \sigma_{z,t} + \eta_t.$$

The results are reported in Table 3. I find that the coefficient on idiosyncratic volatility is positive (and significant) and the coefficient on aggregate uncertainty is negative (and significant). These findings are consistent with Prediction 2 of my theory. As idiosyncratic uncertainty increases, firms allocate less capacity to learn about aggregate shocks, and this decreases the elasticity of labor choice to aggregate signal (φ_a). As all firms learn less about aggregate shocks, co-movement of their inputs decreases. Quantitatively, if idiosyncratic uncertainty increases by one standard deviation, covariance of inputs goes down by 0.57 standard deviation. For robustness, I also do the analysis using quarterly COMPUSTAT data using investment as the main input variable.[19] The results are similar and reported in the Online Appendix Table OA2. I also did the analysis at the sectoral level and the results are very similar.

[17] For robustness, I estimate β_l as total staff expenses over value added for each firm in a given year. Results are reported in table OA4 of the revised draft. The drawback of this approach is that β_l is measured with lot of noise in the estimation since it is estimated for every firm and year, and hence, I moved these results to Online Appendix.

[18] Prediction 1 follows from model implications about coefficient φ_z in Eq. 17, and Prediction 2 follows from coefficient φ_a.

[19] At the quarterly frequency, COMPUSTAT doesn't report number of employees employed at firm level.

Table 3
Covariance of inputs at firm level. The table presents the results from estimating the regression equation:

$$Cov_t(inputs) = b_0 + b_1\sigma_{a,t} + b_2\sigma_{z,t} + \eta_t$$

The sample used is yearly COMPUSTAT data to estimate covariance of inputs. The dependent variable is the covariance of labor expense growth across firms. The independent variables are aggregate uncertainty and idiosyncratic uncertainty. Refer to variable definitions for more information on each proxy. Different columns correspond to various permutations of proxies.

	(1)	(2)
$\sigma_{a,t}$: Agg. Uncert	0.005**	0.009***
	(0.002)	(0.002)
$\sigma_{z,t}$: Idio. Uncert		-0.006***
		(0.002)
Constant	0.000	0.000
	0.000	0.000
Observations	37	37
R squared	18.93%	41.82%

Table 4
Aggregate implications. The table presents the results from estimating the regression equation as follows:

$$\Delta y_t = b_0 + b_1\Delta y_{t-1} + b_2\Delta\sigma_{a,t} + b_3\Delta\sigma_{z,t} + b_4\Delta\sigma^2_{z,t} + \eta_t.$$

The sample used is quarterly-level GDP and consumption data from FRED (Federal Reserve Economic Data). The dependent variable Δy_t represents change in the logarithm of GDP (first three columns) and consumption (next three columns). Δ represents the first-difference operator. The main independent variables are differences in aggregate uncertainty, idiosyncratic uncertainty, and squared idiosyncratic uncertainty. In parenthesis below, I report Newey-West standard errors with four lags .

	y: GDP			y: Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
Δy_{t-1}	-0.14	-0.14	-0.15*	-0.28***	-0.27***	-0.30***
	(0.084)	(0.085)	(0.085)	(0.088)	(0.088)	(0.088)
$\Delta\sigma_{a,t}$: Agg. Uncert.	-0.07***		-0.05*	-0.06***		-0.05*
	(0.02)		(0.026)	(0.02)		(0.027)
$\Delta\sigma_{z,t}$: Idio. Uncert.		-0.37***	-0.26**		-0.37***	-0.30**
		(0.112)	(0.125)		(0.115)	(0.129)
$\Delta\sigma^2_{z,t}$: Idio. Uncert.^{2}		0.44***	0.36**		0.45***	0.39**
		(0.163)	(0.169)		(0.168)	(0.174)
Constant	0.007***	0.007***	0.007***	0.009***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	161	161	161	161	161	161
R-squared	8.13%	9.11%	11.11%	9.16%	11.68%	12.42%

4.3. Testing aggregate implications

My model implies that an increase in aggregate uncertainty leads to drop in measured productivity and, hence, output. On the other hand, my model implies than measured productivity is U-shaped in idiosyncratic uncertainty (Proposition 5). This is a key implication, which distinguishes my theory from other competing theories. In order to test these implications, I run the following regression:

$$\Delta y_t = b_0 + b_1\Delta y_{t-1} + b_2\Delta\sigma_{a,t} + b_3\Delta\sigma_{z,t} + b_4\Delta\sigma^2_{z,t} + \eta_t,$$

where η_t is the residual, y_t represents the log of GDP or consumption, Δ represents the first-difference operator, $\sigma_{a,t}$ denote the aggregate uncertainty, and $\sigma_{z,t}$ denotes the idiosyncratic uncertainty. In order to test whether idiosyncratic uncertainty is U-shaped, I also included a squared idiosyncratic uncertainty term in the regression.

Results are reported in Table 4. As can be seen from Columns (1) and (4), an increase in aggregate uncertainty is associated with a drop in output and consumption. From Columns (2) and (5), notice that the coefficient on idiosyncratic uncertainty is negative, and the coefficient on its squared term is positive and significant. This implies that idiosyncratic uncertainty has a U-shaped relationship with output and consumption. Columns (3) and (6) re-estimates these results using all the variables in the regression specification, finding very similar results.

5. Conclusion

In this paper, I show that endogenizing information choice of firm managers is a fruitful approach to understand how firms' production decisions and aggregate resource misallocation changes with aggregate and idiosyncratic uncertainty. My main insight is that when aggregate (idiosyncratic) uncertainty changes, it is critical to understand how this effects firm managers attention choice and study the implications of this mechanism for misallocation and aggregate economy. I show that firm managers optimally choose to learn less about aggregate shocks when idiosyncratic uncertainty is higher and vice-versa. This mechanism delivers endogenous fluctuations in measured aggregate productivity (MAP) in response to movements in firms' information-processing constraint, aggregate, and idiosyncratic uncertainty. Importantly, my model implies that idiosyncratic uncertainty has non-monotonic affect on aggregate quantities. I show empirical evidence supporting this implication.

