# Monetary Policy and Uncertainty in the Data Economy[*]

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**Abstract**

We build a theoretical model to study how the widespread availability of data to firms affects the transmission of monetary policy and aggregate uncertainty. The presence of data strengthens the investment channel of monetary policy and can amplify cyclical fluctuations. Because data helps firms to reduce their uncertainty, data-rich firms respond relatively more strongly to monetary policy shocks. Heterogeneity in firms' access to data renders aggregate investment more responsive to monetary policy shocks. A data feedback loop can amplify the effects of aggregate uncertainty shocks by raising the market shares of firms whose investment is particularly responsive to uncertainty shocks. Moreover, the data feedback effect amplifies cyclical fluctuations.

**Keywords:** Data, Uncertainty, Investment, Monetary Policy, Business Cycles
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# 1 Introduction

Data is a key resource for businesses in the digital age and is accumulating rapidly (Statista, 2022; Calderón and Rassier, 2022). Data generates value for firms by facilitating targeted advertising, by promoting innovation, and by aligning what consumers demand with what is supplied. The share of retail that is conducted through online channels is trending upward (Statista, 2023), which means that the relevance of data in the economy will only grow further over time. Understanding the role of data for the propagation of business cycles and the transmission of monetary policy is hence of first order importance, as noted by Federal Reserve Chair Jerome H. Powell (Powell, 2021).

We build a theoretical model of firm investment and show that the presence of data strengthens the investment channel of monetary policy and can amplify cyclical fluctuations. We show that data-rich firms respond more strongly to monetary policy shocks, both in absolute terms and relative to their size. If firms differ in their access to data, aggregate investment becomes more responsive to monetary policy shocks. We show that the data feedback effect—which refers to the notion that larger firms have access to better data because data arises as a byproduct of transactions—can amplify the effects of aggregate uncertainty shocks by raising the market shares of firms whose investment is particularly responsive to uncertainty shocks. Moreover, the data feedback effect amplifies cyclical fluctuations that are driven by aggregate productivity shocks.

Our model combines key building blocks from Farboodi and Veldkamp (2022a,b) and Eeckhout and Veldkamp (2022) to study the role of monetary policy and uncertainty in the data economy. Firms produce output using capital, which they accumulate over time. Firms choose their optimal investment based on their expected future productivity. Motivated by the empirical findings that increased levels of uncertainty curb firm investment and production (Bachmann et al., 2013; Kumar et al., 2022), firms in our model explicitly take uncertainty surrounding their future productivity into account. Access to better data allows firms to predict payoff-relevant states with higher accuracy. Thus, data yields value to firms through two channels: it increases the expected level of a firm's productivity and reduces a firm's uncertainty regarding future productivity.[1] Both are relevant for a firm's investment decision and endogenously generate a positive correlation between firm size and data (as documented empirically by Brynjolfsson et al. (2023)).

We also explicitly model a data feedback effect, which is a central feature of the data accumulation process and is based on the fact that data is generated by transactions. Thus, larger firms have access to more or a higher quality of data, which induces the following

[1]Confirming the idea that access to better data reduces uncertainty, Paine (2022) documents that firms who use less effective web analytics experience a higher variance of sales.

feedback loop: Data-rich firms will, by offering superior products, generate a higher volume of sales, which in turn allows them to stay comparatively data-rich. This data feedback effect intensifies the positive correlation between a firm's data and its size.

Within this framework, we then examine how the availability of data to firms affects their investment behavior in response to monetary policy and aggregate uncertainty shocks. To fully focus on the investment channel, we assume that prices are completely rigid and model monetary policy shocks as changes in the real interest rate that firms pay when accumulating new capital.[2] Aggregate uncertainty shocks are modelled as economy-wide changes in the variance of productivity. This way of introducing monetary policy and uncertainty shocks allows us to pin down the effects of data on the transmission of these shocks in closed form.

In response to a monetary policy shock, data-rich firms adjust their investment levels to a greater extent, both in absolute terms and relative to their capital stock. This has two reasons: First, data-rich firms are larger (in terms of their capital stock), which implies that the absolute effect of monetary policy on these firms is stronger. Second, data-rich firms face less uncertainty in regards to their future productivity and thus, respond more strongly to the monetary policy shock. This is because the variance of future productivity enters a firm's marginal cost of raising capital, which means that the marginal cost of data-rich firms is relatively more responsive to interest rate changes.

Further, we find that these effects are state dependent. In particular, they are especially pronounced at low interest-rate levels. Thus, accounting for heterogeneity in firms' data holdings offers a potential explanation for the empirical finding in Kroen et al. (2021) that larger firms adjust their investment more aggressively in response to a monetary shock, especially at low interest rates.

Data is accumulating unevenly in digital markets and certain firms have significant advantages in terms of the data they possess (Statista, 2022). We show that such data advantages further magnify the aggregate effects of monetary policy. Formally, we establish that a mean-preserving spread in the quality of data increases the responsiveness of aggregate investment to monetary policy shocks, both in absolute and in relative terms. This is because the responsiveness of a firm which attains better data in such an aforementioned mean-preserving spread increases more strongly than the responsiveness of the other firm falls.

The data feedback effect amplifies the effects of monetary policy on firm investment. The benefits of attaining a higher expected level of productivity (and lower uncertainty) are greater, the more output the firm produces. Thus, the data feedback effect makes the marginal product of capital less responsive to changes in capital. This, in turn, directly

[2] Our results on monetary policy shocks on firm investment are thus more general, as real interest rates might be driven by other exogenous shocks than monetary policy, as, for example, risk premia shocks.

implies that the effects of monetary policy shocks on investment are amplified.

We then show that the data feedback effect can also amplify the effects of aggregate uncertainty shocks. Intuitively, this is because the data feedback effect may induce more risk-averse firms—which respond strongly to uncertainty shocks—to hold higher levels of capital. This follows from the notion that better data, which a firm obtains by investing into capital and attaining scale, reduces the variance of a firm's productivity. This beneficial effect of capital accumulation weighs more strongly for firms that are more risk averse, thus granting these firms higher incentives to attain scale. A positive correlation between the size of a firm and its responsiveness to an uncertainty shock exacerbates the overall effects of uncertainty shocks.

The data feedback effect also amplifies cyclical fluctuations driven by changes in aggregate productivity. Consider a firm that expects a productivity decrease in the next period. In anticipation of this, the firm invests less in the current period. Under the data feedback effect, the fact that the firm will make lower sales next period implies that it faces a higher idiosyncratic uncertainty and lower expected productivity, which further reduces its incentives to invest. Thus, such a firm reduces its investment more strongly under the data feedback effect.

The rest of the paper proceeds as follows: We lay out the related literature in section 2 and present our theoretical framework in section 3. We devote section 4 to the analysis of this framework and conclude thereafter.

## 2 Related literature

To the best of our knowledge, ours is the first paper to study how the effects of monetary policy and aggregate uncertainty shocks are affected by firms' access to data. Nevertheless, our work is related to four different strands of literature, namely (i) the recent work studying the role of digitization and (ii) intangibles for macroeconomic outcomes, (iii) the numerous contributions focusing on the investment channel of monetary policy, and (iv) the papers studying the effects of uncertainty on firm investment.

Several recent papers have studied the relevance of digitization and data for macroeconomic outcomes (Veldkamp and Chung (2019) provides a survey of how data matters for the macroeconomy). The firm's per-period objective function we adopt is taken from Eeckhout and Veldkamp (2022), who show that data can be a source of market power. The authors formalize the idea that access to better data increases the incentives of firms to invest into attaining scale and lowering marginal costs, thus granting them higher levels of market power. The data feedback effect we incorporate builds on the work of Farboodi and Veldkamp (2022a), who integrate this channel into a growth model.[3] Acemoglu et al. (2022) show that data markets are not efficient in the presence of data externalities, i.e. when a given user's data reveals information about other users. Bergemann and Bonatti (2022) study, among others, how superior access to data can grant platforms market power.[4] Lashkari et al. (2018) document a positive correlation between firm size and IT intensity and argue that IT generates greater value for larger firms. Brynjolfsson et al. (2023) provide evidence that higher levels of IT investment are associated with greater firm size and higher levels of concentration, both in terms of sales and employment. Begenau et al. (2018) and Veldkamp (2023) show that firms are to a large extent valued for the data they posses. In contrast to our work, none of these papers considers the effects of monetary policy or aggregate uncertainty shocks.

Within this literature, the paper that is closest to ours is Glocker and Piribauer (2021), who show that increases in the amount of sales that are conducted through digital retail will reduce the real effects of monetary policy. This follows from the idea that prices can be adjusted more easily in online settings than in traditional markets, which dampens the real effects of monetary policy.[5] In contrast to our work, Glocker and Piribauer (2021) do not consider the role of data, capital or uncertainty. In Glocker and Piribauer (2021), firms produce output using labor only — hence, firms do not make any capital accumulation choices. Further, there are no firm-level differences in the distribution of productivity in Glocker and Piribauer (2021) and firms do not have access to data that affects their productivity distribution. Furthermore, by modelling monetary policy as steering the *real* interest rate, we abstract from the potential effects that increasing data availability might have in firms' price-setting behavior and purely focus on firms' investment response.

