Title
What Do Inventories Tell about the Future Economy?

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Publication Date
2024

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

What Do Inventories Tell about the Future Economy?

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Management

by

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2024

ABSTRACT OF THE DISSERTATION

What Do Inventories Tell about the Future Economy?

by

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Doctor of Philosophy in Management
University of California, Los Angeles, 2024
Professor Judson Caskey, Chair

In this paper, I provide evidence that the mean and dispersion of manufacturers' inventory growth are negatively associated with *subsequent* changes in economic output growth. I build and calibrate a heterogeneous-firm model with asymmetric adjustment costs to show that this macro-level association is consistent with firms' asymmetric response to news shocks at the micro level. The fact that firms adjust inventories in response to news shocks also highlights the role of inventories in signaling future economic conditions. Additional empirical tests show that inventory growth dispersion, computed from real-time accounting disclosures, can help improve the forecasts and estimates of future GDP growth.

The dissertation of Yuanzhen Lyu is approved.

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2024

I dedicate this work to my parents, Huayang and Hong,
and my girlfriend, Siyang. I hope the sacrifices you have endured
for me to pursue this dream will be repaid to you with
many opportunities for joy in the future.

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ACKNOWLEDGMENTS

I am deeply grateful to my committee, Judson Caskey, Henry Friedman, Bernard Herskovic, and Hugo Hopenhayn, for their invaluable guidance and encouragement. I also thank UCLA faculty, Carla Hayn, Mark Kim, Jessica Kim-Gina, Beatrice Michaeli, Daniel Saavedra, Siew Hong Teoh, and Brett Trueman, for shaping my understanding of the discipline, and offering constructive advice for my research.

The inclusive academic environment at UCLA has been instrumental in facilitating my exploration of the intersection between macroeconomics and financial accounting. I thank the UCLA Anderson Finance and UCLA Economics departments for giving me the opportunity to study macroeconomics and financial markets, and for the helpful discussions with Andrew Atkeson, David Baqaee, Andrea Eisfeldt, Francis Longstaff, Tyler Muir, Lee Ohanian, and Pierre-Olivier Weill. This dissertation is also a continuation of my master thesis completed in Peking University. I am grateful to James Chan, Guohua Jiang, and Laura Xiaolei Liu, for introducing me to the world of academic research and igniting my passion for macro-accounting.

I had the pleasure of working closely with fellow Ph.D. students, Wen-Hsin Chang, Muskan Chawla, Kelly Ju, Noah Kwicklis, Yasutaka Koike-Mori, Millennium Li, Kai Chiu Yang, Zitong Zeng, as well as recent alumni Yuqing Zhou and Kevin Huang. I thank UCLA Anderson's current and former staff for their assistance during my doctoral studies, and acknowledge the generous financial support of UCLA Graduate Division and UCLA Anderson.

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CHAPTER 1

What Do Inventories Tell about the Future Economy?

1.1 Introduction

The relationship between the cross-sectional dispersion of firm behaviors and overall macroeconomic activity has attracted growing attention, prompting much debate over its origins (e.g., Bachmann and Bayer, 2014; Ilut et al., 2018). In this paper, I extend the literature to examine the dispersion of inventory growth, a firm behavior that is of particular interest in accounting.[1] Inventories are unique for their forward-looking nature in predicting future sales or stock returns (e.g., Thomas and Zhang, 2002; Kesavan et al., 2010). Additionally, inventory adjustments are asymmetric, as emphasized in cost behavior studies within managerial accounting literature (e.g., Banker and Byzalov, 2014; Hwang et al., 2021). These findings, from disparate literatures, jointly suggest that the cross-sectional standard deviation of firm-level inventory growth, i.e., inventory dispersion, might be a particularly useful

[1] Inventories, as a crucial component of accruals, have attracted broad attention in the accruals literature (e.g., Bernard and Stober, 1989; Dechow et al., 1998; Thomas and Zhang, 2002). Furthermore, inventory behaviors are indicative of real earnings management (Roychowdhury, 2006), and have been studied extensively in managerial accounting (e.g., Baiman et al., 2010; Hwang et al., 2021).

indicator of future macroeconomic conditions.

Consistent with this conjecture, I find that a bottom-up measure of aggregate inventory dispersion negatively correlates with *subsequent* changes in economic output growth. Furthermore, I show that the aggregate inventory growth mean also negatively predicts *subsequent* output growth changes. The news shock literature (e.g., Crouzet and Oh, 2016; Görtz et al., 2022) suggests that inventory adjustments reveal firms' private information about future economic conditions. The negative correlation between aggregate inventory mean and future economic growth comes from the intertemporal production substitution motive underscored in Crouzet and Oh (2016). When positive productivity news arrives, firms anticipate that producing tomorrow will be cheaper, and they shift their production into the future to save costs and deplete inventories for current sales.[2] In addition, managers tend to reduce resources to a lesser extent when activity decreases compared to when it increases, implying higher adjustment costs for firms with lower productivity, as suggested by the sticky cost studies (e.g., Banker et al., 2013). Consequently, while firms typically decrease inventories in response to positive news shocks, those with low productivity do so at a slower pace than high-productivity firms, narrowing the gap in inventory growth between the two types of firms and reducing dispersion in the cross-section. Therefore, this decreased dispersion indicates positive news shocks and predicts higher future economic growth.

The asymmetric inventory response can be mathematically described in a convex inventory decision rule. I present empirical evidence that suggests a close relation-

[2]Although the news may be about cost of capital (Jones and Tuzel, 2013a; Görtz et al., 2022), the central argument about inventory dispersion remains valid. Specifically, as long as inventory growth mean drops in anticipation of future output growth, due to cost asymmetry, dispersion still decreases.

ship between this decision rule, and the negative association of inventory dispersion and future output growth changes. At the firm level, I estimate an average firm's inventory growth response as a function of idiosyncratic productivity innovations and confirm that this decision rule is indeed convex.[3] Given the convex curve, firms are expected to be more shock-sensitive when they are in the process of upward adjustment, i.e., in the region with steeper gradients. Consistent with this expectation, I find that in response to positive news shocks proxied by high levels of future output growth changes, firms on average reduce inventories and this reduction is more pronounced when firms are in the path of upward adjustment. At the cross-sectional level, the asymmetric response to news shocks endogenously generates variations in cross-sectional inventory growth distributions. These distributions exhibit positive skewness consistent with the convex rule, and in response to positive news, firms generally transition away from the fat right tail and cluster in the left tail of the distribution, thereby reducing the dispersion. To obviate the look-ahead bias, I also measure news shocks using concurrent forecasts of future output growth changes and obtain similar cross-sectional and firm-level results. Overall, these results suggest that the convex inventory rule is central to producing the cross-sectional distribution dynamics and, furthermore, the movements of the aggregate inventory moments.

Given the empirical evidence, I directly model the asymmetric inventory response through adjustment cost asymmetry and remain agnostic about the sources of it, because the center of this paper is to investigate the aggregate implications of firm-level asymmetric responses. Specifically, I assume that firms incur a higher cost when

[3]Throughout the paper, the inventory decision rule refers to the rule governing inventory changes, as opposed to inventory levels. For this reason, the decision rule is a function of the innovations in idiosyncratic productivity.

adjusting inventories downward than upward. This cost asymmetry is common in the neoclassical investment literature (e.g., Belo and Lin, 2012; Dasgupta et al., 2019), and can stem from factors such as costly reversibility, managers' optimistic demand expectation or stockout-avoidance motive. I construct a heterogenous firm model by extending the the news-shock real business cycle framework in Crouzet and Oh (2016). Firms in the model are heterogeneous in terms of idiosyncratic productivity, and they receive a common signal about subsequent aggregate productivity in each period.[4] Given the received news, firms make intertemporal inventory decisions by solving a dynamic problem. The calibrated baseline model successfully replicates several aggregate moments present in the data and suggests the mechanism described earlier. It also indicates that both inventory mean and dispersion are noisy signals of the common news firms receive, with dispersion offering incremental information about the news. Furthermore, counterfactual exercises suggest that cost asymmetry is a necessary condition for the negative correlation between inventory dispersion and future economic growth.

Following the news-shock explanation, a practical question to ask is whether economists and government statistical agencies fully incorporate the news embedded in inventory dynamics in their decision making. By examining this issue, this paper helps address growing market concerns over the quality of economic data.[5] The main

[4]It is worth noting that the assumption of a productivity news shock does not contradict the signaling role of inventory change regarding future sales. In a general equilibrium, productivity improvement results in lower price and higher sales.

[5]On September 2023, the Office for National Statistics in U.K. substantially revised its GDP growth during 2019Q4 to 2021Q4 from an initial -1.2% to 0.6%, changing public perception about the country's recovery from the Covid-19 pandemic. This news captured the attention of many mainstream media. According to an article from *The Wall Street Journal*, GDP revisions are also common in the U.S. with initial estimates often misleading the market.

variables this paper examines are the forecast errors of the Survey of Professional Forecasters (SPF) panelists, and the restatements of Gross Domestic Product (GDP). The SPF published by the Philadelphia Fed is the longest and most well-known publicly available economic survey. Using public companies' accounting disclosures of the preceding quarter available by SPF survey submission deadlines, I compute aggregate inventory mean and dispersion. Although the inventory mean does not exhibit forecasting power, the preceding inventory dispersion significantly predicts errors in the SPF panelists' consensus forecast for current-quarter real GDP growth.

Next, I focus on the final restatements of GDP, because GDP is the most important product from the National Income and Product Accounts (NIPA) system. Final restatements are defined as the differences between latest estimates and initial estimates. Government statistical agencies usually release an initial estimate of quarterly GDP less than one month after a quarter ends and routinely restate it as more comprehensive economic survey information is available. This initial estimate is imprecise, with the standard deviation of real GDP final restatements almost 40% of real GDP growth. While it is commonly believed that government statistical agencies, with their access to extensive real-time economic data, would not make predictable errors in their initial estimates, the results suggest otherwise. I find that the dispersion measure, calculated from financial disclosures available by initial estimate release dates, exhibits remarkable predictive power on the restatements of future real GDP growth. When regressing the final restatements of quarter-ahead real GDP growth on explanatory variables from the prior literature (Faust et al., 2005; Aruoba, 2008; Nallareddy and Ogneva, 2017), I obtain an adjusted R^2 of 10.3%. In contrast, after I add inventory dispersion into the set of existing explanatory variables, the adjusted R^2 increases to 27.7%. A one standard-deviation increase in inventory dispersion indicates that the level of real GDP final restatements is 0.35% lower, which accounts for almost half of the standard deviation of real GDP final restatements. The forecasting power of inventory dispersion on SPF forecast errors and GDP revisions also withstands a battery of out-of-sample tests.

Lastly, I perform several tests to examine the sources of the predictive power of inventory dispersion. On one hand, I find that the predictive power of inventory dispersion predominantly comes from firms characterized by high adjustment cost asymmetry. To proxy for high cost asymmetry, I use two indicators which have been shown to positively associate with inventory adjustment asymmetry in Hwang et al. (2021), including preceding revenue increases (Anderson et al., 2003) and high stock-out to inventory holding costs (Kesavan and Kushwaha, 2014). The results obtained with both measures suggest that the inventory dispersion among firms with high cost asymmetry exerts a stronger predictive power over GDP forecast errors and revisions compared to the dispersion within firms with low cost asymmetry. On the other hand, I provide evidence that the predictive power of inventory growth dispersion on future GDP restatements stems from sector-specific productivity news, consistent with my theory. Specifically, the evidence strongly supports that inventory growth dispersion predicts the restatements of expenditures on nondurable goods, but not the restatements of private inventories, nonresidential investments, or durable good consumption. The fact that dispersion fails to predict revisions to all consumption components suggests that demand news shocks are not likely to be the primary driving force. Instead, the predictive power of inventory dispersion may be due to productivity news shocks in the nondurable sector. According to Beaudry and Portier (2004), because the nondurable sector is susceptible to rapid changes and constant arrival of new products, productivity news is comparatively more crucial in this sector. In addition, the absence of predictive power for the restatements of private inventories suggests that the predictive power of inventory growth dispersion does not arise from a direct relationship with inventories, such as measurement errors in accounting for the inventory component in GDP.

Related literature. The dominant theory in accounting literature that explains the negative relationship between dispersion and future economic growth is sectoral shifting (e.g., Jorgensen et al., 2012; Nallareddy and Ogneva, 2017; Kalay et al., 2018), which links performance dispersion increases to greater labor reallocation and higher future unemployment. However, I find that this theory lacks empirical support in explaining the dispersion of inventory growth. Unlike earnings or stock returns, inventories are not as closely tied to changes in firm fundamentals and are often regarded as a buffer for supply and demand disturbances (e.g., West, 1990; Ramey and West, 1999; Wen, 2005). I show that inventory dispersion exhibits a near-zero correlation with future unemployment changes, and does not correlate with the dispersions of earnings or stock returns. Therefore, I introduce a novel mechanism to explain the association between dispersion and the macroeconomy.

This alternative mechanism relates to the endogenous time-varying dispersion literature.[6] Research by Ilut et al. (2018), Baley and Blanco (2019), Cacciatore and Ravenna (2021), Dew-Becker et al. (2021), and Bernstein et al. (2022) proposes multiple mechanisms to endogenously produce the countercyclical cross-sectional dispersion, such as the concavity in hiring rules, learning, sticky wages, product com-

[6] There are two lines of research in studying dispersion. Many models, such as Bloom (2009), Bloom (2014) and Bachmann and Bayer (2014), assume that firms draw idiosyncratic shocks with time-varying volatility to produce time-varying dispersion. Another line of research, as discussed here, proposes a set of mechanisms aimed at endogenously generating dispersion through asymmetric responsiveness to exogenous shocks with constant volatility.

plementarity, and labor searching and matching frictions. The most relevant to mine is Ilut et al. (2018), who show that symmetric productivity shocks pass through concave hiring rules and endogenously produce countercyclical movements in aggregate and cross-sectional employment volatility. Despite the inventory adjustment rule being convex in my study, the occurrence of positive news leading to a decrease in inventory growth mean results in the cross-sectional dispersion exhibiting a negative correlation with future economic growth changes.

This paper also contributes to the cost accounting literature (e.g., Anderson et al., 2003; Banker and Byzalov, 2014; Rouxelin et al., 2018; Hwang et al., 2021), and relates to the admittedly sparse set of theoretical macro-related studies in accounting (e.g., Choi, 2021; Terry et al., 2023; Terry, 2023). Existing cost accounting studies typically focus on the firm level, with few exceptions such as Rouxelin et al. (2018), who find that aggregate cost stickiness is a leading indicator for future unemployment. I show that asymmetric cost behavior not only holds significance at the firm level but also influences movements in inventory dispersion at the aggregate level. The paper develops, quantifies, and empirically tests a heterogeneous firm model, which provides a micro-to-macro structure to analyze the aggregate implications of asymmetric inventory adjustments.

I also extend the news shock literature by highlighting the important role of news shocks in driving inventory dispersion and its implications for economic forecasting. Studies on news shocks primarily focus on how changes in expectation drive economic fluctuations (e.g., Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009; Beaudry and Portier, 2014). Relevant to my research, Crouzet and Oh (2016) and Görtz et al. (2022) discuss the significance of news shocks in understanding the behavior of aggregate inventory cycles. Given the news received by firms, a natural question to ask is whether inventory adjustments effectively convey this news, thereby enhancing the precision of economic output prediction and estimation. A large body of studies examines economic forecasting (e.g. Giannone et al., 2008; Antolin-Diaz et al., 2017), and the value of business accounting information therein (e.g., Konchitchki and Patatoukas, 2014a,b; Shivakumar and Urcan, 2017; Rouxelin et al., 2018; Ogneva et al., 2020; Hann et al., 2021; Abdalla et al., 2021). I add to this discourse by showing that aggregate inventory dispersion, calculated from real-time financial disclosures, emerges as a significant predictor of both GDP forecast errors and GDP revisions.

The rest of the article is organized as follows. Section 2 provides motivating evidence. Section 3 provides a formal model, presents calibration results, and inspects the mechanism. Section 4 conducts predictability tests on GDP forecast errors and GDP revisions, and Section 5 concludes.

1.2 Empirical Evidence

1.2.1 Aggregate Inventory Moments

To investigate firm heterogeneity, I draw on Compustat as my main data source. I keep U.S. incorporated firms in construction and manufacturing sectors. Firms in the construction sector are classified as manufacturers because it produces durable goods according to Beaudry and Portier (2004). Around 1,500 manufacturers per quarter from 1976Q1 to 2019Q2 are available in the panel. I compute inventory growth on a year-over-year basis to mitigate seasonality, and correspondingly, GDP growth is also calculated on a year-over-year basis. Figure 1.1 plots the time series of the cross-sectional mean and standard deviation of firm-level inventory growth weighted by lagged inventory levels against future real GDP growth changes.[7] Both inventory moments significantly negatively associate with future GDP growth changes.

I interpret future GDP growth changes as a proxy for news shocks, as they reveal expected aggregate productivity innovations. Although this measure is subject to a look-ahead bias, following Jaimovich and Rebelo (2009), I also proxy a news shock using the expected change of quarter-ahead real GDP growth based on concurrent professional forecasts, and examine how aggregate inventory moments respond to it. The results are qualitatively similar, as shown in Figure 1.1.[8] Expected aggregate productivity innovations imply the changes in the relative marginal production costs between the future and the present. Due to the intertemporal production substitution motive in Crouzet and Oh (2016), firms overproduce and accumulate inventories at times with low production costs. When firms receive positive news about future productivity improvements, they typically delay production to a later time and deplete inventories to meet immediate demand. This implies a negative correlation between aggregate inventory growth mean and future GDP growth changes. However, the correlation related to inventory growth dispersion needs further study.

[7] In other words, I compare the aggregate moments of the first difference of inventory log levels (inventory growth) to the second difference of future GDP log levels (changes in GDP growth). The use of the second difference of GDP log level is important, because inventory level is determined by the relative marginal production costs, implied by the first difference in GDP log levels.

[8] The quantitative difference in correlations related to dispersion might be due to the fact that professional forecasts fail to incorporate the information content in inventory dispersion, which I will discuss later. For this reason, I use actual GDP numbers instead of forecasted numbers to identify news shocks in the following quantitative analysis.

1.2.2 Cross-Sectional Distributions

In the next step, I look further into how cross-sectional inventory growth distributions vary with news shocks. Consistent with Figure 1.1, I proxy news shocks using realized or forecasted changes of future real GDP growth. I sort quarters into quintiles based on their corresponding news shock levels, and calculate the average inventory growth distributions of the highest quintile (positive news) and the lowest quintile (negative news). Figure 1.2 shows that the inventory distribution is right-skewed, and in response to positive news, firms on average slow inventory growth, shifting away from the heavy right tail and clustering in the left tail of the distribution. The positive skewness of the distribution signifies that the inventory decision rule is convex.