There are several promising directions for future research. In my modeling approach, I have aimed to strike a balance between realism and transparency of the economic forces at play. In doing so, I have made a couple of admittedly extreme assumptions. For example, the input choice is modeled as static. Similarly, the learning problem is also static, with a perfect revelation at the end of the period, implying that firms are able to quickly correct their past errors. These assumptions limit my ability to do a full-fledged calibration to match moments. Relaxing them is conceptually straightforward but involves substantial computational challenges. Also, in this paper, I assumed that uncertainty shocks are exogenous, like first moment shocks. If uncertainty is endogenous, one could think of a propagation and amplification mechanism.

Data availability

Data will be made available on request.

Appendix A

A1. Useful notation and lemmas'

1. When a variable X is log-normal with $\ln X \sim \mathcal{N}\left(\bar{x}, \sigma^2\right)$, then, for any $\varpi \in \mathbb{R}$, we have that

$$\mathbb{E}[X^{\varpi}] = \exp\left(\varpi \bar{x} + \frac{1}{2}\varpi^2\sigma^2\right) = \left(\exp\left(\bar{x} + \frac{1}{2}\sigma^2\right)\right)^{\varpi} \exp\left(\frac{1}{2}(\varpi - 1)\varpi\sigma^2\right), \tag{A.1}$$

and, therefore,

$$\mathbb{E}[X^{\varpi}] = (\mathbb{E}[X])^{\varpi} \exp\left(\frac{1}{2}(\varpi - 1)\varpi\sigma^2\right).$$

I use this property again and again in the derivations that follow, for various random variable X and constant ϖ.

2. **Notation**

Variable description	Notation
Log aggregate productivity	a
Uncertainty about aggregate productivity shock	τ_a
Log idiosyncratic productivity of firm i	z_i
Uncertainty about idiosyncratic productivity shock	τ_z
Log total output	y
Log labor input chosen by firm i	n_i
Total capacity	κ
Attention allocated to aggregate shocks	κ_a
Attention allocated to idiosyncratic shocks	κ_z
Signal about aggregate shock	s_{ia}
Signal about idiosyncratic shock	s_{iz}
Precision of aggregate signal	τ_a^s
Precision of idiosyncratic signal	τ_z^s

3. Suppose $a \sim \mathcal{N}\left(-\frac{1}{2\tau_a}, \frac{1}{\tau_a}\right)$ and $s_{ia} = a + \nu_{ia}$ where $\nu_{ia} \sim \mathcal{N}\left(0, \frac{1}{\tau_a^s}\right)$. Standard Gaussian updating implies

$$a|s_{ia} \sim \mathcal{N}\left(-\frac{1}{2\tau_a}(1 - r_a) + r_a s_{ia}, \frac{1 - r_a}{\tau_a}\right), \tag{A.2}$$

where $r_a = \frac{\tau_a^s}{\tau_a^s + \tau_a}$ is the weight the firm manager puts on the signal realization s_{ia} to forecast aggregate fundamentals. Also, suppose $z_i \sim \mathcal{N}\left(-\frac{1}{2\tau_z}, \frac{1}{\tau_z}\right)$ and $s_{iz} = z_i + \nu_{iz}$, where $\nu_{iz} \sim \mathcal{N}\left(0, \frac{1}{\tau_z^s}\right)$. Then,

$$z_i|s_{iz} \sim \mathcal{N}\left(-\frac{1}{2\tau_z}(1 - r_z) + r_z s_{iz}, \frac{1 - r_z}{\tau_z}\right), \tag{A.3}$$

where $r_z = \frac{\tau_z^s}{\tau_z^s + \tau_z}$ is the weight the firm manager puts on the signal realization s_{iz} to forecast idiosyncratic fundamentals.

A2. Proofs

Even though our baseline model does not feature financial markets, the proofs assume that there exists a financial market (as described in section Online Appendix A.5) which aggregates the information of managers and managers can learn from it. In order to prove the propositions in the baseline model, simply assume $\tau_\epsilon = 0$ and $s_q = 0$ in the proofs.

Proof of Lemma 1.

1. At time 2, the revenue of firm i is given by $P_iY_i = P_iAZ_iN_{i,d}^{\alpha}$, where subscript '$d$' indicates labor demanded by each firm's given wages. This implies firm profits are given by $\pi_i = P_iY_i - W_iN_{i,d} = P_iAZ_iN_{i,d}^{\alpha} - W_iN_{i,d}$. So, at time 1, firm i's objective is to maximize NPV:

$$\max_{N_{i,d}} E\left[U'(C)\left(P_iAZ_iN_{i,d}^{\alpha} - W_iN_{i,d}\right)|\mathcal{I}_i^1\right], \tag{A.4}$$

where the expectation is taken with respect to the firm manager's information set $\mathcal{I}_i^1 = \{s_{ia}, s_{iz}, s_q\}$. The final good is our numeraire, and so $P_i = 1$. The first-order condition for firms' demand of labor is given by

$$\alpha E_i\left[U'(C)AZ_i\right]\left(N_{i,d}\right)^{\alpha-1} = E_i\left[U'(C)W_i\right]. \tag{A.5}$$

At time 1, since workers who work for firm i share the same information set as the firm, the optimal labor supply ($N_{i,s}$) solves the first-order condition:

$$E_i\left[U'(C)W_i\right] = N_{i,s}^{\nu}. \tag{A.6}$$

Combining Eqs. (A.5) and (A.6) and imposing market clearing in the labor market ($N_{i,d} = N_{i,s} = N_i$) implies that the equilibrium is pinned down by the condition:

$$\alpha E_i\left[U'(C)AZ_i\right](N_i)^{\alpha-1} = N_i^{\nu}.$$

2. Manager beliefs about the aggregate state can be ordered by their private signals, and so we posit a threshold strategy: the managers purchase one unit of equity if $s_{ia} > h(a,\epsilon)$; otherwise, they hold only the risk-free security. Substituting this into the market clearing condition,

$$\underbrace{1 - \Phi(\epsilon)}_{\text{Total Supply}} = \underbrace{1 - \Phi\left(\sqrt{\tau_a^s}(h(a,\epsilon) - a)\right)}_{\text{Total Demand}}.$$

Rewriting this condition shows that markets clear if and only if $h(a,\epsilon) = a + \frac{\epsilon}{\sqrt{\tau_a^s}}$. Moreover, the marginal investor, whose information set is $\{s_{ia} = h(a,\epsilon), q\}$, sets the price equal to her conditional expectation, which implies that the information content of price $s_q = h(a,\epsilon) = a + \frac{\epsilon}{\sqrt{\tau_a^s}}$.