Our work is also related to the macroeconomic literature on research and development (R&D) and intangible assets. De Ridder (2019) and Chiavari and Goraya (2022) study how the increasing importance of intangible inputs (R&D, intellectual property, and software) matters for macroeconomic outcomes. De Ridder (2019) shows that these trends can account for the rise of market power, reduced business dynamism, and lower productivity growth. Similarly, Chiavari and Goraya (2022) show that the rise of intangibles, via entailing higher sunk costs, can explain increases in profit rates and concentration. Neither De Ridder (2019) nor Chiavari and Goraya (2022) study the effects of monetary policy or aggregate uncertainty

[3]Wang et al. (2022), Xie and Zhang (2022), and Wu and Zhang (2022) build on the work of Farboodi and Veldkamp (2022a) and also study the role of data in growth models.

[4]Jones and Tonetti (2020) establish how the non-rivalry of consumers' data and privacy concerns shape the optimal design of property rights for data.

[5]Empirical evidence for lower nominal rigidities in digital markets is put forth by Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018).

shocks. On the empirical side, Döttling and Ratnovski (2022) and Caggese and Pérez-Orive (2022) document that the investment of firms with high levels of intangible capital is less responsive to monetary policy. This is in opposition to our prediction that data-rich firms would be more responsive to monetary policy shocks.

The key distinction between our paper and previous work in this literature lies in the fact that data is not the same thing as intangible capital. From a theoretical perspective, intangible capital is modeled as a factor of production: Investment into intangible capital increases output, but does not affect the variance of productivity. This is in stark contrast to our work, in which the role of data in reducing a firm's uncertainty is central. Moreover, there is no equivalent of the data feedback effect in the papers that study intangibles. Empirically, measures of intangible assets contain R&D expenditures, overhead, intellectual property, and software (Peters and Taylor, 2017; Döttling and Ratnovski, 2022). This notion also explains the discrepancy between our theoretical predictions and the empirical results of Döttling and Ratnovski (2022) and Caggese and Pérez-Orive (2022).

A major focus of our paper is how data shapes the investment channel of monetary policy. Thus, it is related to the classic paper by Bernanke et al. (1999), who study the effectiveness of monetary policy in the context of the financial accelerator. Our work also relates to papers which demonstrate heterogeneity in the responsiveness of firms to monetary policy, namely with respect to a firm's size (Gertler and Gilchrist, 1994; Kroen et al., 2021), liquidity (Jeenas, 2019), default risk (Ottonello and Winberry, 2020), industry (Durante et al., 2022), and age (Cloyne et al., 2023). How the impact of monetary policy shocks is affected by a firm's access to data is not considered by any of these papers.

Finally, our paper relates to the work on the role of uncertainty for firm-level investment. The seminal contribution of Bloom (2009) documents that increases of uncertainty reduce firm-level hiring and investment. Using survey expectations data, Bachmann et al. (2013) show that increases in uncertainty reduce output. Kumar et al. (2022) provide new causal evidence that increases in perceived uncertainty lead firms to reduce employment, investment, and sales. Mirroring the theoretical prediction of our paper, Lakdawala and Moreland (2022) document that the investment response of firms to a monetary policy shock is lower when the firms face a high level of uncertainty.

Closest to our work within this literature is Fajgelbaum et al. (2017), which builds on Veldkamp (2005) and Ordonez (2013). In these papers, there is a data feedback loop on the aggregate level, which formalizes the following idea: In recessions, firm activity is low, which means that there is little public information available about underlying states. The resulting aggregate uncertainty disincentivizes investment. Fajgelbaum et al. (2017) show how this feedback effect can amplify business cycle fluctuations. However, the authors do not study monetary policy. In addition, our feedback loop runs at the firm level. This means that our results regarding the relationship between firm size and risk aversion, together with the implications for the propagation of uncertainty shocks, are exclusive to our paper.

# 3 Framework

In this section, we present our theoretical model of firm investment, monetary policy shocks, and data. The model is kept deliberately stylized to focus on the main channels of how data affects the transmission of monetary policy and uncertainty shocks to firm investment.

## Output, productivity, and data

There is a unit mass of infinitely-lived firms, indexed by $i \in [0,1]$, and time is discrete and denoted by $t = 1, 2, ..., \infty$. Each firm produces according to its production function

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha}, \tag{1}$$

where $Y_{i,t}$ denotes the output produced by firm $i$, $A_{i,t}$ its productivity, and $K_{i,t}$ its capital stock. The parameter $\alpha \in (0,1)$ is assumed to be identical across firms.

Firms choose their capital before observing their productivity. That is, firm $i$ chooses its capital stock $K_{i,t+1}$ in $t$ before observing $A_{i,t+1}$. Firms have access to data, which grants them a signal about some payoff-relevant state. We say that a firm with better or more data has a smaller $\sigma_{i,t+1}$, i.e., faces less uncertainty about the future payoff-relevant state. We are purposefully agnostic about the exact way in which firms use data, but impose that having better data favorably changes the distribution of a firm's productivity in two ways. First, having access to better data (i.e. a lower $\sigma_{i,t+1}$) increases the firm's expected productivity, i.e.:

$$\frac{\partial \mathbb{E}_t[A_{i,t+1}; \sigma_{i,t+1}]}{\partial \sigma_{i,t+1}} < 0. \tag{2}$$

Second, access to better data reduces the firm's forecast uncertainty. Let $VAR_t\left[A_{i,t+1}; \sigma_{i,t+1}\right]$ denote firm $i$'s uncertainty about its productivity in period $t+1$ based on information available in period $t$. Better data reduces a firm's uncertainty, i.e.:

$$\frac{\partial VAR_t\left[A_{i,t+1}; \sigma_{i,t+1}\right]}{\partial \sigma_{i,t+1}} > 0. \tag{3}$$

The idea that access to better data raises the average productivity of a firm and reduces its variance can be microfounded using the ideas of Farboodi and Veldkamp (2022a). Suppose a firm receives an unbiased signal $\hat{\theta}_{i,t}$ about some payoff-relevant state (call this $\theta_{i,t}$). Having access to better data is equivalent to observing a signal with lower variance ($\sigma_{i,t}$), ceteris paribus. As elaborated in Farboodi and Veldkamp (2022a), $\theta_{i,t}$ can be understood as the optimal product variety or the ideal form of marketing in a given period, which the firm wishes to mirror by its choice of marketing/production approach (which we refer to as $a_{i,t}$). The firm benefits by matching $a_{i,t}$ with the state $\theta_{i,t}$ as closely as possible. This is formalized by assuming that productivity in a given period ($A_{i,t}$) can be expressed as

$$A_{i,t} = f(|a_{i,t} - \theta_{i,t}|), \tag{4}$$

where $f(.)$ is a strictly decreasing function. If the firm's optimal choice of production technique ($a_{i,t}$) is equal to the signal it receives, which holds true if $\hat{\theta}_{i,t}$ is unbiased and observed in period $t$, then $A_{i,t}$ is just a monotonic transformation of the difference $|\hat{\theta}_{i,t} - \theta_t|$. Then, reductions in the variance of $\hat{\theta}_{i,t}$ will generally go along with lower differences $|\hat{\theta}_{i,t} - \theta_{i,t}|$, which raises $\mathbb{E}_t[A_{i,t}]$ and reduces $VAR[A_{i,t}]$. Analytically, this can be shown when considering $f(x) = x^2$ and supposing that $\hat{\theta}_{i,t} \sim N(0, \sigma_{i,t})$.

## The data feedback effect

A key feature of the way in which data accumulates is the data feedback effect, as discussed by Farboodi and Veldkamp (2022a). The nature of the data feedback effect is based on the idea that data is a byproduct of production and transactions: A firm that produces more learns more about its customers' preferences, about the optimal inventory, etc. The bigger a firm, the more data it accumulates. We capture this formally by imposing that the quality of a firm's data is a function of its capital stock, i.e. that $\sigma_{i,t} = \tilde{\sigma}(K_{i,t})$, where:

$$\frac{\partial \tilde{\sigma}\left(K_{i,t}\right)}{\partial K_{i,t}} < 0. \tag{5}$$

Figure 1 captures the data feedback loop graphically (see Farboodi and Veldkamp (2022a) for a very similar graph).

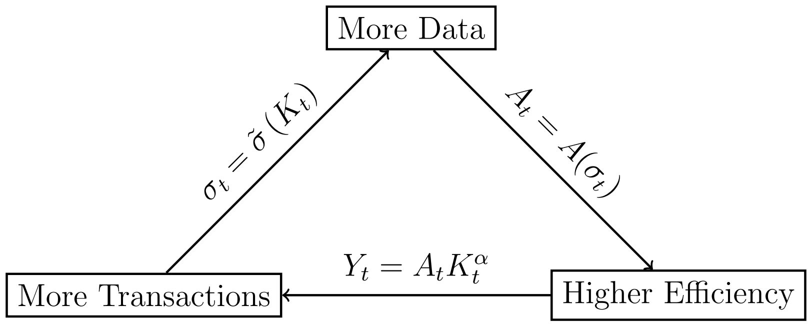

Figure 1: Data Feedback Loop

For simplicity, we also impose the following functional form assumptions on the equations governing the relationship between data and productivity as well as the data feedback loop:

$$\mathbb{E}[A_{i,t}] = \max\{\bar{A} - \kappa_e \sigma_{i,t}, 0\} \quad ; \quad VAR[A_{i,t}; \sigma_{i,t}] = \max\{\bar{V} + \kappa_v \sigma_{i,t}, 0\} \tag{6}$$

$$\sigma_{i,t} = \underbrace{\bar{\sigma}_i - zK_{i,t}}_{:=\tilde{\sigma}(K_{i,t})} \tag{7}$$

We assume that $\kappa_e \geq 0$ and that $\kappa_v \geq 0$. When $\kappa_v$ is high, relative to $\kappa_e$, this means that the primary economic value of access to better data is the associated reduction in the variance of the firm's outcomes. The parameter $z \geq 0$ can be understood as the strength of the data feedback effect.