Figure 1.3 illustrates the relationship between decision rule convexity and positive skewness, as well as how this convexity produces cross-sectional distribution variations. The inventory decision rule, when evaluated under negative news (colored in blue), processes normally distributed idiosyncratic total factor productivity (TFP) innovations through a convex function, resulting in a right-skewed cross-sectional inventory growth distribution. With the arrival of positive news (colored in red), the convexity inherent in the decision rule induces a nonparallel downward shift in the curve because firms with low productivity are less responsive to both idiosyncratic and aggregate shocks. Specifically, the region corresponding to high TFP innovation levels descends more significantly compared to the area associated with low TFP innovations. As a result, the updated decision rule becomes less convex. Given the same distribution of TFP innovations, the updated decision rule prompts a leftward shift in the distribution, and renders it less dispersed. Because positive news indicates better future economic conditions, current aggregate inventory growth mean and dispersion negatively associate with future output growth. This example demonstrates that understanding aggregate moments requires an investigation of the firm-level inventory decision rule.

1.2.3 Asymmetric Inventory Response

To obtain an insight into the curvature of the decision rule, I follow the methodology outlined in Ilut et al. (2018). I first estimate the inventory decision rule nonparametrically, without accounting for other state variables, and then estimate the rule in panel regressions with controls. I focus on U.S. incorporated Compustat manufacturers with a minimum of ten years of observations. This restriction gives me around 2,500 firms in the sample. Estimating the inventory decision rule first requires the estimation of TFP innovations. I follow Herskovic et al. (2023) using Compustat financial data to estimate TFP innovations. The detailed procedure can be found in the appendix.

Figure 1.4 presents the nonparametric estimate of the rule. The solid blue line represents the fitted curve, while the dashed lines delineate the 95% confidence interval. The density of TFP innovations is plotted in red bars. A key takeaway is that inventory growth exhibits a stronger response to positive shocks compared to negative shocks, indicating a convex curvature in the decision rule. This pattern is particularly evident within the range where TFP innovations are densely distributed.

Next, I estimate the inventory rule using the following regression with firm fixed effect $\bar{Invt}_i$ and quarter fixed effect $\bar{Invt}_t$:

$$Invt_{it} = \bar{Invt}_i + \bar{Invt}_t + F(\varepsilon_{x,it}) + \gamma_1 Invt_{i,t-1} + \gamma_2 x_{i,t-1}$$

where $\varepsilon_{x,it}$ is the TFP innovation, $x_{i,t-1}$ is the $t-1$ log TFP level, and $F(\varepsilon_{x,it})$ is a function of $\varepsilon_{x,it}$ under various specifications. I include $Invt_{i,t-1}$ because the first-order approximation of inventory growth is a function of its lagged values as discussed later in the theory section. I also incorporate the lagged TFP level same as Ilut et al. (2018), because a given TFP shock is likely to have varying impacts at different TFP levels.

Table 1.2 Columns (1) and (2) imply that the decision rule is an increasing and convex function of TFP innovations. Specifically, a one standard deviation increase in TFP innovation (14.5%) amplifies inventory growth by 1.5%, while a decrease of the same magnitude diminishes inventory growth by 1.0%. In addition, in Columns (3) and (4), the results about the third and fourth specifications indicate a piecewise linear relationship with a higher slope above $\varepsilon_{x,it} = 0$ or $Invt_{i,t-1} = 0$. The inventory response exhibits asymmetry with respect to the direction of adjustments and the direction of TFP innovations. In conclusion, inventory adjustments are asymmetric and react more strongly to positive TFP innovations.

Given the asymmetric inventory response to idiosyncratic TFP shocks, it is natural that inventory adjustments should also respond to news shocks in an asymmetric manner. Specifically, upon receiving positive news, as firms in general have the tendency to cut down their inventories, those on a downward adjustment path should do so at a lesser extent than firms on an upward path, recalling the nonparallel downward shifting of the decision curve in Figure 1.3. I examine this conjecture in

Table 1.3. For each firm, I sort quarterly inventory growth observations by news shocks and adjustment directions measured by lagged inventory growth rates, and calculate the firm-level average in each bucket. Next, I calculate the average across firms in each news shock-adjustment direction bucket. Overall, Table 1.3 reflects how a representative average firm reacts to news shocks, conditional on its adjustment paths. The results indicate that firms in general reduce their inventories in response to positive news shocks, and the reduction in inventories is more pronounced when firms are in the process of upward adjustments. When receiving positive news, firms' inventory growth rates on average reduce by 7.3% at upward adjustments, and 4.9% at downward, and the gap 2.4% is statistically different from zero. The results with news shocks measured by concurrent professional forecasts give the same conclusion.

In the subsequent theoretical section, I directly model asymmetric inventory response through adjustment cost asymmetry, where the cost associated with upward adjustment is lower than that with downward adjustment.[9] This assumption is common in the neoclassical investment literature (e.g., McCarthy and Zakrajsek, 2000; Belo and Lin, 2012; Dasgupta et al., 2019) and aligns with the finding in cost behavior studies that managers' resource commitment decisions are asymmetric (e.g., Banker et al., 2013; Banker and Byzalov, 2014). One possible explanation is costly reversibility, where the price paid to build up inventories is higher than the price received from liquidating them. The potential loss from liquidating inventories is captured by higher downward adjustment cost. Second, the cost asymmetry may

[9]According to the Oi-Hartman-Abel effect (after Oi, 1961; Hartman, 1972; Abel, 1983), if firms can expand to exploit positive shocks and contract to insure themselves against negative shocks, their investment decision rule is also convex. However, it is important to note that the Oi-Hartman-Abel effect does not necessarily guarantee the convexity of the decision rule when it comes to changes in investment.

result from the stockout-avoidance motive. Holding inventories helps in reducing the likelihood of stockouts. According to Kesavan and Kushwaha (2014), firms are more likely to build up inventories when the loss from stockouts is larger than the inventory holding cost. Third, managers' optimistic demand expectation (Anderson et al., 2003) and "empire building" tendencies (Chen et al., 2012a) may also lead firms to be more inclined to commit resources.

1.2.4 Alternative Explanations

Demand shifting. While this paper primarily focuses on the role of relative production costs in producing the negative correlation between inventory mean and future economic growth, the demand shift theory proposed by Thomas and Zhang (2002) may offer an alternative explanation. Thomas and Zhang (2002) use this theory to explain the negative association between inventory changes and future stock returns in the cross-section. According to their reasoning, increases in inventories may signal negative demand shifts in these firms, indicating a reversal in profitability trends that investors are not aware of. Due to the earnings management motive and inventories being an important component of accruals, firms have incentives to inflate inventories so that the impending reversals are masked in reported profitability. If this demand shift theory is applicable at the aggregate level, we might anticipate that the negative relationship between inventory mean and future economic growth is primarily driven by periods with increases in inventories. However, conditional on inventory mean being higher than the historical average, the correlation magnitude between future economic growth changes and inventory growth mean is much smaller ($\mathrm{Corr}(\Delta GDP_{t+1}, Invt_t | Invt_t \geq \bar{Invt}) = -0.05$) compared to the magnitude when inventory mean is lower (Corr($\Delta GDP_{t+1}, Invt_t | Invt_t < \bar{Invt}$) $= -0.40$). Because low inventory growth typically appears towards the end of a recessionary period as indicated in Figure 1.1, these results suggest that the predictive power of inventory growth becomes stronger upon recovery from a recession. To sum up, the demand shift theory does not provide a satisfactory explanation for the observed evidence.

In contrast, the theory proposed in this paper is silent about the periods where the forecasting power of inventory mean originates, but predicts that the forecasting power of inventory dispersion should be stronger when inventory adjustments are more asymmetric or costs are more sticky. Rouxelin et al. (2018) argue that towards the end of a recession, firms tend to retain slack resources in anticipation of demand recovery, thus resulting in more cost stickiness. Accordingly, they find that the predictive power of cost stickiness becomes stronger when the economy recovers from a recession. Consistent with this prediction, I also find that the predictive power of dispersion becomes stronger during these periods. Conditional on the inventory mean being higher than the historical average, the correlation magnitude between dispersion and future economic growth (Corr($\Delta GDP_{t+1}, InvtDisp_t | Invt_t \geq \bar{Invt}$) $= -0.14$) is much smaller compared to the magnitude when the inventory mean is lower (Corr($\Delta GDP_{t+1}, InvtDisp_t | Invt_t < \bar{Invt}$) $= -0.25$).

Sectoral shifting. A usual explanation in accounting studies for the relationship between the dispersion of economic variables and future aggregate outcomes is the sectoral shift theory (e.g., Jorgensen et al., 2012; Nallareddy and Ogneva, 2017; Kalay et al., 2018). According to this theory, cross-sectional dispersion serves as an indicator of labor reallocation in the economy, with greater labor reallocation suggesting higher future unemployment due to job search frictions. Given that labor reallocation is a crucial link between cross-sectional dispersion and future aggregate outcomes, if the sectoral shift theory is applicable, we might expect a positive association between inventory dispersion and future unemployment rates. I obtain unemployment rate data from the FRED database and calculate the correlation between cross-firm/sector inventory dispersion and changes in quarter-ahead unemployment rates. The results show that these inventory dispersions do not significantly correlate with future unemployment changes, with the correlation coefficients being 0.07 for cross-firm dispersion and 0.08 for cross-sector dispersion. Since inventories primarily serve to buffer demand and production disruptions, unlike earnings or stock returns previously studied, changes in inventories are not closely tied to firm performance and thus do not directly reflect a firm's employment decisions.

Overall, the results presented above are inconsistent with prior studies' demand and sectoral shift theories. Both theories also fall short of providing a cohesive explanation for the behaviors of inventory mean and dispersion jointly. In contrast, the above cross-sectional and firm-level results paint a consistent picture about how news shocks and asymmetric adjustment costs collaboratively generate the time-varying dispersion. In the subsequent theoretical section, I provide a formal structure consistent with these empirical findings to quantitatively investigate the mechanism.

1.3 Theory

1.3.1 Model Setup

I develop a heterogenous-firm model that incorporates news shocks and asymmetric adjustment costs. The economy is composed of a final-good firm and a continuum of firms producing intermediate goods, as outlined in David et al. (2016). Each intermediate firm, facing stock-elastic demand akin to Crouzet and Oh (2016), solves a dynamic problem upon receiving news about the next-period condition. I concentrate on the production side of a discrete-time, infinite-horizon economy with a constant interest rate. The household side of the economy is purposely kept simple.[10]

Market structure. I assume labor supply is perfectly elastic and treat wage price as a numeraire. In the final good market, the demand function is

$$P_t = s_t^{-\eta} \tag{1.1}$$

with s_t the total demand, and the inverse of $\eta \in (0,1)$ measures the price elasticity of demand. The final good is made of a bundle of intermediate goods s_{jt}, and is produced according to a cost-minimizing problem:

$$\min_{\{s_{jt}\}} \int_0^1 P_{jt} s_{jt} dj, \quad \text{s.t.} \quad \left(\int_0^1 v_{jt}^{\frac{1}{\theta}} s_{jt}^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}} \geq s_t$$

with $\theta > 0$ the elasticity of substitution and v_{jt} the preference shifter. By solving the problem, each intermediate firm j faces a demand function:

$$s_{jt} = v_{jt} \left(P_{jt}/P_t \right)^{-\theta} s_t, \quad \text{with} \quad P_t = \left(\int_0^1 v_{jt} P_{jt}^{1-\theta} dj \right)^{\frac{1}{1-\theta}}.$$

[10]This is an important simplification from Crouzet and Oh (2016). Because the household problem is time separable, expectations regarding future wealth gains from positive news shocks do not directly impact current consumption. I intentionally mute the household channel for two reasons. First, Crouzet and Oh (2016) demonstrate that intertemporal substitution in production is the primary mechanism driving the business-cycle behavior of inventories. Second, this paper focuses on examining cross-sectional inventory dispersion under firm heterogeneity, and introducing household dynamics would further complicate the analysis.

The taste shifter for good j is assumed to depend on the amount of goods stocked on shelf a_{jt}, where $v_{jt} = a_{jt}^{\zeta}$. A larger stock facilitates matching with more potential purchasers, but the marginal benefit of this stock diminishes, as $\zeta \in [0, 1]$. At $\zeta = 0$, this collapses into a pure cost-smoothing model, where the firm decouples production timing from sales timing. At the extreme with $\zeta = 1$, this gives the model a flavor of stockout motive where the level of stocks sets a constraint for the amount of goods the firm can sell.

Exogenous shocks. Firms are heterogenous in terms of their productivity. As is common in the literature, firm productivity is the sum of idiosyncratic productivity x_{jt} and aggregate productivity g_t, both of which follow AR(1) processes: $x_{jt} = \rho_x x_{jt-1} + \varepsilon_{x,jt}$, $g_t = (1-\rho_g)\bar{g} + \rho_g g_{t-1} + \varepsilon_{g,t}$. In addition, prior research suggests that inventories are a forward-looking variable that conveys information about future economic conditions (e.g., Bernard and Noel, 1991; Kesavan et al., 2010; Alan et al., 2014). Hence, following Jaimovich and Rebelo (2009), I assume that, in period t, firms in the economy receive a common noisy signal regarding aggregate productivity in the subsequent period $t+1$, where $r_{t+1} = g_{t+1} + \varepsilon_{r,t+1}$. News shocks are hereby defined as the difference between the signal and the expected future aggregate productivity in absence of the signal, i.e., $r_{t+1} - (1-\rho_g)\bar{g} - \rho_g g_t$. The aggregate state in each period can be represented as (g_t, r_{t+1}).[11]

Firm problem. In each period, an intermediate firm makes inventory and employment decisions by maximizing the discounted sum of future profits after knowing the aggregate state (g_t, r_{t+1}), its idiosyncratic productivity x_{jt}, and its previous inventory holdings $inv_{j,t-1}$. Since price is formed after firm decisions, firms must make conjec-

[11] I later rewrite the aggregate state into a vector autoregressive process and discretize it for further numerical analysis using the methodology outlined in Tauchen (1986).

tures about current market price P_t. While each firm possesses complete information about its own state and the states of other firms from the preceding period, I later show that according to Krusell and Smith (1998), by knowing the aggregate first moments, (g_t, r_{t+1}, p_{t-1}), a firm can accurately infer p_t where $p_t = \log(P_t)$. Therefore, the firm's problem can be expressed recursively as:

$$\begin{aligned} V(inv_{j,t-1}, x_{jt}; g_t, r_{t+1}, p_{t-1}) = \max_{inv_{jt}, n_{jt}} \; & e^{p_{jt}} s_{jt} - n_{jt} - \frac{1}{2} inv_{j,t-1} \phi_{jt} \left(\frac{y_{jt} - s_{jt}}{inv_{j,t-1}} \right)^2 \\ & + \beta \mathbb{E}_t \left[V(inv_{jt}, x_{j,t+1}; g_{t+1}, r_{t+2}, p_t) \right] \end{aligned} \tag{1.2}$$

s.t.

$$inv_{jt} = (1-\delta) inv_{j,t-1} + y_{jt} - s_{jt} \quad \text{(Inventory Accumulation Rule)}$$

$$y_{jt} = e^{x_{jt} + g_t} n_{jt}^{\alpha} \quad \text{(Production Function)}$$

$$a_{jt} = (1-\delta) inv_{j,t-1} + y_{jt} \quad \text{(Definition of Goods Available)}$$

$$s_{jt} = a_{jt}^{\zeta} \left(\frac{e^{p_{jt}}}{e^{p_t}} \right)^{-\theta} s_t \quad \text{(Demand Function)}$$

where inv_{jt} is the inventory level of firm j, y_{jt} is the quantity produced, s_{jt} is the quantity sold, and n_{jt} is the labor input. The available quantity on shelf a_{jt} includes the prior depreciated inventories $(1-\delta) inv_{j,t-1}$ and the current production y_{jt}. Similar to Belo and Lin (2012), the adjustment coefficient is given by $\phi_{jt} = \phi_+ 1_{y_{jt} \geq s_{jt}} + \phi_- 1_{y_{jt} < s_{jt}}$.

Aggregation. I proceed to characterize the aggregate behavior of the economy. In a competitive equilibrium, the final-good price P_t is determined such that the final-good market clears, with the final-good supply being a CES aggregator of intermediate goods. As a result, the aggregate dynamics of the economy depends upon the cross-sectional distribution of intermediate firms. These firms can be sufficiently differentiated in two dimensions (inv_{t-1}, x_t) with the firm index j suppressed. Denote Θ as any measurable set in the space of (inv, x). Let $\mu_t(\Theta; g_t, r_{t+1})$ be the fraction of firms with $(inv_{t-1}, x_t) \in \Theta$ given (g_t, r_{t+1}). The measure μ_t transitions from t to $t+1$ as:

$$\mu_{t+1}(\Theta; g_{t+1}, r_{t+2}) = \int 1_{\{((1-\delta)inv_{t-1}+y_t-s_t, x_{t+1})\in\Theta\}} \mathbb{P}[x_{t+1}|x_t]\mathbb{P}[g_{t+1}, r_{t+2}|g_t, r_{t+1}] \\ d\mu_t(inv_{t-1}, x_t; g_t, r_{t+1}) \tag{1.3}$$

where $y_t - s_t$ is the optimal inventory accumulation decision that will be determined in an equilibrium. Equation 1.3 describes how the cross-sectional distribution μ_t of intermediate firms over the space (inv_{t-1}, x_t), evolves based on the optimal inventory decision and the exogenous processes x_t and (g_t, r_{t+1}). The final-good supply is aggregated from the sales of intermediate goods weighted by the density of the cross-sectional distribution.

Stochastic competitive equilibrium. A competitive equilibrium consists of a market price p_t, a production rule $y(inv_{t-1}, x_t; g_t, r_{t+1}, p_{t-1})$, a selling rule $s(inv_{t-1}, x_t; g_t, r_{t+1}, p_{t-1})$, a value function $V(inv_{t-1}, x_t; g_t, r_{t+1}, p_{t-1})$, and a cross-sectional measure μ_t such that:

(i) y, s and V solve the firm's problem (1.2);

(ii) The measure μ_t evolves following (1.3), and is consistent with the optimal inventory choices of all firms;

(iii) p_t is given by the market clearing condition (1.1) and the final-good supply condition, the latter of which can be solved by y, s and μ_t.

1.3.2 Analytical Results

1.3.2.1 Inventory Decision Rule

The statistics I am interested in are the mean and dispersion of intermediate firm inventory growth. Because the model is not analytically tractable in a stochastic equilibrium, I start from an individual firm's inventory decision to understand inventory mean variation, and then discuss its aggregate implication on dispersion in a stationary equilibrium. To make the underlying intuition more transparent, I first set adjustment costs to zero.

Proposition 1 *If $\phi_+ = \phi_- = 0$, the optimal inventory choice follows the Euler equation:*

$$\mathbb{E}_{jt}\left[\beta(1-\delta)\frac{mc_{j,t+1}}{mc_{jt}}\right] = \frac{1}{1+\frac{\zeta}{\theta-1}\frac{1}{is_{jt}+1}}. \tag{1.4}$$

where mc_{jt} is the marginal cost of production for firm j at time t, and $is_{jt} = inv_{jt}/s_{jt}$.

Proof. See appendix. ■

According to the Euler equation, the inventory-to-sales ratio is_{jt} increases with the expected relative marginal production costs $\mathbb{E}_{jt}[mc_{j,t+1}/mc_{jt}]$. This suggests that inventory dynamics in response to news shocks are influenced by the incentive for intertemporal substitution in production. Firms tend to schedule their production in periods when their marginal production costs are lower. Positive news shocks indicate lower future marginal production costs $mc_{j,t+1}$ relative to today mc_{jt}, prompting firms to postpone production until the next period. This delay results in a decrease in inventories inv_{jt}. In other words, positive news about future productivity leads to a decrease in current inventory growth mean.