□

Proof of Proposition 1. I first conjecture that the total (log) output and each firm's optimal input take the following log-linear forms:

$$y = \psi_0 + \psi_a a + \psi_\epsilon \epsilon$$
$$n_i = \varphi_0 + \varphi_a s_{ia} + \varphi_z s_{iz} + \varphi_q s_q,$$

where the coefficients will be determined by equilibrium conditions. From Eq. (5), define $X_i \equiv C^{-\gamma}AZ_i$ to be the equilibrium object that firm manager i has to forecast given his information set. Substituting the conjectured forms into the logof this variable (X_i) gives

$$\begin{aligned} x_i &= (-\gamma)(\psi_0 + \psi_a a + \psi_\epsilon \epsilon) + a + z_i \\ &= (-\gamma)\psi_0 + (-\gamma\psi_a + 1)a + z_i - \gamma\psi_\epsilon\epsilon \\ &\equiv \pi_0 + z_i + \pi_a a + \pi_\epsilon \epsilon, \end{aligned}$$

where $\pi_0 = -\gamma\psi_0; \pi_a = -\gamma\psi_a + 1$ and $\pi_\epsilon = -\gamma\psi_\epsilon$. Also,

$$\begin{pmatrix} \pi_a a + \pi_\epsilon \epsilon \\ s_{ia} \\ s_q \end{pmatrix} \sim N\left(\begin{pmatrix} -\frac{\pi_a}{2\tau_a} \\ -\frac{1}{2\tau_a} \\ -\frac{1}{2\tau_a} \end{pmatrix}, \begin{pmatrix} \frac{\pi_a^2}{\tau_a} + \frac{\pi_\epsilon^2}{\tau_\epsilon} & \frac{\pi_a}{\tau_a} & \left(\frac{\pi_a}{\tau_a} + \frac{\pi_\epsilon}{\tau_\epsilon\sqrt{\tau_a^s}}\right) \\ \frac{\pi_a}{\tau_a} & \left(\frac{1}{\tau_a} + \frac{1}{\tau_a^s}\right) & \frac{1}{\tau_a} \\ \left(\frac{\pi_a}{\tau_a} + \frac{\pi_\epsilon}{\tau_\epsilon\sqrt{\tau_a^s}}\right) & \frac{1}{\tau_a} & \frac{1}{\tau_a} + \frac{1}{\tau_\epsilon\tau_a^s} \end{pmatrix}\right).$$

The projection theorem implies that

$$(\pi_a a + \pi_\epsilon \epsilon)|\{s_{ia}, s_q\} \sim N\left(-\frac{\pi_a}{2\tau_a} + \Delta_a\left(s_{ia} + \frac{1}{2\tau_a}\right) + \Delta_q\left(s_q + \frac{1}{2\tau_a}\right), \Sigma\right)$$

where $\Delta_a = \frac{\tau_a^s(-\pi_\epsilon\sqrt{\tau_a^s}+\pi_a)}{\tau_a+\tau_a^s(\tau_\epsilon+1)}$, $\Delta_q = \frac{\tau_a^s\tau_\epsilon\pi_a+\pi_\epsilon\sqrt{\tau_a^s}(\tau_a+\tau_a^s)}{\tau_a+\tau_a^s(\tau_\epsilon+1)}$, and $\Sigma = \frac{(\pi_a-\pi_\epsilon\sqrt{\tau_a^s})^2}{\tau_a+\tau_a^s(\tau_\epsilon+1)}$.

Combining these expressions with (A.3) implies that

$$\mathbb{E}_i(x_i) = \pi_0 - \frac{1}{2\tau_z} + r_z\left(s_{iz} + \frac{1}{2\tau_z}\right) - \frac{\pi_a}{2\tau_a} + \Delta_a\left(s_{ia} + \frac{1}{2\tau_a}\right) + \Delta_q\left(s_q + \frac{1}{2\tau_a}\right)$$

$$\text{Var}_i(x_i) = \frac{1-r_z}{\tau_z} + \Sigma.$$

I next evaluate the integral in (6). The firm idiosyncratic productivity z_i and $E_i(x_i)$ are jointly distributed as

$$\begin{pmatrix} z_i \\ E_i(x_i)\end{pmatrix} \mid a,\epsilon \sim \mathcal{N}\left(\begin{pmatrix} \frac{-1}{2\tau_z} \\ \pi_0 - \frac{1}{2\tau_z} + \frac{\Delta_a+\Delta_q-\pi_a}{2\tau_a} + \Delta_a a + \Delta_q s_q\end{pmatrix}, \begin{pmatrix} \frac{1}{\tau_z} & \frac{r_z}{\tau_z} \\ \frac{r_z}{\tau_z} & \left(\frac{\Delta_a^2}{\tau_a^s} + \frac{r_z}{\tau_z}\right)\end{pmatrix}\right). \tag{A.7}$$