## A firm's optimization problem

A firm's objective function in any period $t$ can be written as follows:

$$\max_{\{K_{i,t+1+j}\}_{j=0}^{\infty}} \quad \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \Pi_{i,t+j}, \tag{8}$$

where the flow profits $\Pi_{i,t+j}$ are, as in Eeckhout and Veldkamp (2022), given by the following function:

$$\Pi_{i,t+1} = \mathbb{E}_t \left[Y_{i,t+1}\right] - \frac{\rho}{2} VAR_t \left[Y_{i,t+1}\right] - r_t I_{i,t} \tag{9}$$

The interest rate at which a firm can acquire capital $K_{i,t+1}$ is given by $r_t$, and a firm's investment in period $t$ is $I_{i,t} = K_{i,t+1} - (1-\delta)K_{i,t}$, where $\delta$ is the rate of capital depreciation.

We include risk in the firm's profit function for two reasons: First, there is extensive evidence that firms take risk into account when making decisions — see Eeckhout and Veldkamp (2022). Second, we will focus on the effect of monetary policy on the optimal investment of firms. It is well known that higher uncertainty affects the investment incentives of firms (e.g. because of adjustment costs), which implies that it is quite relevant to consider this channel in our work. Furthermore, the preference setup we specify can be interpreted, for example, as a reduced form way of capturing the role in which adjustment costs shape the optimal investment levels.

In period $t$, a firm optimally picks tomorrow's capital ($K_{i,t+1}$). We impose the following assumptions throughout the analysis.

**Assumption 1** *We assume that:*

- *The flow profit function is always concave in capital, i.e.* $\frac{\partial^2 \Pi_{i,t+1}}{\partial K_{i,t+1}^2} < 0$.
- *At the optimally chosen levels of* $K_{i,t+1}$*, both* $E_t[A_{i,t+1}; \sigma_{i,t+1}]$ *and* $VAR[A_{i,t+1}; \sigma_{i,t+1}]$ *remain strictly positive.*

The first assumption is necessary to ensure that a unique optimal capital choice exists for every firm. It also suffices to ensure that the basic comparative statics result with respect to the effect of an increase in $r_t$ is such that that a firm's chosen level of capital is falling in the interest rate.

# 4 Analysis

We now study the impact of uncertainty shocks and monetary policy in partial equilibrium. A monetary policy shock is modelled as a one-time change in the interest rate $r_t$. An aggregate uncertainty shock is understood as a one-time increase in the variance of productivity ($\bar{V}$). For notational convenience, we drop the subscript $i$ when unambiguous.

## 4.1 Data and the optimal investment choices

In this section, we treat the level of a firm's data as exogenous, i.e. we assume that $\sigma_{t+1}$ is fixed for every firm and that there is no data feedback effect (i.e $z = 0$). Consider the optimization problem of a firm in some period $t$, which chooses the level of capital $K_{t+1}$. The variable $K_{t+1}$ only enters the flow profits of this firm in periods $t+1$ and $t+2$. Thus, the relevant part of the firm's objective function (when deciding $K_{t+1}$) is given by:

$$\mathbb{E}_t[A_{t+1}; \sigma_{t+1}] K_{t+1}^{\alpha} - \frac{\rho}{2} VAR_t[A_{t+1}; \sigma_{t+1}] K_{t+1}^{2\alpha} - r_t(K_{t+1} - (1-\delta)K_t) +$$

$$\beta\bigg(\mathbb{E}_t[A_{t+2}; \sigma_{t+2}] K_{t+2}^{\alpha} - \frac{\rho}{2} VAR_t[A_{t+2}; \sigma_{t+2}] K_{t+2}^{2\alpha} - \mathbb{E}_t[r_{t+1}](K_{t+2} - (1-\delta)K_{t+1})\bigg). \quad (10)$$

Crucially, the optimal level of $K_{t+2}$ (or any optimal level of capital chosen for periods thereafter) cannot depend on the chosen level of $K_{t+1}$. This is because $K_{t+1}$ only enters a firm's objective function in $t+1$ (when the firm chooses $K_{t+2}$) as a fixed constant and can hence not influence its optimization calculus. Thus, the first-order condition for $K_{t+1}$ reads as follows:

$$\underbrace{\left(\bar{A} - \kappa_e \sigma_{t+1}\right)}_{\mathbb{E}_t[A_{t+1};\sigma_{t+1}]} \alpha K_{t+1}^{\alpha-1} - \rho \underbrace{\left(\bar{V} + \kappa_v \sigma_{t+1}\right)}_{VAR_t[A_{t+1};\sigma_{t+1}]} \alpha K_{t+1}^{2\alpha-1} = r_t - \beta(1-\delta)\mathbb{E}_t r_{t+1} \tag{11}$$

When $\alpha = 1/2$, one can solve for the optimal capital stock in closed form, which is given by:

$$K_{t+1}^{*} = \left( \frac{\mathbb{E}[A_{t+1};\sigma_{t+1}]}{2(r_t - \beta(1-\delta)\mathbb{E}_t r_{t+1}) + \rho VAR[A_{t+1};\sigma_{t+1}]} \right)^2 \tag{12}$$

When $\alpha = 1/2$, one can thus analytically establish that firms with better access to data (lower $\sigma_{t+1}$) respond more to monetary policy shocks, modelled as a one-time change in the interest rate $r_t$. To see this, note that the absolute and relative effects of a monetary policy shock on the optimal capital stock are given by:

$$\frac{\partial K_{t+1}^{*}}{\partial r_t} = \frac{-4[\mathbb{E}[A_{t+1};\sigma_{t+1}]]^2}{[VAR[A_{t+1};\sigma_{t+1}]\rho + 2r]^3} \quad ; \quad \frac{\partial K_{t+1}^{*}/\partial r_t}{K_{t+1}^{*}} = \frac{-4}{[VAR[A_{t+1};\sigma_{t+1}]\rho + 2r]}, \tag{13}$$

where $r \equiv r_t - \beta(1-\delta)\mathbb{E}_t[r_{t+1}]$. Thus, firms respond to a contractionary monetary policy shock (an increase of $r_t$) by reducing their investment. The following proposition formalizes how these effects are shaped by a firm's access to data:

**Proposition 1** *Suppose $\alpha = 1/2$ and $z = 0$. Firms with access to better data respond more strongly to monetary policy, both in absolute and in relative terms:*

$$\frac{\partial K_{t+1}^{*}}{\partial r_t} < 0 \quad ; \quad \frac{\partial^2 K_{t+1}^{*}}{\partial r_t \partial \sigma_{t+1}} > 0 \quad ; \quad \frac{\partial \left( \frac{\partial K_{t+1}^{*}/\partial r_t}{K_{t+1}^{*}} \right)}{\partial \sigma_{t+1}} \geq 0 \tag{14}$$

*The latter inequality is strict if and only if $\kappa_v > 0$.*

To understand the results regarding the absolute effects, note that the optimal capital choice of the firm has to solve the following first-order condition when $\alpha = 1/2$:

$$\frac{\mathbb{E}[A_{t+1};\sigma_{t+1}]}{\sqrt{K_{t+1}^{*}}} = \rho VAR[A_{t+1};\sigma_{t+1}] + 2r \tag{15}$$

One can show that the optimally chosen level of capital is higher when $\sigma_{t+1}$ is lower, i.e. for firms with better data. Intuitively, this reflects the fact that data raises the marginal product of capital (the left-hand side in equation (15)) and decreases the marginal cost of acquiring capital (the right-hand side in equation (15)).

The fact that firms with better data hold more capital implies that, in absolute terms, these firms respond more strongly to monetary policy shocks. In response to a rise of $r_t$, a firm responds by adjusting capital in a way that re-equates the marginal product of capital and its marginal cost. Because the flow profit function is concave in capital by assumption, the marginal product of capital is more responsive to changes in the chosen capital stock at low levels of capital. Thus, a monetary policy shock induces smaller changes in the amount of capital selected by low data firms, because their capital levels were already low ex ante.

In relative terms, the effects of a monetary policy shock depend on the level of $\sigma_{t+1}$ if and only if access to better data reduces the variance of output. If $\kappa_v = 0$, increases of $\mathbb{E}[A_{t+1}; \sigma_{t+1}]$ through better data merely shift up the marginal product of data. Because data-rich firms are larger, the effects of a monetary policy shock on firms, relative to their size, thus stay unaffected by the access to data.