It is worth noting that this channel is consistent with the signaling role of inventory change with respect to future sales documented in prior studies. Because in a monopolistic competitive economy, a firm productivity increase implies lower price and higher sales for this firm. Marginal production cost decreases and sales increases are essentially equivalent. Moreover, empirical evidence supports sales increases driven by productivity shocks rather than demand shocks. If a future sales increase was driven by a positive news shock on the demand shifter, firms would respond to this news by building up current inventories to smooth their convex production costs.[12] This contradicts the observed negative correlation between aggregate inventory growth mean and future output growth changes.

1.3.2.2 Aggregate Inventory Dispersion

In this section, I investigate the relationship between firm-level decisions and cross-sectional dispersion. To facilitate a tractable examination of dispersion, following David and Venkateswaran (2019), I deliberately mute aggregate shocks, including the news shocks and aggregate productivity, in a stationary equilibrium, while preserving idiosyncratic shocks. I define a stationary equilibrium as follows: (1) the joint distribution over (inv_{t-1}, x_t) remains unchanged over time; (2) aggregate states remain constant, meaning that aggregate productivity $g_t \equiv \bar{g}$ and there is no news shock.

Without loss of generality, I assume that the steady-state aggregate productivity is equal to zero, $\bar{g} = 0$, and idiosyncratic productivity follows a random walk, $\rho_x = 1$.

[12]Since $mc_{jt} = y_{jt}^{\frac{1-\alpha}{\alpha}} / (\alpha z_{jt}^{\frac{1}{\alpha}})$, future marginal production cost increases if there is expected to be more production in the next period.

Additionally, I set adjustment costs $\phi_+ = \phi_- = \phi$ and output elasticity of labor $\alpha = 1$ to maintain analytical tractability.[13] To assess the impact of ϕ_{jt} on aggregate dispersion, I first assume ϕ_{jt} constant and then examine its effect under various values. I use perturbation methods to solve the model. In particular, I log-linearize the firm's optimality conditions around the steady-state idiosyncratic productivity $\bar{x} = 0$. Let $\Phi = (\beta, \theta, \zeta, \delta, \phi)$ be the vector of parameters, and $\tilde{inv}_{jt}$ represent the log difference between the inventory level and its steady-state level.

Proposition 2 *To a first order, given the existence of a unique solution in the stationary equilibrium, the cross-sectional variance of inventory growth can be approximated as*

$$\text{Var}_j(\Delta \tilde{inv}_{jt}) = \frac{\psi_2(\Phi)^2}{1 - \psi_1(\Phi)^2}\sigma_x^2$$

where $\psi_1(\Phi)$ and $\psi_1(\Phi)$ are the response coefficients in the inventory policy function[14]

$$\tilde{inv}_{jt} = \psi_1(\Phi)\tilde{inv}_{j,t-1} + \psi_2(\Phi)x_{jt}$$

Proof. See appendix. ■

The response coefficients ψ_1 and ψ_2 play a crucial role in determining cross-sectional dispersion. ψ_1 transmits previous shocks to the current period, while ψ_2 governs the sensitivity of inventory adjustments to shocks. Thus, higher values of ψ_1 and ψ_2 result in increased cross-sectional dispersion. In addition, when adjustment

[13] Because ϕ_{jt} is a discrete variable, its presence results in nonlinearities within the system. In addition, the assumption of $\alpha = 1$ is not restrictive. Although firm production technology exhibits constant return of scale if $\alpha = 1$, the firm still has incentive to smooth production over time given that its output price decreases in sales.

[14] The full characterization of $\psi_1(\Phi)$ and $\psi_2(\Phi)$ can be found in the appendix.

costs become higher, inventories become more sticky (higher ψ_1) and less responsive to productivity shocks (lower ψ_2). The numerical results in Figure 1.5 indicate that the impact of ψ_2 prevails ψ_1, resulting in a decrease in inventory dispersion with an increase in adjustment costs. This finding is established through an analysis performed over a wide range of adjustment cost values, taking into consideration the baseline calibrated values of $(\beta, \theta, \zeta, \delta)$ in subsequent quantitative section. A news shock effectively acts as a "switcher", affecting the average adjustment cost in the economy. For instance, a positive news shock prompts more firms to adjust their inventories downward, indicating higher adjustment cost on average. Consequently, the dispersion of inventory growth is expected to decrease following the arrival of positive news shocks.

1.3.3 Quantitative Analysis

1.3.3.1 Baseline Calibration

Identifying news shocks. An obvious challenge in the quantitative analysis is that we do not observe agents' private information sets. I must rely on certain aggregate moments to identify the precision of news shocks. Recall that in Equation 1.4, the inventory level is determined by the relative marginal production cost tomorrow compared to today. While the expected future marginal production cost is influenced by the signal of aggregate productivity r_{t+1}, which is not directly observable, we can approximate it using g_{t+1}. In a log-linearized system, the aggregate inventory level becomes a function of Δg_{t+1}, and thus inventory growth becomes a function of $\Delta g_{t+1} - \Delta g_t$. Therefore, the aggregate correlations I am interested in are $\text{Corr}(Invt_{t-1}, \Delta GDP_t)$ and $\text{Corr}(InvtDisp_{t-1}, \Delta GDP_t)$, where ΔGDP_t is the firstdifferenced GDP growth rate at t, $Invt_{t-1}$ and $InvtDisp_{t-1}$ are the cross-sectional mean and dispersion of inventory growth. The precision of news shocks and firms' responsiveness to these shocks jointly determine the magnitudes of the two correlations.

Parameterization. In the calibration process, certain parameter values are externally constrained based on existing studies, while others, for which there is limited guidance from prior research, are adjusted to match specific data moments. The baseline calibration adopts the parameters summarized in Table 1.4. For parameters unrelated to inventories, I use the values based on those calibrated and estimated in Cooper and Haltiwanger (2006) and Zhang (2005), adjusting them into a quarterly frequency basis. These parameters include the discount factor β, the labor share α, the inverse price elasticity of demand η, the idiosyncratic and aggregate TFP persistency ρ_x, ρ_g, and the standard deviation of idiosyncratic TFP shocks σ_x. For parameters related to inventories, I use the values in Crouzet and Oh (2016) to set the elasticity of substitution in final good production θ and the depreciation rate δ. The remaining parameters to match target moments include the positive adjustment cost ϕ_+, the negative adjustment cost ϕ_-, the elasticity of sales to on-shelf goods ζ, the aggregate TFP standard deviation σ_g, and the relative signal precision σ_g/σ_r. Specifically, ϕ_+ and ϕ_- are calibrated to match the average inventory growth conditional on adjustment directions, capturing the cost asymmetry. The parameters ζ and σ_g are adjusted to reflect the inventory-to-sales ratio and the volatility of aggregate output growth, respectively. Lastly, the signal precision σ_g/σ_r is set to capture the correlation between aggregate inventory moments and ΔGDP_t.

The calibration yields $\phi_+ = 0.94$ and $\phi_- = 4.03$. Considering that inventories are generally adjusted more rapidly than capital, the value of $\phi_+ = 0.94$ is substantially lower in comparison to the range of 5 to 25 employed for capital in Zhang (2005). Furthermore, the derived adjustment cost asymmetry is $\phi_{-}/\phi_{+} = 4.29$, which is also notably smaller than the level of 10 used for capital adjustment in Zhang (2005).[15] The value of $\zeta = 0.224$ is similar to the 0.25 level in Crouzet and Oh (2016). The signal precision ratio $\sigma_g/\sigma_r = 1.4$ implies that firms mostly rely on common news shocks to infer future economic conditions. Such a precision level is plausible. According to the Livingson survey forecast mentioned in Jaimovich and Rebelo (2009), in a two-state economy, conditional upon a forthcoming high (low) state, the economy receives positive (negative) news with a likelihood of 0.99 (0.62).

Table 1.5 Panel A shows that the model effectively replicates the reality, with target aggregate-level moments closely aligning between the actual and simulated data.[16] The model successfully approximates the correlation coefficients between inventory moments and ΔGDP_t. Additionally, it yields significant cross-sectional variations in inventory growth and notable fluctuations in aggregate output growth.

1.3.3.2 Inspecting the Mechanism

Aggregate inventory moments. With calibrated parameters, I re-simulate the model by setting $\sigma_g = 0.04$ in order to produce more pronounced distribution variation to illustrate the intuition.[17] The remaining parameters are the same as in

[15]Given the stockout-avoidance motive, the asymmetry in inventory adjustment costs might exceed that of capital adjustment. However, the model remains robust to the choice of asymmetry, as long as it is sufficiently high.

[16]The Krusell-Smith algorithm also performs well in approximating the equilibrium. Details regarding the calibration process and the approximation quality are elaborated in the appendix.

[17]Although the model effectively replicates the observed aggregate moments, one caveat is that it fails to produce sizable time-series variation of aggregate inventory moments. In the data, the

the baseline model. I simulate a panel consisting of 5000 firms over a span of 7000 quarters, and discard the initial 1000 quarters to exclude the impact from initial conditions. The results of this simulation exercise are depicted in Figure 1.6.

Subfigure (a) illustrates inventory policy functions inferred from the simulated dataset. To achieve this, in consistent with the empirical news shock measures, I first sort simulated periods into deciles based on news shock innovations, $(r_{t+1} - \rho_g g_t) - (g_t - \rho_g g_{t-1})$. The top decile receives positive news and the bottom decile receives negative news. Next, I estimate the inventory response to idiosyncratic TFP innovations conditional on positive or negative news by running a fourth-order polynomial regression. The decision rules presented in Subfigure (a) are identical to the ones in the Figure 1.3 illustrative example.[18] Discussions have been provided in the earlier section.

Subfigure (b) illustrates the average cross-sectional distributions of inventory growth. This distribution is characterized by a fat right tail, attributable to the asymmetric cost structure. Additionally, a significant majority of firms exhibit inventory growth rates ranging from -50% to 100%, which aligns with the empirical results in Figure 1.2. With positive news compared to negative news, the distribution not only shifts leftward but also becomes less dispersed, consistent with Figure

standard deviations of $Invt_t$ and $InvtDisp_t$ are 0.055 and 0.041, whereas in the model, these two values are 0.006 and 0.005 respectively. This is due to the oversimplification of this model where inventories are the only intertemporal asset. As a result, by adjusting the value of σ_g, it is difficult to reconcile the high aggregate inventory moment volatility and the low aggregate output volatility at the same time.

[18]Despite the inventory policy function being convex compared to the concave decision rule of employment, aggregate inventory dispersion continues to have a negative association with future economic growth changes, similar to the negative correlation between employment dispersion and current economic growth in Ilut et al. (2018). This seemingly contradiction stems from the fact that positive aggregate productivity shocks lead to an inventory reduction in this model, contrary to the employment increase in Ilut et al. (2018).

1.2. This leftward shift indicates an increasing number of firms deciding to reduce their inventories. Given the higher cost associated with downward adjustment, these transitioning firms tend to adjust at a more gradual pace, resulting in a less dispersed distribution.

Adjustment cost asymmetry. I also perform several counterfactual experiments by adjusting upward adjustment costs holding the remaining parameters unchanged. Table 1.5 Panel B presents the results. The output growth innovations have persistent negative correlations with inventory mean even though the magnitude is slightly less when the upward adjustment cost increases. In contrast, Corr($InvtDisp_{t-1}, \Delta GDP_t$) declines dramatically and even becomes positive in the absence of cost asymmetry. Corr($InvtDisp_{t-1}, \Delta GDP_t$) becomes positive because of the substitutability across intermediate goods ($\theta > 1$). In a first-order approximation,

$$\log GDP_t = \frac{\theta}{\theta - 1}(1 - \eta) \left[\log as + \frac{1}{2}\mathrm{Var}_j \left(\frac{\zeta}{\theta}\tilde{a}_{jt} + \frac{\theta - 1}{\theta}\tilde{s}_{jt}\right)\right]$$

where a and s are steady-state values, $\tilde{a}_{jt}$ and $\tilde{s}_{jt}$ are log deviations from their steady-state values. As $\theta > 1$ and $\eta < 1$, the lagged cross-sectional dispersion mechanically amplifies the dispersion in $\tilde{a}_{jt}$ and $\tilde{s}_{jt}$, consequently boosting aggregate outputs, especially in scenarios where adjustment costs are high so that inventories are sticky. These results highlight the importance of cost asymmetry as a prerequisite for the negative correlation between inventory dispersion and future economic growth.

Signal independence. Table 1.5 Panel C indicates that even in this simple model, inventory dispersion offers added information about future economic conditions compared to inventory mean, although its predictive strength is less than the mean. In the third row of Panel C, after controlling for the inventory mean, the dispersion remains a significant predictor of future GDP growth changes. I also compare the sum of squared errors from a regression with $Invt_t$ against that from a regression including both moments, and report the F-statistic in the first row. The significance of this F-statistic confirms that inventory dispersion possesses incremental predictive power. One can think about the two moments contain independent information about the news shock firms receive. This is because the extent in which inventory mean responds to news shocks also depends on the average adjustment cost level in the economy, which is signaled by the inventory dispersion.

1.4 GDP Forecast Error and Revision Predictability

Considering that both aggregate inventory mean and dispersion possess information about forthcoming economic conditions, I further investigate whether these two metrics have been incorporated by SPF panelists or government statistical agencies in GDP forecasting and estimation.

1.4.1 Background and Empirical Design

Survey of Professional Forecasters. The SPF published by the Philadelphia Fed is the longest and most well-known publicly available survey of quarterly GDP growth. The survey polls professional economists regarding their projections for the economy in current and forthcoming quarters. As illustrated in Figure 1.7, the SPF is typically disseminated towards the conclusion of the initial month of each calendar quarter. SPF panelists are then expected to remit their responses by the midpoint of the subsequent month within the same quarter. Next, the Fed releases the results to the public by the end of the second month. According to Stark (2010), the SPF forecasts perform quite well at short horizons, and often outperform the forecasts of benchmark time-series models. However, Konchitchki and Patatoukas (2014a,b) find that the SPF forecast errors are predictable based on corporate profitability information aggregated from accounting disclosures.

GDP revisions. Figure 1.7 also illustrates the GDP revision cycle. The GDP revision cycle includes current quarterly estimates (advance, second and third, about 30, 60, and 90 days after the end of the reference quarter), annual revision estimates over the next three years and comprehensive revision estimates every five years. As more and more comprehensive and accurate source data are incorporated, GDP estimates progressively reflect the actual state of the economy, resulting in the latest GDP estimate being the most accurate. Advance estimates are usually released less than one month after a quarter ends. The lack of accurate information in advance estimates is one of the most important reasons for later GDP revisions. According to Katz et al. (2006), source data largely determine the schedule for advance estimates and the schedule on which they are revised. In advance estimates, 27.9% of source data are trend-based, and 34.4% are indirect indicator data (Holdren, 2014). Restatements are primarily the result of data updates rather than updates to concepts and definition. Data-related restatements account for two-thirds of the comprehensive revisions in recent years (1985, 1991, 1995, 1999, 2003, 2009) (Fixler et al., 2011). Prior studies find slight inefficiency in GDP advance estimates. According to Faust et al. (2005) and Aruoba (2008), advance estimates and past restatements can predict a small portion of future GDP restatements. Nallareddy and Ogneva (2017) show that in a sample from 1975 to 2012, 16% or less of future real GDP restatement variation could be explained by earnings dispersion and previously documented predictors.

Research design. Because GDP final estimates contain the most accurate information about the economy, I define the SPF forecast error for quarter t as the difference between the final estimate of real GDP growth for quarter t and the SPF forecast for quarter t made within the same quarter. Similarly, GDP final revisions are calculated as the difference between the final and advance estimates. Given the specialized expertise of SPF panelists and the comprehensive real-time economic data held by government statistical agencies, there is a prevailing assumption that SPF forecast errors and GDP revisions are inherently unpredictable based on the available information at the time of estimation. Formally, I test the null hypothesis:

$$\mathbb{E}(Error_t|\Omega_t) = 0,$$

where $Error_t$ denotes the final revision of quarter t advance estimate (the SPF forecast error for quarter t), and Ω_t represents the aggregate inventory information of quarter $t-1$ available at the time of advance estimation (forecast making). In SPF forecast error tests, I calculate aggregate inventory moments of quarter $t-1$ based on financial disclosures accessible by the initial week of the second month in quarter t (Konchitchki and Patatoukas, 2014a). Notably, this is the week prior to the SPF submission deadline. In contrast, for GDP revision tests, I calculate aggregate inventory moments using disclosures available at the advance estimate release date of quarter t GDP, which typically falls at the end of the month following t quarter's conclusion (Nallareddy and Ogneva, 2017).

1.4.2 Sample and Variable Description

I obtain accounting data from Compustat and stock price data from CRSP for US-incorporated firms listed on NYSE, AMEX, and NASDAQ with fiscal year ends on March, June, September, or December. The sample period spans from 1976Q1 to 2019Q2. Because Compustat data do not contain historical NAICS codes before 1985 and SIC codes before 1987, I approximate the industry classification of firms in earlier years using the earliest available NAICS code and keep firms in construction and manufacturing industries with two-digit NAICS codes 23, 31, 32, and 33. Quarterly GDP and GDP component vintage data as well as the SPF data are obtained from the Real-Time Data Set for Macroeconomists maintained by the Federal Reserve Bank of Philadelphia.[19] GDP advance estimate historical release dates are also provided by the Philadelphia Fed. The Chicago Fed National Activity Index (CFNAI) is downloaded from the Chicago Fed. The final estimates available in my dataset are the ones available by the end of December 2019.

In SPF forecast error and GDP revision tests, I calculate aggregate inventory moments separately based on accounting disclosures available by forecasting or estimation dates, and follow the same aggregation method outlined in the previous empirical section. In an effort to minimize the impact from significant firm-level productivity variance — especially in cases with limited firm-level observations — I also calculate the inventory dispersion at the sectoral level in addition to the cross-firm dispersion. This approach mirrors the sectoral-level methodology employed in

[19]Although the Bureau of Economic Analysis (BEA) transitioned its primary aggregate production metric from GNP to GDP in November 1991, this alteration does not affect the results in this paper. This transition primarily redefines net exports to exclude net receipts of factor income. However, I find that the predictive power of inventory dispersion on GDP revisions predominantly comes from the revisions of personal consumption expenditure and non-residential investment.

Abdalla et al. (2021).[20] For the cross-sector inventory dispersion, I first calculate the size-weighted inventory growth average for each three-digit NAICS sector and then compute the size-weighted standard deviation of inventory growth across these sectors. In each quarter, I winsorize the top and bottom one percent of firm observations to remove outliers, although trimming these outliers does not qualitatively change the results.

The appendix provides details on the construction of main variables. Table 1.6 reports the descriptive statistics of variables used in the GDP revision analysis, and the statistics in the SPF forecast error analysis are similar. Although the means of GDP restatements and SPF forecast errors are nearly zero, their variances exhibit magnitudes akin to economic fluctuations. During the sample period, the real GDP restatements (SPF forecast errors) have a standard deviation of 0.8% (1.0%), which is around half of 1.8%, the standard deviation of real GDP growth based on advance estimates. The revisions of real investment in private inventories are the most volatile among GDP component revisions, with revisions to non-residential investment ranking second. Both cross-firm and cross-sector inventory dispersions show similar standard deviations (4.3% and 2.9%, respectively), but the level of cross-firm dispersion is around three times larger than cross-sector dispersion. This underscores the importance of averaging out the impact from firm-level productivity variance.