Let $\delta \equiv \frac{\alpha}{\nu+1-\alpha}$. Using (A.1), we can write

$$\begin{aligned}\log\left\{\int_i Z_i(E_i[X_i])^\delta di\right\} &= \log\left\{\int_i \exp\left(z_i + \delta\left(\mathbb{E}_i(x_i) + \frac{1}{2}\text{Var}_i(x_i)\right)\right)di\right\} \\ &= \delta\left(\pi_0 - \frac{1}{2\tau_z} + \frac{\Delta_a+\Delta_q-\pi_a}{2\tau_a} + \Delta_a a + \Delta_q s_q\right) \\ &\quad + \frac{\delta}{2}\left(\frac{1-r_z}{\tau_z} + \Sigma\right) + \frac{1}{2}\delta^2\left(\frac{\Delta_a^2}{\tau_a^s} + \frac{r_z}{\tau_z}\right) + \frac{\delta r_z}{\tau_z}.\end{aligned}$$

Substituting the expression above in (6), we get

$$\psi_0 + \psi_a a + \psi_\epsilon \epsilon = a + \delta\log\alpha + \log\left\{\int_i Z_{it}(E_{it}[X_{it}])^\delta di\right\}.$$

Comparing corresponding coefficients in the equation above, we get

$$\psi_a = 1 + \delta(\Delta_a + \Delta_q) \quad ; \quad \psi_\epsilon = \frac{\delta\Delta_q}{\sqrt{\tau_a^s}} \quad \text{and}$$

$$\psi_0 = \delta\log\alpha + \delta\left(\pi_0 - \frac{1}{2\tau_z} + \frac{\Delta_a+\Delta_q-\pi_a}{2\tau_a}\right) + \frac{\delta}{2}\left(\frac{1-r_z}{\tau_z} + \Sigma\right) + \frac{1}{2}\delta^2\left(\frac{\Delta_a^2}{\tau_a^s} + \frac{r_z}{\tau_z}\right) + \frac{\delta r_z}{\tau_z}.$$

Simplifying these expressions, we get

$$\pi_a = -\frac{(\gamma-1)((\gamma\delta+1)(\tau_a+\tau_a^s)+\tau_a^s\tau_\epsilon)}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))} \qquad \psi_a = \frac{\tau_a(\gamma\delta+1)+(\delta+1)\tau_a^s(\gamma\delta+\tau_\epsilon+1)}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}$$

$$\pi_\epsilon = \frac{(\gamma-1)\gamma\delta\sqrt{\tau_a^s}\tau_\epsilon}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))} \qquad \psi_\epsilon = -\frac{(\gamma-1)\delta\sqrt{\tau_a^s}\tau_\epsilon}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}$$

$$\Delta_a = -\frac{(\gamma-1)\tau_a^s}{\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1)} \qquad \Delta_q = -\frac{(\gamma-1)\tau_a^s\tau_\epsilon}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}$$

$$\psi_0(1+\delta\gamma) = \delta\log\alpha + \frac{\delta}{2}\left(\frac{\Delta_a+\Delta_q+\gamma\psi_a-1}{\tau_a} + \Sigma + \delta\frac{\Delta_a^2}{\tau_a^s}\right) + \frac{r_z}{2\tau_z}\delta(1+\delta).$$

The labor input chosen by each firm is given by

$$n_i = \frac{1}{\nu+1-\alpha}\left[\mathbb{E}_i(x_i) + \frac{1}{2}\text{Var}_i(x_i) + \log\alpha\right],$$

which reduces to

$$n_i = const + \frac{1}{\nu+1-\alpha}\left(r_z s_{iz} - \frac{(\gamma-1)\tau_a^s}{\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1)}s_{ia} - \frac{(\gamma-1)\tau_a^s\tau_\epsilon}{(\gamma\delta+1)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}s_q\right),$$

which implies that $\varphi_a = -\frac{(\gamma-1)\tau_a^s}{(\nu+1-\alpha)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}$, $\varphi_z = \frac{r_z}{\nu+1-\alpha}$ and $\varphi_q = -\frac{(\gamma-1)\tau_a^s\tau_\epsilon}{(\gamma\delta+1)(\nu+1-\alpha)(\tau_a+\tau_a^s(\gamma\delta+\tau_\epsilon+1))}$. Hence, our conjecture is verified. □

Proof of Proposition 2. Before solving information acquisition, it is useful to rewrite the updating formula. Here, let firm i choose a signal of precision $\{\tau_{a,i}^s, \tau_{z,i}^s\}$ and all other firms signal precision be denoted by $\{\tau_a^s, \tau_z^s\}$. The projection theorem implies that

$$(\pi_a a + \pi_\epsilon\epsilon)|\{s_{ia}, s_q\} \sim N\left(-\frac{\pi_a}{2\tau_a} + \Delta_{a,i}\left(s_{ia} + \frac{1}{2\tau_a}\right) + \Delta_{q,i}\left(s_q + \frac{1}{2\tau_a}\right), \Sigma_i\right),$$

where $\Delta_{a,i} = \frac{\tau^s_{a,i}\left(-\pi_\epsilon\sqrt{\tau^s_a}+\pi_a\right)}{\tau_a+\tau^s_a\tau_\epsilon+\tau^s_{a,i}}$; $\Delta_{q,i} = \frac{\tau^s_a\tau_\epsilon\pi_a+\pi_\epsilon\sqrt{\tau^s_a}\left(\tau_a+\tau^s_{a,i}\right)}{\tau_a+\tau^s_a\tau_\epsilon+\tau^s_{a,i}}$ and $\Sigma_i = \frac{\left(\pi_a-\pi_\epsilon\sqrt{\tau^s_a}\right)^2}{\tau_a+\tau^s_a\tau_\epsilon+\tau^s_{a,i}}$. Let $r_{z,i} = \frac{\tau^s_{z,i}}{\tau^s_{z,i}+\tau_z}$. Then,

$$\mathbb{E}\left(x_i|\mathcal{I}^1_i\right) = \pi_0 - \frac{1}{2\tau_z} + r_{z,i}\left(s_{iz} + \frac{1}{2\tau_z}\right) - \frac{\pi_a}{2\tau_a} + \Delta_{a,i}\left(s_{ia} + \frac{1}{2\tau_a}\right) + \Delta_{q,i}\left(s_q + \frac{1}{2\tau_a}\right)$$

$$\text{Var}\left(x_i|\mathcal{I}^1_i\right) = \frac{1-r_{z,i}}{\tau_z} + \Sigma_i.$$