However, if better data reduces the uncertainty a firm faces, firms with access to better data will also respond more to monetary policy shocks in relative terms. This is because the variance of future productivity enters the marginal cost of raising capital. When this variance is large (i.e. when a firm only has access to low-quality data), changes in the interest rate only imply small relative changes in the marginal cost of capital. As a result, changes in the interest rate affect data-poor firms to a lesser extent.

In figure 2, we show that these insights extend beyond the analytically tractable case of $\alpha = 1/2$. We visualize the effect of a contractionary monetary policy shock (during which the interest rate rises from $r' = 0.1$ to $r'' = 0.11$) on the optimal capital choice for different levels of $\sigma$ (horizontal axis). We do this for varying $\kappa_v$ while we set $\kappa_e = 0$.[6] For the different $\kappa_v$, we first plot the difference $K^*_{t+1}(r'') - K^*_{t+1}(r')$, which can be considered the rough equivalent of the absolute effects. Moreover, we plot the ratio $\frac{K^*_{t+1}(r'') - K^*_{t+1}(r')}{K^*_{t+1}(r')}$, which can be considered the rough equivalent of the relative effects.

We see from Figure 2 that our analytical results from Proposition 1 continue to hold. Firms with more data (lower $\sigma$) respond more strongly to monetary policy shocks, both in absolute and in relative terms. We further see that this relationship is concave in $\sigma$, especially for higher values of $\kappa_v$. This follows from the fact that with a higher $\kappa_v$, more data reduces the firm's uncertainty more, which induces the firm to respond more forcefully to the interest rate change.

Before moving forward, we confirm that the optimal investment behaviour in our model

[6] We use the following parameters: $\rho = 0.5$, $\delta = 0.1$, $\alpha = 0.4$, $\bar{A} = 2$, and $\bar{V} = 1$.

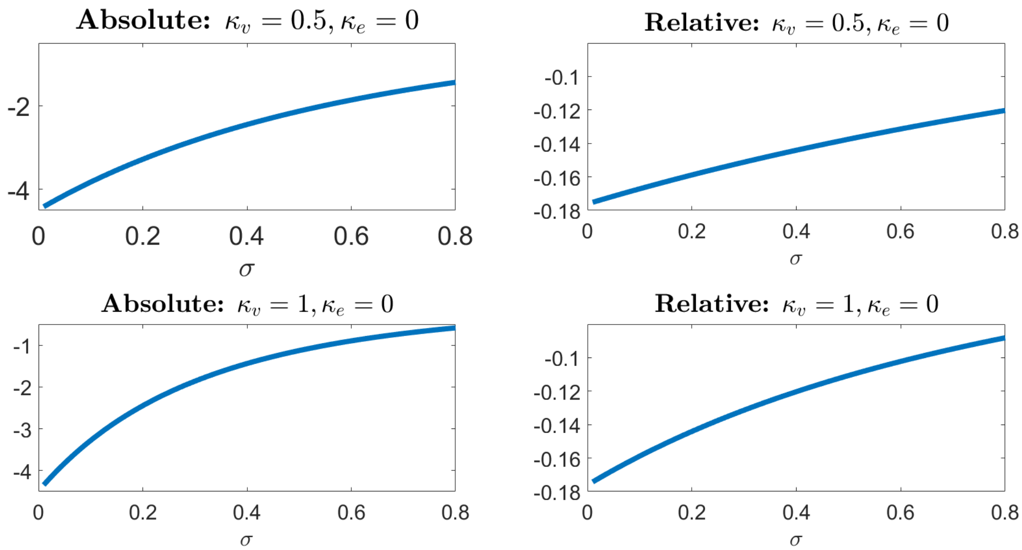


Figure 2: Effects of a contractionary MP shock

matches several empirically documented facts on the relationship between uncertainty, monetary policy, and invesment. To see this, recall that the optimal capital stock and the semielasticity of capital w.r.t changes in $r_t$ can be expressed in closed form when $\alpha = 1/2$:

$$K^*_{t+1} = \frac{[\mathbb{E}[A_{t+1}]]^2}{[VAR[A_{t+1}]\rho + 2r]^2} \quad ; \quad \frac{\partial K^*_{t+1}/\partial r_t}{K^*_{t+1}} = \frac{-4}{[VAR[A_{t+1}]\rho + 2r]} \tag{16}$$

Thus, firms that face higher uncertainty invest less in our model (consistent with Bachmann et al. (2013); Kumar et al. (2022)) and firms with access to better data grow larger (consistent with Brynjolfsson et al. (2023)). When the uncertainty a firm faces is higher, its responsiveness to a monetary policy shock becomes smaller (because the semielasticity is closer to zero). This mirrors the findings of Lakdawala and Moreland (2022). Matching the results of Kroen et al. (2021), firms that are larger (i.e., firms with access to better data and lower $VAR[A_{t+1}]$) respond more strongly to monetary policy shocks, especially when interest rates are low. This holds because the derivative of $\frac{\partial K^*_{t+1}/\partial r_t}{K^*_{t+1}}$ with respect to the variance term $VAR[A_{t+1}]$ is positive, but moves closer towards zero as the interest rate increases.

Data is accumulating unevenly. Our previous results have important implications for the impact of monetary policy in settings where firms have heterogeneous access to data. For example, will monetary policy be more effective when access to data is more unequally distributed? The following proposition, which analyses these issues in partial equilibrium, provides insights regarding these questions.

**Proposition 2** *Suppose that $\alpha = 1/2$, $z = 0$, $\kappa_e = 0$, and consider an economy with two firms $i \in \{l, h\}$ with data levels given by $\sigma^l = \sigma^m - y$ and $\sigma^h = \sigma^m + y$, with $y > 0$. Mean-preserving spreads of $(\sigma^l, \sigma^h)$ amplify the effects of monetary policy on aggregate investment (in absolute and relative terms), i.e.*

$$\frac{\partial\left(\frac{\partial(K^*_{t+1}(\sigma^l)+K^*_{t+1}(\sigma^h))}{\partial r_t}\right)}{\partial y} < 0 \quad ; \quad \frac{\partial\left(\frac{\frac{\partial(K^*_{t+1}(\sigma^l)+K^*_{t+1}(\sigma^h))}{\partial r_t}}{K^*_{t+1}(\sigma^l)+K^*_{t+1}(\sigma^h))}\right)}{\partial y} < 0 \tag{17}$$

This insight follows directly from the previously established result that the relationship between $\sigma$ and the effects of a monetary policy shock is concave. The responsiveness of the firm that attains better data in the considered mean-preserving spread increases more strongly than the responsiveness of the other firm falls. Given that the data disparaties will likely grow further over time, the result in the above proposition indicates that the effects of monetary policy on firm investment will be further amplified.

## 4.2 The data feedback effect

In this subsection, we focus on the role of the data feedback effect, which we abstracted from in the previous section. Formally, we consider arbitrary levels of $z > 0$ in this subsection (under the constraint that assumption 1 is still satisfied). The key insight of this section is that the presence of the data feedback effect amplifies the effects of monetary policy as such, holding $\bar{\sigma}$ fixed. This notion is formalized in the following proposition:

**Proposition 3** *Suppose that $\alpha = 1/2$ and that $\kappa_e = 0$. The data feedback effect amplifies the effect of a monetary policy shock, i.e.:*

$$\frac{\partial^2 K_{t+1}}{\partial r_t \partial z} < 0 \tag{18}$$

For general $z$ and $\kappa_e$, a firm's optimal capital choice must solve the following first-order condition:

$$\left(\bar{A} - \kappa_e \sigma_{t+1}\right) \alpha K_{t+1}^{\alpha-1} - \rho\left(\bar{V} + \kappa_v \sigma_{t+1}\right) \alpha K_{t+1}^{2\alpha-1} + \underbrace{\kappa_e z K_{t+1}^{\alpha} + \frac{\rho}{2}(\kappa_v z) K_{t+1}^{2\alpha}}_{\text{data feedback effect}} = r_t - \beta(1-\delta)\mathbb{E}_t r_{t+1} \tag{19}$$

The key insight from this first order condition is that the data feedback effect makes the flow profits of the firm more convex in capital. To see this, consider the two terms in the firm's first order condition that reflect the beneficial effect of higher capital accumulation through the data feedback effect. Both these terms are increasing in capital, which reflects a simple idea: The benefits of attaining a higher expected level of productivity (or a lower variance) are greater, the more output the firm produces.

Thus, increases in $z$ (which reflect a stronger data feedback effect) make the marginal product of capital less responsive to changes in capital. This, in turn, directly implies that the effects of a monetary policy shock are amplified when $z$ increases (i.e., when the data feedback effect becomes stronger).

