Industry Concentration, Sticky Profits, and Return Dynamics

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Abstract

Firms in highly concentrated industries have higher return volatility. This is due to the increased sensitivity to economic cycles in expected returns and conditional volatility. This paper analyzes the relationship between industry concentration and returns by estimating a dynamic factor model with systematic and industry-specific factors. Empirical findings show that concentrated industries experience larger expected profit growth persistence relative to competitive industries. Consistent with theory, this paper demonstrates that concentrated industries offer a higher risk premium relative to competitive ones, but face larger volatility during economic downturns.

Keywords: Competition, Profit Growth Persistence, Risk Premium, Cash Flow News, Return Volatility.

1 Introduction

Industry concentration is increasing across the board, giving rise to higher profits and returns for firms in such industries. The Herfindahl-Hirschman index (HHI) reflects a 40 percent increase for the overall market since the beginning of the 21st century, with an even steeper increase in the business equipment (51 percent) and retail (44 percent) sectors.[1] Although the reason behind this rise is still a debated topic,[2] previous literature notes a positive relationship between profits, return, and industry concentration. This paper empirically analyzes the relationship between industry concentration and returns by estimating a dynamic factor model with *systematic* and industry-specific factors. Empirical findings show that firms in highly concentrated industries offer higher risk premia relative to competitive ones, but are also exposed to higher risk during economic downturns.

In this paper, I analyze the relationship between industry concentration, expected profit growth, expected returns, and return volatility from an asset pricing perspective. I show that concentrated industries have a higher contribution of the cash flow component in total returns and a higher profit sensitivity to economic cycles. This dual effect, in turn, presents two empirical findings; higher risk premia and higher sensitivity to economic cycles by expected returns and conditional volatility. Economic downturns, marked by a larger increase in conditional volatility relative to expected returns, also lead to a significant decrease in the conditional Sharpe ratio in concentrated industries. Thus, from an asset pricing perspective, this paper contributes to the literature by quantitatively analyzing the relationship between industry concentration and returns. From an investments perspective, this paper provides empirical evidence that higher industry concentration is associated with lower Sharpe ratios due to higher contributions of profit growth shocks in total volatility.

Existing literature notes the secular decline in dividend paying firms and new firms initiating dividends, making it difficult to apply the log-linear present value framework to industries (Fama and French (2001), Hoberg and Prabhala (2008), Pettenuzzo et al. (2020)).[3]

[1] For example, Grullon et al. (2019) shows an increase in concentration for over 75 percent of industries in the last two decades. Within the same period, Campbell et al. (2023) shows an increase in the cross sectional average of industry return volatility relative to the period covering mid to late 1990's.

[2] Akcigit and Ates (2023) argue that the decline in knowledge diffusion between industry leaders and laggards leads to an increase in concentration, whereas Liu et al. (2022) points out that low interest rates motivate industry leaders to invest aggressively and increase their market power.

[3] Michaely and Moin (2022) note that there is an increase in the number of dividend paying firms in

Although, the dividend irrelevance theory of Modigliani and Miller (1958) and Miller and Modigliani (1961) is still a debated topic,[4] dividend payouts depend on firms' dividend policies and are difficult to link to economic fundamentals.[5] The analysis in this paper is based on the latent variables representation of the log-linear present value framework (Van Binsbergen and Koijen (2010)).[6] I replace dividends with gross profits using the clean surplus accounting relationship[7] and generalize the state-space model used in Van Binsbergen and Koijen (2010) by including local and global factors. I estimate them using a dynamic factor model (DFM) using the Fama-French 30 industry classification and capture industry-specific and *systematic* expected profit growth and returns. By using profits, the model developed in this paper provides a link between industry competition and cash flow growth persistence.

Model results show that highly concetrated industries have more persistent expected profit growth relative to competitive industries. The DFM estimates show that industry-level quarterly expected returns are highly persistent and similar across industries, ranging between 0.78 (Beer/Liquor) and 0.94 (Business Equipment) with a mean of 0.87. However, expected profit growth persistence estimates show large heterogeneity across industries, ranging between 0.03 (Steel) and 0.80 (Business Equipment) with a mean of 0.45. Highly concentrated industries, specifically, have more persistent expected profit growth relative to competitive industries, with a correlation coefficient of 50 percent between the persistence coefficient and the HHI score. Large firms, which comprise concentrated industries, tend to invest aggressively and protect their investments through decreased knowledge diffusion, leading to a decrease in product fluidity in the industry and an increase in profit accumu-

recent years (23% in 2000 and 36% in 2018). Yet, the number in dividend paying firms is still very small. Furthermore, technology firms, which make up approximately 20 percent of the S&P 500 in value weights, are known for not issuing dividends.

[4]See for example DeAngelo and DeAngelo (2006).

[5]Although this study is not concerned with cash flow proxies in present value models, I present empirical results for the aggregate market comparing dividends and profits as cash flow proxies in Appendix A. Additional cash flow proxies, such as share repurchases, have been favored as an alternative to the sole use of dividends (Grullon and Michaely (2002), Pruitt (2023)).

[6]Typically, the present value framework is used to model aggregate market returns and dividend growth. See for example Campbell (1991), Campbell and Ammer (1993), Cochrane (2008).

[7]The clean surplus accounting (CSA) relationship relates firms dividends to the difference between profits and the change in book equity (total asset less total liabilities). The use of CSA led to the formulation of the Abnormal Earnings Model of Ohlson (1995) and Feltham and Ohlson (1995).

lation.[8] This mechanism is the primary driver of *sticky* profits in concentrated industries, where the positive relationship between expected profit growth *persistence* and industry concentration highlights the importance of persistence in addition to profit levels.[9]

The empirical evidence provided in this paper is consistent with the production-based asset pricing (PBAP) model.[10] The PBAP model predicts that firms for which corporate payouts are highly correlated with the stochastic discount factors (SDF) need to offer a higher risk premium. In the PBAP model, aggregate shocks enter corporate payouts through profits. Hence, firms with profits that are highly correlated with economic cycles need to offer a higher premium. I regress recession dummies on profit growth to corroborate the intuition provided by the PBAP model. Coefficient estimates for the recession dummies are significant and negative for highly concentrated industries (-4 percent), whereas competitive industries' coefficient estimates are smaller in magnitude and insignificant (-1.9 percent). This indicates a higher covariance between profits of concentrated industries and the business cycle, providing a link between empirical results and theory.

Product fluidity provides a potential explanation to the mechanism behind the high covariance between profits of concentrated industries and the business cycle. Competitive industries, such as retail, offer substitutable products that have high *fluidity*, whereas concentrated industries, such as machinery or household durables, offer products that are *rigid*. A negative aggregate shock would affect producers of fluid products relatively less than producers of rigid products as consumers may find substitutes for fluid goods and services. On the other hand, consumers may hold off from purchasing goods with higher costs and low substitutability, such as household durables, decreasing profits for producers of rigid products. Statistical tests show a positive monotonic relationship between industry concentration and product rigidity.[11] Combined with the regression output (which indicates a larger profit growth decrease in higher concentration), these results suggest that concentrated industries tend to have low product fluidity and higher covariance with systematic shocks relative to competitive industries, leading to a higher risk premium. Following this intuition, economic

[8] Akcigit and Ates (2023), Liu et al. (2022), and Hoberg et al. (2014)

[9] Gutiérrez and Philippon (2017), Grullon et al. (2019), Covarrubias et al. (2020), De Loecker et al. (2020), Kwon et al. (2024)

[10] See for example Liu et al. (2009).

[11] I use the fluidity measure introduced by Hoberg et al. (2014) and take the inverse to measure product rigidity.

downturns then lead profits of concentrated industries to decline more than competitive industries, corroborating the empirical evidence.

Concentrated industries are also more sensitive to aggregate cash flow news due to larger expected profit growth persistence, resulting in higher risk premium. This is because an adverse cash flow shock results in lower returns today with unchanged future investment opportunities. Larger expected profit growth persistence also results in higher sensitivity of unexpected returns to cash flow news. Conversely, an adverse discount rate shock results in lower returns today but better investment opportunities in the future.[12] These findings are consistent with the unexpected returns framework, which states that stocks with higher covariance with cash flow news ought to offer higher risk premia. As such, concentrated industries offer higher risk premia due to higher loadings on systematic cash flow news, leading to a higher contribution of cash flow news in unexpected returns.

Recent literature, such as Corhay et al. (2020) and Dou et al. (2021), argues that industry concentration leads to higher return volatility due to the higher sensitivity of profits to new entrants and systematic shocks. This is, in essence, an empirical question: is the share of expected profit growth shocks in return volatility larger in concentrated industries relative to competitive industries? Existing literature, such as Cochrane (2008) and Van Binsbergen and Koijen (2010), shows that all variation in the dividend yield and unexpected return is accounted by discount rate news. However, cross-sectional variation in cash flow news share is directly tied to expected cash flow persistence and expected return persistence. In this paper, variance decompositions show that cash flow news and discount rate news contributions to unexpected returns range between 8 and 74 percent and 39 and 101 percent, respectively. These results highlight the importance of cash flow news in unexpected return variation. As the gap between expected profit growth persistence and expected return persistence narrows, the share of cash flow news in total unexpected return variance increases. It follows, then, that cash flow news share is larger for concentrated industries relative to competitive industries.

Based on unexpected returns, time variation in conditional return volatility must be due to the time variation in cash flow news and discount rate news. Thus, I leverage a multivariate GARCH (MGARCH) to jointly model cash flow and discount rate news and compute conditional return volatility. The MGARCH results indicate higher persistence of

[12]See Campbell and Vuolteenaho (2004).

conditional variation in cash flow news relative to discount rate news across all industries. I regress recession dummies on conditional return volatility to test the effect of economic downturns across industries. The recession dummy estimate is twice as large and significant in concentrated industries relative to competitive industries (0.28 vs 0.14). Combined with the larger cash flow news share in concentrated industries, conditional return volatility is more sensitive to economic cycles and increases relatively more during economic downturns.

Empirical findings from this paper show that firms in highly concentrated industries offer a higher risk premium relative to competitive ones, but are also exposed to higher risk during economic downturns. Higher risk premia in concentrated industries can be accredited to two key factors. First, higher covariance with systematic cash flow news. Second, higher return volatility resulting from a higher cash flow news share in unexpected returns. Furthermore, based on empirical evidence, conditional Sharpe ratios of concentrated industries decrease more during economic downturns, indicating a larger rise in conditional volatility. In conclusion, this paper contributes to the existing literature by empirically highlighting the importance of cash flow shocks in concentrated industries' return volatility and linking cash flow growth persistence to economic fundamentals based on profits and concentration.

1.1 Related Literature

The results of this paper are related to three strands of literature. I estimate the expected profit growth persistence coefficients using the dynamic factor model for 26 different sectors and show a positive correlation between industry concentration and profit growth persistence. This finding is related to the growing literature documenting the rise in industry concentration. The results from Autor et al. (2020) and Barkai (2020) relate increasing industry concentration to the decline in labor share of GDP and the rise in profits. Gutiérrez and Philippon (2017) shows that the decline in aggregate investment is due to the rise in concentration. Covarrubias et al. (2020) reiterates the negative correlation between industry concentration, investment, and labor share, and finds a positive relationship between concentration and profits. Grullon et al. (2019), De Loecker et al. (2020), and Kwon et al. (2024) provide further evidence on the positive correlation between industry concentration and profit growth. In light of these stylized facts, Liu et al. (2022) develop a general equilibrium model explaining the rise in industry concentration and argue that low interest rate environments increase industry concentration by allowing industry leaders to invest more aggressively. In turn, industry followers do not want to enter into a neck-to-neck competition and are discouraged, thus increasing concentration. Akcigit and Ates (2023) propose that knowledge diffusion between industry leaders and followers decreased through increased R&D protection, hence, increasing the technology gap and discouraging followers and new entrants.

My results are also related to the recent production based theoretic asset pricing literature. I find that cash flow news share increases with industry concentration. As industry concentration rises, return movements due to cash flow shocks increase. Corhay et al. (2020) build a production based general equilibrium asset pricing model in which price markups vary due to oligopolistic firm competition. The authors show a strong positive relationship between market power, profits, and expected returns. As competition weakens, high market power firms increase their markups which leads to high profits. However, under weak competition, cash flow risk increases due to the sensitivity of profits to markups. Dou et al. (2021) develop a game theoretic dynamic competition model which allows for collusive Nash equilibria. A main result of the model is that low interest rates yield high industry concentration which lead to high profits through collusion.[13] Furthermore, the model shows that highly concentrated industries are exposed to interest shocks to a greater degree, which in turn, offer higher compensation through higher expected returns. Indirectly, these results imply that concentrated industries have higher cash flow news contribution to return variance, which I model directly and present empirical evidence for this relationship.

Methodologically, I use the Campbell and Shiller (1988) log-linear present value model as the starting point for the analysis and extend it to the industry level. The original model uses aggregate log price-to-dividend ratio and dividend growth (Campbell (1991), Campbell and Ammer (1993), Cochrane (2008), Van Binsbergen and Koijen (2010)). Other studies extend the analysis to the firm level using earnings and book-to-market ratios using clean surplus accounting (Vuolteenaho (2002), Campbell and Vuolteenaho (2004), Campbell et al. (2010), Kelly and Pruitt (2013)). I use industry level value-weighted gross profits in the analysis to explore the relationship between industry concentration, profits, and return volatility. The literature typically relies on vector autoregressions. I generalize the Van Binsbergen

[13] This finding is directly related to Liu et al. (2022), in which the authors relate high concentration to low interest rates.

and Koijen (2010) latent variables framework to industries and include two common factors capturing systematic variation in expected returns and expected profit growth.

Within the same umbrella, my results are also related to the variance decomposition literature pioneered by Campbell (1991), which decompose return movements into expected discount rate shocks and expected cash flow shocks. Mainly, the literature indicates that return movements are due to expected discount rate shocks with minimal contribution from expected cash flow shocks (Campbell and Ammer (1993), Campbell and Vuolteenaho (2004), Cochrane (2008), Van Binsbergen and Koijen (2010)). My results indicate that expected cash flow shocks are non-negligible contributors to return volatility, especially in concentrated industries.

The rest of the paper is organized as follows. Section 2 develops the present value framework, Section 3 presents summary statistics of the data and describes the variable construction procedure. Section 4 presents empirical results, Section 5 shows the unconditional variance decomposition of unexpected returns and multivariate GARCH results. Section C presents out of sample forecasting results. Finally, Section 6 concludes.

2 Present Value Model and Latent Variables

Since Campbell and Shiller (1988), empirical work on present value models predominantly used dividends as measure of cash flows (Campbell (1991), Campbell and Ammer (1993), Van Binsbergen and Koijen (2010)). I use the Clean Surplus Accounting (CSA) relationship, defined in equation (2.1), to derive a log-linear present value model that uses profits as the fundamental measure of cash flows. The CSA originates from the work of Ohlson (1995) and Feltham and Ohlson (1995), where the authors relate fundamental stock prices to discounted abnormal profits. In the finance literature, Vuolteenaho (2002) and Kelly and Pruitt (2013) use the CSA to develop an approximate present value model that relates the log book to market ratio to the discounted infinite sum of return on equity less the risk free rate and excess returns[14]. Though Campbell and Vuolteenaho (2004) base their econometric

[14] Vuolteenaho (2002) defines the book to market ratio as

$$\theta_t = log\left(\frac{BE_t}{ME_t}\right) = log\left(\frac{(1 + \Pi_t/BE_{t-1} - D_t/BE_{t-1})}{(1 + (\Delta ME_t + D_t)/ME_{t-1} - D_t/ME_{t-1})}\frac{BE_{t-1}}{ME_{t-1}}\right).$$

framework on the dividend discount model, the empirical model uses the market price-to-earnings ratio, value spread, and the term yield spread. Which indicates the potential use of the CSA relationship.

The CSA equation is defined as:

$$BE_t = BE_{t-1} + \Pi_t - D_t, \tag{2.1}$$

where D_t are dividends, BE_t is book equity, and Π_t are profits at time t. With some rearranging, $D_t = \Pi_t - \Delta BE_t$, expressing dividends as a function of profits and change in book equity. I start with the definition of returns and substitute dividends out using the CSA.

$$\begin{aligned}
R_{t+1} &= \frac{P_{t+1} + D_{t+1}}{P_t} \\
&= \frac{P_{t+1} + \Pi_{t+1} - \Delta BE_{t+1}}{P_t} \\
r_{t+1} &\approx \Delta\pi_{t+1} - pe_t + \log\left[1 + \exp(pe_{t+1}) + \exp\left(\log\left(\frac{\Pi_{t+1}}{\Delta BE_{t+1}}\right)\right)\right],
\end{aligned}$$

where $pe_{t+1} \equiv \log\left(\frac{P_{t+1}}{\Pi_{t+1}}\right)$, and $\Delta\pi_{t+1} \equiv \log\left(\frac{\Pi_{t+1}}{\Pi_t}\right)$. I define the variable $\frac{\Pi_{t+1}}{\Delta BE_{t+1}} = EV_{t+1}$ as the economic value generated from operations. Based on the Taylor Expansion, I get the following expression

$$r_{t+1} \approx \kappa + \Delta\pi_{t+1} - pe_t + \rho_1 pe_{t+1} + \rho_2 ev_{t+1},$$

where:

$$
\begin{aligned}
ev_{t+1} &\equiv \log\left(\frac{\Pi_{t+1}}{\Delta BE_{t+1}}\right)\\
\rho_1 &= \frac{\exp(\bar{pe})}{1+\exp(\bar{pe})+\exp\left(\bar{ev}\right)}\\
&0<\rho_1<1\\
\rho_2 &= \frac{\exp(\bar{ev})}{1+\exp(\bar{pe})+\exp\left(\bar{ev}\right)}\\
&0<\rho_2<1\\
&0<\rho_1+\rho_2<1\\
\kappa &= \log[1+\exp(\bar{pe})+\exp\left(\bar{ev}\right)]-(\rho_1\bar{pe}+\rho_2\bar{ev})
\end{aligned}
$$

The return equation takes the following form:

$$
\begin{aligned}
r_{t+1} &\approx \kappa+\Delta\pi_{t+1}-pe_t+\rho_1 pe_{t+1}+\rho_2 ev_{t+1}\\
pe_t &\approx \kappa+\Delta\pi_{t+1}+\rho_1 pe_{t+1}+\rho_2 ev_{t+1}-r_{t+1}
\end{aligned}
$$

Because of the autoregressive component in the above equation, I iterate it forward and get the log-linear present value relationship:

$$
pe_t \approx \frac{\kappa}{1-\rho_1}+\sum_{h=1}^{\infty}\rho_1^{h-1}\left(\Delta\pi_{t+h}+\rho_2 ev_{t+h}-r_{t+h}\right).
$$

The above representation is only valid for one time series, the same is valid for J industries, hence, I represent the present value relationship as:

$$
pe_{j,t} \approx \frac{\kappa_j}{1-\rho_{1,j}}+\sum_{h=1}^{\infty}\rho_{1,j}^{h-1}\left(\Delta\pi_{j,t+h}+\rho_2 ev_{j,t+h}-r_{j,t+h}\right). \tag{2.2}
$$

Equation(2.2) states that the log price-to-profits ratio depends on the discounted infinite sum of future returns, profit growth, and economic value add from operations at the industry level. Moreover, it predicts that current price-to-profits would fall if the discounted sum of returns increases, or if the discounted sum of profit growth falls.