The objective function of a firm manager at stage 1 can be written as

$$\begin{aligned}
\kappa^*_{a,i} &= arg\max_{\kappa_{a,i}} E\left[[E_i[X_i]]^{1+\delta}\right] = arg\max_{\kappa_{a,i}} E\left[\exp\left\{(1+\delta)E_i(x_i) + \frac{1+\delta}{2}\text{Var}_i(x_i)\right\}\right] \\
&= arg\max_{\kappa_{a,i}} \exp\left(\frac{1+\delta}{2}\left(\frac{1-r_{z,i}}{\tau_z} + \Sigma_i\right)\right) \\
&\qquad \exp\left((1+\delta)\left(\pi_0 - \frac{1}{2\tau_z} - \frac{\pi_a}{2\tau_a}\right)\right) \\
&\qquad \exp\left(\frac{(1+\delta)^2}{2}\left((r_{z,i})^2\left(\frac{1}{\tau_z} + \frac{1}{\tau^s_{z,i}}\right) + \frac{\left(\Delta_{a,i}+\Delta_{q,i}\right)^2}{\tau_a} + \frac{\Delta^2_{a,i}}{\tau^s_{a,i}} + \frac{\Delta^2_{q,i}}{\tau_\epsilon\tau^s_a}\right)\right) \\
&= arg\max_{\kappa_{a,i}} (1+\delta)\left(\frac{\left(\Delta_{a,i}+\Delta_{q,i}\right)^2}{\tau_a} + \frac{\Delta^2_{a,i}}{\tau^s_{a,i}} + \frac{\Delta^2_{q,i}}{\tau_\epsilon\tau^s_a}\right) + \Sigma_i + \frac{\delta r_{z,i}}{\tau_z} \\
&= arg\max_{\kappa_{a,i}} \frac{\delta r_{z,i}}{\tau_z} - \delta\Sigma_i \\
&= arg\max_{\kappa_{a,i}} \frac{r_{z,i}}{\tau_z} - \frac{\left(\pi_a - \pi_\epsilon\sqrt{\tau^s_a}\right)^2}{\tau_a + \tau^s_a\tau_\epsilon + \tau^s_{a,i}},
\end{aligned}$$

subject to the entropy constraint:

$$\underbrace{\frac{1}{2}\log_2\left[\frac{\tau^s_{a,i}}{\tau_a}+1\right]}_{\kappa_{a,i}} + \underbrace{\frac{1}{2}\log_2\left[\frac{\tau^s_{z,i}}{\tau_z}+1\right]}_{\kappa_{z,i}} \leq \kappa.$$

The objective can be rewritten as

$$arg\min_{\kappa_{a,i}} \frac{2^{2\kappa_{a,i}-2\kappa}}{\tau_z} + \frac{\left(\pi_a - \pi_\epsilon\sqrt{\tau^s_a}\right)^2}{\tau_a 2^{2\kappa_{a,i}} + \tau^s_a\tau_\epsilon}.$$

The FOC of objective function can be written as

$$\left(2^{2\kappa_{a,i}} + \frac{\tau^s_a}{\tau_a}\tau_\epsilon\right) = \left(\pi_\epsilon\sqrt{\tau^s_a} - \pi_a\right)\sqrt{\frac{\tau_z}{\tau_a}}2^\kappa,$$

and the second-order condition always holds. The equation above simplifies to

$$\left(2^{2\kappa_{a,i}} + \left(2^{2\kappa_a}-1\right)\tau_\epsilon\right) = \frac{\left(2^{2\kappa_a} + \left(2^{2\kappa_a}-1\right)\tau_\epsilon\right)}{\left(1+\left(2^{2\kappa_a}-1\right)(\gamma\delta+\tau_\epsilon+1)\right)}(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^\kappa.$$

□

Proof of Lemma 2. Note that optimal $\kappa^*_{a,i}$ solves

$$\left(2^{2\kappa_{a,i}} + \left(2^{2\kappa_a}-1\right)\tau_\epsilon\right) = \frac{\left(2^{2\kappa_a} + \left(2^{2\kappa_a}-1\right)\tau_\epsilon\right)}{\left(1+\left(2^{2\kappa_a}-1\right)(\gamma\delta+\tau_\epsilon+1)\right)}(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^\kappa.$$

If the optimal $\kappa^*_{a,i}$ is not in $(0,\kappa)$, then choose the boundary values. Differentiating the equation above with respect to κ_a, it is easy to check that

$$\frac{\partial\kappa_{a,i}}{\partial\kappa_a} < 0,$$

which implies that there is substitutability across agents. Managers' optimization problem has a unique symmetric solution when the FOC has a unique solution. Assuming that $\kappa_{a,i} = \kappa_a$, the FOC simplifies to

$$1 + \left(2^{2\kappa_a} - 1\right)(\gamma\delta + \tau_\epsilon + 1) = (\gamma - 1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa},$$

which has a unique solution. □

Proof of Proposition 3. Note that the unique symmetric equilibrium will imply that

$$1 + \left(2^{2\kappa_a} - 1\right)(\gamma\delta + \tau_\epsilon + 1) = (\gamma - 1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}. \tag{A.8}$$

From Eq. (A.8), it is obvious that κ_a increases with τ_z and decreases with τ_a. Differentiating (A.8), the partial derivative of κ_a with respect to γ is given by:

$$\left(2^{2\kappa_a} - 1\right)\delta + 2^{2\kappa_a}(\log 2)2(\gamma\delta + \tau_\epsilon + 1)\frac{\partial\kappa_a}{\partial\gamma} = \sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}.$$