We now illustrate the effects of the data feedback effect on the response of investment to monetary policy graphically. Figure 3 shows the absolute and relative effects of a change in $r_t$ from 0.1 to 0.11 on $K_{t+1}$ for varying degrees of the data feedback effect, $z$ (horizontal axis). In all cases, we set $\kappa_e = 0$ and consider different $\kappa_v$.[7]

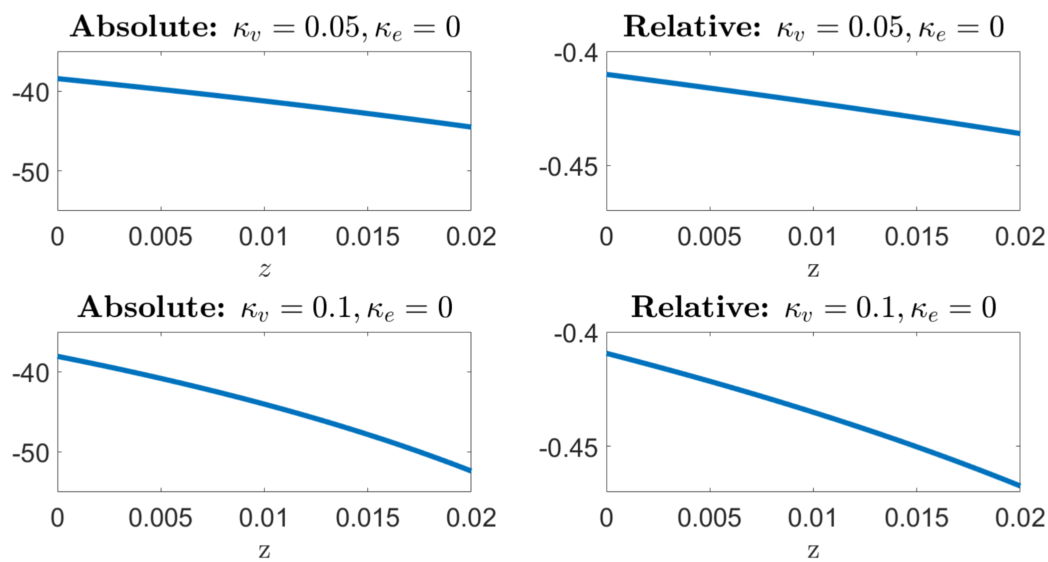


Figure 3: The data feedback effect & the effects of a MP shock ($\kappa_e = 0$)

We see that the results that we derived analytically in Proposition 3 continue to hold. A stronger data feedback effect, i.e., a higher $z$, amplifies the investment effects of monetary policy. This is especially the case at higher values of $\kappa_v$ (see bottom panel in Figure 3). When $\kappa_v$ is higher, more data reduces the firm's uncertainty more effectively, and hence, the effects are further amplified.

Figure 4 turns to the role of $\kappa_e$. We set $\kappa_v = 0$ and vary $\kappa_e$. The rest of the calibration is the same as in Figure 3. Again, and consistent with Proposition 3, the data feedback

[7] In all cases, we keep $\bar{A} = 2$, $\bar{V} = 1$, $\alpha = 0.3$ and $\rho = 0.1$, $\delta = 0.2$ and $\bar{\sigma} = 0.5$.

effect amplifies the investment response to a monetary policy shock. We further see that increasing $\kappa_e$ has similar effects than increasing $\kappa_v$. A higher $\kappa_e$ implies that data increases the firm's expected productivity more strongly, and hence, the overall effects increase.

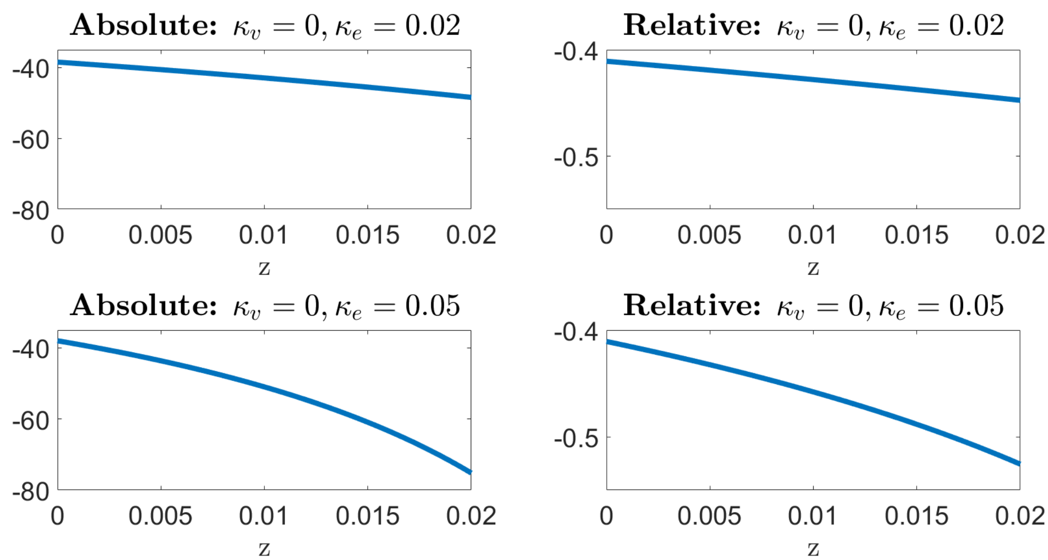


Figure 4: The data feedback effect & the effects of a MP shock ($\kappa_v = 0$)

### 4.3 Aggregate uncertainty shocks & the data feedback effect

In this section, we consider how the data feedback effect affects the impact of aggregate uncertainty shocks. We model aggregate uncertainty shocks as unexpected (one-time) increases of $\bar{V}$, i.e., the fixed term in the variance of productivity. In a nutshell, we show that the presence of the data feedback effect may induce firms who are highly sensitive to risk (high $\rho$) to hold higher levels of capital. This exacerbates the total effect of aggregate uncertainty shocks, because firms that are more sensitive to risk would thus grow larger and gain greater market shares. Given that recessions coincide with high levels of uncertainty (Bloom, 2009), these insights thus suggest that data may exacerbate cyclical fluctuations.

We begin by studying how the presence of data affects the relationship between the risk preferences of firms and how much capital they hold, as formalized in the following proposition:

**Proposition 4** *The strength of the data feedback effect* ($z$) *determines whether more risk averse firms (higher* $\rho$*) hold more or less capital. Suppose* $\alpha = 1/2$. *If* $z = 0$, *then* $\frac{\partial K_{t+1}}{\partial \rho} < 0$.

*By contrast,* $\frac{\partial K_{t+1}}{\partial \rho} > 0$ *holds if* $z$ *is high enough, i.e. when:*

$$0.5\left(\bar{V} + \kappa_v \bar{\sigma} - \kappa_v z K_{t+1}\right) - 0.5\kappa_v z K_{t+1} < 0 \tag{20}$$

When $z = 0$, firms that are more risk averse (higher $\rho$) hold less capital, because increases in $\rho$ go along with lower marginal products of capital by giving higher weights to the risk associated with production. When $z > 0$, there is an opposing effect: Attaining scale by increasing $K_{t+1}$ allows a firm to reduce the idiosyncratic risk it faces through the data feedback loop. The economic benefits of this channel are particularly high for firms that are very sensitive to risk. If this channel becomes strong enough, which happens if $z$ becomes large, then the sign of the relationship between a firm's level of risk aversion ($\rho$) and it's capital level may flip.

Figure 5 illustrates this graphically.[8] We plot a firm's optimal capital stock (vertical axis) as a function of its risk aversion, $\rho$ (horizontal axis). We do this for different degrees of the data feedback effect, $z$. We see that when $z$ is relatively low (the two left panels), an increase in $\rho$ decreases a firm's optimal capital stock. If $z$ is large enough, however, more risk-averse firms grow larger, because their increase in size reduces their uncertainty through the data feedback loop.

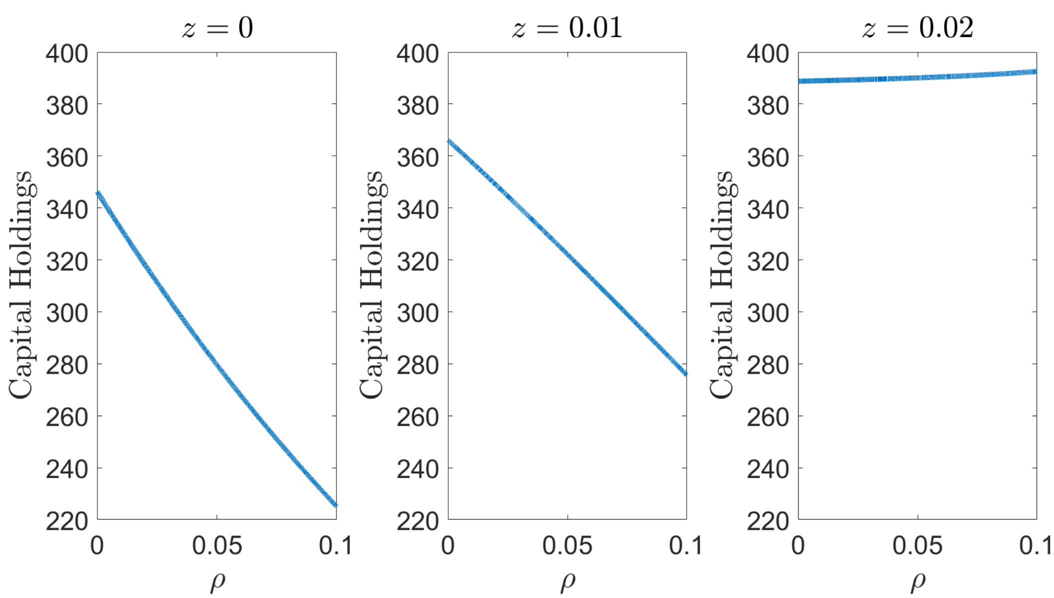


Figure 5: Risk aversion & optimal capital levels

Figure 6 shows how this channel exacerbates the effects of uncertainty shocks. In particular,

[8]We set $\delta = 0.1$, $\alpha = 0.3$, $\bar{\sigma} = 0.5$, $\kappa_v = 0.05$, $\kappa_e = 0.005$, $\bar{A} = 2$, and $r = 0.1$.

we plot the responsiveness of a firm's capital choice (as a function of $\rho$) to an increase in $\bar{V}$ (from 1 to 1.1) for the different levels of $z$ we have considered. In all cases, the uncertainty shock induces a stronger investment response when firms are more risk averse and these effects are amplified through the data feedback effect.