I model industry level expected profit growth ($g_{j,t+1}$) and expected returns ($\mu_{j,t+1}$) as AR(1) with exogenous global factors ($F_{t+1}^{(1)}$, $F_{t+1}^{(2)}$), and model expected economic value add as an AR(1) process. The global factors capture common variation across industries and are meant to capture systematic variation in expected returns and expected profit growth.

$$\begin{aligned}
\mu_{j,t+1} &= \delta_{0,j} + \delta_{1,j}(\mu_{j,t} - \delta_{0,j}) + \delta_{2,j}(F_{t+1}^{(1)} - \gamma_0) + \varepsilon_{j,t+1}^{\mu} \\
F_{t+1}^{(1)} &= \gamma_0 + \gamma_1(F_t^{(1)} - \gamma_0) + \varepsilon_{t+1}^{F^{(1)}} \\
g_{j,t+1} &= \omega_{0,j} + \omega_{1,j}(g_{j,t} - \omega_{0,j}) + \omega_{2,j}(F_{t+1}^{(2)} - \phi_0)\varepsilon_{j,t+1}^{\psi} \\
F_{t+1}^{(2)} &= \phi_0 + \phi_1(F_t^{(2)} - \phi_0) + \varepsilon_{t+1}^{F^{(2)}} \\
\eta_{j,t+1} &= \lambda_{0,j} + \lambda_{1,j}(\eta_{j,t} - \lambda_{0,j}) + \varepsilon_{j,t+1}^{\eta},
\end{aligned}$$

where

$$\begin{aligned}
\mu_{j,t} &\equiv \mathbb{E}_t[r_{j,t+1}] \\
g_{j,t} &\equiv \mathbb{E}_t[\Delta\pi_{j,t+1}] \\
\eta_{j,t} &\equiv \mathbb{E}_t[ev_{j,t+1}].
\end{aligned}$$

Taking expectations on both sides:

$$pe_{j,t} = \mathcal{A}_j + \mathcal{B}_{1,j}(g_{j,t} - \omega_{0,j}) + \mathcal{B}_{2,j}(\eta_{j,t} - \lambda_{0,j}) - \mathcal{B}_{3,j}(\mu_{j,t} - \delta_{0,j}),$$

where:

$$\begin{aligned}
\mathcal{A}_j &= \frac{\kappa_j + \omega_{0,j} + \rho_{2,j}\lambda_{0,j} - \delta_{0,j}}{1 - \rho_{1,j}} \\
\mathcal{B}_{1,j} &= \frac{1}{1 - \rho_{1,j}\omega_{1,j}} \\
\mathcal{B}_{2,j} &= \frac{\rho_{2,j}}{1 - \rho_{1,j}\lambda_{1,j}} \\
\mathcal{B}_{3,j} &= \frac{1}{1 - \rho_{1,j}\delta_{1,j}}.
\end{aligned}$$

I further define the following variables to simplify notation:

$$\begin{aligned}
\widetilde{g}_{j,t} &= (g_{j,t} - \omega_{0,j}) \\
\widetilde{F}^{(2)}_t &= (F^{(2)}_t - \phi_0) \\
\widetilde{\mu}_{j,t} &= (\mu_{j,t} - \delta_{0,j}) \\
\widetilde{F}^{(1)}_t &= (F^{(1)}_t - \gamma_0) \\
\widetilde{\eta}_{j,t} &= (\eta_{j,t} - \lambda_{0,j}),
\end{aligned}$$

and obtain the log price to profit ($pe_{j,t}$) relationship with future expected returns, future expected profit growth, and future expected economic value add from operations.

$$pe_{j,t} = \mathcal{A}_j + \mathcal{B}_{1,j}\widetilde{g}_{j,t} + \mathcal{B}_{2,j}\widetilde{\eta}_{j,t} - \mathcal{B}_{3,j}\widetilde{\mu}_t \tag{2.3}$$

2.1 State Space Representation

I model equation (2.3) using a state space model with 2J observation equations and 3J+2 state equations.

$$\begin{aligned}
&\underline{\text{Observations Equations:}} \\
pe_{j,t} &= \mathcal{A}_j + \mathcal{B}_{1,j}\widetilde{g}_{j,t} + \mathcal{B}_{2,j}\widetilde{\eta}_{j,t} - \mathcal{B}_{3,j}\widetilde{\mu}_{j,t} \\
\Delta\pi_{j,t+1} &= \omega_{0,j} + \widetilde{g}_{j,t} + \varepsilon^{\Delta\pi}_{j,t+1} \\
&\underline{\text{State Equations:}} \\
\widetilde{\mu}_{j,t+1} &= \delta_{1,j}\widetilde{\mu}_{j,t} + \delta_{2,j}\widetilde{F}^{(1)}_{t+1} + \varepsilon^{\widetilde{\mu}}_{j,t+1} \\
\widetilde{F}^{(1)}_{t+1} &= \gamma_1\widetilde{F}^{(1)}_t + \varepsilon^{F^{(1)}}_{t+1} \\
\widetilde{g}_{j,t+1} &= \omega_{1,j}\widetilde{g}_{j,t} + \omega_{2,j}\widetilde{F}^{(2)}_{t+1} + \varepsilon^{\widetilde{g}}_{j,t+1} \\
\widetilde{F}^{(2)}_{t+1} &= \phi_1\widetilde{F}^{(2)}_t + \varepsilon^{F^{(2)}}_{t+1} \\
\widetilde{\eta}_{j,t+1} &= \lambda_{1,j}\widetilde{\eta}_{j,t} + \varepsilon^{\widetilde{\eta}}_{j,t+1}
\end{aligned}$$

This system is under-identified, hence, I impose $\rho_{2,j} = 0$, which implies $\mathcal{B}_{2,j} = 0$. Furthermore, because the first observation equation does not have an error term, I substitute the expected returns ($\widetilde{\mu}_{j,t+1}$) equation into equation (2.3), and obtain the following state space model which has 2J observation and J+2 state equations.

Observation Equations:

$$pe_{j,t+1} = (1-\delta_{1,j})\mathcal{A}_j + \delta_{1,j} pe_{j,t} - (\delta_{1,j}-\omega_{1,j})\mathcal{B}_{1,j}\widetilde{g}_{j,t} + \mathcal{B}_{1,j}\omega_{2,j}\widetilde{F}^{(2)}_{t+1} - \mathcal{B}_{3,j}\delta_{2,j}\widetilde{F}^{(1)}_{t+1} + \mathcal{B}_{1,j}\varepsilon^{\widetilde{g}}_{j,t+1} - \mathcal{B}_{3,j}\varepsilon^{\widetilde{\mu}}_{j,t+1} \tag{2.4}$$

$$\Delta\pi_{j,t+1} = \omega_{0,j} + \widetilde{g}_{j,t} + \varepsilon^{\Delta\pi}_{j,t+1} \tag{2.5}$$

State Equations:

$$\widetilde{F}^{(1)}_{t+1} = \gamma_1 \widetilde{F}^{(1)}_t + \varepsilon^{F^{(1)}}_{t+1} \tag{2.6}$$

$$\widetilde{g}_{j,t+1} = \omega_{1,j}\widetilde{g}_{j,t} + \omega_{2,j}\widetilde{F}^{(2)}_{t+1} + \varepsilon^{\widetilde{g}}_{j,t+1} \tag{2.7}$$

$$\widetilde{F}^{(2)}_{t+1} = \phi_1 \widetilde{F}^{(2)}_t + \varepsilon^{F^{(2)}}_{t+1} \tag{2.8}$$

Implied Expected Returns:

$$\widetilde{\mu}_{j,t|t} = \mathcal{B}^{-1}_{3,j}\left[\frac{\mathbb{E}_t[pe_{j,t+1}]}{\delta_{1,j}} - \left(\frac{1+\delta_{1,j}}{\delta_{1,j}}\right)\mathcal{A}_j - \mathcal{B}_{1,j}\left(1-\frac{\delta_{1,j}-\omega_{1,j}}{\delta_{1,j}}\right)\widetilde{g}_{j,t|t}\right] + \frac{\delta_{2,j}\gamma_1}{\delta_{1,j}}\widetilde{F}^{(1)}_{t|t} - \frac{\mathcal{B}_{1,j}\omega_{2,j}\phi_1}{\mathcal{B}_{3,j}\delta_{1,j}}\widetilde{F}^{(2)}_{t|t} \tag{2.9}$$

There are three industry specific shocks, namely, shocks to expected returns ($\varepsilon^{\widetilde{\mu}}_{t+1}$), shocks to expected profit growth ($\varepsilon^{\widetilde{g}}_{t+1}$), and shocks to realized profit growth ($\varepsilon^{\Delta\pi}_{t+1}$). Additionally, there are 2 systematic shocks, $\varepsilon^{F^{(1)}}_{t+1}$ and $\varepsilon^{F^{(2)}}_{t+1}$, which describes shocks to global factors. For a given industry (j) the covariance matrix takes the following form:

$$\Sigma_j \equiv \text{var}\left(\begin{bmatrix}\varepsilon^{\widetilde{\mu}}_{j,t+1}\\ \varepsilon^{\widetilde{g}}_{j,t+1}\\ \varepsilon^{\Delta\pi}_{j,t+1}\\ \varepsilon^{F^{(1)}}_{t+1}\\ \varepsilon^{F^{(2)}}_{t+1}\end{bmatrix}\right) = \begin{bmatrix}\sigma^2_{j,\mu} & \sigma_{j,\mu g} & 0 & 0 & 0\\ \sigma_{j,\mu g} & \sigma^2_{j,g} & 0 & 0 & 0\\ 0 & 0 & \sigma^2_{j,\Delta\pi} & 0 & 0\\ 0 & 0 & 0 & \sigma^2_{F^{(1)}} & \sigma_{F^{(1)}F^{(2)}}\\ 0 & 0 & 0 & \sigma_{F^{(1)}F^{(2)}} & \sigma^2_{F^{(2)}}\end{bmatrix}.$$

Equations (2.6) and (2.8) describe the dynamics of the two global factors with their respective shocks. γ_1 and ϕ_1 are the persistence coefficients of the first and second global factor, respectively. The global factors enter the observation equations ((2.4) and (2.5)), $\widetilde{F}^{(1)}_{t+1}$ and $\widetilde{F}^{(2)}_{t+1}$ enters (2.4) through expected returns ($\widetilde{\mu}_{j,t+1}$) and expected profits growth ($\widetilde{g}_{j,t+1}$), respectively. Equation (2.5) describes the dynamics of expected industry specific profit growth. $\omega_{1,j}$ is the persistence coefficient of industry specific expected profit growth, and $\omega_{2,j}$ captures the contemporaneous effect of the second global factor on expected profit growth. $\delta_{1,j}$ represents the persistence of industry specific expected returns, and $\delta_{2,j}$ captures the contemporaneous effect of the first global factor ($\widetilde{F}^{(1)}_{t+1}$) on expected returns.

Lastly, equation (2.9) links expected price-to-profit, expected profit growth and global factors to industry specific expected returns. The novelty in this relationship is the link between expected returns and global factors. The first term in (2.9) relates industry specific movements to expected returns. The loading on expected profit growth ($\widetilde{g}_{j,t}$) is negative, which implies that high expected profit growth leads to lower expected returns for the subsequent period. This finding is related to Van Binsbergen et al. (2023), where stocks with optimistic earnings forecasts earn lower returns in the following period. The last two terms in (2.9) relate expected returns to the global factors.

3 Data

I collect firm level data at the quarterly frequency from COMPUSTAT for all publicly traded firms between 1976Q2 and 2021Q4. I assign each firm to their respective industries based on the Fama-French 30 industry classification, and exclude the finance industry from the analysis. Table 1 presents the industries included in the sample. The main variables of interest that bridge the gap between the theoretical model and the empirical model are profits, book equity (BE_t), and prices. I focus on gross profits (equation (3.1)) because of the wider data availability and use in previous literature.

$$\Pi_t^{gma} = \text{Revenue}_t - \text{COGS}_t. \tag{3.1}$$

3.1 Variable Construction

To estimate the latent variables model, I construct value weighted price and profit indexes at the industry level.

$$p_{j,t} = \log\left(\sum_{i=1}^{N} \frac{ME_{i,j,t}}{\sum_{i=1}^{N} ME_{i,j,t}} P_{i,j,t}\right) \mid \text{for firm i in industry j}$$
$$\pi_{j,t} = \log\left(\sum_{i=1}^{N} \frac{ME_{i,j,t}}{\sum_{i=1}^{N} ME_{i,j,t}} \Pi_{i,j,t}\right) \mid \text{for firm i in industry j}$$
$$d_{j,t} = \log\left(\sum_{i=1}^{N} \frac{ME_{i,j,t}}{\sum_{i=1}^{N} ME_{i,j,t}} \text{Div}_{i,j,t}\right) \mid \text{for firm i in industry j}$$

In the above equations, $P_{i,t}$ indicates the stock price, $ME_{i,t}$ indicates market equity, $\Pi_{i,t}$ indicates profit (measured as gross profits), and $\text{Div}_{i,t}$ indicates dividends paid for firm i in industry j at time t. For the sector portfolios I look at the top 80$^{\text{th}}$ percentile of firms by market equity to ensure that the firms included are tradeable. To smooth out the seasonal components in dividends and profits, I use the one sided X13 ARIMA-SEATS procedure from Census Bureau[15]. Then, I construct the log price to profits ratio ($pe_{j,t}$), log price to dividend ratio ($pd_{j,t}$), dividend growth($\Delta d_{j,t}$), and profit growth ($\Delta\pi_{j,t}$) as follows:

$$pe_t = p_t - \pi_t$$
$$pd_t = p_t - d_t$$
$$\Delta\pi_t = \pi_t - \pi_{t-1}$$
$$\Delta d_t = d_t - d_{t-1}.$$

3.2 Descriptive Statistics

Table 2 presents summary statistics for quarterly returns, and seasonally adjusted price-to-profits and profit growth. The value weighted market average return is 3.1 percent per quarter, and value weighted profit and dividend growth are approximately 2 percent. Value

[15] Please see link.

weighted sector returns do not show much variation relative to market returns. However, average log price-to-profits displays notable heterogeneity across industries. The two most expensive industries are business equipment and health with and average log price-to-profits of 3.61 and 3.62, respectively. The cheapest sectors include beer/liquor, autos, coal and textiles with an average log price-to-profits of approximately 1.4. The average quarterly market profit growth is 1.8 percent, which is close to the pooled average. Profit growth across industries exhibit heterogeneity, the business equipment sector's average quarterly profit growth is 2.3 percent, which is the highest in the sample. The lowest average profit growth is 0.6 percent per quarter, which corresponds to the electrical equipment sector. The summary statistics highlight the heterogeneity in profit growth and log price-to-profit across sectors with very similar returns. In the following sub-section I test the relationship between industry concentration and returns, and Sharpe ratios.

3.3 Industry Concentration, Returns, and Sharpe Ratios

Recent literature highlights a positive relationship between industry concentration and returns. In this subsection, I present stylized facts on the relationship between HHI scores, returns, and Sharpe ratios. Figure 1 shows HHI scores for the business equipment, services, retail, and health industries between 1990 and 2019. The figure shows a clear upward trend since the early 2000. Panel B of Table 3 presents HHI growth rates in percent between 2000 and 2019 for all industries in the sample and shows an increase in HHI for the majority of the industries. The table shows a decrease in concentration for extractive industries, such as coal, mines, and oil. However, I observe an increase in concentration for the majority of the industries. The business equipment's, which combines software and hardware industries, HHI score grew by 44 percent between 2000 and 2019 and the retail industry's HHI grew by 51 percent.

One of the main goal of this study is to analyze the relationship between industry concentration, returns, and volatility. Hence, I test for a monotonic relationship between industry concentration and returns, and industry concentration and Sharpe ratios. I sort industry returns and Sharpe ratios into increasing HHI portfolios and use the Patton and Timmermann (2010) monotonic relationship test. First, I test the hypothesis of increasing returns and concentration, and second decreasing Sharpe ratios with increasing concentration. Economically, these test imply that industry concentration leads to higher volatility and lower Sharpe ratios. The test results indicate a weak increasing monotonic relationship between industry concentration and returns and a strong decreasing monotonic relationship between industry concentration and Sharpe ratios (Table 4).

3.4 Industry Concentration and Product Fluidity

Product market fluidity is an important indicator of the level of competition in an industry. Intuitively, product fluidity should be higher in competitive industries relative to concentrated industries, as fluidity measures competitive threats to the products offered by a firm. Following the same intuition, firms operating in an industry in which product fluidity is high do not enjoy persistent profits or profit growth. I use the Hoberg et al. (2014) firm-year level product fluidity data available from 1989 to 2021 to construct industry-year product fluidity as follows:

$$\text{Fluid}_{j,t} = \sum_{i}^{N} \omega_{i,t} \text{Fluid}_{i,t}, \text{ for all } i \text{ in industry } j,$$

in which $\omega_{i,t}$ is the value weight of firm i in industry j at time t, and $\text{Fluid}_{i,t}$ is product fluidity for firm i in industry j at time t. Then I construct the rigidity measure as the inverse of fluidity:

$$\text{Rigid}_{j,t} = \frac{1}{\text{Fluid}_{j,t}}.$$

Using the computed industry-year level rigidity, I test the null of no increasing monotonic relationship between industry concentration and product rigidity. I reject the null hypothesis at the 5 percent level for all combinations of the null (Table 5). Statistical tests present evidence confirming the positive relationship between industry concentration and product rigidity.

4 Empirical Results

This section presents estimation results of the Dynamic Factor Model described in equations (2.4)-(2.9). Expected returns are highly persistent across industries. However, there is large heterogeneity in expected profit growth persistence. I find that expected profit growth persistence is larger in concentrated industries relative to competitive industries. An explanation for the positive relationship between the persistence parameter and industry concentration is product fluidity. Low fluidity indicates low competitive threats to a firm's product within that industry. Thus, large firms in such industries are able to hold and accumulate more profits. Furthermore, this allows large firms in concentrated industries to increase markups, which is consistent with the recent literature.[16] This has clear implications for expected industry returns, a 1 percent increase in expected profit growth leads to lower expected returns for concentrated industries relative to competitive industries.