[20] Although the model presented in the theory only considers firm heterogeneity, it can be easily expanded to incorporate sectoral heterogeneity by introducing a nested-CES technology in the final good production function (e.g., Burstein et al., 2020). In such a model, a firm's productivity becomes the sum of its firm-level, industry-level, and aggregate-level productivities. When dealing with a limited sample size, as is the situation in the predictability analysis, large firm-level productivity variance introduces extraneous noise in aggregate moments. Therefore, by calculating cross-sector dispersion, I average out the large firm-level productivity variance, and obtain a more precise signal for future output growth, although cross-firm dispersion gives quantitatively similar results.

1.4.3 Predictability Test Results

1.4.3.1 In-Sample Predictability

To assess the predictability of the SPF forecast error for quarter t, I incorporate aggregate inventory moments along with additional accounting variables that may have predictive power on future output growth, including aggregate earnings Ear_{t-1} in Konchitchki and Patatoukas (2014a), aggregate changes in return on net operating assets $RNOA_{t-1}$ in Konchitchki and Patatoukas (2014b) and earnings dispersion $EarDisp_{t-1}$ in Nallareddy and Ogneva (2017). These variables are computed from financial disclosures of quarter $t-1$ available by the initial week of the second month in quarter t. Beyond these accounting metrics, regressions also control for the advance estimate of $t-1$ real GDP growth, the CFNAI for the third month of quarter $t-1$, the dispersion of sample-firm stock returns in $t-1$, and the CRSP value-weighted returns for quarter $t-1$. This corpus of information is readily available to SPF panelists at the time when they make forecasts.

Interestingly, Table 1.7 shows that while SPF panelists seem to fully consider the signals present in inventory mean, they tend to overlook the information inherent in inventory dispersion.[21] Recall that inventory mean and dispersion both contain independent information about future economic conditions. Moreover, cross-firm and cross-sector dispersions consistently demonstrate significant predictive power regarding SPF forecast errors. In Columns (5) and (6), a one-standard-deviation increase in cross-firm (cross-sector) dispersion suggests a decrease in the SPF forecast

[21]This may be due to the fact that forecasting models economists use already consider the means of many macroeconomic variables, which correlate with the mean of inventories. However, these models fail to address the firm heterogeneity in the economy.

error by 0.21% (0.28%), which is approximately a fifth of the SPF forecast error's standard deviation. While cross-sector dispersion surpasses cross-firm dispersion in terms of statistical significance, their effect magnitudes are almost identical, implying that the standard error of the estimated cross-firm dispersion coefficient is higher. This highlights the larger noise in cross-firm dispersion due to the restricted sample size in inventory moment computation.

In the next step, I test the ability of aggregate inventory moments to predict future GDP revisions. I closely follow the specification in Nallareddy and Ogneva (2017). Specifically, I control for information from various sources that is available at advance estimate release dates, including earlier GDP estimates, SPF forecasts, a recession dummy, and a set of aggregate moments computed from stock returns and accounting disclosures. Table 1.8 indicates that the coefficients of earnings dispersion are significantly negative, consistent with previous findings. However, the coefficients of $RNOA_{t-1}$ are significantly negative. Untabulated results reveal that $RNOA_{t-1}$ still positively predicts advance and final estimates, suggesting an overreaction to $RNOA_{t-1}$ information in advance estimates. Inventory dispersion measures persistently significantly predict final restatements, and their predictive powers are largely orthogonal to the set of control variables. According to Column (5) and (6), a one standard-deviation increase in cross-firm (cross-sector) inventory dispersion predicts a 0.35% (0.33%) reduction in real GDP final revisions. Compared to the standard deviation of real GDP final revisions at 0.80%, this forecasting power is of strong economic significance. A similar conclusion can be drawn from the improvement in the adjusted R^2. By including inventory moments in regressions in Columns (5) and (6), the adjusted R^2 increases from 10% to around 27%. It is noteworthy that cross-firm dispersion appears to have sizable predictive power compared to cross-sector dispersion in GDP revision predictability tests (0.35% to 0.33%), while it trails behind in SPF forecast error tests (0.21% to 0.28%). This discrepancy might be attributed to the fact that the GDP revision tests allow for the inclusion of a larger number of firms in inventory calculation. This, in turn, reduces the noise introduced by firm-level productivity in the cross-firm dispersion.

In summary, although SPF panelists and government statistical agencies fully incorporate the information content in inventory mean, they fall short in integrating inventory dispersion. Consequently, inventory dispersion emerges as a salient predictor of both SPF forecast errors and GDP revisions. Notably, the predictive power of inventory dispersion in future GDP revisions surpasses that of other predictors identified in existing studies.

1.4.3.2 Adjustment Cost Asymmetry

As discussed earlier, adjustment cost asymmetry is a necessary condition for the negative correlation between inventory dispersion and future output growth. To test this mechanism, I select preceding revenue trend from Anderson et al. (2003) and service level from Kesavan and Kushwaha (2014) as empirical proxies for cost asymmetry. I then investigate the cross-sectional variation in the predictive performance of inventory dispersion. These proxies have been validated by Hwang et al. (2021), who provide firm-level evidence supporting that inventory adjustments become more asymmetric with positive preceding revenue growth and high service levels.

Regarding preceding revenue trend, the research on cost behaviors explores how managers' demand expectation affects their resource commitment. Anderson et al. (2003) finds that SG&A costs become less sticky following a decline in revenue in the preceding period. According to their findings, managers are more inclined to view a decline in revenue as a persistent trend if it follows previous periods of revenue losses. Managers are then more likely to scale down resources in such cases, leading to decreased stickiness in costs. In essence, a preceding decline in revenue discourages managers from committing resources, thereby reducing the cost of downward adjustments and resulting in lower cost asymmetry.

For service level, it represents the net benefits of holding inventories. Kesavan and Kushwaha (2014) define it among U.S. public retailers as the ratio of stockout cost to inventory holding cost. Following their method, I measure stockout cost by gross margin, reflecting the opportunity cost of lost sales due to inventory shortages. Inventory holding cost, on the other hand, is proxied by the cost of capital, computed as the size-weighted average of debt cost (interest expense divided by total debt) and equity cost (net income divided by market capitalization). To address issues with negative values in gross margin and cost of capital, particularly in larger samples beyond retailers, I calculate the difference rather than the ratio between stockout cost and cost of capital to derive the service level. I anticipate that firms with higher service levels would be more inclined to stock up on inventories, thereby subjecting their inventory decisions to greater cost asymmetry.

I divide firms into a high (low) asymmetry group depending on whether a firm's revenue increased (decreased) in the preceding period, or whether its service level is higher (lower) than the median in its corresponding two-digit NAICS sector. Subsequently, I compute inventory dispersions within these two groups, and repeat the GDP forecast error and revision predictability tests with the same controls as previously discussed. Across Table 1.9 Columns (1)-(3) for preceding revenue trend and Columns (4)-(6) for service level, the results consistently indicate that dispersions within high-asymmetry firms exhibit stronger predictive power compared to dispersions within low-asymmetry firms in forecasting SPF forecast errors and GDP revisions. In conclusion, adjustment cost asymmetry plays a crucial role in the effectiveness of inventory dispersion in predicting future economic conditions.

1.4.3.3 Predicting GDP Component Restatements

To gain further insight into the mechanism behind the predictive power of inventory dispersion, I leverage the detailed vintage data about GDP component estimates. First, the predictive power of inventory dispersion on GDP revisions may arise from its ability to forecast the revisions of change in private inventories. This is because there could be potential mismeasurement within this GDP component, and accounting disclosures can provide more accurate information. The inventory component in GDP exhibits considerable volatility, contributing to roughly 20 percent of the volatility observed in quarterly GDP growth (Cecchetti et al., 2006). Moreover, change in private inventories has the highest mean absolute revision among all GDP components (Fixler et al., 2011). Second, it is also possible that the main reason for the predictive power of inventory dispersion is through its ability to forecast the revisions of real fixed investment. Inventory investment is closely linked to cost of capital (Jones and Tuzel, 2013a), implying a likely covariance between inventory investment and capital investment.

However, empirical evidence refutes the first hypothesis and provides only weak support for the second. Neither cross-firm nor cross-sector inventory dispersion predicts the restatements of change in private inventories in Table 1.10. Additionally, only cross-firm dispersion significantly predicts the restatements of non-residential investment.[22] Particularly noteworthy is that Columns (1) and (4) in both panels reveal that dispersions' predictive performance for GDP revisions largely stems from their ability to forecast the revisions of personal consumption expenditures, especially expenditures on nondurable goods. Despite the technological improvement in inventory management within the durable sector, which has been found to contribute to the Great Moderation since the early 1980s (Kahn et al., 2002), I find no evidence that inventory dispersion can predict the restatements of durable goods consumption.

This finding strongly suggests that sector-specific productivity news drives the predictive performance of aggregate inventory dispersion. Interestingly, Beaudry and Portier (2004) also model productivity news shocks in the nondurable goods sector rather than in the durable sector to explain the comovement of output, employment and investment. They argue that the expectation of technological improvement in the nondurable goods sector is more important than that in the durable goods sector in driving business cycles. This is because the nondurable goods sector changes more rapidly and experiences constant arrival of new products, implying the importance of anticipating these changes. As dispersion only predicts the revisions of nondurable goods consumption instead of all household consumption components, it is unlikely that news shocks about future consumer demand are the driving force behind the association between aggregate inventory moments and future output growth. In conclusion, the findings from the GDP component analysis paint a picture consistent with the productivity news shock theory discussed earlier.

[22]Neither metric significantly predicts the restatements of future residential investment either.

1.4.3.4 Out-of-Sample Predictability

Given the remarkable in-sample predictive power of inventory dispersion, I further examine whether SPF forecasts and GDP estimates can be enhanced using real-time accounting disclosures. Because GDP final estimates are not available at real time, following the methodology of Nallareddy and Ogneva (2017), I use one-year (five-quarter) and two-year (nine-quarter) revised GDP estimates to calculate SPF forecast errors and GDP revisions to avoid a look-ahead bias.

I perform the same out-of-sample tests as in Nallareddy and Ogneva (2017). Specifically, for forecasting models incorporating one-year revised GDP estimates, I first estimate coefficients using an expanding window from the beginning of the sample to quarter t and then compute the predicted SPF forecast error for quarter $t+6$ or the predicted GDP revision for quarter $t+6$. This approach guarantees that the one-year revised GDP estimate for quarter t used in model estimation is readily available by the forecasted quarter. Similarly, for the forecasting model using two-year revised GDP estimates, I compute the predicted variables for quarter $t+10$. To prevent overfitting, in testing SPF forecast errors, I incorporate significant variables from the regressions in Table 1.7 into forecasting models. The model includes variables $InvtDisp_{t-1}/InvtDispInd_{t-1}$, $CFNAI_{t-1}$, Ear_{t-1}, $RetDisp_{t-1}$, and the benchmark model is its nested model excluding $InvtDisp_{t-1}/InvtDispInd_{t-1}$. Correspondingly, in testing GDP revision predictability, the prediction model includes $InvtDisp_{t-1}/InvtDispInd_{t-1}$, $RSPF_t$, $CFNAI_t$, $EarDisp_{t-1}$, $RNOA_{t-1}$ due to their significance in Table 1.8. The benchmark model is its nested model excluding $InvtDisp_{t-1}/InvtDispInd_{t-1}$. In addition to testing the incremental predictive power of inventory dispersion, I also examine its standalone predictive power by comparing the historical revision or forecast error averages in the same window with the predicted values from a model containing inventory dispersion and a constant.[23]

Similar to Aruoba (2008) and Nallareddy and Ogneva (2017), I choose *MSPE-adjusted* (MSPE, mean squared prediction error) in Clark and West (2007) for statistical inference. This statistic corrects for the biased expected difference between the MSPE of a larger model and its nested model in rolling or expanding forecasting schemes. Clark and West (2007) demonstrate that this statistic is asymptotic normal, and recommend constructing the usual t-statistic and rejection regions to test whether *MSPE-adjusted* is different from zero. Sample *MSPE-adjusted* equals to the sample average of f_t, where

$$f_t = (r_t - \bar{r}_t)^2 - \left[(r_t - \hat{r}_t)^2 - (\bar{r}_t - \hat{r}_t)^2\right],$$

r_t is the actual value, $\bar{r}_t$ is the predicted value from a parsimonious benchmark model, and $\hat{r}_t$ is the predicted value from a larger model. *MSPE-adjusted* > 0 implies that the prediction model has lower MSPE relative to the benchmark model. I calculate the p-value with respect to *MSPE-adjusted* in an upper-tailed t test to assess the null hypothesis that *MSPE-adjusted* is no larger than zero.

Table 1.11 indicates the robust out-of-sample predictive power of inventory dispersion on SPF forecast errors and GDP revisions calculated based on two-year revised estimates. In contrast, the predictive strength is relatively weaker for one-year revised estimates, especially for the forecast error tests in Panel A. One plausible interpretation for this decline is that early revised estimates do not fully reflect

[23]Since a moving-average model reduces to a nested linear model with a constant, the *MSPE-adjusted* statistic is still applicable in this comparison.

actual economic conditions. Yet, as I shift my focus to the results about two-year revised estimates in Panel A, cross-sector dispersion emerges as a significant predictor, both incrementally alongside existing variables and in isolation. At the same time, cross-firm dispersion retains significant standalone predictive power on SPF forecast errors. Panel B further reveals that the dispersion measures manifest substantial standalone predictive power on one-year real GDP revisions, and both standalone and incremental predictive power on two-year GDP revisions.

1.5 Concluding Remarks

Bottom-up measures of inventory mean and dispersion negatively associate with future output growth changes. This paper uses a heterogenous firm model that incorporates news shocks and adjustment cost asymmetry to show that this aggregate pattern originates from asymmetric inventory response at the firm level. Further analysis reveals that, in contrast to inventory mean, SPF panelists and government statistical agencies largely overlook inventory dispersion in their GDP forecasting and estimation. Consequently, inventory dispersion emerges as a significant predictor of GDP forecast errors and, notably, ranks as the most robust known predictor of future GDP revisions.

In this paper, firm heterogeneity is shown to be important to understand the connection between aggregate accounting information and economic output. This finding opens up the possibility of using a disaggregate macroeconomic framework to comprehend the aggregate implications of the rich firm-level dynamics found in the accounting literature. Future work could explore an alternative scenario in which information is heterogenous, and information communication is imperfect, meaning that firms may disagree about the future. In this model, I assume that firms receive a common signal and exclude this mechanism to highlight asymmetric inventory response. Nevertheless, an emerging body of literature (e.g., Lorenzoni, 2009; Angeletos and La'o, 2010; Baley and Blanco, 2019) emphasizes the role of dispersed information and social learning frictions in shaping news-driven economic fluctuations.

1.6 Appendices

1.6.1 TFP Estimation

I follow Herskovic et al. (2023) using Compustat financial data to estimate TFP innovations. Specifically, I first compute the log TFP level of firm i as the Solow residual from a panel regression with firm and quarter fixed effects ran by each three-digit NAICS sector:

$$y_{it} = \bar{y}_i + \bar{y}_t + \beta_1 k_{i,t-1} + \beta_2 n_{it} + x_{it}$$

where y_{it} is the log revenue of firm i at quarter t, $k_{i,t-1}$ is the log real capital stock at quarter $t-1$, n_{it} is the log employee number, and $\bar{y}_i$, $\bar{y}_t$ represent firm and time fixed effects respectively. β_1 and β_2 are sector specific. Since the number of employees is not reported on a quarterly basis, I use the corresponding annual figures. The reported revenue is adjusted into real terms using the GDP deflator. The real capital stock is computed employing the perpetual inventory method, and the net investment for each quarter is adjusted using the nonresidential private investment deflator. To match the year-over-year inventory growth, I also calculate TFP innovations on a year-over-year basis. I use the estimated TFP level x_{it} from the first step and run the following panel regression also by three-digit NAICS sectors:

$$x_{it} = \bar{x}_i + \bar{x}_t + \rho_x x_{i,t-4} + \varepsilon_{x,it}$$

where $x_{i,t-4}$ is the TFP level at the same quarter one year before, $\bar{x}_i$, $\bar{x}_t$ represent firm and time fixed effects, and the residual $\varepsilon_{x,it}$ is the TFP innovation I use in the inventory rule estimation.

1.6.2 Analytical Proofs

1.6.2.1 Proof of Proposition 1

The Lagrangian associated with the firm's problem is

$$
\begin{aligned}
\mathcal{L} = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Bigg[& P_{jt}s_{jt} - n_{jt} - \frac{1}{2} inv_{j,t-1}\phi_{jt} \left(\frac{y_{jt} - s_{jt}}{inv_{j,t-1}} \right)^2 \\
& + \gamma_{jt} \left((1-\delta) inv_{j,t-1} + y_{jt} - s_{jt} - inv_{jt} \right) \\
& + mc_{jt}(z_{jt} n_{jt}^{\alpha} - y_{jt}) \\
& + \mu_{jt} \left(a_{jt}^{\zeta} \left(\frac{P_{jt}}{P_t} \right)^{-\theta} s_t - s_{jt} \right) \\
& + \kappa_{jt} \left((1-\delta) inv_{j,t-1} + y_{jt} - a_{jt} \right) \Bigg]
\end{aligned}
$$

where $\log z_{jt} = x_{jt} + g_{jt}$ summarizes the exogenous shocks, and mc_{jt} is the shadow price of the production constraint. The set of equations characterizing the problem solution is

$$
-\phi_{jt} \left(\frac{y_{jt} - s_{jt}}{inv_{j,t-1}} \right) + \gamma_{jt} - mc_{jt} + \kappa_{jt} = 0
$$

$$
-1 + \alpha mc_{jt} z_{jt} n_{jt}^{\alpha - 1} = 0
$$

$$
P_{jt} + \phi_{jt} \left(\frac{y_{jt} - s_{jt}}{inv_{j,t-1}} \right) - \gamma_{jt} - \mu_{jt} = 0
$$

$$
s_{jt} - \theta \mu_{jt} a_{jt}^{\zeta} \left(\frac{P_{jt}}{P_t} \right)^{-\theta - 1} \frac{s_t}{P_t} = 0
$$

$$-\gamma_{jt} + \beta\mathbb{E}_{jt}\left[\frac{1}{2}\phi_{j,t+1}\left(\frac{y_{j,t+1} - s_{j,t+1}}{inv_{jt}}\right)^2 + \gamma_{j,t+1}(1-\delta) + \kappa_{j,t+1}(1-\delta)\right] = 0$$

$$\zeta\mu_{jt}\frac{s_{jt}}{a_{jt}} - \kappa_{jt} = 0$$

along with the four constraints listed in the Lagrangian. Reformulating the above equations, I solve the Euler equation about the optimal choice of inventories:

$$\beta\mathbb{E}_t\left[\frac{\phi_{j,t+1}}{2}\left(\frac{inv_{j,t+1}}{inv_{jt}} - (1-\delta)\right)^2 + (1-\delta)\phi_{j,t+1}\left(\frac{inv_{j,t+1}}{inv_{jt}} - (1-\delta)\right) + (1-\delta)mc_{j,t+1}\right]$$
$$= \phi_{jt}\left(\frac{inv_{jt}}{inv_{j,t-1}} - (1-\delta)\right) + \frac{1}{1 + \frac{\zeta}{\theta-1}\frac{1}{1+is_{jt}}}mc_{jt} \tag{1.5}$$

The Euler equation in the main text can be obtained by setting $\phi_{jt} \equiv 0$.