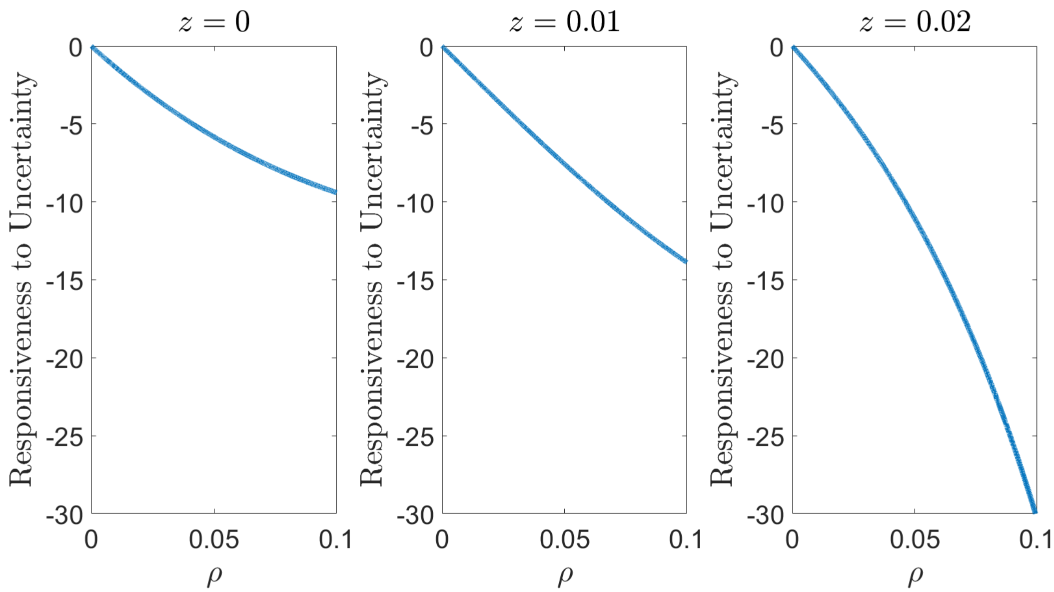


Figure 6: Risk aversion & responsiveness to an uncertainty shock

We now quantify these effects of an aggregate uncertainty shock (during which $\bar{V}$ increases from 1 to 1.1) in partial equilibrium. Assume there is a unit mass of firms and the risk preference of firms in the economy is distributed according to $\rho \sim U[0, 0.1]$. The absolute effects of the uncertainty shock on aggregate investment are $-5.4$ (when $z = 0$) and $-12.4$ (when $z = 0.02$) respectively. The relative effects of an uncertainty shock (i.e. the change in aggregate investment, divided by the ex-ante value of aggregate investment) are $-1.9\%$ (when $z = 0$) and $-3.2\%$ (when $z = 0.02$), respectively. The presence of the data feedback effect thus substantially amplifies the effect of an aggregate uncertainty shock.

## 4.4 Business cycles & the data feedback effect

In the following, we document that the data feedback effect amplifies cyclical fluctuations. To demonstrate this, we model a business cycle as a cyclical process for $\bar{A}$, which is the fixed component of the expected productivity as defined in equation (6). The exogenously-imposed path for $\bar{A}$ is plotted in the left graph of figure 7 and firms have perfect foresight about this path. In the right graph, we plot the optimal investment of a representative firm when $z = 0$ (there is no data feedback effect, captured by the red-dotted line) and when $z = 0.01$ (the data feedback effect is active, captured by the blue-solid line). All other parameters are set as in the previous section.

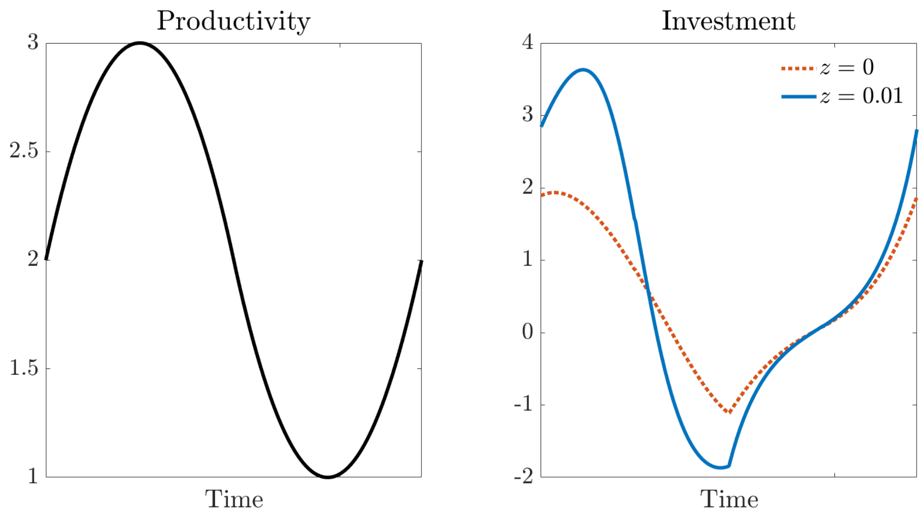


Figure 7: The Data Feedback Loop & Cyclical Fluctuations

We see that the data feedback effect amplifies the fluctuations of investment along the business cycle: When the data feedback effect is active, investment (disinvestment) is higher in booms (recessions) than in the absence of the data feedback effect. The intuition is the following: When a firm anticipates that there will be a recession next period, it adjusts its investment downward. This downward adjustment is reinforced by the data feedback effect, because the lower volume of future sales reduces a firm's expected productivity and raises its uncertainty through the data feedback effect. Given the central role of aggregate investment in short-run GDP fluctuations, the data feedback effect thus likely amplifies business cycles.

# 5 Conclusion

Modern economies increasingly revolve around data, which yields value to firms by facilitating targeted advertising, by guiding innovation, and by allowing firms to tailor their products to the desires of consumers. In this paper, we study how the widespread availability of data to firms affects the transmission of monetary policy and aggregate uncertainty shocks. We build a theoretical model of firm investment and focus on the investment channel of monetary policy. In the model, data yields value by raising a firm's expected productivity and by reducing the uncertainty the firm faces. We also incorporate a data feedback loop, which captures the idea that firms who generate a lot of sales receive high-quality data as a byproduct.

We find that the investment of data-rich firms responds comparatively strongly to monetary policy shocks, both in absolute and relative terms. This follows from the facts that data rich firms are both larger and face lower idiosyncratic uncertainty. Moreover, we show that unequal access to data can exacerbate the effects of a monetary policy shock on aggregate investment. The data feedback effect strengthens the impact of a monetary policy shock, and may induce firms which are sensitive to uncertainty to attain greater scale, thus raising the vulnerability of the economy to aggregate uncertainty shocks. Moreover, the data feedback effect amplifies cyclical fluctuations.

Our framework is deliberately kept stylized to highlight how some of the key features of data affect the transmission of monetary policy and uncertainty shocks. Quite naturally, there is a wide range of other frictions or channels that we abstract from for now—for example, price setting, general equilibrium or competition—which we plan to incorporate in follow-up work.