4.1 Dynamic Factor Model

I estimate the latent variables model derived in Section 2 using a dynamic factor model (DFM) with local and global factors, which has the advantage of estimating industry specific and common dynamics across sectors. To the best of my knowledge, this paper is the first in using the DFM framework in the estimation of industry specific expected returns and expected cash flow growth. Table 6 present the DFM estimates at the quarterly frequency for 26 industries. Persistence parameters for expected returns ($\delta_{1,j}$) range between 0.78 (Beer/Liquor) and 0.94 (Business equipment and Textiles). The average expected return persistence across sectors is 0.87 with a standard deviation of 0.04. This confirms that expected returns are highly persistent at the industry level as well as at the market level.[17]

Expected return persistence does not vary significantly across sectors. However, expected profit growth persistence is heterogeneous across sectors. The average cash flow growth persistence ($\omega_{1,j}$) is 0.45 with a standard deviation of 0.25. Business equipment and automotive sectors have the highest expected cash flow growth at 0.80 and 0.79, respectively. I measure industry concentration with the Herfindahl–Hirschman index (HHI) and sort $\omega_{1,j}$ by the HHI to explore the relationship between concentration and expected profit growth persistence. Figure 2 shows a scatter plot of HHI rank and cash flow growth persistence rank with correlation of approximately 50 percent. This suggests that concentrated sectors have

[16] See for example, Liu et al. (2022), Dou et al. (2021), and Corhay et al. (2020).

[17] Pástor and Stambaugh (2009), Campbell and Cochrane (1999), and Fama and French (1988) show that expected market returns are highly persistent at the annual frequency at approximately 0.94.

higher profit growth persistence relative to competitive sectors.[18] The positive relationship between industry concentration and expected profit growth persistence is a key finding of this paper. Product fluidity, introduced by Hoberg et al. (2014), measures the potential competitive threat to a firm's product, and by extension to its profits, within that industry. Thus, product fluidity offers an insight to profit growth persistence and the level of competition within an industry. Firms operating in industries in which product fluidity is low face low levels of competition (Table 5). Hence, they are able to accumulate more profits due to their protective moats (Akcigit and Ates (2023)) or increased price markups (Corhay et al. (2020), Dou et al. (2021)).

There are two present value coefficients in the DFM, $\mathcal{B}_{1,j}$ is the present value coefficient on expected profit growth and $\mathcal{B}_{3,j}$ is the present value coefficient on expected returns. As in the Van Binsbergen and Koijen (2010) model, present value coefficients are directly linked to industry specific log-linearization constants ($\rho_{1,j}$) and persistence coefficients. Mechanically, cross-sectional variation in the present value coefficients are due to variation in $\rho_{1,j}$, $\delta_{1,j}$, and $\omega_{1,j}$. Industries with large $\rho_{1,j}$ and $\delta_{1,j}$ have larger $\mathcal{B}_{3,j}$, implying that expensive industries with highly persistent expected returns have larger expected return present value coefficients. The same reasoning applies to $\mathcal{B}_{1,j}$. Highly concentrated industries tend to have a relatively larger expected profit growth persistence parameter, thus, $\mathcal{B}_{2,j}$ tend to be larger for those industries. Across sectors, $\mathcal{B}_{3,j}$ is larger than $\mathcal{B}_{1,j}$, this is because expected returns are more persistent than expected profit growth.

Expected returns and cash flow growth also load on the global factors. Specifically, expected returns load on the first global factor ($\widetilde{F}^{(1)}$), and expected cash flow growth load the second global factor ($\widetilde{F}^{(2)}$). The DFM extracts $\widetilde{F}^{(1)}$ from log price-to-profits, and $\widetilde{F}^{(2)}$ from profit growth. The persistence parameter (γ_1) of $\widetilde{F}^{(1)}$ is 0.89 which is close yet smaller than the estimated expected market persistence parameter in Appendix Table E1. The persistence parameter (ϕ) of $\widetilde{F}^{(2)}$ is 0.63, which is smaller expected market cash flow growth persistence. $\delta_{2,j}$ and $\omega_{2,j}$ are the loadings of expected returns and expected cash flow growth on the global factors. $\delta_{2,j}$ ranges between 0.01 (telecom, health, and business equipment) and 0.10 (carry), and $\omega_{2,j}$ ranges between 0.81 (steel) and -0.47 (fabricated products). For

[18]The antitrust division of the Department of Justice classifies industries with an HHI between 1000 and 1800 to be moderately concentrated, and highly concentrated for industries with an HHI above 1800. However, they use a less granular industry classification.

certain sectors, such as, retail, services, and fabricated products, the loading on the second global factor is negative. These results are direct contributions to the accounting literature that analyzed mean reversion in profits and profitability (Brooks and Buckmaster (1976), Beaver (1970), Lookabill (1976), Albrecht et al. (1977)), and the finance literature that modeled mean reversion in profitability across firms (Fama and French (2000)). Overall, expected profit growth persistence is heterogeneous across industries and tend to be larger in concentrated industries.

The three most interesting variables that enter implied expected returns, equation (2.9), are expected industry profit growth, and two systematic factors. Expected industry profit growth has a negative coefficient, as expected profit growth increase, prices increase, which lowers expected returns. The effect of a change in expected profit growth on expected returns depends on the magnitude of expected profit growth persistence ($\omega_{1,j}$). As $\omega_{1,j}$ approaches the expected return persistence ($\delta_{1,j}$), an increases expected profit growth leads to lower expected returns. Concentrated industries tend to have larger $\omega_{1,j}$ relative to competitive industries, implying that a 1 percent increase in expected profit growth leads to lower expected returns in concentrated industries. This result is related to the recent literature on industry concentration and expected returns,[19] where studies show that concentrated industry returns are more volatile due to larger movements in profits.

Expected returns load on systematic factors, for industries with a positive loading on the systematic cash flow factor ($\widetilde{F}^{(2)}$), an increase in $\widetilde{F}^{(2)}$ leads to a decrease in expected returns. However, the effect of $\widetilde{F}^{(2)}$ depends on the present value coefficient ratio ($\mathcal{B}_{1,j}/\mathcal{B}_{3,j}$). The ratio increases as $\omega_{1,j}$ increases, meaning that an increase in the systematic cash flow factor leads to lower expected returns for concentrated industries. Thus, concentrated industries tend to be more correlated with the systematic cash flow factor. Lastly, there is a positive relationship between expected returns and the systematic discount rate factor ($\widetilde{F}^{(1)}$). The sensitivity of expected returns to the changes in the systematic discount factor depends on the ratio of $\delta_{2,j}/\delta_{1,j}$. Table 6 shows little cross-sectional variation across industries for $\delta_{2,j}$ and $\delta_{1,j}$ which indicates a homogeneous response to changes in the systematic discount rate. These results suggests that cross-sectional variation in expected returns originates from the sensitivity to movements in systematic cash flow factor.

As an attempt to assign economic meaning to the global factors, I graph the filtered fac-

[19] See for example Corhay et al. (2020) and Dou et al. (2021).

tors against market returns and profit growth in Figure 3 and present the contemporaneous R^2 statistics. The first global factor has an in sample R^2 of 28 percent when evaluated against market returns, and the second global factor has an R^2 of 65 percent evaluated against market profit growth. Yet, it would be a mistake to take these factors as expected market returns and expected market profit growth, we should think of them as two *systematic factors*.

Lastly, I focus on the variances of expected return and profit growth shocks, $\sigma^2_{j,\mu}$ and $\sigma^2_{j,g}$ respectively. On average, variances of expected profit growth shocks are 2.5 times larger than variances of expected return shocks, implying that expected profit growth have more variability than expected returns. This result is consistent with Vuolteenaho (2002), in which the author shows that expected cash flow growth shocks are three times larger than expected return shocks. On the extremes, the service sector's $\sigma^2_{j,g}$ is almost 10 times larger than $\sigma^2_{j,\mu}$, and business equipment's $\sigma^2_{j,g}$ is as large as $\sigma^2_{j,\mu}$. Textiles is the only industry for which the variance expected profit growth shocks is smaller than the variance of expected return shocks.

4.2 Comparison of Filtered Series

In Table 7, I present the in sample R^2 values for expected returns and expected cash flow growth at the market and industry level, for which the R^2 values are computed as:

$$R^2_{\mu,j} = 1 - \left(\frac{\widehat{var}(r_{j,t+1} - \mu_{j,t})}{\widehat{var}(r_{j,t})}\right)$$
$$R^2_{y,j} = 1 - \left(\frac{\widehat{var}(y_{j,t+1} - g_{j,t})}{\widehat{var}(y_{j,t})}\right),$$

where y indicates either profit growth or dividends growth, g indicates expected cash flow growth, and $\widehat{var}(\cdot)$ indicates the sample variance. I first compare the filtered series for market returns and cash flow growth (profits and dividends). The model using dividends has an in sample predictive R^2 of 1.4 percent which is approximately 0.5 percentage point greater than the model using profits. The filtered series' R^2 for cash flow growth is similar across the two models with 59 and 52 percent for the dividends and profits model respectively. In the row denoted "Global Factors", I show the predictive R^2 of the global factors. The R^2 for returns is 5.7 percent using the first global factor ($\widetilde{F}^{(1)}$), and the R^2 for market profit growth is 37.5 percent using the second global factor ($\widetilde{F}^{(2)}$). Figure 4 plots the time series evolution of the expected returns and the first global factor from the DFM against market returns. Until 1990, expected returns obtained using profits are lower relative to expected returns calculated using dividends. Between 1990 and 2000, expected returns using either cash flow proxies are visually equivalent. The second part of Table 7 shows the results for 27 industries. R^2 values for returns range between 14.8 percent and 0 percent. The industries with the highest R^2 values include, business equipment (14.8 percent), coal (5.5 percent), paper (5.1 percent), and health (3.6 percent). The lowest R^2 values include, retail (0.3 percent), services (0.8 percent), textiles (0.03 percent). Figure 5 plots in sample R^2 values for returns and profit growth persistence against profit growth persistence. There is a positive correlation between in sample return and profit growth predictability, and profit growth persistence ($\omega_{1,j}$). For returns the correlation is 19 percent and for profit growth it is 43 percent. These results suggest that returns and profit growth of industries with highly persistent profit growth tend be more predictable relative to industries less persistent profit growth.

5 Risk Premium and Return Volatility

In Section 4, I show that expected profit growth persistence plays an important role in describing the effects of expected profit growth movements on expected returns. Specifically, I show that expected returns of concentrated industries are more susceptible to movements in expected profit growth. In this section, I use the Campbell (1991) framework to decompose unexpected industry returns into industry specific and systematic cash flow news (expected profit growth shock) and discount rate new (expected return shock). I show that due to higher expected profit growth persistence, concentrated industries' returns are more correlated with systematic cash flow news and offer a higher premium. Recent literature also suggests that concentrated industries' profits are more susceptible to cash flow shocks. In turn, this means that expected profit growth shocks are of key importance in return volatility for concentrated industries. I show a novel relationship between expected profit growth persistence and cash flow news share in return volatility. As expected profit growth persistence increases, the contribution of cash flow news to return volatility increases. Implying that cash flow news contribution is larger in concentrated industries relative to competitive industries. Yet, these results are based on unconditional estimates of cash flow news and discount rate news. Thus, I use the Dynamic Conditional Correlation GARCH model to estimate the conditional time variation in cash flow news and discount rate news and compute the time varying shares of cash flow and discount rate news. To solidify the relationship between industry concentration and cash flow news share, I sort industries into HHI portfolios and use the Patton and Timmermann (2010) monotonic relationship test and reject the null hypothesis of no increasing monotonic relationship between HHI and cash flow news share. The test result confirm the increasing relationship between cash flow news share and HHI, suggesting that highly concentrated industries' return volatility is more susceptible to expected profit growth shocks.

5.1 Industry Risk Premium

As noted in recent literature, concentrated industries tend to offer higher returns. I use the Campbell (1991) framework to decompose unexpected returns, defined as returns less expected returns, into cash flow news (expected profit growth shocks) and discount rate news (expected return shocks). I use this decomposition to analyze the loadings of returns on systematic shocks and present an explanation of higher returns offered by concentrated industries.

$$r_{j,t+1} - \mu_{j,t} = -\rho_{1,j}\mathcal{B}_{3,j}\left(\varepsilon^{\mu}_{j,t+1} + \delta_{2,j}\varepsilon^{F^{(1)}}_{t+1}\right) + \rho_{1,j}\mathcal{B}_{1,j}\left(\varepsilon^{g}_{j,t+1} + \omega_{2,j}\varepsilon^{F^{(2)}}_{t+1}\right) + \varepsilon^{\Delta\pi}_{j,t+1} \tag{5.1}$$

Equation (5.1) shows unexpected returns ($r_{j,t+1} - \mu_{j,t}$) for each industry j for quarter t. The first part of the equation indicates discount rate news for each industry and the second part indicates cash flow news. This representation is very similar to the Van Binsbergen and Koijen (2010) unexpected return decomposition. However, thanks to the systematic factors in the model, I separate discount rate and cash flow news into industry specific ($\varepsilon^{\mu}_{j,t+1}$ and $\varepsilon^{g}_{j,t+1}$) and systematic ($\varepsilon^{F^{(1)}}_{t+1}$ and $\varepsilon^{F^{(2)}}_{t+1}$) components. $\rho_{1,j}$ indicates the industry specific log-linearization constant, $\mathcal{B}_{3,j}$ and $\mathcal{B}_{1,j}$ are the present value coefficient for expected returns and expected profit growth, respectively. The magnitude of the present value coefficients depend on the persistence coefficients of expected returns ($\delta_{1,j}$), expected profit growth ($\omega_{1,j}$), and $\rho_{1,j}$.

The equation states that high loading on systematic cash flow news increases unexpected returns, and a high loading on systematic discount rate news decreases unexpected returns.

As described in Campbell and Vuolteenaho (2004), risk-averse investors require a higher premium from assets that covary more with systematic cash flow news. This is because negative cash flow news lead to a decrease in the investor's wealth without offering better investment opportunities in the future. However, an adverse discount rate shock decreases wealth, but lead to better investment opportunities in the future.

Cross-sectional variation in unexpected returns comes from the magnitudes of the present value coefficients ($\mathcal{B}_{3,j}$ and $\mathcal{B}_{1,j}$). A higher $\mathcal{B}_{1,j}$ leads to higher covariance with systematic cash flow news, and a higher $\mathcal{B}_{3,j}$ leads to higher covariance with systematic discount rate news. Coefficient estimates in Table 6 indicates a higher cash flow present value coefficient ($\mathcal{B}_{1,j}$) for concentrated industries due to the relatively larger expected profit growth persistence ($\omega_{1,j}$). The positive relationship between industry concentration and expected profit growth persistence leads to higher correlation of returns with systematic cash flow news. Therefore, concentrated industries tend to offer a higher premium; which explains the findings in recent literature (Grullon et al. (2019)) and test results indicating a weak increasing monotonic relationship between concentration and returns (Table 4 Panel C).

These results are consistent with the production-based asset pricing (PBAP) model developed in Liu et al. (2009), in which firms maximize the firm's equity value. Instead of focusing on the consumers utility function, the PBAP starts with a firm's production function: $\Pi(K_{i,t}, X_{i,t})$, in which $K_{i,t}$ denotes the stock of capital for firm i at time t, and $X_{i,t}$ denotes aggregate and firm specific shocks. The firm faces an adjustment cost for investing:

$$\Phi(I_{i,t}, K_{i,t}) = \frac{a}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t},$$

in which $a > 0$ and $I_{i,t}$ denotes investment of firm i at time t. Corporate payout is defined as:

$$CP_{i,t} = \Pi(K_{i,t}, X_{i,t}) - \Phi(I_{i,t}, K_{i,t}) - I_{i,t},$$

I omit taxes and debt for simplicity. Lastly, the firms' optimization problem is given by:

$$V_{i,t} = \max_{K_{i,t}, I_{i,t}} \mathbb{E}_t\left[\sum_{s=0}^{\infty} M_{t+s} CP_{i,t+s}\right],$$

in which M_{t+s} denotes the stochastic discount factor. Accordingly, firms for which corporate payouts are highly correlated with the stochastic discount factor (SDF) need to offer higher premiums. In the model, aggregate shocks ($X_{i,t}$) enter corporate payouts through firm profits. Therefore, by extension, firms for which profits are highly correlated with systematic shocks need to offer higher premiums.

I test the intuition highlighted by the PBAP model using simple regressions of recession dummies on industry profit growth. I rank industries by their HHI score in each year and construct sort industry profit growth into HHI quintiles. For each quintile I run the following regression:

$$\Delta \pi_{j,t} = \alpha + \beta D_t^{Reces.} + \varepsilon_{j,t},$$

in which $D_t^{Reces.}$ is a recession dummy. The coefficient on the recession dummy is negative and statistically insignificant for competitive industries (-2 percent). However, it is significant and twice as large for concentrated industries (Table 8). Economically, the regression results corroborate the intuition of the PBAP model. Aggregate shocks, such recessions, have a larger impact on concentrated industries. Therefore, risk-averse investors require larger risk premiums from such industries.

5.2 Unconditional Variance Decomposition

Recent literature suggests that concentrated industries' profits are more susceptible to cash flow shocks either due to the sensitivity of profits to markups and new entrants(Corhay et al. (2020), Dou et al. (2021)). In turn, this means that expected profit growth shocks are of key importance in return volatility for concentrated industries. Unexpected returns (equation (5.1)) describe the variance of realized returns as the sum of two main components: cash flow news, and discount rate news. I use this framework to analyze the share of each of these shocks in the total volatility of returns by industry. Previous research[20] shows that almost all variability in returns are due to discount rate news. However, the emerging literature analyzing competition and returns imply that cash flow news, specifically in concentrated industries, are non-negligible. Here, I use an empirical framework to analyze the contributions of cash flow news and discount rate news.

Table 9 shows the contribution of discount rate news, cash flow news, and their covariance to the total variance of unexpected returns. In general, the table shows that systematic

[20] See for example Campbell and Vuolteenaho (2004).

shocks have a minor contribution to the variance of unexpected returns, ranging between 0.3 percent and 4.8 percent with an average of 1.5 percent. Mechanically, the small contribution is due to small $\delta_{2,j}$ and $\omega_{2,j}$. Intuitively, because systematic factors enter expected returns, they are already accounted in expected returns, and therefore have a minor contribution in unexpected returns. Across sectors, discount rate news contribution vary between 39 percent and 99 percent and cash flow news contribution vary between 8 and 74 percent. These results suggests that in general discount rate news account for a larger share in return volatility. However, cash flow news contribution is still non-negligible and play an important role for industries such as autos and textiles.