1.6.2.2 Proof of Proposition 2

Log-linearizing the firm's optimality conditions around the steady-state idiosyncratic productivity $\bar{x} = 0$, I obtain the set of equations that characterizes the system.

$$\frac{y}{inv}\tilde{y}_{jt} - \frac{s}{inv}\tilde{s}_{jt} = i\tilde{n}v_{jt} - (1-\delta)i\tilde{n}v_{j,t-1}$$

$$\tilde{z}_{jt} + \alpha\tilde{n}_{jt} - \tilde{y}_{jt} = 0$$

$$(1-\delta)i\tilde{n}v_{j,t-1} + \frac{y}{inv}\tilde{y}_{jt} - \frac{a}{inv}\tilde{a}_{jt} = 0$$

$$\left(\phi\frac{y}{inv} + \phi(1-\delta) - \phi\frac{s}{inv}\right)i\tilde{n}v_{j,t-1} - \phi i\tilde{n}v_{jt} + \gamma\tilde{\gamma}_{jt} - mc\tilde{m}c_{jt} + \kappa\tilde{\kappa}_{jt} = 0$$

$$\tilde{m}c_{jt} + \tilde{z}_{jt} + (\alpha-1)\tilde{n}_{jt} = 0$$

$$\left(\phi\frac{y}{inv}+\phi(1-\delta)-\phi\frac{s}{inv}\right)\tilde{inv}_{j,t-1}-\phi\tilde{inv}_{jt}+\gamma\tilde{\gamma}_{jt}+\frac{1}{\theta}Gs^{-\frac{1}{\theta}}a^{\frac{\zeta}{\theta}}\tilde{s}_{jt}-\frac{\zeta}{\theta}Gs^{-\frac{1}{\theta}}a^{\frac{\zeta}{\theta}}\tilde{a}_{jt}+\mu\tilde{\mu}_{jt}=0$$

$$\tilde{\mu}_{jt}-\frac{\zeta}{\theta}\tilde{a}_{jt}+\frac{1}{\theta}\tilde{s}_{jt}=0$$

$$\beta\mathbb{E}_{jt}\left[\gamma(1-\delta)\tilde{\gamma}_{j,t+1}+\kappa(1-\delta)\tilde{\kappa}_{j,t+1}+\phi\frac{y-s}{inv}\tilde{inv}_{j,t+1}-\phi\frac{y-s}{inv}\left(1-\delta+\frac{y-s}{inv}\right)\tilde{inv}_{jt}\right]=\gamma\tilde{\gamma}_{jt}$$

$$\tilde{\mu}_{jt}+\tilde{s}_{jt}-\tilde{a}_{jt}-\tilde{\kappa}_{jt}=0$$

where $G=P_tS_t^{\frac{1}{\theta}}$ is a constant according to the stationary equilibrium, and $\{y,s,inv,a,n,\kappa,\gamma,mc,\mu\}$ are values at the steady state which can be solved from the equation system below.

$$y-s=\delta\cdot inv$$

$$z\cdot n^{\alpha}=y$$

$$(1-\delta)\cdot inv+y-a=0$$

$$-\phi\frac{y}{inv}+\phi\frac{s}{inv}+\gamma-mc+\kappa=0$$

$$\alpha\cdot mc\cdot z\cdot n^{\alpha-1}=1$$

$$Gs^{-\frac{1}{\theta}}a^{\frac{\zeta}{\theta}}+\phi\frac{y-s}{inv}-\gamma-\mu=0$$

$$G=\theta\cdot\mu\cdot a^{-\frac{\zeta}{\theta}}s^{\frac{1}{\theta}}$$

$$-\gamma+\beta\gamma(1-\delta)+\beta\kappa(1-\delta)+\frac{1}{2}\beta\phi\left(\frac{y-s}{inv}\right)^2=0$$

$$\kappa\cdot a=\mu\zeta\cdot s$$

After tedious, if straight-forward, algebra, by setting $\alpha=1$, $z=1$ and $\rho_x=1$, I rewrite Equation 1.5 in a log-linear form:

$$c_1 \tilde{inv}_{j,t} + c_2 \mathbb{E}_{jt} \tilde{inv}_{j,t+1} + c_3 \tilde{inv}_{j,t-1} + c_4 \tilde{z}_{jt} = 0 \tag{1.6}$$

where

$$c_1 = -(\beta + 1)\phi + \frac{\mu(1-\zeta)(\theta - 1)(\theta\mu - \mu - 1)\mathrm{IS}}{-\zeta + (\theta - 1)(\theta\mu - 1)\mathrm{IS} + 1}$$

$$c_2 = \beta\phi, \quad c_3 = \phi$$

$$c_4 = \beta(\delta - 1) + \frac{\mu(\theta - 1)(-\zeta + \mathrm{IS} + 1)}{-\zeta + (\theta - 1)(\theta\mu - 1)\mathrm{IS} + 1}$$

$$\mu = \frac{\mathrm{IS} + 1}{\zeta + \theta + (\theta - 1)\mathrm{IS} - 1}$$

$$\mathrm{IS} = \frac{\beta[-\delta^2\phi + 2\delta(\phi - 1) + 2](\zeta + \theta - 1) + 2[\delta(\zeta - 1)\phi + \delta\theta\phi + \theta - 1]}{(\theta - 1)[\beta\left(\delta^2\phi - 2\delta\phi + 2\delta - 2\right) + 2\delta\phi + 2]}$$

IS is the steady-state inventory-to-sales ratio, and μ is the shadow price of the demand constraint. Note that Equation 1.6 is independent with respect to G, the aggregate state. Although steady-state inventories are related to G, its deviation from the steady state is not. This feature greatly simplifies the process of solving a closed-form inventory policy function. Conjecture that the inventory policy function takes the form

$$\tilde{inv}_{jt} = \psi_1 \tilde{inv}_{j,t-1} + \psi_2 \tilde{z}_{jt}.$$

Then plug into Equation 1.6,

$$(c_1 + \psi_1 c_2)\tilde{inv}_{jt} + c_3 \tilde{inv}_{j,t-1} + (c_4 + \psi_2 c_2)\tilde{z}_{jt} = 0$$

Compared to the conjectured policy function, matching coefficients gives

$$c_1\psi_1 + c_2\psi_1^2 + c_3 = 0$$

$$\psi_2 = -\frac{c_4}{c_1 + \psi_1 c_2 + c_2}$$

Given the existence of a unique solution, ψ_1 and ψ_2 can be characterized by Φ, i.e., $\psi_1 = \psi_1(\Phi)$, $\psi_2 = \psi_2(\Phi)$. Because $\Delta\tilde{z}_{jt} = \varepsilon_{x,jt}$ and $\varepsilon_{x,jt}$ is i.i.d. in the cross-section and time-series,

$$\Delta\tilde{inv}_{jt} = \psi_1(\Phi)\Delta\tilde{inv}_{j,t-1} + \psi_2(\Phi)\Delta\tilde{z}_{jt}.$$

$$\Rightarrow \quad \Delta\tilde{inv}_{jt} = \psi_1(\Phi)(\psi_1(\Phi)\Delta\tilde{inv}_{j,t-2} + \psi_2(\Phi)\varepsilon_{x,j,t-1}) + \varepsilon_{x,jt}.$$

$$\Rightarrow \quad \mathrm{Var}_j(\Delta\tilde{inv}_{jt}) = \frac{\psi_2(\Phi)^2}{1-\psi_1(\Phi)^2}\sigma_x^2$$

Therefore, the proposition is proved.

1.6.3 Computation Method

The primary challenge in solving the model comes from the fact that the final-good price depends on the cross-sectional distribution of intermediate firms. Consistent with Zhang (2005), I adopt the approximate aggregation approach proposed by Krusell and Smith (1998). This approach assumes a log-linear relationship among aggregate states:[24]

$$p_t = \gamma_1 + \gamma_2 p_{t-1} + \gamma_3 g_t + \gamma_4 r_{t+1}.$$

[24]Since Krusell and Smith (1998) use aggregate capital stock in their log-linear approximation, I also replace the output price with lagged aggregate inventory stock in the formulation but do not find improvement in approximation quality.

The algorithm follows the iterative procedure: (i) An initial guess is made for those γ values. (ii) Based on this conjectured price formation rule, I can solve the firm's dynamic problem. (iii) With solved policy functions, I simulate the behavior of 5000 firms over 7000 periods and dispose the first 1000 periods. (iv) A new set of γ values is estimated based on the simulated sample. (v) Use these new values as an initial guess and redo (ii)-(iv) until γ converges.

In solving the dynamic programming problem in Step (ii), I specify a grid with 50 points for inventories, and construct the grid recursively using $inv_i = inv_{i-1} + c_1 \exp(c_2(i-2))$, where $i = 1, 2..., 50$, following McGrattan (1999). I use 5 grid points to discretize x_t and p_t, and 2 grid points for g_t and r_{t+1} respectively. I follow the similar approach in Zhang (2005) to discretize p_t. Due to the high persistency of the idiosyncratic process, x_t is discretized using Rouwenhorst (1995) method. Given that g_t and r_{t+1} are correlated, I discretize the vector process (g_t, r_{t+1}) according to Tauchen (1986). Once the discrete space is available, the value function is evaluated on a (inv_{t-1}, inv_t) grid with 50×1000 points for each exogenous state. The remaining control variables can be solved in this grid through an implicit equation system derived from the first-order conditions of the firm's problem. This approach significantly reduces dimensions and speeds up the algorithm. The value function iteration process is further accelerated using Howard's policy function iteration algorithm.

I simulate a panel comprising 5000 firms over 7000 quarters and discard the initial 1000 quarters to allow transient conditions to dissipate. A pivotal assumption in the Krusell-Smith algorithm posits that firms can accurately infer the log output price p_t based on (p_{t-1}, g_t, r_{t+1}). This ensures that the high-dimensional cross-sectional distribution can be neglected in firms' decision making. The Krusell-Smith algorithm proves to be efficient in approximating the equilibrium in this study. As depicted in

Figure 1.8 Subfigure (a), the following linear conjecture attains an R^2 nearing one. Subfigure (b) shows the prediction error as a fraction of the actual price. Throughout the 6000-period simulation, cases where absolute prediction errors surpass 1% of the actual price is around 2%. The impact of forecast errors on the firm's decision-making process is trivial.

$$p_t = -0.071 + 0.055p_{t-1} - 0.692g_t - 0.016r_{t+1}, \quad R^2 = 0.9918$$

Given that inventories in data are valued at cost basis, I do not adjust inventory levels using intermediate output prices when calculating simulated aggregate inventory moments. This approach allows me to focus on the dynamics of inventories measured in wage price. Because production equals consumption plus changes in inventories in this model, I approximate aggregate output using aggregate consumption, although similar results are obtained if firm-level production y_{jt} is implemented in the CES aggregator below.[25]

$$\log GDP_t = \frac{\theta}{\theta - 1}(1-\eta)\log \int_0^1 a_{jt}^{\frac{\zeta}{\theta}} s_{jt}^{\frac{\theta-1}{\theta}}\, dj$$

1.6.4 Variable Description

Table 1.1: Definition of Main Variables

Items	Description

[25]This is because the change in inventories accounts for a very small portion in total output. In the simulated sample, the portion of inventory investment in total output is 0.59% close to the level of 0.33% computed based on the quarterly data from 1976Q1 to 2019Q2. Because capital investment is not included in the model, the portion calculated from the simulated sample will be overstated.

$RGDPRe$	Difference between the final estimate available by December 2019 and the advance estimate of year-over-year real GDP growth.
$RSPFErr$	Difference between the final estimate available by December 2019 and the forecast consensus mean made by SPF panelists in the middle of the same quarter.
$ConsRe$	Final restatements of real personal consumption expenditure.
$InvestRe$	Final restatements of real non-residential investment.
$ChgInvtRe$	Final restatements of real change in private inventories.
$NondurRe$	Final restatements of real non-durable goods consumption.
$DurRe$	Final restatements of real durable goods consumption.
$ServiceRe$	Final restatements of real service consumption.
$RGDP1_t$	Advance estimate of quarter t real GDP growth.
$RGDP_{t-1}$	Most recent quarter $t-1$ real GDP growth estimate available by the release date of quarter t advance estimate.
$RSPF_t$	Consensus mean of quarter t real GDP growth forecasts made by SPF panelists in the middle of quarter t.
$CFNAI_t$	CFNAI value in the third month of quarter t. Since the CFNAI is issued at monthly frequency, I follow the same method as in Nallareddy and Ogneva (2017).

$Invt_{t-1}$	Aggregate year-over-year inventory growth average weighted by lagged inventory levels. $Invt_{t-1}$ is calculated using $t-1$ quarterly accounting disclosures available one week before the SPF submission deadline in forecast error analysis, and disclosures available by the BEA advance estimate release date in GDP revision analysis. The financial disclosure sets used to calculate $InvtDisp(Ind)_{t-1}$, $EarDisp_{t-1}$, $RetDisp_{t-1}$, $RNOA_{t-1}$, Ear_{t-1} are selected in the same way.
$InvtDisp(Ind)_{t-1}$	Cross-firm (cross-sector) standard deviation of inventory growth weighted by lagged inventory levels. Sectors are classified based on three-digit NAICS codes.
$EarDisp_{t-1}$	Earnings dispersion as used in Nallareddy and Ogneva (2017). I first calculate the standard deviation of firm-level earnings changes scaled by lagged book value and then detrend the variable using an AR(2) model estimated on a rolling scheme.
$RetDisp_{t-1}$	Return dispersion as used in Nallareddy and Ogneva (2017).
Ret_t	CRSP value-weighted index return for quarter t.
$RNOA_{t-1}$	Change in return on net operating assets for quarter $t-1$ as used in Konchitchki and Patatoukas (2014b). Operating income is defined as sales minus cost of goods sold, selling, general, and administrative expense, and depreciation expense. Net operating assets are defined as operating assets (total assets minus cash and short-term investments) minus operating liabilities (total liabilities minus long- and short-term debt).

Ear_{t-1}	Change in net income scaled by sales as used in Konchitchki and Patatoukas (2014a).
$RetAnn_t$	CRSP value-weighted index return on the release day of quarter t advance estimate.
$Recession$	Equals to one if a quarter is in NBER recessionary periods, otherwise zero.

1.6.5 Market Return Predictability

The aforementioned results confirm that inventory dispersion predicts future economic conditions. Given this predictive power, it is interesting to explore its implications on stock market valuations. Specifically, I analyze if quarter $t-1$ aggregate inventory moments can forecast the quarterly CRSP value-weighted returns starting i month after quarter $t-1$ ends. In the aggregation process, financial disclosures available by the outset of the stock return evaluation period are used.

The findings in Table 1.12 reveal that inventory moments, for the most part, do not substantially foretell forthcoming returns, except for Column (3) in Panel B. Untabulated results highlight a more pronounced influence of inventory dispersion on stock market returns during recessionary times, periods when investors appear more attuned to unexpected shifts in economic growth. This resonates with the findings from Gilbert (2011) and Clements and Galvão (2017), who show that GDP second revisions have a significantly negative impact on market pricing but only during recessions. Cumulatively, the results do not support the notion that investors fail to incorporate the news shocks embedded in aggregate inventory movements.

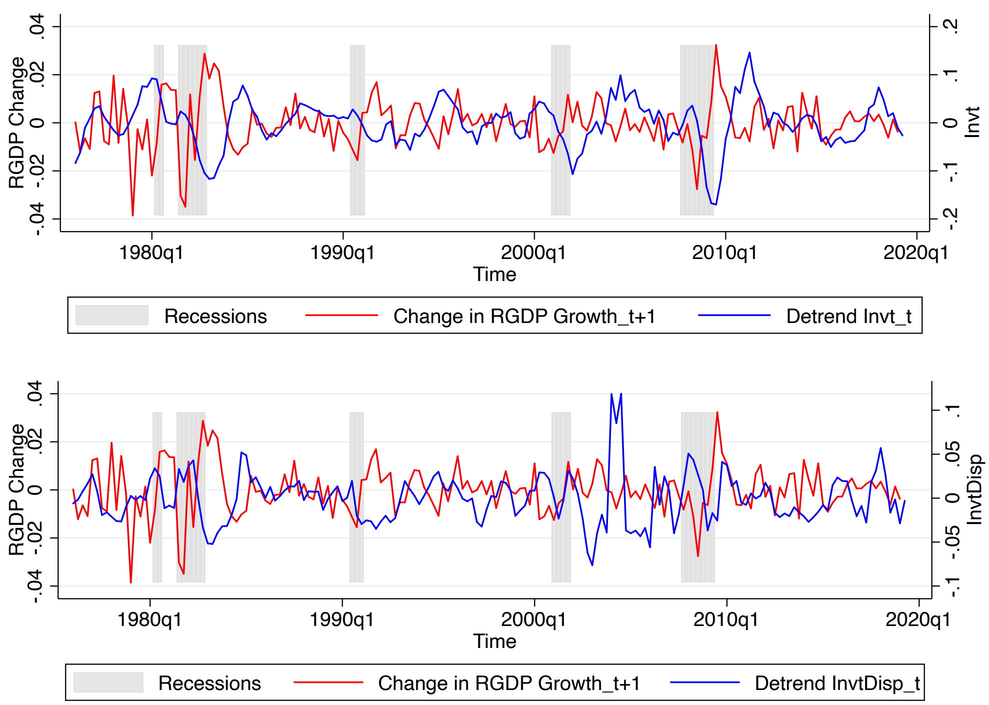
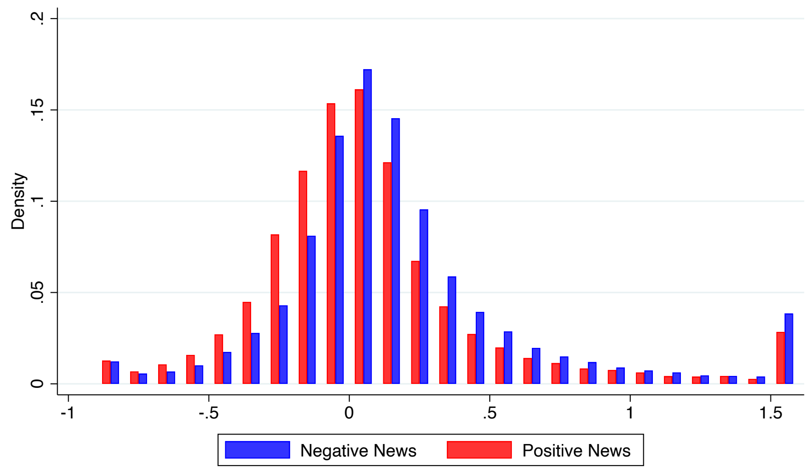
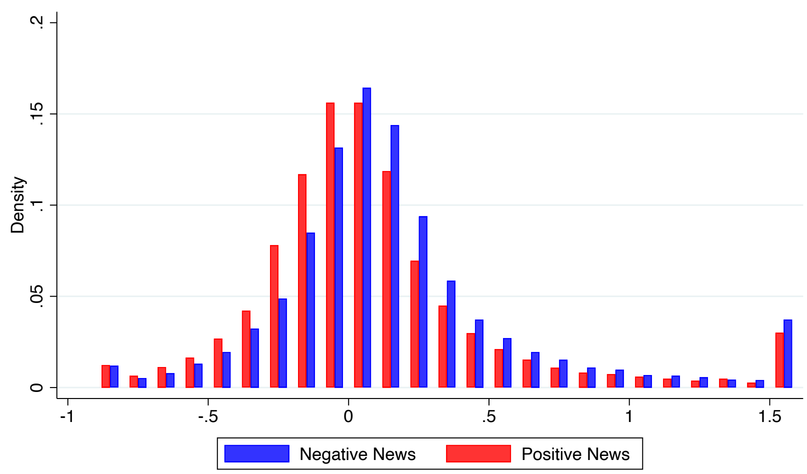


Figure 1.1: Aggregate Inventory Moments and Future Real GDP Growth Changes

This figure plots the time series of size-weighted cross-sectional mean and standard deviation of firm-level inventory growth from 1976Q1 to 2019Q2. The shaded area indicates quarters in NBER recessions. All U.S. incorporated Compustat manufactures are included in the calculation of aggregate inventory moments. I winsorize the top and the bottom 1% inventory growth in each quarter to remove outliers. Aggregate inventory moments are HP-filtered with parameter $\lambda = 1600$. $\text{Corr}(\Delta GDP_{t+1}, Invt_t) = -0.37(0.00)$, $\text{Corr}(\Delta GDP_{t+1}, InvtDisp_t) = -0.26(0.00)$, with p-values reported in parenthesis. To avoid a look-ahead bias, I also compute the correlation between inventory moments and concurrent forecasted future real GDP growth changes, $\text{Corr}(\Delta SPF_{t+1}, Invt_t) = -0.40(0.00)$, $\text{Corr}(\Delta SPF_{t+1}, InvtDisp_t) = -0.16(0.04)$.