# A Mathematical proofs

## A.1 Proof of proposition 1:

Part 1: Calculating the effects of a contractionary MP shock:

Suppose firstly that there is no data feedback effect (i.e. $z = 0$) and that $\alpha = 1/2$. Then, the corresponding first order condition becomes:

$$0.5K_{t+1}^{-0.5}\left(\bar{A} - \kappa_e \sigma_{t+1}\right) - 0.5\rho\left(\bar{V} + \kappa_v \sigma_{t+1}\right) K_{t+1}^{0} - r_t + \beta(1-\delta)\mathbb{E}_t r_{t+1} = 0$$

Thus, the optimal capital stock will satisfy:

$$K_{t+1}^{-0.5}\mathbb{E}[A_{t+1};\sigma_{t+1}] = 2\underbrace{\left(r_t - \beta(1-\delta)\mathbb{E}_t r_{t+1}\right)}_{:=r} + \rho VAR[A_{t+1};\sigma_{t+1}] \iff$$

$$K_{t+1}^{*} = \left(\frac{\mathbb{E}[A_{t+1};\sigma_{t+1}]}{2r + \rho VAR[A_{t+1};\sigma_{t+1}]}\right)^2$$

Thus, we have:

$$\frac{\partial K_{t+1}^{*}}{\partial \sigma_{t+1}} = 2\left(\frac{\mathbb{E}[A_{t+1}]}{VAR[A_{t+1}]\rho + 2r}\right)\left(\frac{[VAR[A_{t+1};\sigma_{t+1}]\rho + 2r]\frac{\partial \mathbb{E}[A_{t+1}]}{\partial \sigma} - \mathbb{E}[A_{t+1}]\frac{\partial VAR[A_{t+1}]}{\partial \sigma_{t+1}}\rho}{[VAR[A_{t+1}]\rho + 2r]^2}\right) \implies$$

$$\frac{\partial K_{t+1}^{*}}{\partial \sigma_{t+1}} = 2\left(\frac{\mathbb{E}[A_{t+1}]}{[VAR[A_{t+1}]\rho + 2r]^3}\right)\left([VAR[A_{t+1}]\rho + 2r]\frac{\partial \mathbb{E}[A_{t+1}]}{\partial \sigma_{t+1}} - \mathbb{E}[A_{t+1}]\frac{\partial VAR[A_{t+1}]}{\partial \sigma_{t+1}}\rho\right) < 0 \tag{21}$$

Now let's examine the effect of a monetary policy shock. The relevant derivative is:

$$\frac{\partial K_{t+1}^{*}}{\partial r_t} = \frac{-4[\mathbb{E}[A_{t+1}]]^2[VAR[A_{t+1}]\rho + 2r]}{[VAR[A_{t+1}]\rho + 2r]^4} \implies \frac{\partial K_{t+1}^{*}}{\partial r} = \frac{-4[\mathbb{E}[A_{t+1}]]^2}{[VAR[A_{t+1}]\rho + 2r]^3} \tag{22}$$

Now let's examine how this function depends on $\sigma_{t+1}$. To see this, note that:

$$\frac{\partial^2 K_{t+1}^{*}}{\partial r_t \partial \sigma_{t+1}} = \frac{[VAR[A_{t+1}]\rho + 2r]^3\left(-8\mathbb{E}[A_{t+1}]\frac{\partial \mathbb{E}[A_{t+1}]}{\partial \sigma_{t+1}}\right) + 4[\mathbb{E}[A_{t+1}]]^2\left(3[VAR[A_{t+1}]\rho + 2r]^2\rho\frac{\partial VAR[A_{t+1}]}{\partial \sigma_{t+1}}\right)}{[VAR[A_{t+1}]\rho + 2r]^6}$$

$$\implies$$

$$\frac{\partial^2 K^*_{t+1}}{\partial r_t \partial \sigma_{t+1}} = \frac{[VAR[A_2]\rho + 2r]^3\big(8\mathbb{E}[A_{t+1}]\kappa_e\big) + 4[\mathbb{E}[A_{t+1}]]^2\big(3[VAR[A_{t+1}]\rho + 2r]^2\rho\kappa_v\big)}{[VAR[A_{t+1}]\rho + 2r]^6} > 0 \tag{23}$$

This also implies that:

$$\frac{\partial^2 K^*_{t+1}}{\partial r \partial \sigma_{t+1}} = \frac{8\mathbb{E}[A_{t+1}]\kappa_e}{[VAR[A_{t+1}]\rho + 2r]^3} + \frac{12[\mathbb{E}[A_{t+1}]]^2\rho\kappa_v}{[VAR[A_{t+1}]\rho + 2r]^4}$$

In turn, this means that:

$$\frac{\partial^3 K^*_{t+1}}{\partial r_t \partial \sigma^2_{t+1}} = \frac{[VAR[A_{t+1}]\rho + 2r]^3\big(-8\kappa_e^2\big) - 8\mathbb{E}[A_{t+1}]\kappa_e\big(3[VAR[A_{t+1}]\rho + 2r]^2\kappa_v\rho\big)}{[VAR[A_{t+1}]\rho + 2r]^6} +$$

$$\frac{[VAR[A_{t+1}]\rho + 2r]^4\big(-24\mathbb{E}[A_{t+1}]\kappa_e\rho\kappa_v\big) - 12[\mathbb{E}[A_{t+1}]]^2\rho\kappa_v\big(4[VAR[A_{t+1}]\rho + 2r]^3\kappa_v\rho\big)}{[VAR[A_{t+1}]\rho + 2r]^8}$$

$$\implies \frac{\partial^3 K^*_{t+1}}{\partial r_t \partial \sigma^2_{t+1}} < 0 \tag{24}$$

Part 2: The effects in relative terms

Let's also examine the changes in the relative effects of monetary policy. These are given by:

$$\gamma(\sigma_{t+1}) := \frac{\frac{\partial K^*_{t+1}}{\partial r_t}}{K^*_{t+1}} = \frac{\frac{-4[\mathbb{E}[A_{t+1}]]^2}{[VAR[A_{t+1}]\rho + 2r]^3}}{\frac{[\mathbb{E}[A_{t+1}]]^2}{[VAR[A_{t+1}]\rho + 2r]^2}} = \frac{-4}{[VAR[A_{t+1}]\rho + 2r]}$$

We can analyse whether these relative effects are larger for high-data firms by investigating:

$$\frac{\partial \gamma(\sigma_{t+1})}{\partial \sigma_{t+1}} = 4\kappa_v\rho[VAR[A_{t+1}]\rho + 2r]^{-2} > 0 \tag{25}$$

$$\frac{\partial^2 \gamma(\sigma_{t+1})}{\partial \sigma^2_{t+1}} = -8(\kappa_v\rho)^2[VAR[A_{t+1}]\rho + 2r]^{-3} < 0 \tag{26}$$

## A.2 Proof of proposition 2

Part 1: Absolute effects

Now we investigate the effect of an MP shock on two different economies: one where data is unequally distributed (in the sense of a mean preserving spread) and one where all firms have the same level of $\sigma$. There are two different firms with data levels given by $\sigma^l$ and $\sigma^h$. We define that $\sigma^h = \sigma^m + y$, while $\sigma^l = \sigma^m - y$. If $y = 0$, both firms have access to the same level of data. Increases of $y$ constitute mean-preserving spreads in the access to data.

Total investment is $K^*_{t+1}(\sigma^l) + K^*_{t+1}(\sigma^h)$. The effect of a monetary policy shock on total investment is given by:

$$\frac{\partial K^*_{t+1}(\sigma^h)}{\partial r_t} + \frac{\partial K^*_{t+1}(\sigma^l)}{\partial r_t} \tag{27}$$

We know that the function $\frac{\partial K^*_{t+1}(\sigma)}{\partial \sigma}$ is a strictly concave function in $\sigma$. We can write the $\sigma^m$ of the firm in the economy without data dispersion as $\sigma^m = 0.5\sigma^l + 0.5\sigma^h$. Thus, the effect of an MP shock on total investment in this economy is given by:

$$2\frac{\partial K^*_{t+1}(\sigma^m)}{\partial r_t} \tag{28}$$

By strict concavity, we have:

$$\frac{\partial K^*_{t+1}(\sigma^m)}{\partial r_t} \geq 0.5\frac{\partial K^*_{t+1}(\sigma^l)}{\partial r_t} + 0.5\frac{\partial K^*_{t+1}(\sigma^h)}{\partial r_t} \tag{29}$$

Thus, there is a mean-preserving spread in the access to data, the total effect of a monetary policy shock becomes more negative. In words, MP is more effective in the economy where data is dispersed.

Part 2: Relative effects.

Consider the effect of an MP shock on investment, relative to the initial level of investment. This is given by:

$$\frac{\sum(\partial K^*_{t+1}(\sigma)/\partial r_t)}{\sum K^*_{t+1}(\sigma)}$$

Let's focus on the simple case $\kappa_e = 0$ again. We have shown that:

$$\frac{\partial K^*_{t+1}}{\partial r_t} = \frac{-4[\mathbb{E}[A_{t+1}]]^2}{[VAR[A_{t+1}]\rho + 2r]^3} = \frac{-4[\bar{A}]^2}{[VAR[A_{t+1}]\rho + 2r]^3}$$

Moreover, we have:

$$K^*_{t+1} = \left(\frac{\bar{A}}{2(r_t + \beta(1-\delta)\mathbb{E}_t r_{t+1}) + \rho VAR[A_{t+1}; \sigma_{t+1}]}\right)^2$$

Thus, we can write:

$$\frac{\sum(\partial K^*(\sigma)/\partial r)}{\sum K^*(\sigma)} = \frac{-\frac{4}{[VAR[A_{t+1};\sigma^l]\rho+2r]^3} - \frac{4}{[VAR[A_{t+1};\sigma^h]\rho+2r]^3}}{\frac{1}{[VAR[A_{t+1};\sigma^l]\rho+2r]^2} + \frac{1}{[VAR[A_{t+1};\sigma^h]\rho+2r]^2}} \approx \frac{-\frac{1}{[VAR[A_{t+1};\sigma^l]\rho+2r]^3} - \frac{1}{[VAR[A_{t+1};\sigma^h]\rho+2r]^3}}{\frac{1}{[VAR[A_{t+1};\sigma^l]\rho+2r]^2} + \frac{1}{[VAR[A_{t+1};\sigma^h]\rho+2r]^2}}$$

A mean-preserving spread of $\sigma$ is a equivalent to an increase of $y$. Thus, we can derive the effects of a mean preserving spread in $\sigma$ on the relative effects of monetary policy on aggregate investment by studying the derivative of $\frac{\sum(\partial K^*(\sigma)/\partial r)}{\sum K^*(\sigma)}$ with respect to $y$.