What explains the cross-sectional differences in cash flow news contribution? Equation (5.2) analytically shows the contribution of cash flow news ($\sigma^2_{j,CFN}$) to total unexpected return variance ($\sigma^2_{j,Total}$). It turns out, main drivers of cross sectional variation in cash flow news contribution are the relative sizes of $\sigma^2_{j,g}$ against $\sigma^2_{j,\mu}$, $\mathcal{B}_{1,j}$ against $\mathcal{B}_{3,j}$ (equation (5.3)), and $\sigma^2_{j,g}$ against the covariance between cash flow news and discount rate news ($\sigma_{j,g\mu}$).

$$\frac{\sigma^2_{j,CFN}}{\sigma^2_{j,Total}} = \frac{1}{1 + \left[\left(\frac{\mathcal{B}_{1,j}}{\mathcal{B}_{3,j}}\right)^2 \frac{\sigma^2_{j,g}}{\sigma^2_{j,\mu}}\right]^{-1} - 2\left[\left(\frac{\mathcal{B}_{1,j}}{\mathcal{B}_{3,j}}\right) \frac{\sigma^2_{j,g}}{\sigma_{j,g\mu}}\right]^{-1}} \tag{5.2}$$

where,

$$\frac{\mathcal{B}_{1,j}}{\mathcal{B}_{3,j}} = 1 - \rho_{1,j}\mathcal{B}_{1,j}(\delta_{1,j} - \omega_{1,j}). \tag{5.3}$$

Equations (5.2) and (5.3) have two implications.[21] As the gap between expected return persistence ($\delta_{1,j}$) and expected profit growth persistence ($\omega_{1,j}$) narrows, cash flow news contribution increases. Second, as the log-linearization constant gets close to 1, the effect of the gap in the persistence coefficients become large. This means that as the log-linearization constant becomes large, even a small gap in persistent coefficients will decrease the contribution of cash flow news to the total variance in unexpected returns. Figure 6 illustrates the relationship between the log-linearization constant, the gap in persistence coefficients, and cash flow news contribution to total unexpected return variance. These relationships hold empirically as well. Panel A of Figure 7 shows a correlation of 0.25 between the relative magnitude of cash flow shocks and cash flow news contribution. Meaning that as the vari-

[21] I provide a detailed derivation of equation (5.2) and (5.3) in Appendix B.

ance of cash flow shocks grow relative to expected return shocks, cash flow news share tend to increases. Panel B of Figure 7 plots the relative size of present value coefficients and cash flow news contribution to the variance of unexpected returns. The figure shows a stronger linear relationship with a correlation coefficient of 0.79 between cash flows news contribution and relative size of present value coefficients.

The relationship between expected profit growth persistence and cash flow news share hints to a relationship between industry concentration and cash flow news share. Knowing that concentrated industries' expected profit growth persistence tend to be relatively higher than competitive industries, cash flow news share should be larger in concentrated industries. Figure 8 shows a 64 percent correlation between HHI and cash flow news share. Indicating that cash flow news share tend to be higher in concentrated industries. These results contribute to recent studies suggesting higher cash flow volatility in concentrated industries. However, these results are based on unconditional estimates of discount rate and cash flow news, yet there is burgeoning literature documenting time variation in return volatility. Moreover, industry HHI scores vary over time. In the following section, I analyze the conditional time variation in discount rate news and cash flow news using a multivariate GARCH model, and sort them into yearly HHI portfolios to solidify the relationship between industry concentration and cash flow news share.

5.3 Multivariate GARCH Models

There is a large body of literature that present evidence of time-varying conditional volatility in returns.[22] However, based on unexpected returns (equation (5.1)), it must be that either cash flow news or discount rate news, or both exhibit time-varying conditional volatility. I conduct an AutoRegressive Conditional Heteroskedasticity (ARCH) tests on cash flow news and discount rate news and find supporting evidence that both exhibit ARCH effects (Table 10). In this section, I model the conditional volatility of industry returns using a multivariate GARCH (MGARCH) to analyze the relationship between industry concentration and the conditional time variation in return volatility.

[22] See for example Ng et al. (1992), Chou and Kroner (1992), Bollerslev and Engle (1993), Ding et al. (1993), and Engle (2004).

Proposition 5.1. *Because of higher cash flow news share in concentrated industries, concentrated industries' return volatility is higher during economic downturns.*

To present empirical evidence for Proposition 5.1, first, I assume that cash flow news and discount rate news follow a GARCH(1,1) process, and represent equation (5.1) as a Scalar BEKK:[23]

$$
\begin{aligned}
r_{j,t+1} - \mu_{j,t+1} &= \varepsilon^{r}_{j,t+1} \\
\varepsilon^{r}_{j,t+1} &= \sigma^{r}_{j,t+1} e^{r}_{j,t+1} && (5.4)\\
\sigma^{2}_{r,j,t+1} &= c^{r}_{j} + \alpha^{r}_{j}\varepsilon^{2}_{r,j,t} + \beta^{r}_{j}\sigma^{2}_{r,j,t} && (5.5)\\
\sigma^{2}_{r,j,t+1} &= c^{r}_{j} + \alpha^{r}_{j}\left[\gamma_{j,CF}(\varepsilon^{g}_{j,t+1} + \omega_{2,j}\varepsilon^{F^{(2)}}_{j,t+1}) - \gamma_{j,DR}(\varepsilon^{\mu}_{j,t+1} + \delta_{2,j}\varepsilon^{F^{(1)}}_{j,t+1})\right]^{2} \\
&\quad + \beta^{r}_{j}\left[\gamma_{j,CF}(\sigma^{g}_{j,t+1} + \omega_{2,j}\sigma^{F^{(2)}}_{t+1}) - \gamma_{j,DR}\sigma^{\mu}_{j,t+1} + \delta_{2,j}\sigma^{F^{(1)}}_{t+1})\right]^{2}, && (5.6)
\end{aligned}
$$

in which $\gamma_{j,CF} = \rho_{1,j}\mathcal{B}_{1,j}$, and $\gamma_{j,DR} = \rho_{1,j}\mathcal{B}_{3,j}$.

Equation (5.6) decomposes conditional time variation in unexpected returns into industry-specific and systematic conditional time variation in cash flow news, discount rate news, and the covariance between them. However, the scalar BEKK imposes that loadings on squared residuals (α^{r}_{j}) and lagged variances of cash flow news and discount rate news are equivalent (β^{r}_{j}). To relax this assumption and allow for heterogeneous estimates, I write equation (5.6) in matrix form:

$$
\begin{aligned}
\mathbf{\Sigma}_{j,t+1} &= \begin{bmatrix} \mathcal{J}_{j,t+1} & \mathbf{0} \\ \mathbf{0} & \mathcal{S}_{j,t+1} \end{bmatrix} && (5.7)\\
\mathcal{J}_{j,t+1} &= \begin{bmatrix} \gamma^{2}_{j,CF}\sigma^{2}_{j,g,t+1} & \gamma_{j,CF}\gamma_{j,DR}\sigma^{g}_{j,t+1}\sigma^{\mu}_{j,t+1} \\ \gamma_{j,CF}\gamma_{j,DR}\sigma^{g}_{j,t+1}\sigma^{\mu}_{j,t+1} & \gamma^{2}_{j,DR}\sigma^{2}_{j,\mu,t+1} \end{bmatrix} \\
\mathcal{S}_{j,t+1} &= \begin{bmatrix} \gamma_{j,CF}\omega_{2,j} & 0 \\ 0 & \gamma_{j,DR}\delta_{2,j} \end{bmatrix} \begin{bmatrix} \sigma^{2}_{F^{(2)},t+1} & \sigma^{F^{(2)}}_{t+1}\sigma^{F^{(1)}}_{t+1} \\ \sigma^{F^{(2)}}_{t+1}\sigma^{F^{(1)}}_{t+1} & \sigma^{2}_{F^{(1)},t+1} \end{bmatrix} \begin{bmatrix} \gamma_{j,CF}\omega_{2,j} & 0 \\ 0 & \gamma_{j,DR}\delta_{2,j} \end{bmatrix} \\
\mathcal{S}_{j,t+1} &= \mathcal{L}_{j}\mathcal{S}_{t+1}\mathcal{L}_{j}
\end{aligned}
$$

Accordingly, the variance covariance matrix of unexpected returns (equation (5.7)) is a 4x4 block diagonal matrix, in which $\mathcal{J}_{j,t+1}$ is a 2x2 matrix capturing industry-specific cash

[23] I provide mathematical derivations in Appendix D.

flow and discount rate news, and $\mathcal{S}_{t+1}$ is the 2x2 matrix capturing systematic shocks. I estimate $\mathcal{J}_{j,t+1}$ and $\mathcal{S}_{t+1}$ using the Engle (2002) Dynamic Conditional Correlation GARCH(1,1) (DCC-GARCH(1,1)) model.[24]

Table 11 presents DCC-GARCH(1,1) estimates of $\mathcal{J}_{j,t+1}$ and $\mathcal{S}_{t+1}$. The top panel of the table presents coefficient estimates of $\mathcal{S}_{t+1}$, which represents the conditional variance covariance matrix of the systematic shocks. The only significant coefficient is $\alpha^r_{F^{(2)}}$, estimated at 0.22, which loads on the lagged squared residual of $\widetilde{F}^{(2)}$. Moreover the "DCC" estimates (α_{dcc} and β_{dcc}) are equal to 0, implying constant conditional correlation. The bottom panel of the table presents industry specific estimates of $\mathcal{J}_{j,t+1}$. Just like the estimates of the systematic variance covariance matrix, industry specific "DCC" estimates imply a constant conditional correlation model, except for the textiles industry. GARCH(1,1) estimates of cash flow news and discount rate news are statistically insignificant for certain industries,[25] implying no ARCH effects. The sum of GARCH coefficients ($\alpha^r_{j,\cdot} + \beta^r_{j,\cdot}$) are on average larger for cash flow news relative to discount rate news. This implies that an increase in cash flow news leads to a relatively more persistent increase in return volatility.

Figure 10 plots the time varying conditional volatility of unexpected returns and its components. The figure illustrates the persistent but smooth effect of cash flow news on the conditional volatility of unexpected returns and the effect of relatively short lived spikes in discount rate news. Figure 11 shows the decomposition of time varying conditional variance of unexpected returns into cash flow news and discount rate news. Consistent with previous literature, discount rate news account for the majority of the conditional volatility in returns. However, as indicated by unconditional estimates, conditional cash flow news share show large heterogeneity across industries.

I formally test the relationship between industry concentration and time varying cash flow news share using the Patton and Timmermann (2010) monotonic relationship test. I sort cash flow news shares of the industries into five HHI portfolios. The first portfolio captures the most competitive industries and the fifth portfolios captures the most concentrated industries. As demonstrated by the unconditional estimates of cash flow news share, concentrated industries have larger cash flow news share relative to competitive industries.

[24] I provide details for the DCC-GARCH in the Appendix D.

[25] GARCH(1,1) estimates of cash flow news and discount rate news are insignificant for the carry, clothes and apparel, games, oil, telecom, and wholesale sectors.

Thus, I test the null of no increasing monotonic relationship between industry concentration and cash flow news share. Test results indicate that as industry concentration increases, the share of expected profit growth shocks increases which provides supporting evidence for the primitives of Proposition 5.1 (Table 12).

Finally, I test for cyclicality in return volatility. I sort the conditional volatility for each industry into HHI quintiles and run a panel regression of recession dummies on the conditional industry volatility for each HHI quintile:

$$\text{Vol}_{j,t} = \alpha_j + \beta D_t^{Reces.} + \varepsilon_{j,t}$$

in which α_j is an intercept for each industry, and $D_t^{Reces.}$ is the recession dummy. Coefficient estimates indicate for a positive relationship between industry concentration and the β coefficient which captures the sensitivity of volatility to recessions (Table 13). The recession dummy is statistically insignificant and small (0.14) for the industries in the first HHI quintile. Whereas, for industries in the fifth HHI quintile the recession dummy is significant and twice as large (0.28). Regression results provide supporting evidence for Proposition 5.1. As industry concentration increases return volatility tends to be more sensitive to economic downturns.

5.4 Conditional Sharpe Ratios

Conditional Sharpe ratios cover the essence of the empirical evidence provided in this paper. The discussion in Sections 5.1-5.3 show that concentrated industries offer higher risk premium due to higher covariance with systematic cash flow shocks and have higher return volatility during recessions. These findings suggest that concentrated industries' returns and volatility are more sensitivity to economic cycles.

As suggested by Perez-Quiros and Timmermann (2000), it would be difficult to explain an increase in expected returns without an associated increase in the level of risk (conditional volatility). Thus, I test whether conditional Sharpe ratios of concentrated industries are more sensitive to economic cycles relative to competitive industries. I regress recession dummies on conditional Sharpe ratios for each HHI quintile to analyze the effects of the business cycle. Coefficient estimates on the recession dummy are small, in magnitude, and insignificant for industries in the first HHI quintile (-0.02). Whereas, for industries in the fifth HHI quintile, the estimates are statistically significant and large (-0.09) (Table 14).

Based on the regression results, I conclude that concentrated industries conditional Sharpe ratios are more sensitive to economic cycles. Moreover, these results provide an insight into the price of risk of concentrated industries. Due to higher sensitivity of concentrated industries to systematic cash flow shocks, expected returns in such industries increases more than competitive industries during recessionary periods. However, because of the higher cash flow news share in concentrated industries, adverse aggregate shocks lead to a larger increase in return volatility. Hence, during recessionary periods, the conditional Sharpe ratio of concentrated industries decreases more relative to competitive industries.

6 Conclusion

This study contributes to the emerging literature that analyzes the effects of industry concentration on asset prices. I develop a latent variables framework to jointly model industry-level and *systematic* expected returns and expected profit growth using a dynamic factor model. The estimation results indicate that concentrated industries tend to have larger expected profit growth persistence relative to competitive industries. This has important implications for expected returns and return volatility. First, highly concentrated industries' expected returns are more susceptible to changes in expected profit growth relative to competitive industries. This implies a higher correlation with systematic cash flow news, which leads to a higher risk premium. Second, as industry concentration increases, the share of cash flow news increases, leading to higher sensitivity of return volatility to economic downturns. Third, concentrated industries tend to have lower conditional Sharpe ratios, especially during economic downturns, resulting in a negative relationship between industry concentration and the risk-return trade-off. In conclusion, the results indicate that concentrated industries offer a higher risk premium compared to competitive ones, but face larger volatility during economic downturns.

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Autos	Fabricated Products	Retail
Beer	Food	Services
Books	Games	Steel
Business Equipment	Health	Telecom
Carry	Household	Textiles
Chemicals	Meals	Transport
Clothes	Oil	Wholesale
Coal	Other	
Construction	Paper	
Electrical Equipment	Real Estate	

Table 1: **List of Industries**. This table presents all the tables included in the analysis. We follow the Fama-French 30 Industry classification. I exclude the finance and utilities sectors due to high regulation and barriers to entry. The total number of industries included is 28.

	r_t^{VW}	pe_t^{GM}	pd_t	$\Delta\pi_t^{GM}$	Δd_t
Market	3.13 (7.970)	3.45 (0.487)	2.98 (0.327)	1.80 (2.902)	1.92 (7.572)
Autos	3.59 (14.451)	1.43 (0.629)		0.70 (12.427)	
Beer	3.81 (8.780)	1.22 (0.352)		2.27 (18.72)	
Books	3.03 (10.973)	2.49 (0.512)		1.73 (6.736)	
BusEq.	3.54 (12.626)	3.61 (0.525)		2.34 (5.892)	
Carry	3.75 (11.509)	2.27 (0.247)		1.70 (7.083)	
Chemicals	3.12 (10.267)	2.82 (0.509)		0.97 (6.303)	
Clothes	3.72 (11.816)	2.15 (0.349)		2.45 (5.844)	
Coal	2.35 (21.042)	1.35 (0.709)		0.88 (27.210)	
Const	3.37 (11.334)	3.47 (0.466)		1.23 (6.674)	
ElcEq	3.83 (11.011)	2.48 (0.666)		0.61 (11.260)	
FabProd	3.24 (11.597)	3.25 (0.393)		1.27 (8.765)	
Food	3.36 (7.416)	2.90 (0.244)		1.73 (4.737)	
Games	3.80 (12.462)	2.80 (0.562)		1.83 (20.026)	
Health	3.45 (8.373)	3.62 (0.403)		1.92 (3.443)	
Hshld	2.90 (8.491)	1.82 (0.289)		1.53 (3.918)	
Meals	3.61 (9.835)	2.73 (0.486)		1.92 (4.953)	
Oil	3.09 (11.059)	2.66 (0.377)		1.11 (13.249)	
Paper	2.80 (9.135)	2.57 (0.255)		1.33 (3.502)	
RealEstate	2.80 (14.129)	2.54 (0.674)		1.63 (10.896)	
Retail	3.72 (9.711)	2.72 (0.429)		2.19 (11.102)	
Services	4.05 (11.447)	2.71 (1.266)		1.02 (7.905)	
Steel	2.42 (14.225)	2.97 (0.518)		1.80 (25.312)	
Telecom	2.90 (8.723)	2.52 (0.901)		0.84 (13.735)	
Textiles	3.27 (13.841)	1.56 (0.829)		1.57 (8.806)	
Transport	3.28 (10.152)	3.17 (0.246)		1.92 (6.976)	
Wholesale	3.19 (9.427)	3.22 (0.295)		1.88 (6.103)	
Pooled	3.28 (9.026)	2.69 (0.498)		1.58 (9.796)	

Table 2: **Quarterly seasonally adjusted mean and standard deviation of the state space model variables (1976Q2-2021Q4).** I present the mean and standard deviation (in parenthesis) of the observable variables of the state space model at the quarterly frequency. Because of the seasonality of the data I adjust the series using the X13 ARIMA-SEATS procedure to obtain the seasonally adjusted series. All statistics presented in this table are seasonally adjusted. The first row indicates the market mean and standard deviation of the variables. r_t^{vw} indicates the value weighted return in percent, pe_t^{GM} indicates the log price-to-profit ratio, for which profits are defined as gross profits. pd_t indicates the log price to dividend ratio, Δd_t is dividend growth, $\Delta\pi_t^{GM}$ is gross profit growth. Value weighted returns, profit growth, and dividend growth are multiplied by 100.