This implies

$$\begin{aligned}
2^{2\kappa_a}(\log 2)2(\gamma\delta + \tau_\epsilon + 1)\frac{\partial\kappa_a}{\partial\gamma} &= \sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa} - \left(2^{2\kappa_a} - 1\right)\delta. \\
&= \sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa} - \frac{\delta\left((\gamma - 1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa} - 1\right)}{\gamma\delta + \tau_\epsilon + 1} \\
&= \frac{\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}(\gamma\delta + \tau_\epsilon + 1) - \delta\left((\gamma - 1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa} - 1\right)}{\gamma\delta + \tau_\epsilon + 1} \\
&= \frac{\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}(\tau_\epsilon + 1 + \delta) + \delta}{\gamma\delta + \tau_\epsilon + 1} > 0,
\end{aligned}$$

which in turn implies that optimal attention paid to aggregate conditions increases with risk aversion. □

Proof of Proposition 6. covariance of inputs across firms is given by

$$\mathrm{Cov}\left(n_i, n_j\right) = \frac{1}{\tau_a} \times (\varphi_a + \varphi_q)^2 + \frac{\varphi_q^2}{\tau_\epsilon\tau_a^s}.$$

Part 1: *If $\tau_\epsilon = \infty$, then covariance in inputs should be of similar magnitude as covariance in TFP. For finite value of τ_ϵ, covariance in inputs is higher than covariance in productivity.*

Part 2: Note that

$$\begin{aligned}
\mathrm{Cov}\left(n_i, n_j\right) &= \frac{1}{\tau_a} \times (\varphi_a + \varphi_q)^2 + \frac{\varphi_q^2}{\tau_\epsilon\tau_a^s} \\
&= \frac{(\gamma - 1)^2}{(\nu + 1 - \alpha)^2(1 + \gamma\delta)^2}\left(\left(\frac{\tau_{\mathrm{a}}^s(1 + \gamma\delta + \tau_\epsilon)}{\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1)}\right)^2\frac{1}{\tau_a} + \frac{\tau_{\mathrm{a}}^s\tau_\epsilon}{(\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1))^2}\right) \\
&\propto \left(\left(\frac{\tau_{\mathrm{a}}^s(1 + \gamma\delta + \tau_\epsilon)}{\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1)}\right)^2 + \frac{\tau_a\tau_{\mathrm{a}}^s\tau_\epsilon}{(\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1))^2}\right).
\end{aligned}$$

Without endogenous learning, covariance of inputs does not change with idiosyncratic uncertainty, since φ_a, and φ_q does not depend on idiosyncratic uncertainty. With endogenous learning, as idiosyncratic uncertainty increases, agents pay less attention to aggregate uncertainty, which implies that τ_{a}^s decreases.

$$\begin{aligned}
\frac{\partial\mathrm{Cov}\left(n_i, n_j\right)}{\partial\tau_z} &\propto \frac{\partial}{\partial\tau_z}\left\{\frac{(\tau_{\mathrm{a}}^s(1 + \gamma\delta + \tau_\epsilon))^2 + \tau_a\tau_{\mathrm{a}}^s\tau_\epsilon}{(\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1))^2}\right\} \\
&= \frac{\tau_a^2\tau_\epsilon + \tau_a\tau_\epsilon\tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1) + 2\tau_a\tau_{\mathrm{a}}^s(1 + \gamma\delta + \tau_\epsilon)(1 + \gamma\delta)}{(\tau_a + \tau_{\mathrm{a}}^s(\gamma\delta + \tau_\epsilon + 1))^3}\frac{\partial\tau_a^s}{\partial\tau_z} \\
&> 0.
\end{aligned}$$

The last inequality follows from agents substituting learning away from aggregate conditions as idiosyncratic uncertainty increases. □

Proof of proposition 4. Using equation $Y = A\int Z_i(\alpha_1 E_i[X_i])^{\frac{\alpha}{\nu+1-\alpha}} di$, I first calculate aggregate output in the economy. As before, we can write aggregate output as

$$y = \log Y = \psi_0 + \psi_a a + \psi_\epsilon \epsilon.$$

Then, using equation $N^{1+\nu} = \int_i N_i^{1+\nu}$, I calculate aggregate labor supply,

$$N^{1+\nu} = \int_i (\alpha E_i[X_i])^{\frac{1+\nu}{\nu+1-\alpha}} di = \alpha^\beta \int_i (E_i[X_i])^\beta di,$$

where $\beta \equiv \frac{1+\nu}{\nu+1-\alpha}$. Taking log on both sides of the above equation and using Eq. (A.7),

$$\begin{aligned}(1+\nu)n &= \beta\log\alpha + \log\int_i (E_i[X_i])^\beta di \\ &= \beta\log\alpha + \beta\left(\pi_0 - \frac{1}{2\tau_z} + \frac{\Delta_a + \Delta_q - \pi_a}{2\tau_a} + \Delta_a a + \Delta_q s_q\right) + \frac{\beta}{2}\left(\frac{1-r_z}{\tau_z} + \Sigma\right) + \frac{\beta^2}{2}\left(\frac{\Delta_a^2}{\tau_a^s} + \frac{r_z}{\tau_z}\right) \\ &= \beta\log\alpha + \beta(\Delta_a + \Delta_q)a + \frac{\beta\Delta_q}{\sqrt{\tau_a^s}}\epsilon + \beta\pi_0 + \beta\frac{\Delta_a + \Delta_q - \pi_\epsilon}{2\tau_a} + \frac{\beta}{2}\Sigma + \frac{\beta^2\Delta_a^2}{2\tau_a^s} + \frac{\beta(\beta-1)r_z}{2\tau_z}\end{aligned}$$