In the following, we show that this derivative is negative, i.e. that mean preserving spreads of $\sigma$ exacerbate the effects of monetary policy on aggregate investment. To do this, we define:

$$H(y) := -\frac{1}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^3} - \frac{1}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^3} \tag{30}$$

$$L(y) := \frac{1}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^2} + \frac{1}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^2} \tag{31}$$

Recall that $\frac{VAR[A_{t+1}]}{\partial\sigma_{t+1}} = \kappa_v$. Thus, one can compute the derivative of this expression:

$$\frac{\partial L}{\partial y} = +\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^3} - \frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^3} > 0$$

$$\frac{\partial H}{\partial y} = -\frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^4} + \frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^4} < 0$$

We can write:

$$\frac{\sum(\partial K^*(\sigma)/\partial r)}{\sum K^*(\sigma)} = \frac{H(y)}{L(y)} \implies \frac{\partial\left(\frac{\sum(\partial K^*(\sigma)/\partial r)}{\sum K^*(\sigma)}\right)}{\partial y} = \frac{L(y)H'(y) - H(y)L'(y)}{[L(y)]^2}$$

Thus, we show our desired result by proving that $L(y)H'(y) - H(y)L'(y) < 0$. We have:

$$L\frac{\partial H}{\partial y} =$$

$$\left(\frac{1}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^2} + \frac{1}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^2}\right)\left(\frac{-3\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^4} + \frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho + 2r]^4}\right)$$

$$=$$

$$\frac{-3\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^6} + \frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho + 2r]^2[VAR[A_{t+1};\sigma^h]\rho + 2r]^4}$$

$$-\frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^2[VAR[A_{t+1};\sigma^l]\rho+2r]^4}+\frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^6}$$
$$=$$
$$\frac{-3\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^6}+\frac{3\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^6}$$
$$+\frac{3\rho\kappa_v\big([VAR[A_{t+1};\sigma^l]\rho+2r]^2-[VAR[A_{t+1};\sigma^h]\rho+2r]^2\big)}{[VAR[A_{t+1};\sigma^h]\rho+2r]^4[VAR[A_{t+1};\sigma^l]\rho+2r]^4}$$

Moreover, we have:

$$-H\frac{\partial L}{\partial y}=$$
$$\left(\frac{1}{[VAR[A_{t+1};\sigma^l]\rho+2r]^3}+\frac{1}{[VAR[A_{t+1};\sigma^h]\rho+2r]^3}\right)\left(\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^3}-\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^3}\right)$$
$$=$$
$$\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^6}-\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^3[VAR[A_{t+1};\sigma^h]\rho+2r]^3}$$
$$+\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^3[VAR[A_{t+1};\sigma^l]\rho+2r]^3}-\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^6}$$
$$=$$
$$\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^6}-\frac{2\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^6}$$

Thus, we can calculate:

$$L\frac{\partial H}{\partial y}-H\frac{\partial L}{\partial y}=$$
$$\frac{-\rho\kappa_v}{[VAR[A_{t+1};\sigma^l]\rho+2r]^6}+\frac{\rho\kappa_v}{[VAR[A_{t+1};\sigma^h]\rho+2r]^6}+$$
$$\frac{3\rho\kappa_v\big([VAR[A_{t+1};\sigma^l]\rho+2r]^2-[VAR[A_{t+1};\sigma^h]\rho+2r]^2\big)}{[VAR[A_{t+1};\sigma^h]\rho+2r]^4[VAR[A_{t+1};\sigma^l]\rho+2r]^4}<0$$

This expression is negative because $VAR[A_{t+1};\sigma^l]<[VAR[A_{t+1};\sigma^h]$.

## A.3 Proof of proposition 3

Part 1: Absolute effects:

Our first-order condition reads:

$$\alpha K_{t+1}^{\alpha-1}\left(\bar{A}-\kappa_e\sigma_t\right)+\kappa_e zK_{t+1}^{\alpha}-\rho\left(\bar{V}+\kappa_v\sigma_{t+1}\right)\alpha K_{t+1}^{2\alpha-1}-\frac{\rho}{2}(-\kappa_v z)K_{t+1}^{2\alpha}-r_t+\beta(1-\delta)\mathbb{E}_t r_{t+1}=0$$

For $\alpha = 1/2$ and $\kappa_e = 0$, the first-order condition that the optimal capital stock has to satisfy reads:

$$0.5K_{t+1}^{-0.5}\left(\bar{A}\right) - 0.5\rho\left(\bar{V} + \kappa_v\bar{\sigma} - \kappa_v z K_{t+1}\right) - \frac{\rho}{2}(-\kappa_v z)K_{t+1} - r_t + \beta(1-\delta)\mathbb{E}_t r_{t+1} = 0$$

The effect of a monetary policy shock is given by:

$$\frac{\partial K_{t+1}}{\partial r_t} = \frac{1}{-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z} < 0 \tag{32}$$

Similarly, one can show that:

$$\frac{\partial K_{t+1}}{\partial z} = \frac{-\rho\kappa_v K_{t+1}}{-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z} > 0 \tag{33}$$

Thus: if the data feedback effect is stronger, firms hold more capital. This makes perfect sense, as a stronger data feedback effect shifts up the marginal product of capital.

Note: These derivatives are derived using the implicit function theorem. All cross-derivative from now on cannot be derived this way, but have to be manually differentiated. When evaluating the effects of parameter changes, we also have to take into account how these changes affect the optimal $K_{t+1}$.

Now we can analyse how the data feedback effect will come into play:

$$\frac{\partial K_{t+1}}{\partial r_t \partial z} = \frac{-\left[(3/8)\bar{A}K_{t+1}^{-2.5}\frac{\partial K_{t+1}}{\partial z} + \rho\kappa_v\right]}{\left[-0.25(\bar{A})K_{t+1}^{-1.5} + \rho\kappa_v z\right]^2} < 0 \tag{34}$$

Part 2: Relative effects

We begin by defining the relative effect of an interest rate increase:

$$\phi(\sigma_{t+1}) := \frac{\frac{\partial K_{t+1}}{\partial r_t}}{K_{t+1}} \tag{35}$$

When $\alpha = 1/2$ and $\kappa_e = 0$, the first-order condiiton the optimal capital stock has to satisfy reads:

$$0.5K_{t+1}^{-0.5}\left(\bar{A}\right) - 0.5\rho\left(\bar{V} + \kappa_v\bar{\sigma} - \kappa_v z K_{t+1}\right) - 0.5\rho(-\kappa_v z)K_{t+1} - r_t + \beta(1-\delta)\mathbb{E}_t r_{t+1} = 0$$

Thus, we have:

$$\phi(\sigma_{t+1}) = \frac{1}{(-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z)K_{t+1}}$$

Thus, we can write:

$$\frac{\partial\phi(\sigma_{t+1})}{\partial z} = \frac{-1}{[-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z)K_{t+1}]^2}$$

$$\left[(-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z)\frac{\partial K_{t+1}}{\partial z} + \left((3/8)\bar{A}K_{t+1}^{-2.5}\frac{\partial K_{t+1}}{\partial z} + \rho\kappa_v\right)K_{t+1}\right]$$

$$=$$

$$\frac{-1}{[-0.25\bar{A}K_{t+1}^{-1.5} + \rho\kappa_v z)K_{t+1}]^2}\left[(1/8)\bar{A}K_{t+1}^{-1.5}\frac{\partial K_{t+1}}{\partial z} + \rho\kappa_v z\frac{\partial K_{t+1}}{\partial z} + \rho\kappa_v K_{t+1}\right] < 0$$

## A.4 Proof of proposition 4

Examine first whether firms who are more sensitive to risk will hold more or less capital. We begin, once again, by examining the FOC when $\alpha = 1/2$:

$$0.5K_{t+1}^{-0.5}\left(\bar{A} - \kappa_e\sigma_{t+1}\right) + \kappa_e z K_{t+1}^{0.5} - \rho\left(\bar{V} + \kappa_v\sigma_{t+1}\right)0.5K_{t+1}^{0} - \frac{\rho}{2}(-\kappa_v z)K_{t+1} - r_t - \beta(1-\delta)\mathbb{E}_t r_{t+1} = 0$$

Let's investigate the following derivative:

$$\frac{\partial K_{t+1}}{\partial\rho} = \frac{0.5\left(\bar{V} + \kappa_v\bar{\sigma} - \kappa_v z K_{t+1}\right) - 0.5\kappa_v z K_{t+1}}{\partial^2\Pi_{t+1}/\partial K_{t+1}^2} \tag{36}$$

If $z = 0$, this derivative is clearly negative, because the denominator is negative. If $z$ is high enough such that the numerator becomes negative, the result flips.

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