Ind	Panel A: Average		Panel A: Growth (in %)	
	1976-2021	2000-2019	1976-2021	2000-2019
Autos	3824	3731	-24.5	-19.2
Beer	6074	7102	43.1	32.2
Books	3700	4406	136.0	44.7
BusEq.	1706	1619	-10.1	44.1
Carry	3591	3485	14.6	-10.3
Chemicals	2552	2331	-21.9	-33.1
Clothes	3103	3340	54.2	35.8
Coal	3534	2631	-37.4	-60.8
Const	1836	2002	59.2	9.3
ElcEq	3463	3198	-22.6	-18.9
FabProd	2176	2307	5.8	-5.6
Food	3404	3691	36.6	16.1
Games	2679	2541	-12.2	-8.3
Health	1519	1144	-55.4	6.6
Hshld	3102	3067	-7.7	-4.8
Meals	2726	2685	-10.5	-9.4
Oil	2044	1904	-24.5	-26.9
Paper	2409	2575	59.5	0.6
Retail	1973	2055	69.2	51.2
Services	1900	1399	-61.2	-1.2
Steel	2508	2684	36.8	75.0
Telecom	2903	2129	-51.5	28.7
Textiles	5032	6628	134.9	144.9
Transport	2004	1650	21.7	28.4
Wholesale	2688	3143	74.6	10.6

Table 3: **Average HHI and HHI growth across industries for the 1976-2021 sample and 2000-2021 sample**. I present the average HHI across industries ($\overline{HHI}_j = \sum_t^{2021} HHI_{j,t}$, for $t = 1976$ and $t = 2000$, and industry j) in "Panel A" of the table. In "Panel B" of the table, I present HHI growth across industries ($\Delta HHI_j = \frac{HHI_{j,2021}}{HHI_{j,t}}$, for $t = 1976$ and $t = 2000$, and industry j).

Panel A: Decreasing Monotonic Relationship between Concentration and Sharpe Ratios			
		$H_0 : \mathbf{\Delta} \geq 0$	
	$H_1 : \min_{i=2,\ldots,5} \Delta_i > 0$	Adjacent Pairs	All Pairs
P-value	0.300	0.029	0.029
Panel B: Increasing Monotonic Relationship between Concentration and Returns			
		$H_0 : \mathbf{\Delta} \leq 0$	
	$H_1 : \min_{i=2,\ldots,5} \Delta_i > 0$	Adjacent Pairs	All Pairs
P-value	0.673	0.808	0.702
Panel C: Weak Monotonic Relationship between Concentration and Returns			
	$H_0 : \Delta_i \geq 0, \ldots, \Delta_N \geq 0$ $H_1 : \Delta_i < 0, \ldots, \Delta_N < 0$ for some i		
P-value	0.231		
	$H_0 : \Delta_i \leq 0, \ldots, \Delta_N \leq 0$ $H_1 : \Delta_i > 0, \ldots, \Delta_N > 0$ for some i		
P-value	0.055		

Table 4: **Monotonic Relationship Test between Industry Concentration, Returns, and Sharpe Ratios**. In "Panel A" I test the null hypothesis of no decreasing monotonic relationship between industry concentration and industry Sharpe ratios. For each year in the sample (1976-2021), I sort industries into HHI portfolios. Then I compute the average Sharpe ratio $\bar{sr}_{i,t} = \frac{1}{J}\sum_j^J sr_{j,t}$ for each portfolio i, where $sr_{j,t}$ is the Sharpe ratio of industry j in year t. As described in Patton and Timmermann (2010), there are three alternative hypothesis corresponding to the null. The first is $H_1 : \max_{i=i,\ldots,N} \Delta_i < 0$, where $\Delta_i = \mathbb{E}[\bar{sr}_{i,t}] - \mathbb{E}[\bar{sr}_{i-1,t}]$. This test makes sense because if the maximum Δ_i portfolio is significantly smaller than zero, it must be that the other portfolios are also smaller than zero. Yet this test works if the relationship is linear. Hence, there are 2 additional alternative tests, "Adjacent Pairs", and "All Pairs". In "Panel B" I test the increasing monotonic relationship between industry concentration and returns. The procedure to form portfolios is identical to that of "Panel A". However, instead of using Sharpe ratios, "Panel B" uses industry returns. "Panel C" tests for a weak relationship between industry concentration and returns using Bonferroni bounds. There are two sets of hypotheses. The first set tests for an increasing relationship, the rejection of the null means that at least some portfolios show an increasing relationship between concentration and returns. The second set of tests for a decreasing relationship, rejection of the null implies at least some portfolios show a decreasing relationship between industry concentration and returns.

Increasing Monotonic Relationship between Concentration and Product Rigidity			
		$H_0 : \mathbf{\Delta} \leq 0$	
	$H_1 : \min_{i=2,\ldots,5} \Delta_i > 0$	Adjacent Pairs	All Pairs
P-value	0.000	0.047	0.040

Table 5: **Monotonic Relationship Test between Industry Concentration and Product Fluidity**. I test the null hypothesis of no increasing monotonic relationship between industry concentration and product rigidity. For each year in the sample (1989-2021), I sort industries into HHI portfolios. As described in Patton and Timmermann (2010), there are three alternative hypothesis corresponding to the null. The first is $H_1 : \max_{i=i,\ldots,N} \Delta_i > 0$. This test makes sense because if the maximum Δ_i portfolio is significantly smaller than zero, it must be that the other portfolios are also smaller than zero. Yet this test works if the relationship is linear. Hence, there are 2 additional alternative tests, "Adjacent Pairs", and "All Pairs".

	$pe_{j,t+1}$	Latent Variables			Implied					Variance			
	$\delta_{2,j}\mathcal{B}_{3,j}$	$\delta_{1,j}$	$\omega_{1,j}$	$\omega_{2,j}\phi_1$	$\omega_{2,j}$	$\delta_{2,j}$	$\rho_{1,j}$	$\mathcal{B}_{3,j}$	$\mathcal{B}_{1,j}$	$\sigma^2_{j,\Delta\pi}$	$\sigma^2_{j,\mu}$	$\sigma^2_{j,g}$	$\sigma_{j,\mu g}$
Industry													
Autos	**0.16** (0.016)	**0.89** (0.015)	**0.79** (0.083)	0.05 (0.038)	0.07	0.05	0.81	3.49	2.72	**0.31** (0.026)	**0.17** (0.028)	**0.46** (0.007)	0.04 (0.082)
Beer	**0.12** (0.006)	**0.78** (0.047)	0.11 (0.077)	-0.02 (0.020)	-0.04	0.05	0.77	2.51	1.09	0.02 (0.078)	**0.74** (0.035)	**1.32** (0.031)	0.14 (0.719)
Books	**0.16** (0.024)	**0.90** (0.015)	**0.58** (0.111)	0.04 (0.050)	0.06	0.03	0.92	6.08	2.17	**0.55** (0.075)	**0.10** (0.025)	**0.44** (0.023)	0.03 (0.035)
BusEq.	**0.16** (0.025)	**0.94** (0.017)	**0.80** (0.066)	0.06 (0.044)	0.09	0.01	0.97	11.88	4.45	**0.56** (0.003)	**0.14** (0.024)	**0.13** (0.016)	-0.02 (0.013)
Carry	**0.37** (0.023)	**0.81** (0.040)	0.09 (0.094)	-0.13 (0.038)	-0.20	0.10	0.91	3.70	1.09	**0.33** (0.049)	**0.54** (0.034)	**0.52** (0.016)	0.07 (0.251)
Chemicals	**0.16** (0.017)	**0.89** (0.015)	**0.67** (0.085)	**0.10** (0.041)	0.17	0.03	0.94	6.24	2.70	**0.19** (0.009)	**0.13** (0.025)	**0.42** (0.031)	-0.02 (0.056)
Clothes	**0.24** (0.025)	**0.88** (0.027)	**0.70** (0.104)	0.02 (0.054)	0.04	0.05	0.90	4.74	2.69	**0.45** (0.009)	**0.21** (0.031)	**0.24** (0.014)	-0.03 (0.029)
Coal	**0.12** (0.023)	**0.86** (0.034)	**0.63** (0.109)	**0.19** (0.047)	0.30	0.04	0.79	3.13	1.99	**0.65** (0.011)	**0.26** (0.035)	**0.34** (0.015)	0.00 (0.075)
Const	**0.20** (0.018)	**0.90** (0.018)	**0.61** (0.081)	0.06 (0.041)	0.10	0.03	0.97	7.91	2.42	**0.22** (0.008)	**0.11** (0.027)	**0.51** (0.009)	0.00 (0.057)
ElcEq	**0.17** (0.014)	**0.88** (0.017)	**0.33** (0.080)	0.00 (0.032)	0.01	0.03	0.92	5.22	1.44	**0.12** (0.013)	**0.18** (0.026)	**0.62** (0.011)	-0.01 (0.108)
FabProd	**0.25** (0.014)	**0.84** (0.027)	0.11 (0.083)	-0.29 (0.032)	-0.47	0.05	0.96	5.34	1.12	**0.20** (0.032)	**0.34** (0.032)	**0.39** (0.027)	0.02 (0.113)
Food	**0.14** (0.024)	**0.86** (0.026)	**0.64** (0.085)	0.03 (0.044)	0.05	0.03	0.95	5.50	2.57	**0.20** (0.014)	**0.22** (0.031)	**0.45** (0.010)	-0.02 (0.054)
Games	**0.18** (0.017)	**0.85** (0.026)	**0.18** (0.085)	0.05 (0.036)	0.09	0.04	0.94	4.99	1.21	**0.27** (0.064)	**0.35** (0.031)	**0.67** (0.028)	-0.04 (0.190)
Health	**0.10** (0.024)	**0.89** (0.015)	**0.33** (0.118)	**0.14** (0.044)	0.22	0.01	0.97	7.52	1.47	**0.38** (0.021)	**0.11** (0.025)	**0.34** (0.045)	**0.05** (0.026)
Hshld	**0.15** (0.026)	**0.90** (0.016)	**0.67** (0.106)	0.06 (0.055)	0.10	0.03	0.86	4.51	2.35	**0.31** (0.012)	**0.11** (0.026)	**0.29** (0.023)	-0.01 (0.021)
Meals	**0.15** (0.022)	**0.88** (0.015)	**0.64** (0.090)	-0.02 (0.047)	-0.02	0.03	0.94	5.88	2.50	**0.24** (0.006)	**0.14** (0.025)	**0.27** (0.010)	0.01 (0.032)
Oil	**0.15** (0.014)	**0.84** (0.035)	0.15 (0.083)	**0.08** (0.029)	0.13	0.03	0.93	4.65	1.16	0.02 (0.021)	**0.36** (0.034)	**0.75** (0.008)	-0.03 (0.225)
Other	**0.23** (0.010)	**0.84** (0.030)	**0.24** (0.075)	-0.06 (0.022)	-0.10	0.04	0.99	5.93	1.31	0.00 (0.014)	**0.38** (0.032)	**0.83** (0.021)	0.10 (0.307)
Paper	**0.25** (0.019)	**0.90** (0.026)	**0.72** (0.083)	0.07 (0.046)	0.10	0.04	0.93	6.16	3.00	**0.65** (0.004)	**0.19** (0.031)	**0.16** (0.015)	0.01 (0.022)
Real Estate	**0.13** (0.022)	**0.90** (0.019)	**0.71** (0.073)	**0.15** (0.044)	0.24	0.02	0.93	5.92	2.94	**0.19** (0.003)	**0.15** (0.027)	**0.30** (0.008)	0.01 (0.036)
Retail	**0.08** (0.014)	**0.87** (0.023)	**0.18** (0.081)	-0.12 (0.033)	-0.19	0.02	0.94	5.45	1.20	**0.49** (0.025)	**0.19** (0.030)	**0.49** (0.014)	0.05 (0.094)
Services	**0.06** (0.020)	**0.93** (0.006)	**0.49** (0.083)	-0.07 (0.042)	-0.11	0.01	0.94	7.64	1.85	**0.33** (0.010)	**0.04** (0.012)	**0.42** (0.024)	-0.01 (0.010)
Steel	**0.24** (0.008)	**0.80** (0.051)	0.03 (0.077)	**0.50** (0.022)	0.81	0.06	0.95	4.23	1.03	0.00 (0.001)	**0.62** (0.040)	**0.75** (0.010)	-0.02 (0.435)
Telecom	**0.07** (0.014)	**0.91** (0.013)	**0.50** (0.073)	**0.07** (0.034)	0.11	0.01	0.93	6.34	1.88	**0.24** (0.004)	**0.08** (0.021)	**0.45** (0.022)	-0.02 (0.037)
Textiles	**0.12** (0.024)	**0.94** (0.013)	**0.69** (0.069)	-0.10 (0.047)	-0.16	0.03	0.83	4.58	2.35	**1.00** (0.006)	**0.07** (0.023)	0.01 (0.016)	0.00 (0.001)
Transport	**0.33** (0.018)	**0.84** (0.040)	**0.46** (0.082)	**0.28** (0.039)	0.44	0.06	0.96	5.14	1.80	**0.14** (0.009)	**0.39** (0.035)	**0.65** (0.014)	-0.01 (0.260)
Wholesale	**0.25** (0.014)	**0.85** (0.025)	**0.19** (0.083)	**0.11** (0.031)	0.17	0.04	0.96	5.58	1.22	**0.25** (0.056)	**0.31** (0.031)	**0.40** (0.011)	-0.02 (0.090)

Global Factors	γ_1	$\sigma^2_{F^{(1)}}$	ϕ_1	$\sigma^2_{F^{(2)}}$	$\sigma_{F^{(1)},F^{(2)}}$
$\widetilde{F}^{(1)}_{t+1}$	**0.89** (0.052)	**1.14** (0.009)			-0.21 (0.608)
$\widetilde{F}^{(2)}_{t+1}$			**0.63** (0.119)	**0.56** (0.094)	

Table 6: **Dynamic factor parameter estimates**. This tables presents the parameter estimates of the dynamic factor model derived in Section 2. $\delta_{1,j}$ indicates expected return persistence, $\omega_{1,j}$ indicates expected profit growth persistence, $\omega_{2,j}\phi_1$ indicates the loading of expected profit growth on the lagged second global factor ($\widetilde{F}^{(2)}_t$), $\delta_{2,j}$, is the loading of expected returns on the contemporaneous first global factor ($\widetilde{F}^{(1)}_{t+1}$), $\rho_{1,j}$ is the log linearization constant, $\mathcal{B}_{3,j}$ indicates the present value coefficient of expected returns, and $\mathcal{B}_{1,j}$ indicates the present value coefficient of expected profit growth. Bootstrapped standard errors are in parentheses.

Panel A: Market				
	Cash Flow Proxy: Profits		Cash Flow Proxy: Dividends	
	$R^2_{\widetilde{\mu}}$	$R^2_{\widetilde{\Delta\pi}}$	$R^2_{\widetilde{\mu}}$	$R^2_{\widetilde{\Delta d}}$
vBK	1.00	53.14	1.44	59.72
Global Factors	5.70	37.45	-	-

Panel B: Industry (Cash Flow Proxy: Profits)					
	$R^2_{\widetilde{\mu}}$	$R^2_{\widetilde{\Delta\pi}}$		$R^2_{\widetilde{\mu}}$	$R^2_{\widetilde{\Delta\pi}}$
Autos	0.00	3.40	Health	3.58	14.90
Beer	1.80	0.37	Household	0.34	22.11
Books	0.65	1.45	Meals	1.50	22.64
Bus. Eq.	14.83	18.73	Oil	1.91	9.41
Carry	2.65	0.44	Paper	5.07	8.83
Chemicals	3.87	14.37	Real Estate	0.13	33.27
Clothes	2.38	10.81	Retail	0.31	1.48
Coal	5.46	2.09	Services	0.78	12.45
Construction	0.15	15.00	Steel	0.71	28.87
Elc. Eq.	1.17	4.43	Telecom	1.29	10.14
Fab. Prod.	0.85	5.92	Textiles	0.03	6.50
Food	1.13	14.14	Transport	0.33	16.94
Games	0.88	0.34	Wholesale	1.26	3.51

Table 7: **In Sample R^2 (in percent) of expected returns ($\widetilde{\mu}_{j,t}$), realized profit growth ($\Delta\pi_{j,t}$), dividend growth (Δd).** This table presents the in sample R^2 of expected returns, profit growth, and dividend growth at the quarterly frequency. Panel A, compares the in sample R^2 of the market returns and market cash flow growth (either profit growth or dividend growth). I estimate the state space model derived in Van Binsbergen and Koijen (2010) (vBK) for market returns using dividends and profits as cash flow measures. The second line in Panel A,"Global Factors", shows the predictive ability of the common factors extracted from the dynamic factors model (DFM), namely $\widetilde{F}^{(1)}_{t+1}$ and $\widetilde{F}^{(2)}_{t+1}$. Market returns are value-weighted. In panel B, I present the industry level R^2 values estimated using the DFM with cash flows defined as profits.

Eqn.	$\Delta\pi_{j,t} = \alpha + \beta D_t^{Reces.} + \varepsilon_{j,t}$		
Quintiles	β	SE	P-Value
Q1	-1.96	1.028	0.056
Q3	-2.12	1.485	0.155
Q5	-4.01	1.581	0.012

Table 8: **Coefficient estimates of the regression of recession dummy on industry profit growth by HHI quintiles**. I regress a recession dummy on industry profit growth by HHI quintiles to analyze the effects of systematic shocks on industry profit growth. The estimation sample is 1976Q3-2021Q2, which includes the 1980, 1981-1982, 1990-1991, 2001, 2007-2009 (GFC), and 2020 (Covid) recessions.