Once I have total output and total labor, I define measured aggregate productivity as

$$\begin{aligned}a^* &= y - \alpha n \\ &= a + \psi_0(1+\delta\gamma) - \frac{\alpha}{1+\nu}\left(\beta\log\alpha + \beta\frac{\Delta_a + \Delta_q - \pi_a}{2\tau_a} + \frac{\beta}{2}\Sigma + \frac{\beta^2\Delta_a^2}{2\tau_a^s} + \frac{\beta(\beta-1)r_z}{2\tau_z}\right) \\ &= a + \frac{\delta}{2}\left(\delta\frac{\Delta_a^2}{\tau_a^s}\right) + \frac{r_z}{2\tau_z}\delta(1+\delta) - \frac{\alpha}{1+\nu}\left(\frac{\beta^2\Delta_a^2}{2\tau_a^s} + \frac{\delta(\delta+1)r_z}{2\tau_z}\right) \\ &= a + \frac{\delta}{2}\left((\delta-\beta)\frac{\Delta_a^2}{\tau_a^s}\right) + \frac{r_z}{2\tau_z}\delta(2+\delta-\beta) \\ &= a - \frac{\delta\Delta_a^2}{2\tau_a^s} + \frac{\delta r_z}{2\tau_z}.\end{aligned}$$

Substituting $\Delta_a = -\frac{(\gamma-1)\tau_a^s}{\tau_a + \tau_a^s(\gamma\delta + \tau_\epsilon + 1)}$ into the above expression,

$$\begin{aligned}a^* &= a - \frac{\delta}{2}\left(\frac{(\gamma-1)^2\tau_a^s}{(\tau_a + \tau_a^s(\gamma\delta + \tau_\epsilon + 1))^2}\right) + \frac{\delta r_z}{2\tau_z} \\ &= a - \frac{\delta}{2\tau_a}\left(\frac{(\gamma-1)^2(2^{2\kappa_a} - 1)}{(2^{2\kappa_a}(G+1) - G)^2}\right) + \frac{\delta(2^{2\kappa_z} - 1)}{2\tau_z 2^{2\kappa_z}}.\end{aligned} \tag{A.9}$$

where $G \equiv \gamma\delta + \tau_\epsilon$. □

Proof of Corollary 1. Note that

$$\frac{\partial a^*}{\partial \kappa_z} = \frac{\partial}{\partial \kappa_z}\left[\frac{\delta(2^{2\kappa_z} - 1)}{2\tau_z 2^{2\kappa_z}}\right] \tag{A.10}$$

$$= \frac{\delta}{2\tau_z}\frac{\partial[1 - 2^{-2\kappa_z}]}{\partial \kappa_z} \tag{A.11}$$

$$= \frac{\delta 2^{1-2\kappa_z}\log(2)}{2\tau_z} > 0. \tag{A.12}$$

Similarly, note that

$$\frac{\partial a^*}{\partial \kappa_a} = \frac{\partial}{\partial \kappa_z}\left[-\frac{\delta}{2\tau_a}\left(\frac{(\gamma-1)^2(2^{2\kappa_a} - 1)}{(2^{2\kappa_a}(G+1) - G)^2}\right)\right] \tag{A.13}$$

$$= -\frac{\delta(\gamma-1)^2}{2\tau_a}\frac{\partial}{\partial \kappa_a}\frac{(2^{2\kappa_a} - 1)}{(2^{2\kappa_a}(G+1) - G)^2} \tag{A.14}$$

$$\begin{cases} < 0 \text{ if } \ (G+1)(2-2^{2\kappa_a})-G>0 \\ >0 \ \text{ otherwise.} \end{cases} \tag{A.15}$$

□

Proof of Proposition 5. We can rewrite measured aggregate productivity as

$$a^* = a + h_z(\tau_z, \kappa_z) + h_a(\tau_a, \kappa_a),$$

where

$$h_z(\tau_z, \kappa_z) = \frac{\delta\left(1-2^{-2\kappa_z}\right)}{2\tau_z} \quad \text{and} \quad h_a(\tau_a, \kappa_a) = -\frac{\delta}{2\tau_a}\left(\frac{(\gamma-1)^2\left(2^{2\kappa_a}-1\right)}{\left(2^{2\kappa_a}(G+1)-G\right)^2}\right).$$

Note that the effect of aggregate and idiosyncratic uncertainty on measured aggregate productivity are separable. In the benchmark economy with exogenous information, $\frac{\partial a^*}{\partial \tau_a} = \frac{\partial}{\partial \tau_a} h_a(\tau_a, \kappa_a) > 0$ and $\frac{\partial a^*}{\partial \tau_z} = \frac{\partial}{\partial \tau_z} h_z(\tau_z, \kappa_z) < 0$.

With endogenous learning, the optimal attention κ_a is given by Eq. (A.8). Substituting (A.8) into (A.9), we get

$$\begin{aligned} h_a(\tau_a, \kappa_a) &= -\frac{\delta}{2\tau_a}\left(\frac{(\gamma-1)^2\left(2^{2\kappa_a}-1\right)}{\left(2^{2\kappa_a}(G+1)-G\right)^2}\right) \\ &= -\frac{\delta}{2\tau_z}\left(\frac{\left(2^{2\kappa_a}-1\right)}{2^{2\kappa}}\right) \\ &= -\frac{\delta}{2\tau_z 2^{2\kappa}} \frac{\left((\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}-1\right)}{(\gamma\delta+\tau_\epsilon+1)}. \end{aligned}$$

Similarly,

$$\begin{aligned} h_z(\tau_z, \kappa_z) &= \frac{\delta\left(1-2^{-2\kappa_z}\right)}{2\tau_z} \\ &= \frac{\delta\left(2^{2\kappa}-2^{2\kappa_a}\right)}{2\tau_z 2^{2\kappa}} \\ &= \frac{\delta\left(2^{2\kappa}-1-\frac{(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}-1}{\gamma\delta+\tau_\epsilon+1}\right)}{2\tau_z 2^{2\kappa}}. \end{aligned}$$