(a) News shocks measured by realized real GDP growth changes



(b) News shocks measured by concurrent forecasts

Figure 1.2: Cross-Sectional Inventory Growth Distribution

This figure plots the average inventory growth distributions in quarters of positive and negative news. All U.S. incorporated Compustat manufactures are included. The news shock at t is measured by the change of real GDP growth for quarter $t+1$ in Subfigure (a), or by the expected change in real GDP growth for quarter $t+1$ based on forecasts made at quarter t in Subfigure (b). I sort news shocks into quintiles and the group with the highest (lowest) level receives positive (negative) news.

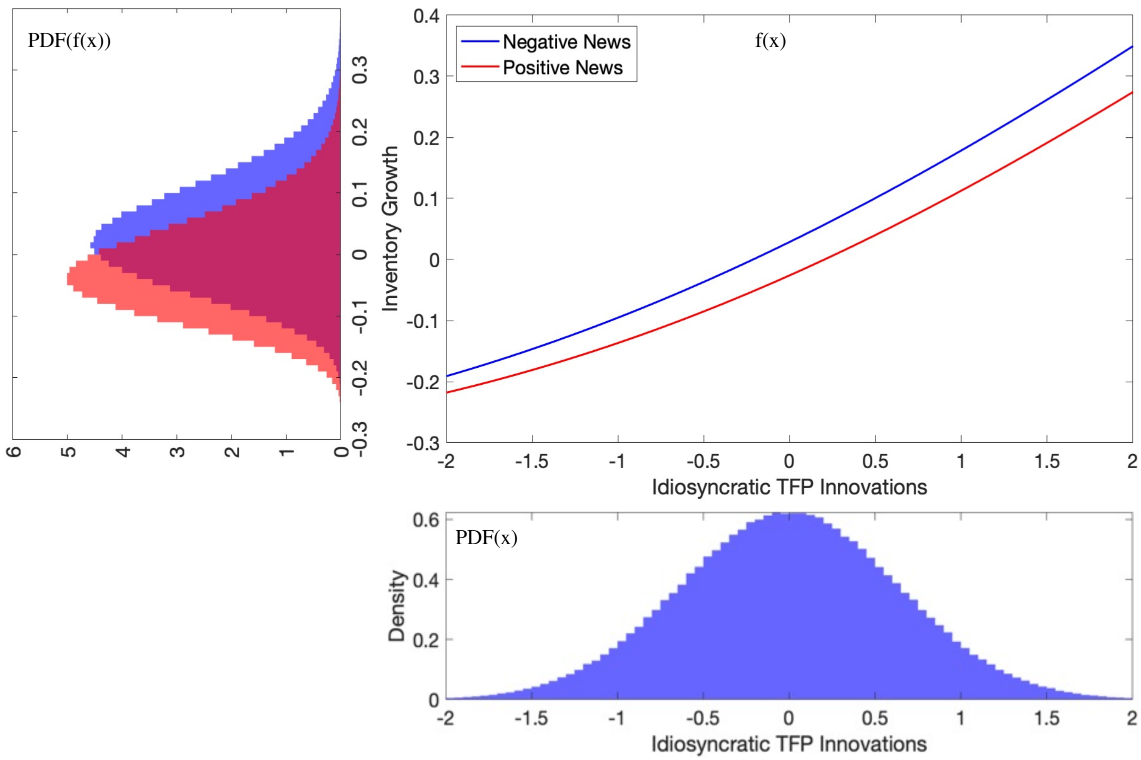


Figure 1.3: Decision Rule Convexity and Distribution Skewness

This figure illustrates the importance of the inventory decision rule in governing the distribution dynamics. Normally distributed idiosyncratic TFP innovations, when processed through a convex decision rule $f(x)$, result in a right-skewed distribution of $f(x)$. When the decision rule shifts downward in response to positive news, the cross-sectional distribution also changes given the same distribution of idiosyncratic TFP innovations.

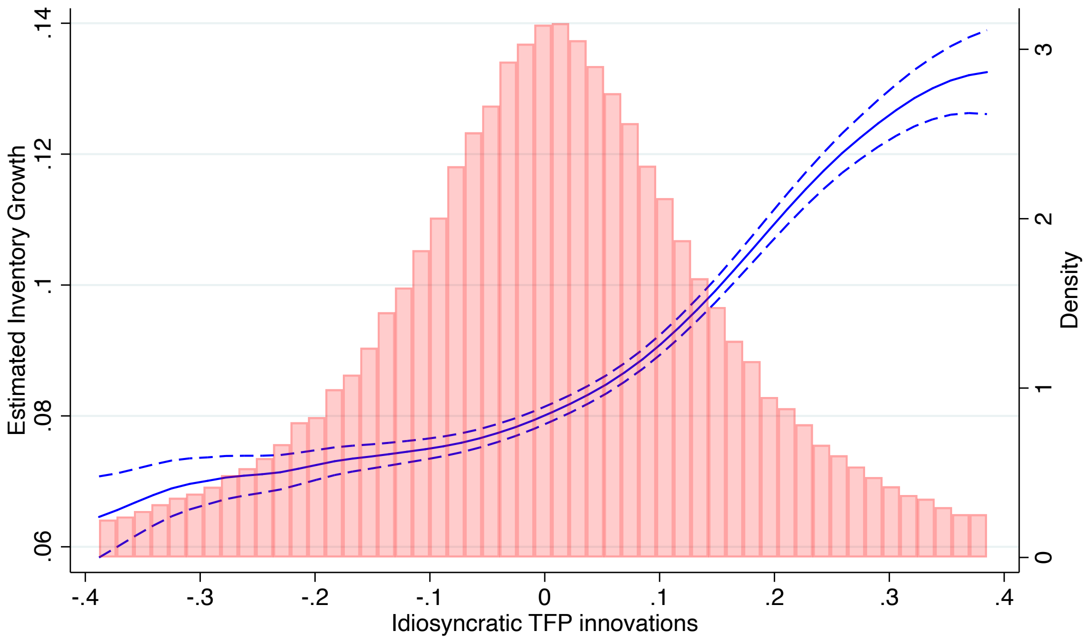
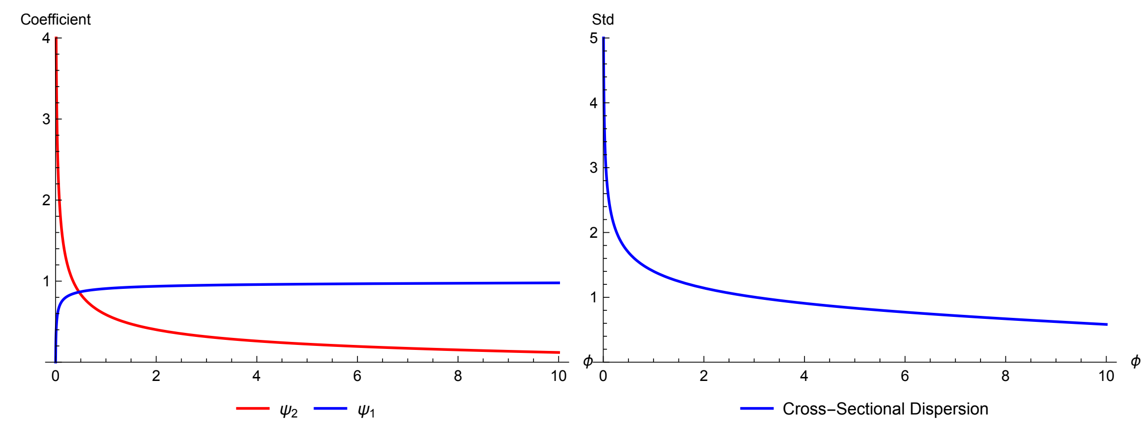


Figure 1.4: Nonparametric Estimation of the Decision Rule

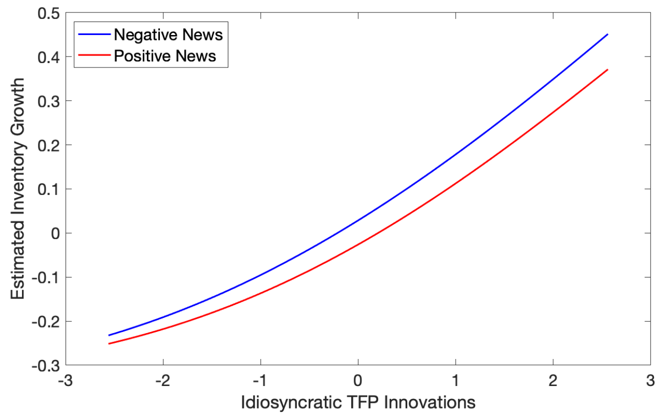
This figure illustrates the nonparametric estimation of the inventory decision rule, with the fitted curve in a solid line and the 95% confidence intervals in dashed lines, alongside the distribution of idiosyncratic TFP innovations plotted in red bars. The sample consists of Compustat manufacturers with a minimum of ten years of observations. I trim the top and the bottom 5% inventory growth rates and TFP innovations. A kernel-weighted local polynomial regression with local-mean smoothing is employed. I compute idiosyncratic TFP innovations based on the procedure described in the appendix.



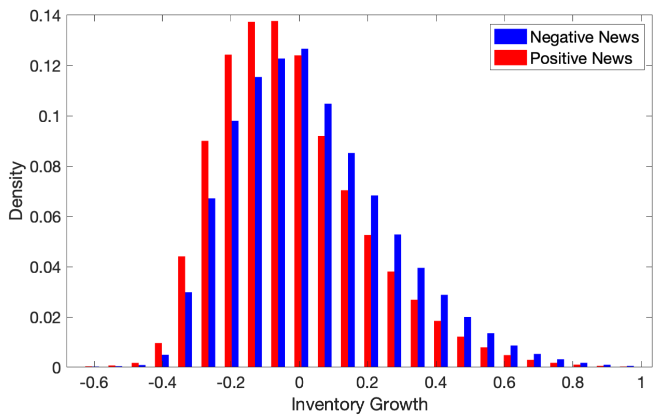
(a) ψ_1, ψ_2 and adjustment costs **(b)** Dispersion and adjustment costs

Figure 1.5: Cross-Sectional Inventory Dispersion to a First-Order

In Subfigures (a) and (b), ψ_1, ψ_2, and inventory dispersion are evaluated around the baseline adjustment cost values, with other parameters $(\beta, \theta, \zeta, \delta)$ in calibrated values from Table 1.4. The adjustment cost parameter ϕ ranges from 0 to 10, compared to the baseline values of $\phi_- = 4.03$ or $\phi_+ = 0.94$.



(a) Average inventory policy function



(b) Average distribution of inventory growth

Figure 1.6: Mechanism Illustration

I re-simulate the model by setting $\sigma_g = 0.04$ in order to produce more pronounced variation. The remaining parameters use the same values as in the baseline model. I sort simulated periods into deciles according to the level of news shocks, $(r_{t+1} - \rho_g g_t) - (g_t - \rho_g g_{t-1})$. The top decile receives positive news and the bottom decile receives negative news. In Subfigure (a), I estimate the inventory decision rules under positive and negative news based on a polynomial regression specification: $Invt_{it} = \beta_0 + \beta_1 \varepsilon_{x,it} + \beta_2 \varepsilon_{x,it}^2 + \beta_3 \varepsilon_{x,it}^3 + \beta_4 \varepsilon_{x,it}^4 + \beta_5 Invt_{i,t-1} + e_{i,t}$, where $Invt_{it}$ is the inventory growth rate, and $\varepsilon_{x,it}$ is the idiosyncratic TFP innovation. The inventory decision rules with respect to idiosyncratic TFP innovations are plotted. In Subfigure (b), I average the cross-sectional distributions of inventory growth rates in periods with negative and positive news.

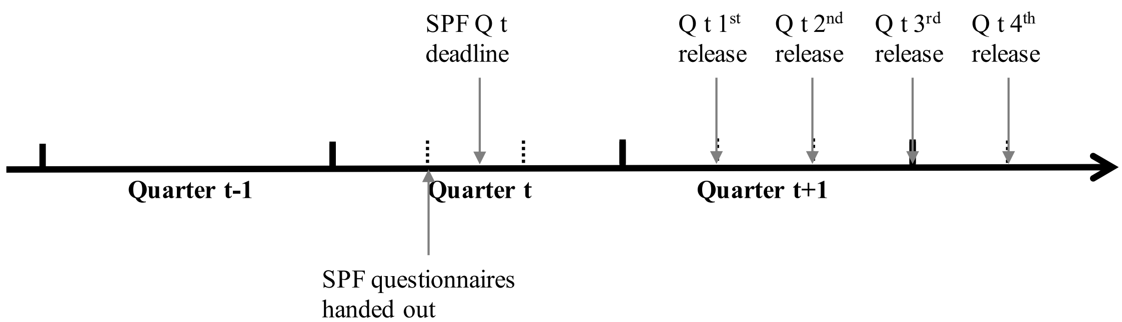
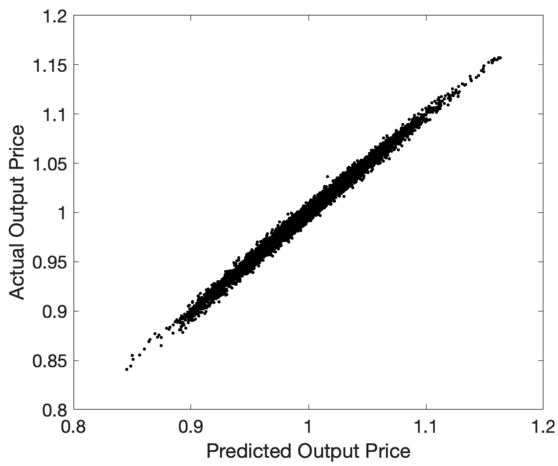
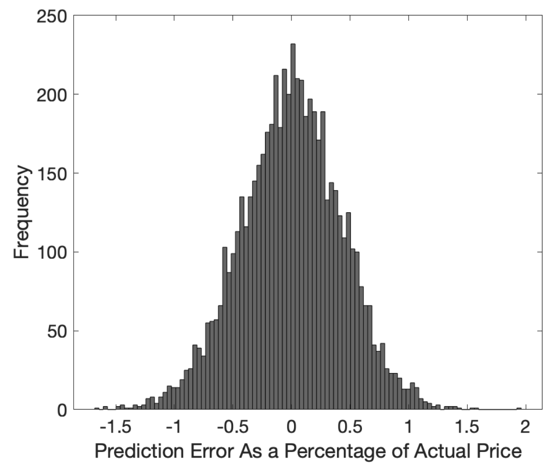


Figure 1.7: Time Line

The Philadelphia Fed's Survey of Professional Forecasters is typically dispatched at the conclusion of the first month of every quarter. SPF panelists are expected to submit their responses by the midpoint of the subsequent month. In the survey, SPF panelists make forecasts about GDP growth in current and future quarters. The BEA releases the advance estimate of the GDP for quarter t in the initial month following the quarter t end, and continuously revises its estimates thereafter.



(a) Predicted versus actual price



(b) Distribution of prediction error

Figure 1.8: Approximation Quality

This figure shows the quality of the log-linear approximation for the conjectured final output price in the following form: $p_t = -0.071 + 0.063p_{t-1} - 0.679g_t - 0.022r_{t+1}, R^2 = 0.9918$. Subfigure (a) plots the predicted output price against the actual price. Subfigure (b) plots the distribution of prediction errors as a percentage of actual prices.

Table 1.2: Firm-Level Asymmetric Response to Idiosyncratic TFP Shocks

The sample consists of U.S. incorporated Compustat manufacturers with a minimum of ten years of observations. The regressions from Columns (1) to (4) are as follows:

$$Invt_{it} = \bar{Invt}_i + \bar{Invt}_t + \beta_1 \varepsilon_{x,it} + \beta_2 \varepsilon_{x,it}^2 + \gamma_1 Invt_{i,t-1} + \gamma_2 x_{i,t-1},$$
$$Invt_{it} = \bar{Invt}_i + \bar{Invt}_t + \beta_1 \varepsilon_{x,it} + \beta_2 \varepsilon_{x,it}^2 + \beta_3 \varepsilon_{x,it}^3 + \gamma_1 Invt_{i,t-1} + \gamma_2 x_{i,t-1},$$
$$Invt_{it} = \bar{Invt}_i + \bar{Invt}_t + \beta_1 \varepsilon_{x,it} + \beta_4 \varepsilon_{x,it} 1_{\varepsilon_{x,it}>0} + \gamma_1 Invt_{i,t-1} + \gamma_2 x_{i,t-1},$$
$$Invt_{it} = \bar{Invt}_i + \bar{Invt}_t + \beta_1 \varepsilon_{x,it} + \beta_5 \varepsilon_{x,it} 1_{Invt_{i,t-1}>0} + \gamma_1 Invt_{i,t-1} + \gamma_2 x_{i,t-1},$$

where $Invt_{it}$ and $\varepsilon_{x,it}$ are the year-over-year inventory growth and idiosyncratic TFP innovation for firm i in quarter t, and $x_{i,t-1}$ is the $t-1$ log TFP level. t-statistics clustered by firm and quarter are reported in parenthesis. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1) *Invt*	(2) *Invt*	(3) *Invt*	(4) *Invt*
β_1	0.086***	0.094***	0.041***	0.058***
	(7.79)	(6.50)	(3.74)	(5.58)
β_2	0.116***	0.116***		
	(3.81)	(3.81)		
β_3		-0.123		
		(-1.15)		
β_4			0.090***	
			(4.46)	
β_5				0.046***
				(4.06)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj R^2	0.182	0.182	0.182	0.182
Obs	156223	156223	156223	156223

Table 1.3: Firm-Level Asymmetric Response to News Shocks

The sample includes U.S. incorporated Compustat manufacturers with a minimum of ten years of observations. News shock at t is measured by the change of real GDP growth for quarter $t+1$ in Panel A, and the expected change of real GDP growth for quarter $t+1$ based on forecasts at quarter t in Panel B. News shock quintiles labelled 1 to 5 are the ones with the lowest to the highest news shock levels. For each firm, I sort quarterly inventory growth observations into news shock-adjustment direction (measured by lagged inventory growth rates) buckets, and calculate the cross-quarter firm-level averages. Next, I calculate the cross-firm average of inventory growth rates in each bucket. Under Column "5-1", I compute the inventory growth differences between the highest and lowest news shock quintiles, and report their t-statistics in parenthesis.