	Discount Rate News		Cash Flow News		Covariance		Total		Total		
	Idio.	Syst.	Idio.	Syst.	Idio.	Syst.	Idio.	Syst.	Discount Rate News	Cash Flow News	Covariance
Autos	38.3	0.6	73.1	0.4	-12.6	0.3	98.8	1.2	38.9	73.5	-12.4
Beer	84.7	0.3	29.3	0.0	-14.2	0.0	99.7	0.3	85.0	29.3	-14.3
Books	66.7	0.5	47.9	0.2	-15.5	0.2	99.2	0.8	67.2	48.1	-15.3
BusEq.	78.0	0.1	13.0	0.4	8.4	0.1	99.4	0.6	78.1	13.4	8.5
Carry	92.0	1.9	12.9	0.3	-6.7	-0.4	98.2	1.8	93.9	13.3	-7.2
Chemicals	56.6	0.3	35.6	1.2	6.0	0.3	98.1	1.9	56.9	36.8	6.3
Clothes	61.1	0.9	29.4	0.1	8.5	0.1	98.9	1.1	62.0	29.4	8.6
Coal	49.1	0.3	46.8	3.8	-0.6	0.6	95.2	4.8	49.4	50.6	0.0
Const	68.9	0.4	31.4	0.3	-1.3	0.2	99.1	0.9	69.4	31.8	-1.1
ElcEq	74.9	0.5	21.9	0.0	2.8	0.0	99.5	0.5	75.3	21.9	2.8
FabProd	93.5	0.7	6.7	1.5	-1.9	-0.5	98.4	1.6	94.2	8.2	-2.5
Food	63.4	0.2	30.1	0.1	6.1	0.1	99.6	0.4	63.7	30.2	6.2
Games	83.2	0.3	12.2	0.1	4.0	0.1	99.5	0.5	83.6	12.3	4.1
Health	98.8	0.2	17.4	0.9	-17.5	0.2	98.7	1.3	99.0	18.3	-17.2
Hshld	49.5	0.5	43.2	0.6	5.8	0.3	98.5	1.5	50.0	43.9	6.1
Meals	73.8	0.4	29.0	0.0	-3.2	-0.1	99.7	0.3	74.2	29.1	-3.3
Oil	84.5	0.3	11.4	0.2	3.6	0.1	99.5	0.5	84.7	11.5	3.7
Other	100.4	0.5	10.9	0.1	-11.7	-0.1	99.6	0.4	100.9	10.9	-11.8
Paper	78.0	0.8	23.8	0.6	-3.6	0.4	98.2	1.8	78.8	24.4	-3.3
Real Estate	63.4	0.2	35.1	3.5	-2.8	0.5	95.7	4.3	63.7	38.6	-2.3
Retail	90.3	0.1	19.6	0.4	-10.4	-0.1	99.6	0.4	90.4	20.1	-10.5
Services	54.3	0.1	38.6	0.5	6.7	-0.1	99.5	0.5	54.3	39.1	6.6
Steel	88.0	0.5	6.3	3.1	1.4	0.7	95.7	4.3	88.5	9.4	2.1
Telecom	57.4	0.1	34.1	0.5	7.9	0.1	99.3	0.7	57.5	34.5	8.0
Textiles	47.6	0.5	48.4	2.8	1.3	-0.6	97.4	2.6	48.1	51.2	0.7
Transport	77.7	0.9	16.9	2.7	1.0	0.8	95.6	4.4	78.6	19.6	1.8
Wholesale	88.3	0.6	7.8	0.2	2.8	0.2	98.9	1.1	88.9	8.0	3.0

Table 9: **Variance decomposition of unexpected industry returns**. This table presents the variance decomposition of unexpected industry returns using equation (5.1). The table is divided into 3 panels. The left most panel present the contribution of idiosyncratic and systematic cash flow news, discount rate news, and covariances to total variation in unexpected industry returns. The middle panel indicates the contribution of the sum of idiosyncratic and systematic components to total variance. Lastly, the right most panel sums systematic and idiosyncratic per component. All rows sum up to 100 percent within each panel.

	Cash Flow News	Discount Rate News
Global	**0.008**	0.605
Industry		
Autos	**0.004**	**0.000**
Beer	**0.000**	**0.036**
Books	**0.001**	**0.001**
BusEq.	**0.000**	**0.000**
Carry	**0.024**	0.485
Chemicals	**0.002**	**0.001**
Clothes	0.284	0.153
Coal	**0.000**	**0.000**
Const	**0.000**	0.185
ElcEq	**0.000**	**0.005**
FabProd	**0.016**	**0.001**
Food	**0.000**	**0.003**
Games	0.222	0.082
Health	0.133	0.052
Hshld	0.115	0.258
Meals	**0.001**	**0.029**
Oil	0.231	0.610
Other	**0.006**	**0.002**
Paper	0.097	**0.026**
Real Estate	**0.018**	**0.016**
Retail	**0.000**	**0.000**
Services	**0.000**	0.203
Steel	**0.005**	**0.000**
Telecom	**0.000**	**0.000**
Textiles	**0.002**	**0.012**
Transport	0.068	**0.012**
Wholesale	0.223	0.147

Table 10: **P-Values of AutoRegressive Conditional Heteroskedasticity tests of Cash Flow News and Discount Rate News**. This table presents the p-values of ARCH tests for Cash Flow News and Discount Rate News. Tests significant at the 5% level are bolded.

	$\varepsilon^{F^{(2)}}_{t+1}$			$\varepsilon^{F^{(1)}}_{t+1}$			DCC		
	$C_{F^{(2)}}$	$\alpha^r_{F^{(2)}}$	$\beta^r_{F^{(2)}}$	$C_{F^{(1)}}$	$\alpha^r_{F^{(1)}}$	$\beta^r_{F^{(1)}}$	W^S	α_{dcc}	β_{dcc}
Systematic ($\mathcal{S}_{t+1}$)	**0.15** (0.055)	**0.22** (0.091)	0.23 (0.212)	**0.86** (0.318)	0.11 (0.083)	0.14 (0.252)	**-0.16** (0.077)	-	-
Idiosyncratic($\mathcal{J}_{j,t+1}$)	Cash Flow News			Discount Rate News			DCC		
	$C_{j,CF}$	$\alpha^r_{j,cf}$	$\beta^r_{j,cf}$	$C_{j,DR}$	$\alpha^r_{j,dr}$	$\beta^r_{j,dr}$	W^J_j	$\alpha_{j,dcc}$	$\beta_{j,dcc}$
Autos	0.10 (0.058)	0.27 (0.146)	**0.51** (0.088)	**0.04** (0.013)	**0.23** (0.072)	**0.44** (0.161)	0.01 (0.076)	-	-
Books	0.05 (0.043)	**0.20** (0.076)	0.48 (0.276)	**0.04** (0.010)	**0.43** (0.105)	0.00 (0.103)	**0.34** (0.076)	-	-
BusEq.	0.01 (0.004)	**0.17** (0.050)	**0.74** (0.073)	**0.03** (0.015)	**0.21** (0.063)	**0.51** (0.152)	-0.10 (0.077)	-	-
Carry	0.06 (0.038)	0.13 (0.078)	**0.64** (0.177)	**0.37** (0.178)	0.15 (0.103)	0.00 (0.420)	**0.14** (0.070)	-	-
Chemicals	**0.06** (0.019)	**0.25** (0.080)	**0.52** (0.088)	**0.07** (0.026)	**0.36** (0.122)	0.00 (0.226)	0.05 (0.083)	-	-
Clothes	0.02 (0.010)	0.06 (0.063)	**0.77** (0.141)	0.09 (0.102)	0.24 (0.125)	0.12 (0.762)	0.04 (0.066)	-	-
Coal	**0.08** (0.028)	**0.40** (0.143)	0.31 (0.166)	**0.03** (0.011)	**0.54** (0.164)	**0.26** (0.132)	**0.23** (0.070)	-	-
Const	0.01 (0.006)	**0.16** (0.045)	**0.81** (0.035)	**0.08** (0.021)	**0.20** (0.100)	0.00 (0.207)	-0.05 (0.078)	-	-
ElcEq	0.02 (0.016)	**0.32** (0.158)	**0.61** (0.196)	0.05 (0.157)	**0.19** (0.077)	0.43 (1.196)	0.08 (0.085)	-	-
FabProd	**0.09** (0.044)	**0.29** (0.114)	0.37 (0.209)	**0.09** (0.037)	**0.31** (0.089)	0.29 (0.200)	-0.23 (0.120)	-	-
Food	**0.09** (0.032)	**0.38** (0.117)	0.19 (0.178)	**0.09** (0.023)	**0.47** (0.204)	0.00 (0.213)	0.02 (0.076)	-	-
Games	0.00 (0.005)	0.08 (0.044)	**0.91** (0.027)	0.17 (0.772)	0.21 (0.461)	0.00 (4.092)	**-0.39** (0.075)	-	-
Hshld	0.12 (0.090)	**0.24** (0.085)	0.00 (0.672)	0.04 (0.062)	0.12 (0.082)	0.47 (0.76)	-0.13 (0.096)	-	-
Meals	**0.02** (0.010)	**0.20** (0.080)	**0.66** (0.100)	**0.08** (0.021)	0.27 (0.147)	0.00 (0.219)	0.16 (0.086)	-	-
Oil	**0.22** (0.074)	0.24 (0.134)	0.10 (0.182)	**0.20** (0.065)	0.21 (0.128)	0.00 (0.284)	**-0.31** (0.067)	-	-
Paper	0.02 (0.021)	0.12 (0.081)	**0.73** (0.239)	0.07 (0.040)	**0.27** (0.134)	0.25 (0.345)	-0.09 (0.110)	-	-
Real Estate	**0.14** (0.054)	0.13 (0.107)	0.00 (0.381)	**0.08** (0.037)	**0.33** (0.155)	0.00 (0.384)	**0.29** (0.097)	-	-
Retail	**0.03** (0.011)	**0.28** (0.094)	**0.58** (0.091)	0.02 (0.011)	**0.40** (0.118)	**0.47** (0.154)	**-0.25** (0.065)	-	-
Services	0.02 (0.012)	**0.31** (0.088)	**0.53** (0.141)	0.00 (0.001)	**0.20** (0.098)	**0.75** (0.107)	**-0.19** (0.074)	-	-
Steel	**0.12** (0.045)	**0.27** (0.092)	**0.47** (0.137)	0.03 (0.019)	**0.22** (0.076)	**0.71** (0.068)	**0.23** (0.089)	-	-
Telecom	0.03 (0.045)	0.23 (0.187)	0.61 (0.428)	**0.02** (0.004)	**0.74** (0.137)	0.00 (0.081)	-0.08 (0.079)	-	-
Textiles	**0.00** (0.001)	**0.26** (0.094)	0.03 (0.195)	**0.03** (0.010)	**0.30** (0.087)	0.04 (0.197)	-0.07 (0.100)	**0.20** (0.095)	0.00 (0.265)
Transport	**0.23** (0.069)	**0.33** (0.158)	0.12 (0.158)	**0.15** (0.046)	**0.21** (0.069)	**0.28** (0.133)	**-0.20** (0.093)	-	-
Wholesale	0.07 (0.067)	0.18 (0.138)	0.53 (0.366)	0.02 (0.048)	0.13 (0.161)	0.74 (0.381)	0.06 (0.079)	-	-

Table 11: **Dynamic Conditional Correlation (DCC) estimates of the systematic and idiosyncratic variance covariance matrices of cash flow news and discount rate news as presented in equations** (D.5)-(D.7). The top panel of the table presents the DCC-GARCH(1,1) estimates of the conditional variance covariance matrix of systematic shocks ($\mathcal{S}_{t+1}$), and the bottom panel present conditional variance covariance matrix of idiosyncratic cash flow news and discount rate news ($\mathcal{J}_{j,t+1}$). Coefficients denoted as $C_{(\cdot)}$ indicate constants in the GARCH(1,1) models, and W^S and W^J_j indicate unconditional correlation matrices. Cells marked with "-" indicate estimates of 0 in the DCC model. Note that for $\alpha_{dcc} = \beta_{dcc} = 0$, the DCC model implies a constant conditional correlation model, thus W^S and W^J_j is the unconditional correlation matrix. Robust standard errors are in parentheses, and boldface coefficients indicate significance at the 5 percent level.

	$\Delta_i = \mathbb{E}[\text{CFN Share}_{i,t}] - \mathbb{E}[\text{CFN Share}_{i-1,t}]$ $H_0 : \boldsymbol{\Delta} <= 0$	
	Unstudentized	Studentized
	$H_1 : \min_{(i=1,\ldots,N)} \Delta_i > 0$	
Test Stat	7.232	7.232
P-Value	0.000	0.000
	Adjacent portfolios	
P-Value	0.020	0.030
	All portfolio pairs	
P-Value	0.020	0.026

Table 12: **Patton and Timmermann (2010) increasing monotonic relationship test between cash flow news (CFN) share and industry concentration**. This table presents the monotonic relationship test of Patton and Timmermann (2010) in which the null hypothesis is no increasing relationship between HHI sorted portfolios and cash flow news share in return volatility. Low p-values indicate the rejection of the null hypothesis and indicate an increasing relationship between cash flow news share and HHI. $\mathbb{E}[\text{CFN Share}_{s,t}]$ indicates the average cash flow news share at time t for portfolio i. $\Delta_i = \mathbb{E}[\text{CFN Share}_{i,t}] - \mathbb{E}[\text{CFN Share}_{i-1,t}]$ is the CFN share difference between portfolio i and $i-1$. $\boldsymbol{\Delta} \equiv [\Delta_i, \ldots, \Delta_N]'$ is a column vector.

Eqn.	$\text{Vol}_{j,t} = \alpha_j + \beta D_t^{Reces.} + \varepsilon_{j,t}$		
Quintiles	β	SE	P-Value
Q1	0.14	0.084	0.088
Q3	0.20	0.068	0.004
Q5	0.28	0.052	0.000

Table 13: **Coefficient estimates of the regression of recession dummy on industry return volatility by HHI quintiles**. I regress a recession dummy on industry return volatility by HHI quintiles to analyze the effects of systematic shocks on industry return volatility. The estimation sample is 1976Q3-2021Q2, which includes the 1980, 1981-1982, 1990-1991, 2001, 2007-2009 (GFC), and 2020 (Covid) recessions.

Eqn.	$\text{SR}_{j,t} = \alpha_j + \beta D_t^{Reces.} + \varepsilon_{j,t}$		
Quintiles	β	SE	P-Value
Q1	-0.02	0.013	0.217
Q3	-0.01	0.023	0.564
Q5	-0.09	0.039	0.021

Table 14: **Coefficient estimates of the regression of recession dummy on conditional Sharpe ratios by HHI quintiles**. I regress a recession dummy on conditional Sharpe ratios by HHI quintiles to analyze the effects of systematic shocks on conditional Sharpe ratios. The estimation sample is 1976Q3-2021Q2, which includes the 1980, 1981-1982, 1990-1991, 2001, 2007-2009 (GFC), and 2020 (Covid) recessions.

Panel A: Decreasing Monotonic Relationship between CFN Share and Sharpe Ratios			
		$H_0 : \mathbf{\Delta} \geq 0$	
	$H_1 : \min_{i=2,\ldots,5} \Delta_i > 0$	Adjacent Pairs	All Pairs
P-value	0.028	0.100	0.098
Panel B: Weak Monotonic Relationship between CFN Share and Sharpe Ratios			
	$H_0 : \Delta_i \geq 0, \ldots, \Delta_N \geq 0$ $H_1 : \Delta_i < 0, \ldots, \Delta_N < 0$ for some i		
P-value	0.014		
	$H_0 : \Delta_i \leq 0, \ldots, \Delta_N \leq 0$ $H_1 : \Delta_i > 0, \ldots, \Delta_N > 0$ for some i		
P-value	0.382		
Panel C: Increasing Monotonic Relationship between CFN Share and Returns			
		$H_0 : \mathbf{\Delta} \leq 0$	
	$H_1 : \min_{i=2,\ldots,5} \Delta_i > 0$	Adjacent Pairs	All Pairs
P-value	0.798	0.448	0.729
Panel D: Weak Monotonic Relationship between CFN Share and Returns			
	$H_0 : \Delta_i \geq 0, \ldots, \Delta_N \geq 0$ $H_1 : \Delta_i < 0, \ldots, \Delta_N < 0$ for some i		
P-value	0.585		
	$H_0 : \Delta_i \leq 0, \ldots, \Delta_N \leq 0$ $H_1 : \Delta_i > 0, \ldots, \Delta_N > 0$ for some i		
P-value	0.354		

Table 15: **Patton and Timmermann (2010) decreasing monotonic relationship test between cash flow news (CFN) share and Sharpe ratios, and increasing monotonic relationship test between CFN share and returns**. "Panel A" of the table test for a decreasing monotonic relationship between CFN share and Sharpe ratios. A rejection (low $p-values$) of the null hypothesis indicates a decreasing monotonic relationship between CFN share and Sharpe ratios, implying that as CFN share increases Sharpe ratios fall. I present $p-values$ for the potential test statistics discussed in Patton and Timmermann (2010). In "Panel B" I show the results of the weak monotonic relationship between CFN share and Sharpe ratios. There are two sets of hypotheses for the weak monotonicity test, the null of the first is no decreasing relationship between CFN Share and Sharpe ratios. A rejection of the null implies that some portfolios have a decreasing relationship. The second null implies no increasing relationship between CFN Share and Sharpe ratios. A rejection of the null indicates that some portfolios have an increasing relationship. "Panel C" tests for an increasing monotonic relationship between CFN share and returns. The rejection of the null hypothesis indicates an increasing monotonic relationship between CFN share and returns. "Panel D" test for a weak relationship between CFN share and returns. A rejection of the first null hypothesis indicates that some portfolios have an increasing relationship between CFN share and returns. A rejection of the second null hypothesis indicates a decreasing relationship between CFN share and returns.

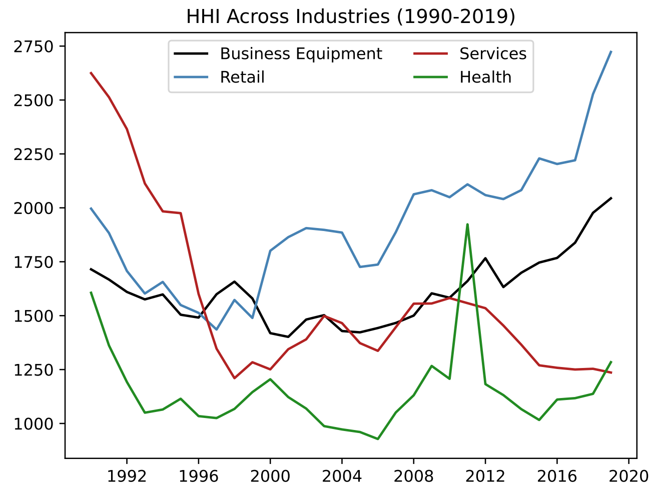

Figure 1: **Time series plot of HHI for the business equipment, retail, services, and health industries between 1990 and 2019**.

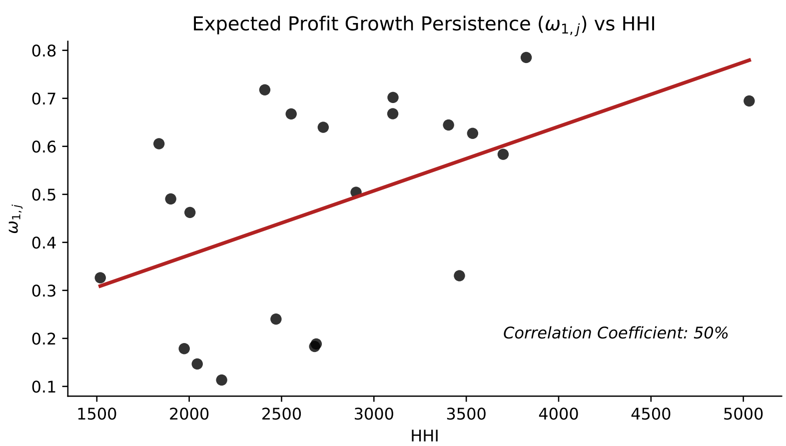

Figure 2: **Scatter plot of HHI and profit growth persistence estimates across industries**. This figures shows a positive correlation between industry specific profit growth persistence ($\omega_{1,j}$) and their respective HHI. The measured correlation coefficient is 50 percent.