This implies that measured aggregate productivity in an economy with endogenous learning is

$$\begin{aligned} a^* &= a + h_z(\tau_z, \kappa_z) + h_a(\tau_a, \kappa_a) \\ &= a + \frac{\delta\left(2^{2\kappa}-1-\frac{(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}-1}{\gamma\delta+\tau_\epsilon+1}\right)}{2\tau_z 2^{2\kappa}} - \frac{\delta}{2\tau_z 2^{2\kappa}} \frac{\left((\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}-1\right)}{(\gamma\delta+\tau_\epsilon+1)} \\ &= a + \frac{\delta\left(2^{2\kappa}-1-2\frac{(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}-1}{\gamma\delta+\tau_\epsilon+1}\right)}{2\tau_z 2^{2\kappa}}. \end{aligned} \tag{A.16}$$

Taking a derivative of Eq. (A.16) with respect to τ_a, we get

$$\frac{da^*}{d\tau_a} = \frac{\delta\left(\frac{(\gamma-1)}{\gamma\delta+\tau_\epsilon+1}\sqrt{\frac{\tau_z}{\tau_a}}\right)}{2\tau_z\tau_a 2^{\kappa}} > 0,$$

which implies that an increase in aggregate uncertainty decreases aggregate productivity. Moreover

$$\frac{d^2 a^*}{d\tau_a d\kappa} < 0.$$

Taking a derivative of (A.16) with respect to τ_z, we get

$$\frac{da^*}{d\tau_z} = -\frac{\delta\left(2^{2\kappa}-1\right)}{2\tau_z^2 2^{2\kappa}} + \frac{\delta}{4\tau_z\sqrt{\tau_z}2^{2\kappa}}\left(\frac{2(\gamma-1)\sqrt{\frac{1}{\tau_a}}2^{\kappa}}{\gamma\delta+\tau_\epsilon+1}\right) - \frac{\delta}{2\tau_z^2 2^{2\kappa}}\left(\frac{1}{\gamma\delta+\tau_\epsilon+1}\right)$$

$$= -\frac{\delta}{2\tau_z^2 2^{2\kappa}}\left(2^{2\kappa} - 1 + \frac{1}{\gamma\delta + \tau_\epsilon + 1} - \frac{(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}}{\gamma\delta + \tau_\epsilon + 1}\right)$$

$$= -\frac{\delta}{2\tau_z^2 2^{2\kappa}}\left(2^{2\kappa}(1+G) - G - (\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa}\right).$$

This implies that idiosyncratic uncertainty increases measured aggregate productivity when

$$2^{2\kappa}(1+G) - G - (\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{\kappa} > 0,$$

which is true when τ_z is small (or idiosyncratic uncertainty is high). On the other hand, when τ_z is high (i.e., idiosyncratic uncertainty is low), the condition above does not hold and idiosyncratic uncertainty decreases measured aggregate productivity. In other words, measured aggregate productivity is non-monotonic in idiosyncratic uncertainty.

Taking derivative of Eq. (A.16) with respect to κ, we get

$$\frac{da^*}{d\kappa} = \frac{\delta}{2\tau_z}\frac{\partial}{\partial\kappa}\left(1 - 2^{-2\kappa} - \frac{2(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{-\kappa} - 2^{-2\kappa}}{\gamma\delta + \tau_\epsilon + 1}\right)$$

$$= \frac{\delta(\log 2)}{\tau_z}\left(2^{-2\kappa}\left(\frac{\gamma\delta + \tau_\epsilon}{\gamma\delta + \tau_\epsilon + 1}\right) + \frac{(\gamma-1)\sqrt{\frac{\tau_z}{\tau_a}}2^{-\kappa}}{\gamma\delta + \tau_\epsilon + 1}\right)$$

$$> 0.$$

This implies that an increase in κ increases measured aggregate productivity. Moreover

$$\frac{d^2 a^*}{d\kappa\, d\tau_\epsilon} < 0,$$

which implies that the effect of information-processing constraint is stronger in an economy with more noise in prices. □

Proposition 25. Objective of social planner is

$$\mathcal{W} = E\left[\frac{Y^{1-\gamma}}{1-\gamma} - \int_i \frac{N_i^{\nu+1}}{\nu+1}di\right],$$

subject to

$$\frac{1}{2}\log_2\left[\frac{\tau_a^s}{\tau_a} + 1\right] + \frac{1}{2}\log_2\left[\frac{\tau_z^s}{\tau_z} + 1\right] \le \kappa.$$

After substituting the output and optimal labor choice in the objective function, it simplifies to

$$\mathcal{W} = \exp\left(\frac{(\gamma-1)(\delta+1)(\gamma\tau_a(\gamma\delta+1) + \tau_a^s(2\gamma\delta+\gamma-\delta)(\gamma\delta+\tau_e+1))}{2\tau_a(\gamma\delta+1)^2(\tau_a + \tau_a^s(\gamma\delta+\tau_\epsilon+1))} + \frac{\delta(1+\delta)(1-\gamma)}{2(1+\delta\gamma)}\frac{r_z}{\tau_z}\right)$$
$$\times\left[\frac{1}{1-\gamma}\exp\left(\frac{(1-\gamma)\delta\log\alpha}{(1+\delta\gamma)}\right) - \frac{1}{1+\nu}\exp\left(\frac{\beta\log\alpha}{1+\delta\gamma}\right)\right].$$

Maximizing welfare is the same as minimizing

$$\frac{\gamma(\gamma\delta+1) + \left(2^{2\kappa_a}-1\right)(2\gamma\delta+\gamma-\delta)(\gamma\delta+\tau_\epsilon+1)}{\tau_a(\gamma\delta+1)\left(1 + \left(2^{2\kappa_a}-1\right)(\gamma\delta+\tau_\epsilon+1)\right)} + \delta\frac{2^{2\kappa_a-2\kappa}}{\tau_z}.$$

The FOC of this objective function is

$$\left[\left(1 + \left(2^{2\kappa_a}-1\right)(\gamma\delta+\tau_\epsilon+1)\right)\right] = \sqrt{\frac{(\gamma\delta+\tau_\epsilon+1)}{(\gamma\delta+1)}}(\gamma-1)2^{\kappa}\sqrt{\frac{\tau_z}{\tau_a}},$$

and the SOC is always satisfied. □

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.01.010

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