(a) News shocks measured by realized changes in real GDP growth

	News Shock Level					
Direction	1	2	3	4	5	5-1
Upward	0.339	0.297	0.291	0.302	0.266	-0.073
						(-11.34)
Downward	-0.086	-0.104	-0.107	-0.099	-0.133	-0.049
						(-11.02)
Difference						-0.024
						(-3.10)

(b) News shocks measured by concurrent professional forecasts

	News Shock Level					
Direction	1	2	3	4	5	5-1
Upward	0.341	0.316	0.291	0.271	0.278	-0.063
						(-9.86)
Downward	-0.096	-0.098	-0.102	-0.116	-0.128	-0.033
						(-8.02)
Difference						-0.027
						(-3.48)

Table 1.4: Parameters in the Baseline Model

This table gives the parameter values of the baseline model and provides descriptions of these values.

Parameter	Value	Description
β	0.987	Quarterly time discount factor, from Cooper and Haltiwanger (2006)
α	0.670	Labor share of income
η	0.450	Inverse price elasticity of demand
θ	5.000	Elasticity of substitution, from Crouzet and Oh (2016)
ζ	0.224	Elasticity of sales to on-shelf goods, to match inventory-to-sales ratio
δ	0.025	Depreciation rate, from Crouzet and Oh (2016)
ϕ_+	0.940	Upward adjustment cost, to match the cross-sectional size-weighted average of inventory growth for firms adjusting upward
ϕ_-	4.030	Downward adjustment cost, to match the cross-sectional size-weighted average of inventory growth for firms adjusting downward
ρ_x	0.974	Persistency of idiosyncratic TFP shocks, from Cooper and Haltiwanger (2006)
σ_x	0.160	Standard deviation of idiosyncratic shock innovations, from Cooper and Haltiwanger (2006)
ρ_g	0.930	Persistency of aggregate TFP shocks, from Cooper and Haltiwanger (2006)
σ_g	0.010	Standard deviation of aggregate shock innovations, to match total output growth volatility
$\bar{g}$	0.480	Mean of aggregate TFP shocks, to adjust the steady-state inventory level to one as in Zhang (2005)
σ_g/σ_r	1.400	Ratio of the standard deviation of aggregate productivity innovation to the standard deviation of signal noise, to match the correlation coefficients between aggregate inventory moments and future output growth

Table 1.5: Quantitative Results

In Panel A, ΔGDP_t is calculated as the first difference of real GDP growth rate for quarter t. $InvtU(D)_t$ is the cross-sectional size-weighted average of inventory growth for firms adjusting upward (downward). GDP_t is the real GDP growth rate. In Panel B, I run several counterfactuals by modifying the upward adjustment costs while holding the rest of the parameters constant. In Panel C, I examine the incremental predictive power of inventory mean and dispersion separately. To examine the incremental predictive power of inventory dispersion, I regress $Invt_{t-1}$ on ΔGDP_t and compare its sum of squared errors against that from a regression with both measures, and report the F-statistic along with its p-value in the row with inventory mean regression results. The test about inventory mean is conducted in a similar way and its result is reported in the row with inventory dispersion regression results. Except for Column "F-statistics", t-statistics from regression results are reported in parenthesis.

(a) Target moments in the baseline model

Moments	Data	Model
Corr($Invt_{t-1}, \Delta GDP_t$)	-0.367	-0.361
Corr($InvtDisp_{t-1}, \Delta GDP_t$)	-0.257	-0.291
Average I/S ratio	0.750	0.733
Mean of $InvtU_t$	0.167	0.156
Mean of $InvtD_t$	-0.125	-0.122
Mean of $InvtDisp_t$	0.215	0.182
Std. of GDP_t	0.018	0.019

(b) Simulated counterfactuals

	ϕ_-	ϕ_+	σ_g/σ_r	Corr($Invt_{t-1}, \Delta GDP_t$)	Corr($InvtDisp_{t-1}, \Delta GDP_t$)
Model	4.03	0.94	1.4	-0.361	-0.291
	4.03	1.44	1.4	-0.311	-0.235
	4.03	1.94	1.4	-0.326	-0.101
	4.03	2.44	1.4	-0.313	-0.049
	4.03	2.94	1.4	-0.325	0.086
	4.03	3.44	1.4	-0.316	0.206
	4.03	4.03	1.4	-0.310	0.217

(c) Signal independence test using the baseline simulated sample

Dependent	Constant	$Invt_{t-1}$	$InvtDisp_{t-1}$	Adj R^2	Obs	F-statistics
ΔGDP_t	0.000	-1.578		0.130	5997	36.56
	(0.01)	(-30.02)				(0.00)
	0.148		-3.265	0.084	5997	358.07
	(23.49)		(-23.50)			(0.00)
	0.049	-1.306	-1.075	0.136	5997	
	(6.04)	(-18.92)	(-6.05)			

Table 1.6: Summary Statistics

This table reports the summary statistics of the main variables used in GDP revision analysis with the exception of $RSPFErr$. Accounting and return aggregates at quarter $t-1$ are calculated based on the information available by the advance estimate release date in quarter $t+1$.

	count	mean	sd	p5	p25	p50	p75	p95
$RSPFErr$	174	0.003	0.010	-0.011	-0.004	0.002	0.009	0.019
$RGDPRe$	174	0.002	0.008	-0.008	-0.003	0.001	0.007	0.017
$ConsRe$	174	0.001	0.007	-0.009	-0.004	0.001	0.005	0.016
$InvestRe$	174	0.002	0.029	-0.048	-0.012	0.001	0.020	0.050
$ChgInvtRe$	174	-0.827	12.950	-12.242	-0.928	-0.027	0.479	6.619
$NondurRe$	174	0.001	0.011	-0.014	-0.007	-0.000	0.009	0.022
$DurRe$	174	0.001	0.017	-0.026	-0.011	0.001	0.012	0.030
$ServiceRe$	174	0.001	0.009	-0.014	-0.004	0.001	0.005	0.017
$RGDP1_t$	174	0.026	0.018	-0.008	0.018	0.026	0.036	0.056
$CFNAI_t$	174	0.005	0.589	-0.950	-0.220	0.045	0.350	0.920
$RSPF_t$	174	0.025	0.018	-0.008	0.019	0.025	0.035	0.056
$RGDP_{t-1}$	174	0.026	0.019	-0.009	0.019	0.026	0.037	0.057
$Invt_{t-1}$	173	0.056	0.059	-0.046	0.024	0.061	0.091	0.151
$InvtDisp_{t-1}$	173	0.209	0.043	0.147	0.178	0.210	0.232	0.282
$InvtDispInd_{t-1}$	173	0.077	0.029	0.044	0.055	0.070	0.087	0.147
Ret_t	174	0.031	0.081	-0.126	-0.010	0.039	0.081	0.165
$RetAnn_t$	174	0.000	0.010	-0.017	-0.005	0.001	0.004	0.019
$EarDisp_{t-1}$	166	0.004	0.031	-0.037	-0.011	0.001	0.017	0.049
$RetDisp_{t-1}$	166	0.009	0.045	-0.044	-0.011	0.003	0.027	0.075
$RNOA_{t-1}$	173	-0.013	0.129	-0.214	-0.085	-0.021	0.057	0.214
Ear_{t-1}	173	-0.097	0.245	-0.444	-0.205	-0.071	0.029	0.241

Table 1.7: Real GDP Growth Forecast Errors and Aggregate Inventory Moments

$RSPFErr$ is the difference between the final real GDP growth estimate for quarter t and the forecast consensus mean for quarter t made by SPF panelists in the middle of quarter t. Accounting and return aggregates are calculated based on the information available by the first week in the second month of quarter t. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging 3 periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1) $RSPFErr$	(2) $RSPFErr$	(3) $RSPFErr$	(4) $RSPFErr$	(5) $RSPFErr$	(6) $RSPFErr$
$Invt_{t-1}$	-0.005				0.009	0.006
	(-0.28)				(0.55)	(0.33)
$InvtDisp_{t-1}$		-0.051**			-0.049***	
		(-2.39)			(-2.67)	
$InvtDispInd_{t-1}$			-0.120***			-0.097***
			(-4.64)			(-4.46)
$RGDP1_{t-1}$				-0.066	-0.034	-0.048
				(-1.18)	(-0.60)	(-0.77)
$CFNAI_{t-1}$				0.009***	0.007***	0.007***
				(5.55)	(4.69)	(5.12)
$RNOA_{t-1}$				-0.006	-0.008	-0.008
				(-0.78)	(-0.93)	(-0.89)
Ear_{t-1}				-0.005*	-0.005	-0.004
				(-1.67)	(-1.65)	(-1.35)
$EarDisp_{t-1}$				0.001	-0.002	0.010
				(0.03)	(-0.09)	(0.41)
$RetDisp_{t-1}$				0.023	0.025*	0.022*
				(1.62)	(1.84)	(1.70)
Ret_{t-1}				0.003	0.001	-0.001
				(0.37)	(0.09)	(-0.12)
Constant	0.003**	0.013***	0.012***	0.004***	0.013***	0.011***
	(2.20)	(2.95)	(5.20)	(2.69)	(3.26)	(5.02)
Adj R^2	-0.005	0.050	0.126	0.171	0.203	0.241
Obs	173	173	173	166	166	166

Table 1.8: Real GDP Final Restatements and Aggregate Inventory Moments

RGDPRe is the difference between the final real GDP growth estimate for quarter t and the advance estimate for quarter t available in the end of the first month at quarter $t+1$. Accounting and return aggregates are calculated based on the information available by the advance estimate release date after quarter t ends. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging 3 periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$
$Invt_{t-1}$	-0.001				0.017	0.008
	(-0.11)				(1.53)	(0.72)
$InvtDisp_{t-1}$		-0.064***			-0.081***	
		(-3.05)			(-4.51)	
$InvtDispInd_{t-1}$			-0.119***			-0.114***
			(-6.54)			(-6.40)
$RGDP1_t$				0.050	0.129	0.077
				(0.45)	(1.18)	(0.73)
$RGDP_{t-1}$				0.062	0.047	0.040
				(0.73)	(0.58)	(0.55)
$RSPF_t$				-0.048	-0.060	-0.038
				(-0.42)	(-0.50)	(-0.34)
$CFNAI_t$				0.003**	0.002*	0.002*
				(2.06)	(1.93)	(1.84)
$RNOA_{t-1}$				-0.015**	-0.019***	-0.017***
				(-2.34)	(-3.00)	(-2.68)
Ear_{t-1}				-0.004	-0.003	-0.002
				(-1.03)	(-1.10)	(-0.73)
$EarDisp_{t-1}$				-0.040***	-0.039***	-0.031***
				(-3.28)	(-3.60)	(-2.71)
$RetDisp_{t-1}$				-0.004	-0.007	-0.009
				(-0.28)	(-0.55)	(-0.77)
Ret_t				0.010	0.009	0.005
				(1.38)	(1.44)	(0.85)
Ret_{t-1}				0.005	0.002	0.002
				(0.59)	(0.28)	(0.26)
$RetAnn_t$				-0.015	-0.022	-0.020
				(-0.30)	(-0.43)	(-0.41)
$Recession$				-0.002	-0.000	0.000
				(-0.68)	(-0.15)	(0.00)
Constant	0.003*	0.016***	0.012***	0.000	0.015***	0.009***
	(1.92)	(3.54)	(6.37)	(0.26)	(3.76)	(3.85)
Adj R^2	-0.006	0.121	0.193	0.103	0.277	0.266
Obs	173	173	173	166	166	166

Table 1.9: Adjustment Cost Asymmetry

$H(L)$ $InvtDisp_{t-1}$ is the inventory dispersion of firms with high (low) adjustment cost asymmetry. I choose two proxies for cost asymmetry, including preceding revenue trend (Anderson et al., 2003) and service level (Kesavan and Kushwaha, 2014). Service level is the difference between stockout cost and inventory holding cost. For revenue trend tests in Columns (1)-(3), I divide firms into a high (low) asymmetry group if a firm's revenue increased (declined) in the preceding quarter. For service level tests in Columns (4)-(6), I divide firms in each quarter into a high (low) asymmetry group if a firm falls in the top (bottom) 50th percentile of service levels within its corresponding two-digit NAICS sector. The cross-sectional standard deviation of inventory growth is computed separately within each group. In Panel A, $RSPFErr$ is the difference between the final real GDP growth estimate for quarter t and the forecast consensus mean for quarter t made by SPF panelists in the middle of quarter t. In Panel B, $RGDPRe$ is the difference between the final real GDP growth estimate for quarter t and the advance estimate for quarter t available in the end of the first month at quarter $t+1$. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging 3 periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) Real GDP forecast error predictability

	(1)	(2)	(3)	(4)	(5)	(6)
	$RSPFErr$	$RSPFErr$	$RSPFErr$	$RSPFErr$	$RSPFErr$	$RSPFErr$
H $InvtDisp_{t-1}$	-0.037**		-0.037**	-0.042**		-0.040**
	(-2.50)		(-2.38)	(-2.04)		(-2.13)
L $InvtDisp_{t-1}$		-0.011	0.001		-0.018	-0.003
		(-0.59)	(0.08)		(-0.87)	(-0.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.201	0.169	0.195	0.192	0.172	0.187
Obs	166	166	166	166	166	166

(b) Real GDP restatement predictability

	(1)	(2)	(3)	(4)	(5)	(6)
	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$	$RGDPRe$
H $InvtDisp_{t-1}$	-0.063***		-0.058***	-0.056***		-0.043***
	(-4.28)		(-4.13)	(-3.01)		(-2.98)
L $InvtDisp_{t-1}$		-0.038**	-0.015		-0.047**	-0.032
		(-2.37)	(-1.25)		(-2.13)	(-1.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.257	0.143	0.259	0.183	0.166	0.205
Obs	166	166	166	166	166	166

Table 1.10: Prediction on GDP Component Restatements

Columns (1)-(6) report the results about the restatements of household consumption, private nonresidential investment, change in private inventories, nondurable-goods consumption, durable-goods consumption and service consumption respectively. Control variables are the same as those used in Table 1.8. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging 3 periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) Cross-firm inventory dispersion

	(1)	(2)	(3)	(4)	(5)	(6)
	$ConsRe$	$InvestRe$	$ChgInvtRe$	$NondurRe$	$DurRe$	$ServiceRe$
$InvtDisp_{t-1}$	-0.035**	-0.186**	13.982	-0.109***	0.017	-0.009
	(-1.99)	(-2.08)	(0.57)	(-5.01)	(0.45)	(-0.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.162	0.145	0.128	0.208	0.119	0.235
Obs	166	166	166	166	166	166

(b) Cross-sector inventory dispersion

	(1)	(2)	(3)	(4)	(5)	(6)
	$ConsRe$	$InvestRe$	$ChgInvtRe$	$NondurRe$	$DurRe$	$ServiceRe$
$InvtDispInd_{t-1}$	-0.073***	-0.109	-36.447	-0.189***	-0.043	-0.010
	(-3.28)	(-1.19)	(-0.89)	(-5.20)	(-0.90)	(-0.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.203	0.085	0.132	0.276	0.122	0.234
Obs	166	166	166	166	166	166

Table 1.11: Out-of-Sample Predictive Power

Prediction models are estimated in an expanding scheme, with the forecasted period starting ten years after the initial available quarter. The longest evaluation period for tests using one-year revised GDP estimates starts from 1987Q2, and the longest for those using two-year revised estimates starts from 1988Q2. Panel A tests professional forecast error predictability, and its columns under "full model" report the results of a forecasting model with variables $InvtDisp_{t-1}/InvtDispInd_{t-1}$, $CFNAI_{t-1}$, Ear_{t-1}, $RetDisp_{t-1}$ and the benchmark model is its nested model excluding $InvtDisp_{t-1}/InvtDispInd_{t-1}$. Panel B tests GDP revision predictability, and the columns under "full model" report the results of a forecasting model with variables $InvtDisp_{t-1}/InvtDispInd_{t-1}$, $RSPF_t$, $CFNAI_t$, $EarDisp_{t-1}$, $RNOA_{t-1}$ and the benchmark model is its nested model excluding $InvtDisp_{t-1}/InvtDispInd_{t-1}$. In both panels, columns under "inventory model" report the results of a model with $InvtDisp_{t-1}/InvtDispInd_{t-1}$ and its benchmark historical moving average model. Reported sample *MSPE-adjusted* statistics have been multiplied by 10^4. p-values are calculated based on a one-tailed t test with the null hypothesis that *MSPE-adjusted* is less than zero. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) Professional real GDP growth forecast error

Since 1987Q2: One-Year Revised GDP Estimates minus Forecasts				
	Full Model		Inventory Model	
	InvtDisp	*InvtDispInd*	*InvtDisp*	*InvtDispInd*
MSPE-adjusted	-0.02	0.00	0.00	0.01
p-value	(0.96)	(0.58)	(0.47)	(0.19)
Since 1988Q2: Two-Year Revised GDP Estimates minus Forecasts				
	Full Model		Inventory Model	
	InvtDisp	*InvtDispInd*	*InvtDisp*	*InvtDispInd*
MSPE-adjusted	0.01	0.09*	0.03*	0.10**
p-value	(0.33)	(0.07)	(0.07)	(0.04)

(b) Real GDP growth restatements

Since 1987Q2: One-Year Real GDP Restatements				
	Full Model		Inventory Model	
	InvtDisp	*InvtDispInd*	*InvtDisp*	*InvtDispInd*
MSPE-adjusted	0.01	0.00	0.03***	0.02*
p-value	(0.00)	(0.51)	(0.00)	(0.09)
Since 1988Q2: Two-Year Real GDP Restatements				
	Full Model		Inventory Model	
	InvtDisp	*InvtDispInd*	*InvtDisp*	*InvtDispInd*
MSPE-adjusted	0.05**	0.08**	0.06***	0.10**
p-value	(0.02)	(0.04)	(0.00)	(0.01)

Table 1.12: Implications on Stock Market Valuation

Dependent variable Ret_{si} are quarterly CRSP cumulative value-weighted returns starting i month after quarter $t-1$ ends (including month i). To avoid a look-ahead bias, the corresponding aggregate inventory moments are calculated based on the information available by the end of month $i-1$ after quarter $t-1$ ends. t-statistics are reported in parenthesis and are corrected for autocorrelation using Newey-West method lagging 3 periods. *, **, *** denote statistical significance at 10%, 5%, 1% levels respectively.