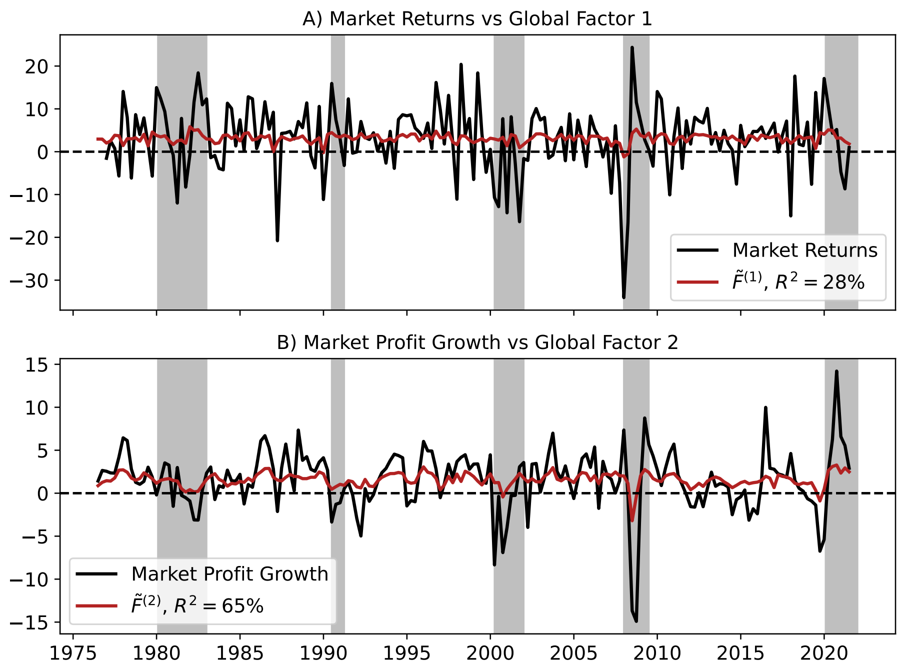

Figure 3: **Time series plot of filtered global factors ($\widetilde{F}^{(1)}$ and $\widetilde{F}^{(2)}$) against market returns and profit growth.**. This plot shows time series evolution of market returns against the first global factor ($\widetilde{F}^{(1)}$) in panel A. Panel B shows the time series evolution of market profit growth and the second global factor ($\widetilde{F}^{(2)}$). The respective is sample contemporaneous R^2 of the global factors are in the legends. The shaded gray areas indicate NBER recessions.

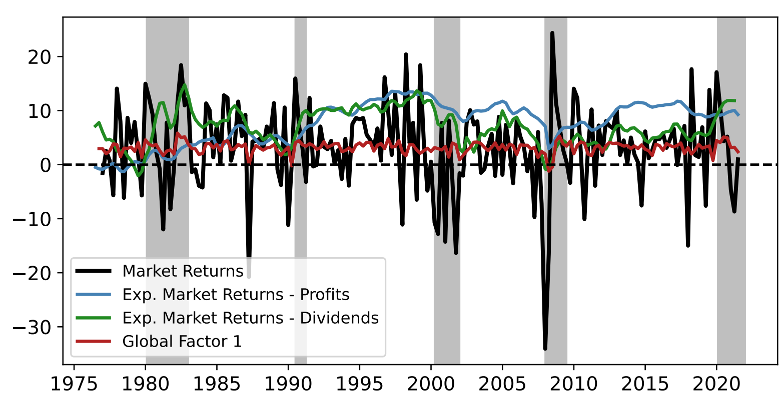

Figure 4: **Time series plot of expected market returns from the vBK model and the first global factor from the DFM**. The figure plots the expected returns from the vBK model and the first global factor from the DFM against market returns.The shaded gray areas indicate NBER recessions.

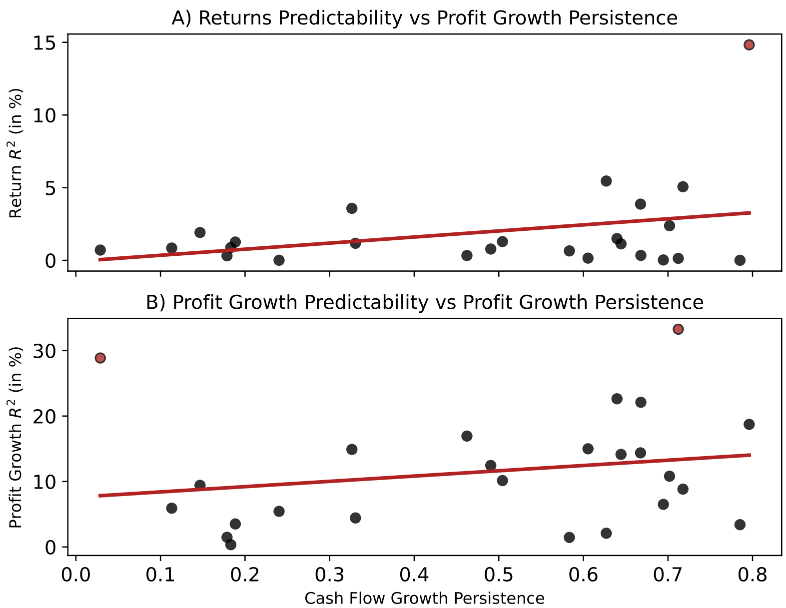

Figure 5: **Scatter plots of industry wise in sample return R^2 (Panel A) and profit growth R^2 (Panel B) against industry profit growth persistence parameter ($\omega_{1,j}$).** The figure shows the R^2 values in percent on the y-axis, and profit growth persistence parameter on the x-axis. The red markers indicate outliers, such as, business equipment in Panel A, and real estate and steel in Panel B. In panel A, the correlation between return R^2 and $\omega_{1,j}$ is 18.6 percent without the business equipment sector, and 32.6 percent including business equipment. In panel B, the correlation between profit growth predictability and profit growth persistence is 43.2 percent removing the outliers, and 22.2 percent including the outliers.

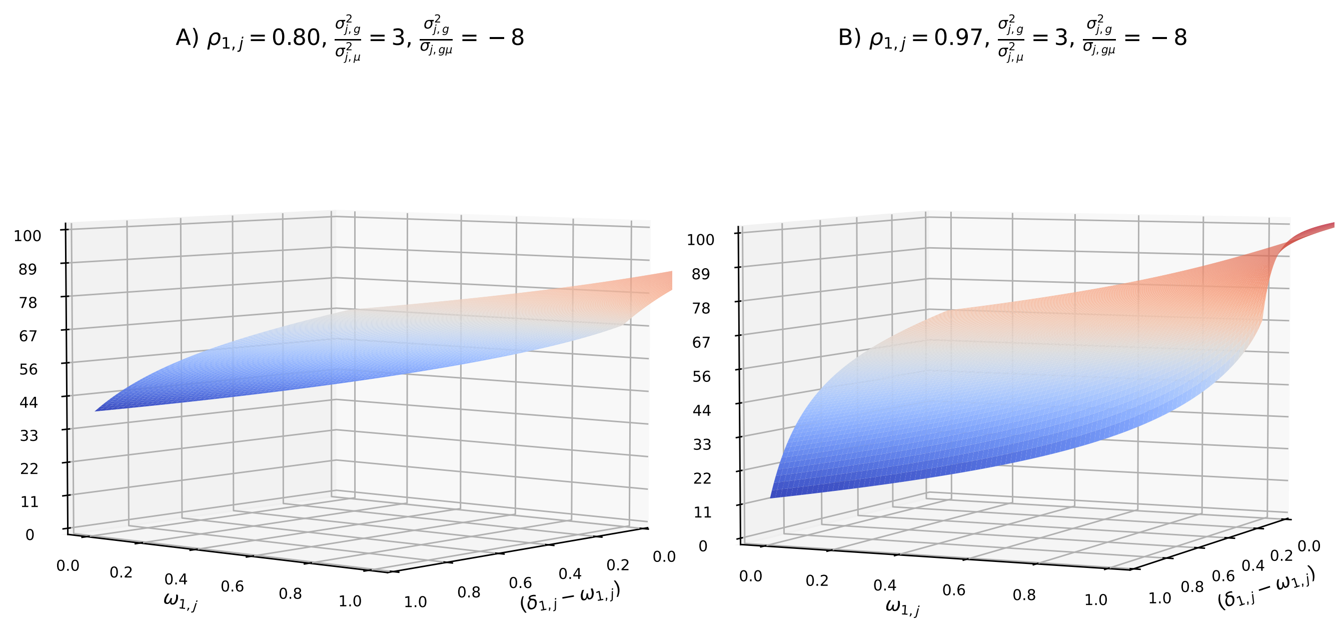

Figure 6: **Surface plots of contribution of cash flow news to total unexpected return variance by varying persistence gap ($\delta_{1,j} - \omega_{1,j}$, log-linearization constant ($\rho_{1,j}$), relative size of cash flow news to discount rate news ($\frac{\sigma^2_{j,g}}{\sigma^2_{j,\mu}}$).**

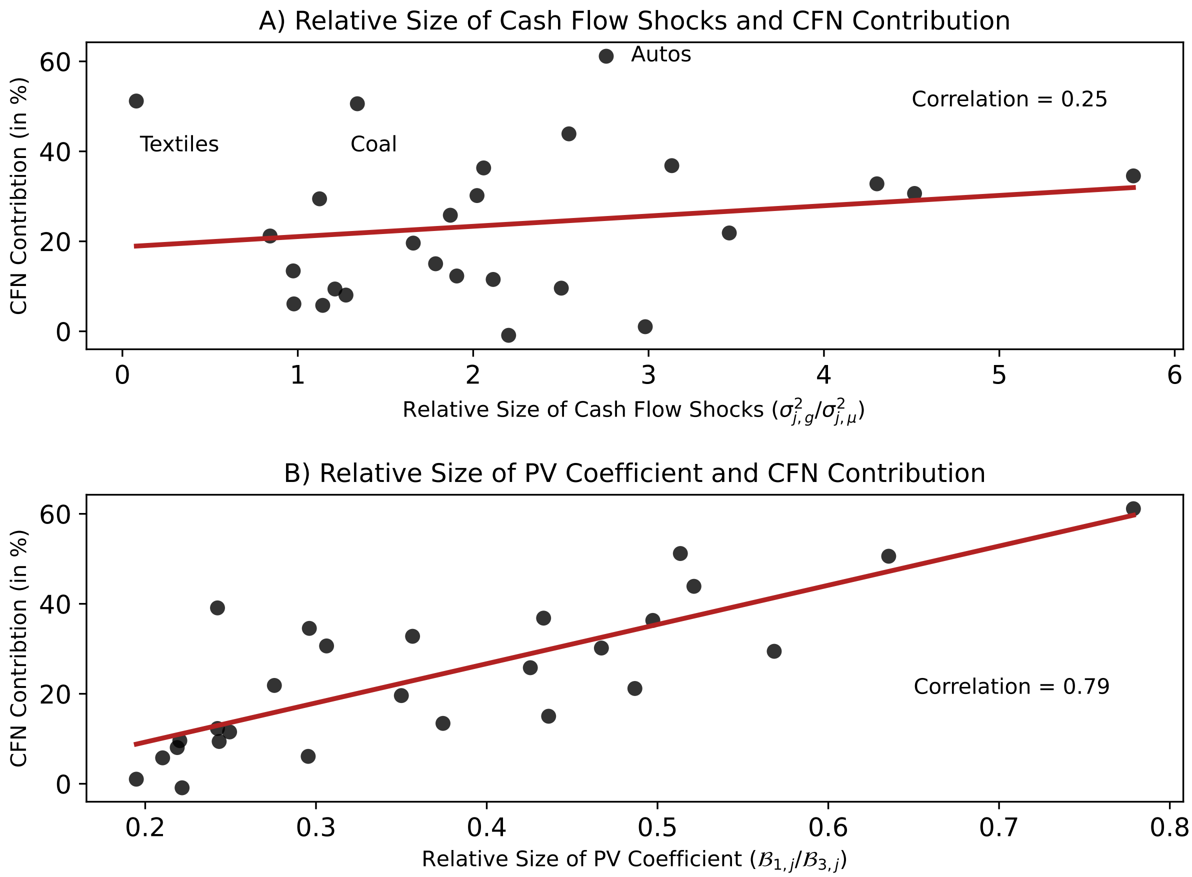

Figure 7: **Scatter plot of the relative size of present value coefficients against cash flow news contribution in percent**. The figure show the scatter plot of $\frac{\mathcal{B}1,j}{\mathcal{B}3,j}$ against cash flow news contribution to unexpected return variance. The correlation coefficient between cash flow news contribution and the relative size of present value coefficients is 79.2 percent.

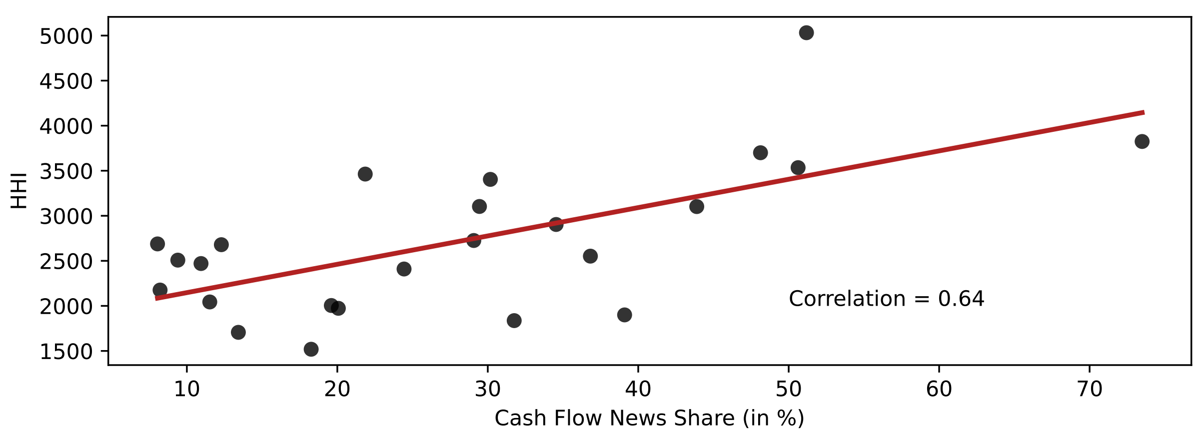

Figure 8: **Scatter plot of cash flow news share and HHI score**. The figure show the scatter plot of cash flow news share ($\frac{\sigma^2_{j,CFN}}{\sigma^2_{j,Total}}$) and HHI score. The scatter plot shows a correlation coefficient of 64 percent between HHI and cash flow news share.

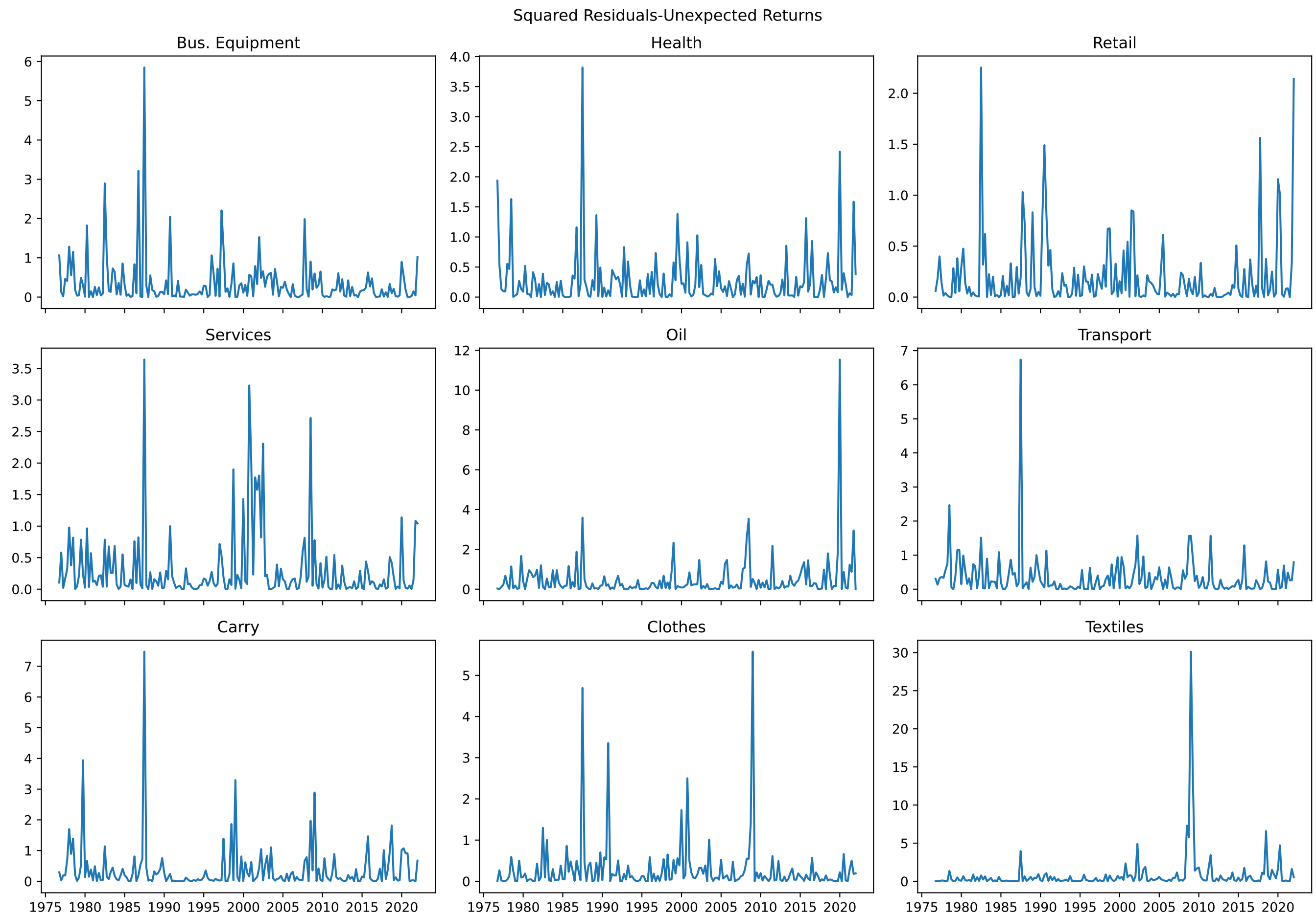

Figure 9: **Quarterly squared unexpected industry returns of equation**. I square unexpected returns to show high volatility periods in unexpected returns.