(a) Cross-firm inventory dispersion

	(1) Ret_{s2}	(2) Ret_{s3}	(3) Ret_{s4}
$Invt_{t-1}$	-0.004	0.022	0.017
	(-0.04)	(0.20)	(0.14)
$InvtDisp_{t-1}$	-0.167	-0.170	-0.215
	(-1.20)	(-1.08)	(-1.35)
Adj R^2	-0.000	-0.004	0.001
Obs	173	173	173

(b) Cross-sector inventory dispersion

	(1) Ret_{s2}	(2) Ret_{s3}	(3) Ret_{s4}
$Invt_{t-1}$	-0.011	0.012	0.003
	(-0.10)	(0.11)	(0.03)
$InvtDispInd_{t-1}$	-0.424	-0.510	-0.540*
	(-1.41)	(-1.61)	(-1.90)
Adj R^2	0.017	0.022	0.026
Obs	173	173	173

Bibliography

Abdalla, A. M., Carabias, J. M., and Patatoukas, P. N. (2021). The real-time macro content of corporate financial reports: A dynamic factor model approach. *Journal of Monetary Economics*, 118:260–280.

Abel, A. B. (1983). Optimal investment under uncertainty. *American Economic Review*, 73(1):228–233.

Alan, Y., Gao, G. P., and Gaur, V. (2014). Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Science*, 60(10):2416–2434.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71(2):579–625.

Anderson, M. C., Banker, R. D., and Janakiraman, S. N. (2003). Are selling, general, and administrative costs "sticky"? *Journal of Accounting Research*, 41(1):47–63.

Angeletos, G.-M. and La'o, J. (2010). Noisy business cycles. *NBER Macroeconomics Annual*, 24(1):319–378.

Angelidis, T., Sakkas, A., and Tessaromatis, N. (2015). Stock market dispersion, the business cycle and expected factor returns. *Journal of Banking & Finance*, 59:265–279.

Antolin-Diaz, J., Drechsel, T., and Petrella, I. (2017). Tracking the slowdown in long-run GDP growth. *Review of Economics and Statistics*, 99(2):343–356.

Arif, S. and Lee, C. M. (2014). Aggregate investment and investor sentiment. *Review of Financial Studies*, 27(11):3241–3279.

Aruoba, S. B. (2008). Data revisions are not well behaved. *Journal of Money, Credit and Banking*, 40(2-3):319–340.

Bachmann, R. and Bayer, C. (2014). Investment dispersion and the business cycle. *American Economic Review*, 104(4):1392–1416.

Baiman, S., Netessine, S., and Saouma, R. (2010). Informativeness, incentive compensation, and the choice of inventory buffer. *The Accounting Review*, 85(6):1839–1860.

Baker, M. and Wurgler, J. (2000). The equity share in new issues and aggregate stock returns. *the Journal of Finance*, 55(5):2219–2257.

Baley, I. and Blanco, A. (2019). Firm uncertainty cycles and the propagation of nominal shocks. *American Economic Journal: Macroeconomics*, 11(1):276–337.

Banker, R. D. and Byzalov, D. (2014). Asymmetric cost behavior. *Journal of Management Accounting Research*, 26(2):43–79.

Banker, R. D., Byzalov, D., and Chen, L. T. (2013). Employment protection legislation, adjustment costs and cross-country differences in cost behavior. *Journal of Accounting and Economics*, 55(1):111–127.

Basu, S., Candian, G., Chahrour, R., and Valchev, R. (2021). Risky business cycles. *NBER Working Paper*.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009). Why do us firms hold so much more cash than they used to? *The Journal of Finance*, 64(5):1985–2021.

Beaudry, P. and Portier, F. (2004). An exploration into Pigou's theory of cycles. *Journal of Monetary Economics*, 51(6):1183–1216.

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *American Economic Review*, 96(4):1293–1307.

Beaudry, P. and Portier, F. (2014). News-driven business cycles: Insights and challenges. *Journal of Economic Literature*, 52(4):993–1074.

Begenau, J. and Palazzo, B. (2021). Firm selection and corporate cash holdings. *Journal of Financial Economics*, 139(3):697–718.

Belo, F., Donangelo, A., Lin, X., and Luo, D. (2023). What drives firms' hiring decisions? an asset pricing perspective. *Review of Financial Studies*, 36(9):3825–3860.

Belo, F. and Lin, X. (2012). The inventory growth spread. *Review of Financial Studies*, 25(1):278–313.

Belo, F., Lin, X., and Bazdresch, S. (2014). Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy*, 122(1):129–177.

Belo, F., Lin, X., and Yang, F. (2019). External equity financing shocks, financial flows, and asset prices. *The Review of Financial Studies*, 32(9):3500–3543.

Bernard, V. and Noel, J. (1991). Do inventory disclosures predict sales and earnings? *Journal of Accounting, Auditing & Finance*, 6(2):145–181.

Bernard, V. L. and Stober, T. L. (1989). The nature and amount of information in cash flows and accruals. *The Accounting Review*, 64(4):624–652.

Bernstein, J., Plante, M., Richter, A. W., and Throckmorton, N. A. (2022). A simple explanation of countercyclical uncertainty. *Federal Reserve Bank of Dallas Working Paper*.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3):623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–76.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., and Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, 86(3):1031–1065.

Burstein, A., Carvalho, V. M., and Grassi, B. (2020). Bottom-up markup fluctuations. *NBER Working Paper*.

Cacciatore, M. and Ravenna, F. (2021). Uncertainty, wages and the business cycle. *The Economic Journal*, 131(639):2797–2823.

Campbell, J. Y. and Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2):205–251.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, 21(4):1509–1531.

Cecchetti, S. G., Flores-Lagunes, A., and Krause, S. (2006). Assessing the sources of changes in the volatility of real growth. *NBER Working Paper*.

Chambers, D., Jennings, R., and Thompson, R. B. (2002). Excess returns to r&d-intensive firms. *Review of Accounting Studies*, 7(2):133–158.

Chan, L. K., Lakonishok, J., and Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of finance*, 56(6):2431–2456.

Chen, C. X., Lu, H., and Sougiannis, T. (2012a). The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research*, 29(1):252–282.

Chen, Q., Chen, X., Schipper, K., Xu, Y., and Xue, J. (2012b). The sensitivity of corporate cash holdings to corporate governance. *Review of Financial Studies*, 25(12):3610–3644.

Choi, J. H. (2021). Accrual accounting and resource allocation: A general equilibrium analysis. *Journal of Accounting Research*, 59(4):1179–1219.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1):291–311.

Clements, M. P. and Galvão, A. B. (2017). Predicting early data revisions to US GDP and the effects of releases on equity markets. *Journal of Business & Economic Statistics*, 35(3):389–406.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *The Journal of Finance*, 46(1):209–237.

Cooper, R. W. and Haltiwanger, J. C. (2006). On the nature of capital adjustment costs. *Review of Economic Studies*, 73(3):611–633.

Crouzet, N. and Mehrotra, N. R. (2020). Small and large firms over the business cycle. *American Economic Review*, 110(11):3549–3601.

Crouzet, N. and Oh, H. (2016). What do inventories tell us about news-driven business cycles? *Journal of Monetary Economics*, 79:49–66.

Dai, R. (2012). International accounting databases on WRDS: Comparative analysis. *SSRN Working Paper*.

Dasgupta, S., Li, E. X., and Yan, D. (2019). Inventory behavior and financial constraints: Theory and evidence. *Review of Financial Studies*, 32(3):1188–1233.

David, J. M., Hopenhayn, H. A., and Venkateswaran, V. (2016). Information, misallocation, and aggregate productivity. *Quarterly Journal of Economics*, 131(2):943–1005.

David, J. M. and Venkateswaran, V. (2019). The sources of capital misallocation. *American Economic Review*, 109(7):2531–2567.

Davis, J. L., Fama, E. F., and French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance*, 55(1):389–406.

Dechow, P. M., Kothari, S. P., and Watts, R. L. (1998). The relation between earnings and cash flows. *Journal of Accounting and Economics*, 25(2):133–168.

Dew-Becker, I., Tahbaz-Salehi, A., and Vedolin, A. (2021). Skewness and time-varying second moments in a nonlinear production network: Theory and evidence. *NBER Working Paper*.

Duchin, R., Gilbert, T., Harford, J., and Hrdlicka, C. (2017). Precautionary savings with risky assets: When cash is not cash. *The Journal of Finance*, 72(2):793–852.

Eiling, E., Kan, R., and Sharifkhani, A. (2023). Sectoral labor reallocation and return predictability. *SSRN Working Paper*.

Eisfeldt, A. L. and Muir, T. (2016). Aggregate external financing and savings waves. *Journal of Monetary Economics*, 84:116–133.

Falato, A., Kadyrzhanova, D., Sim, J., and Steri, R. (2022). Rising intangible capital, shrinking debt capacity, and the US corporate savings glut. *Journal of Finance*, 77(5):2799–2852.

Faust, J., Rogers, J. H., and Wright, J. H. (2005). News and noise in G-7 GDP announcements. *Journal of Money, Credit and Banking*, 37(3):403–419.

Fixler, D. J., Greenaway-McGrevy, R., and Grimm, B. T. (2011). Revisions to GDP, GDI, and their major components. *Survey of Current Business*, 91(7):9–31.

Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4):665–676.

Gilbert, T. (2011). Information aggregation around macroeconomic announcements: Revisions matter. *Journal of Financial Economics*, 101(1):114–131.

Görtz, C., Gunn, C., and Lubik, T. A. (2022). Is there news in inventories? *Journal of Monetary Economics*.

Goyal, A., Welch, I., and Zafirov, A. (2021). A comprehensive look at the empirical performance of equity premium prediction II. *Swiss Finance Institute Research Paper*.

Gu, L. (2016). Product market competition, R&D investment, and stock returns. *Journal of Financial Economics*, 119(2):441–455.

Guo, H. and Jiang, X. (2011). Accruals and the conditional equity premium. *Journal of Accounting Research*, 49(1):187–221.

Guo, H. and Qiu, B. (2023). Conditional equity premium and aggregate corporate investment. *Journal of Money, Credit and Banking*, 55(1):251–295.

Guo, H. and Savickas, R. (2008). Average idiosyncratic volatility in g7 countries. *The review of financial studies*, 21(3):1259–1296.

Hanlon, M., Lester, R., and Verdi, R. (2015). The effect of repatriation tax costs on us multinational investment. *Journal of Financial Economics*, 116(1):179–196.

Hann, R. N., Li, C., and Ogneva, M. (2021). Another look at the macroeconomic information content of aggregate earnings: Evidence from the labor market aggregate earnings and labor market. *The Accounting Review*, 96(2):365–390.

Harford, J., Mansi, S. A., and Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the US. *Journal of Financial Economics*, 87(3):535–555.

Hartman, R. (1972). The effects of price and cost uncertainty on investment. *Journal of Economic Theory*, 5(2):258–266.

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica: Journal of the Econometric Society*, pages 213–224.

Heater, J. C., Nallareddy, S., and Venkatachalam, M. (2021). Aggregate accruals and market returns: The role of aggregate m&a activity. *Journal of Accounting and Economics*.

Herskovic, B., Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2):249–283.

Herskovic, B., Kind, T., and Kung, H. (2023). Micro uncertainty and asset prices. *Journal of Financial Economics*, 149(1):27–51.

Hirshleifer, D., Hou, K., and Teoh, S. H. (2009). Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics*, 91(3):389–406.

Holdren, A. E. (2014). Gross Domestic Product and Gross Domestic Income: Revisions and source data. *Survey of Current Business*, 94(6).

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

Hwang, I., Jung, T., Lee, W.-J., and Yang, D. G. (2021). Asymmetric inventory management and the direction of sales changes. *Contemporary Accounting Research*, 38(1):676–706.

Ilut, C., Kehrig, M., and Schneider, M. (2018). Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news. *Journal of Political Economy*, 126(5):2011–2071.

Jaimovich, N. and Rebelo, S. (2009). Can news about the future drive the business cycle? *American Economic Review*, 99(4):1097–1118.

Jenter, D. and Lewellen, K. (2021). Performance-induced ceo turnover. *The Review of Financial Studies*, 34(2):569–617.

Jones, C. S. and Tuzel, S. (2013a). Inventory investment and the cost of capital. *Journal of Financial Economics*, 107(3):557–579.

Jones, C. S. and Tuzel, S. (2013b). New orders and asset prices. *The Review of Financial Studies*, 26(1):115–157.

Jorgensen, B., Li, J., and Sadka, G. (2012). Earnings dispersion and aggregate stock returns. *Journal of Accounting and Economics*, 53(1-2):1–20.

Kahn, J. A., McConnell, M. M., and Perez-Quiros, G. (2002). On the causes of the increased stability of the US economy. *Economic Policy Review*, 8(1):183–202.

Kalay, A., Nallareddy, S., and Sadka, G. (2018). Uncertainty and sectoral shifts: The interaction between firm-level and aggregate-level shocks, and macroeconomic activity. *Management Science*, 64(1):198–214.

Kang, Q., Liu, Q., and Qi, R. (2010). Predicting stock market returns with aggregate discretionary accruals. *Journal of Accounting Research*, 48(4):815–858.

Katz, A. J. et al. (2006). An overview of BEA's source data and estimating methods for quarterly GDP. In *10th OECD-NBS Workshop on National Accounts. Paris, France*.

Kesavan, S., Gaur, V., and Raman, A. (2010). Do inventory and gross margin data improve sales forecasts for US public retailers? *Management Science*, 56(9):1519–1533.

Kesavan, S. and Kushwaha, T. (2014). Differences in retail inventory investment behavior during macroeconomic shocks: Role of service level. *Production and Operations Management*, 23(12):2118–2136.

Kim, R. (2021). The effect of the credit crunch on output price dynamics: The corporate inventory and liquidity management channel. *The Quarterly Journal of Economics*, 136(1):563–619.

Konchitchki, Y. and Patatoukas, P. N. (2014a). Accounting earnings and Gross Domestic Product. *Journal of Accounting and Economics*, 57(1):76–88.

Konchitchki, Y. and Patatoukas, P. N. (2014b). Taking the pulse of the real economy using financial statement analysis: Implications for macro forecasting and stock valuation. *The Accounting Review*, 89(2):669–694.

Krusell, P. and Smith, Jr, A. A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, 106(5):867–896.

Lamont, O. A. (2000). Investment plans and stock returns. *The Journal of Finance*, 55(6):2719–2745.

Lee, H. (2023). Striking while the iron is cold: Fragility after a surge of lumpy investments. *SSRN Working Paper*.

Li, J., Wang, H., and Yu, J. (2021). Aggregate expected investment growth and stock market returns. *Journal of Monetary Economics*, 117:618–638.

Lorenzoni, G. (2009). A theory of demand shocks. *American Economic Review*, 99(5):2050–84.

Lyandres, E. and Palazzo, B. (2016). Cash holdings, competition, and innovation. *Journal of Financial and Quantitative Analysis*, 51(6):1823–1861.

Maio, P. (2016). Cross-sectional return dispersion and the equity premium. *Journal of Financial Markets*, 29:87–109.

Maio, P. and Santa-Clara, P. (2012). Multifactor models and their consistency with the ICAPM. *Journal of Financial Economics*, 106(3):586–613.

McCarthy, J. and Zakrajsek, E. (2000). Microeconomic inventory adjustment: Evidence from US firm-level data. *FRB of New York Staff Report*, (101).

McCracken, M. W. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, 140(2):719–752.

McGrattan, E. R. (1999). *Application of weighted residual methods to dynamic economic models*. Oxford University Press.

McLean, R. D. (2011). Share issuance and cash savings. *Journal of Financial Economics*, 99(3):693–715.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, pages 867–887.

Murphy, K. J. (1999). Executive compensation. *Handbook of labor economics*, 3:2485–2563.

Nallareddy, S. and Ogneva, M. (2017). Predicting restatements in macroeconomic indicators using accounting information. *The Accounting Review*, 92(2):151–182.

Nilsen, Ø. A., Raknerud, A., Rybalka, M., and Skjerpen, T. (2009). Lumpy investments, factor adjustments, and labour productivity. *Oxford Economic Papers*, 61(1):104–127.

Nilsen, Ø. A. and Schiantarelli, F. (2003). Zeros and lumps in investment: Empirical evidence on irreversibilities and nonconvexities. *Review of Economics and Statistics*, 85(4):1021–1037.

Ogneva, M., Piotroski, J. D., and Zakolyukina, A. A. (2020). Accounting fundamentals and systematic risk: Corporate failure over the business cycle. *The Accounting Review*, 95(5):321–350.

Oi, W. Y. (1961). The desirability of price instability under perfect competition. *Econometrica*, 29(1):58–64.

Palazzo, B. (2012). Cash holdings, risk, and expected returns. *Journal of Financial Economics*, 104(1):162–185.

Ramey, V. A. and West, K. D. (1999). Inventories. *Handbook of Macroeconomics*, 1:863–923.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121(1):46–65.

Riddick, L. A. and Whited, T. M. (2009). The corporate propensity to save. *The Journal of Finance*, 64(4):1729–1766.

Rouwenhorst, K. G. (1995). *Asset pricing implications of equilibrium business cycle models*. Princeton University Press.

Rouxelin, F., Wongsunwai, W., and Yehuda, N. (2018). Aggregate cost stickiness in GAAP financial statements and future unemployment rate. *The Accounting Review*, 93(3):299–325.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3):335–370.

Segal, G. (2019). A tale of two volatilities: Sectoral uncertainty, growth, and asset prices. *Journal of Financial Economics*, 134(1):110–140.

Segal, G. and Shaliastovich, I. (2023). Uncertainty, risk, and capital growth. *SAFE Working Paper*.

Shivakumar, L. and Urcan, O. (2017). Why does aggregate earnings growth reflect information about future inflation? *The Accounting Review*, 92(6):247–276.

Simutin, M. (2010). Excess cash and stock returns. *Financial Management*, 39(3):1197–1222.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

Sodjahin, W. R. (2013). Change in cash-holding policies and stock return predictability in the cross section. *Financial Analysts Journal*, 69(1):53–70.

Stark, T. (2010). Realistic evaluation of real-time forecasts in the survey of professional forecasters. *Federal Reserve Bank of Philadelphia (Research Department Special Report)*.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters*, 20(2):177–181.

Terry, S. J. (2023). The macro impact of short-termism. *Econometrica*, 91(5):1881–1912.

Terry, S. J., Whited, T. M., and Zakolyukina, A. A. (2023). Information versus investment. *Review of Financial Studies*, 36(3):1148–1191.

Thomas, J. K. and Zhang, H. (2002). Inventory changes and future returns. *Review of Accounting Studies*, 7(2-3):163–187.

Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21(4):1455–1508.

Wen, Y. (2005). Understanding the inventory cycle. *Journal of Monetary Economics*, 52(8):1533–1555.

West, K. D. (1990). The sources of fluctuations in aggregate inventories and GNP. *Quarterly Journal of Economics*, 105(4):939–971.

Zhang, L. (2005). The value premium. *Journal of Finance*, 60(1):67–103.