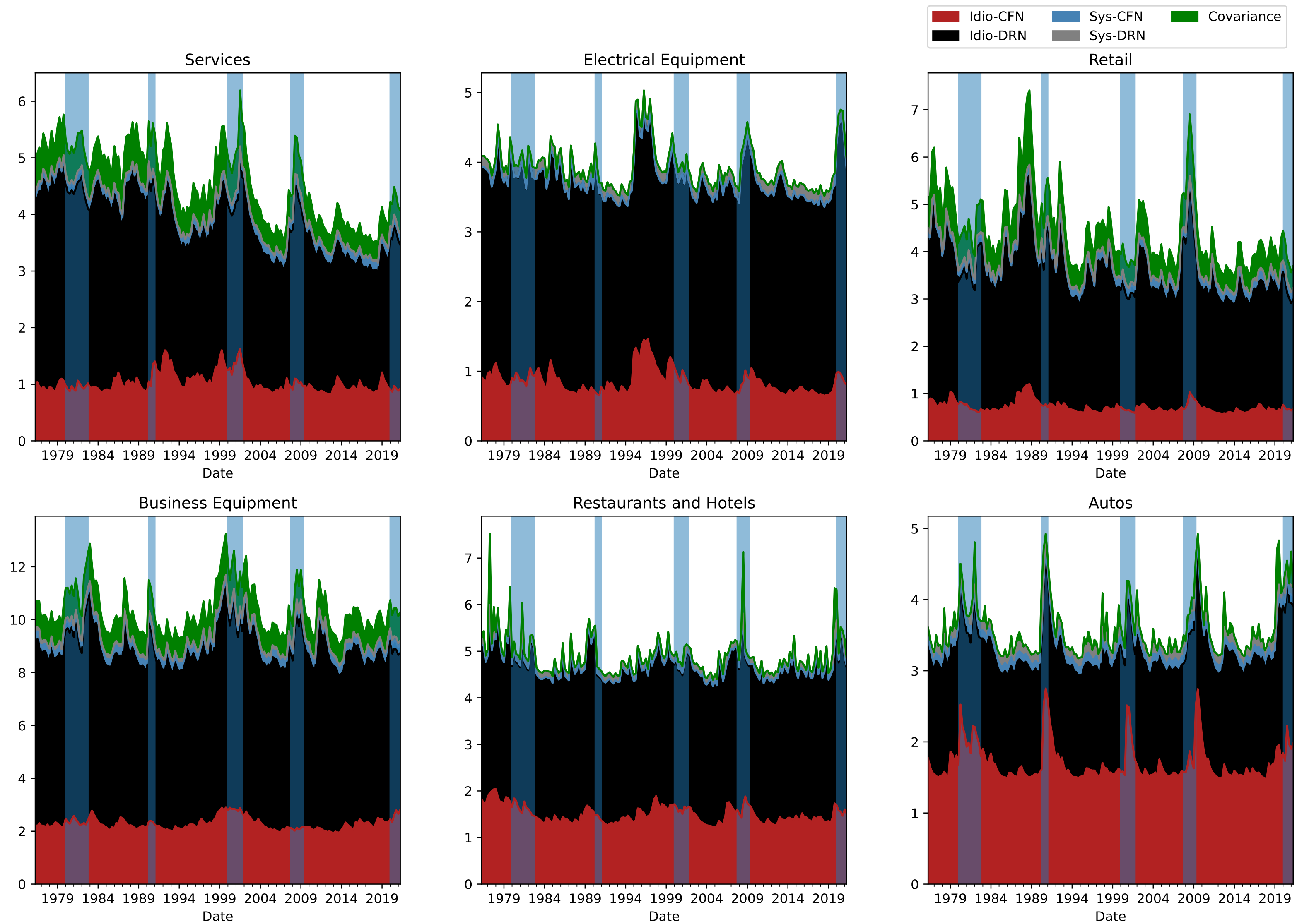

Figure 10: **Conditional time varying volatility of select unexpected industry returns' components**. Vertically shaded blue areas indicate NBER recessions. Shaded red regions indicate idiosyncratic cash flow news contribution to total volatility, shaded black regions indicate idiosyncratic discount rate news contribution to total volatility. Shaded blue regions indicate systematic cash flow news ($\widetilde{F}^{(2)}$) contribution to total volatility. Shaded grey regions indicate systematic discount rate news ($\widetilde{F}^{(1)}$) contribution to total volatility. Finally, shaded green regions indicate the contribution of the total covariance between systematic cash flow news and discount rate news, and idiosyncratic cash flow news and discount rate news.

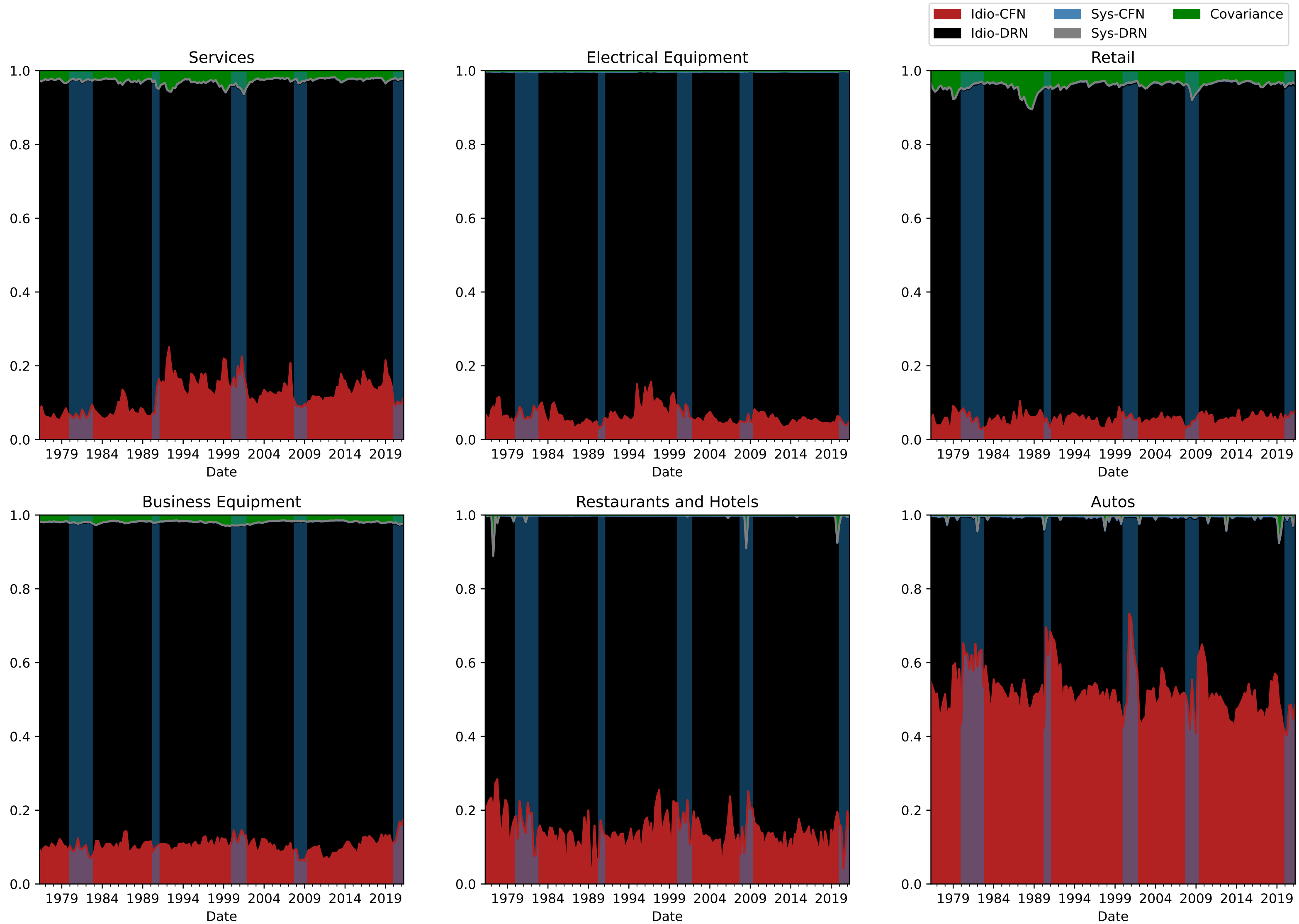

Figure 11: **Time series decomposition of conditional time varying volatility of select unexpected industry returns**. Vertically shaded blue areas indicate NBER recessions. Shaded red regions indicate idiosyncratic cash flow news contribution to total volatility, shaded black regions indicate idiosyncratic discount rate news contribution to total volatility. Shaded blue regions indicate systematic cash flow news ($\widetilde{F}^{(2)}$) contribution to total volatility. Shaded grey regions indicate systematic discount rate news ($\widetilde{F}^{(1)}$) contribution to total volatility. Finally, shaded green regions indicate the contribution of the total covariance between systematic cash flow news and discount rate news, and idiosyncratic cash flow news and discount rate news.

A Latent Variables Model for Aggregate Market Returns

Van Binsbergen and Koijen (2010) modeled returns using the log price to dividend ratio (pd_t) and dividend growht (Δd_t). The model takes the following state space form:

$$
\begin{aligned}
&\text{Observation Equations :}\\
pd_{t+1} &= (1-\delta_1)\mathcal{A} + \delta_1 pd_t + \mathcal{B}_2(\gamma_1-\delta_1)\widehat{g}_t + -\mathcal{B}_1\varepsilon^{\mu}_{t+1} + \mathcal{B}_1\varepsilon^{g}_{t+1}\\
\Delta d_{t+1} &= \gamma_0 + \widehat{g}_t + \varepsilon^{d}_{t+1}\\
&\text{State Equation :}\\
\widehat{g}_{t+1} &= \gamma_1\widehat{g}_t + \varepsilon^{g}_{t+1}\\
&\text{Expected Returns :}\\
\widehat{\mu}_{t|t} &= \mathcal{B}_1^{-1}\left[pd_t - \mathcal{A} - \mathcal{B}_2\widehat{g}_{t|t}\right]\\
&\text{Unexpected Returns :}\\
r_{t+1} - \mu_{t+1} &= -\rho\mathcal{B}_1\varepsilon^{\mu}_{t+1} + \rho\mathcal{B}_2\varepsilon^{g}_{t+1} + \varepsilon^{d}_{t+1}.
\end{aligned}
$$

I use the vBK framework to model aggregate market returns using both dividend growth and profit growth to analyze the implications of different cash flow proxies.

A.1 Market Estimates

I model market expected returns and expected profit growth using the Van Binsbergen and Koijen (2010) model (vBK) and present the estimation results in Table E1. The first column presents the results for the model using profits as cash flow proxy, and the second column indicates estimation results for the model that uses dividends as cash flow proxy. The persistence estimates of the latent factors across the two models are similar, expected market return persistence is around 0.95, which confirms that market expected returns are highly persistent at the quarterly frequency as well as the annual frequency. Expected profit growth persistence is 0.75, which is three times as large as the persistence coefficient of expected dividend growth. The present value coefficient on expected returns ($\mathcal{B}_1^M$) is almost identical across the two models. The magnitude of the present value coefficients depend directly on the magnitude to persistence coefficients and the log-linearization constant. Because the log-linearization constant (ρ) and the expected return persistence (δ_1) is virtually identical across the two models $\mathcal{B}_1^M$ is practically identical across the models. However, because the expected cash flow growth persistence is larger in the model that uses profits growth as proxy, $\mathcal{B}_2^M$ is larger for the profits model. Estimated expected return error variance (σ^2_μ) is three times as large for the model using dividends as cash flow. Cash flow error variance (σ^2_g) is negligible for model using dividends, yet, it is almost as large as the expected return error variance in the profits model. Overall, the only real difference between the models using the different cash flow proxies emerge when looking at cash flow error variances and present value coefficients, which depend on persistence parameters. I present parameter estimates for the Fama-French 5 industries in Table E2.

A.2 Unexpected Market Returns

Following Campbell (1991), I decompose the variance of unexpected market returns, obtained using the vBK model, into discount rate news and cash flow news.

$$r_{t+1} - \mu_t = -\rho \mathcal{B}_1^M \varepsilon_{t+1}^{\mu} + \rho \mathcal{B}_2^M \varepsilon_{t+1}^{g} + \varepsilon_{t+1}^{dd} \tag{A.1}$$

Equation (A.1) is identical to unexpected returns derived in Van Binsbergen and Koijen (2010). However, I use two different measures for cash flows, thus ε_{t+1}^{dd} indicates either shocks to realized dividend growth or realized profit growth. For both models, ε_{t+1}^{μ} indicates discount rate news and ε_{t+1}^{g} indicates cash flow news. In addition, the log-linearization constant ρ and the present value coefficients ($\mathcal{B}_1$ and $\mathcal{B}_2$) enter the decomposition. The differences in $\mathcal{B}_2$ implies that cash flow news play a more important role in the profits model relative to the dividends model. Previous studies show that discount rate news account for almost all variability in unexpected returns. For example, Van Binsbergen and Koijen (2010) show that discount rates account for 118 percent of unexpected annual market returns, cash flow news account for 35 percent, and the covariance between them accounts for -53 percent. The covariance term annuls all variation that comes from cash flow news. Table E3 presents the variance decomposition of unexpected market returns. Discount rate news account for 97 percent of the variability in unexpected returns using dividends as cash flow proxy, cash flow news account for 0.3 percent, and the rest is the covariance. These results are consistent with the literature. Yet, when I use profits instead of dividends, cash flow news account for 11.5 percent of the variability, discount rate news account for 91.1 percent, and the covariance accounts for -2.6 percent. The difference in the contribution of cash flow news comes from three sources. First, the error variance of expected dividend growth is half of to the error variance of expected profit growth. Second, the persistence of expected dividends growth is less than half of expected profit growth. Lastly, error variance of expected returns is three times larger when using dividends as cash flow proxy.

A.3 Variance Decomposition of Market Returns

I follow the procedure described in equations (5.4) - (5.7) for unexpected market returns with the different cash flow proxies, for which the variance covariance matrix ($\mathbf{\Sigma^M_{t+1}}$) is a symmetric 2x2 matrix. I estimate $\mathbf{\Sigma^M_{t+1}}$ using the Engle and Kroner (1995) diagonal BEKK(1,1) model (equation (A.2)).

$$\begin{aligned}
\mathbf{\Sigma^M_{t+1}} &= \begin{bmatrix} (\rho \mathcal{B}_2^M)^2 \sigma_{g,t+1}^2 & \rho^2 \mathcal{B}_1^M \mathcal{B}_2^M \sigma_{t+1}^{g} \sigma_{t+1}^{\mu} \\ \rho^2 \mathcal{B}_1^M \mathcal{B}_2^M \sigma_{t+1}^{g} \sigma_{t+1}^{\mu} & (\rho \mathcal{B}_1^M)^2 \sigma_{\mu,t+1}^2 \end{bmatrix} \\
&= \begin{bmatrix} c_{11}^2 & c_{11}c_{12} \\ c_{11}c_{12} & c_{12}^2 + c_{22}^2 \end{bmatrix} + \begin{bmatrix} \alpha_{11}^r & 0 \\ 0 & \alpha_{22}^r \end{bmatrix}' \left[\begin{pmatrix} (\rho \mathcal{B}_2^M)\varepsilon_t^{g} \\ (\rho \mathcal{B}_1^M)\varepsilon_t^{\mu} \end{pmatrix} \begin{pmatrix} (\rho \mathcal{B}_2^M)\varepsilon_t^{g} \\ (\rho \mathcal{B}_1^M)\varepsilon_t^{\mu} \end{pmatrix}' \right] \begin{bmatrix} \alpha_{11}^r & 0 \\ 0 & \alpha_{22}^r \end{bmatrix} \\
&+ \begin{bmatrix} \beta_{11}^r & 0 \\ 0 & \beta_{22}^r \end{bmatrix}' \Sigma_{j,t} \begin{bmatrix} \beta_{11}^r & 0 \\ 0 & \beta_{22}^r \end{bmatrix}
\end{aligned} \tag{A.2}$$

I present the diagonal BEKK(1,1) estimates of $\mathbf{\Sigma^M_{t+1}}$ in Table E4. Parameter estimates for both models are statistically significant, except for the β_{11}^r and c_{22} estimates in the model using dividends as cash flow proxy. The estimates suggest that market cash flow news and discount rate news exhibit time varying conditional volatility. Comparing estimates across models, sum of cash flow news coefficients $((\alpha_{11}^r)^2 + (\beta_{11}^r)^2)$ is 0.97 for the model using profits as cash flow proxy and 0.42 for the dividends model, suggesting that cash flow shocks are more persistent in the profits model relative to the dividends model. Sum of discount rate news coefficients $((\alpha_{22}^r)^2 + (\beta_{22}^r)^2)$ is 0.67 and 0.77 for the profits and dividends models, respectively. This suggests that discount rate shocks are more persistent in the dividends model. Accordingly, comparing cash flow news and discount rate news coefficients within models, cash flow shocks are more persistent than discount rate shocks in the profits model, whereas, the opposite is true for the dividends model. Therefore, effects of cash flow shocks have longer lasting effects on unexpected market returns relative to discount rate shocks, in which profits are used as cash flow proxy. To further illustrate this point, Figure E1 plots the conditional time varying volatility of unexpected returns and its components. Cash flow news play little to no role in unexpected return volatility when dividends are used cash flow proxy. This is consistent with the decomposition of unconditional variance of unexpected returns. On the other hand, when profits are used as cash flow proxy, conditional cash flow news volatility is persistent and non-negligible. Figure E2 plots the time series decomposition of unexpected market returns and its components such that contributions from each component sum to 1. This figure further shows that cash flow news contribute almost 0 percent at any point in time in the dividends model. However, the profits model tells a different story. On average cash flow news account for 15 percent of total variation in unexpected returns. During times of recession, cash flow news contribution increases to 20-25 percent. Overall, Figures E1 - E2 demonstrate that cash flow news is a persistent and non-negligible component of conditional time varying volatility of unexpected return in which profits are used as cash flow proxy. Moreover, the figures provide further evidence that when dividends are used as cash flow proxy, cash flow news contribution is approximately 0 percent.

B Variance Decomposition of Unexpected Returns and Cash Flow News Contribution

I use the variance decomposition framework of Campbell (1991) to decompose industry unexpected returns into cash flow news, discount rate news, and covariances. I re-state equation (5.1) below and write out the variance.

$$
\begin{aligned}
r_{j,t+1} - \mu_{j,t} &= -\rho_{1,j}\mathcal{B}_{3,j}\left(\varepsilon^{\mu}_{j,t+1} + \delta_{2,j}\varepsilon^{F^{(1)}}_{t+1}\right) + \rho_{1,j}\mathcal{B}_{1,j}\left(\varepsilon^{g}_{j,t+1} + \omega_{2,j}\varepsilon^{F^{(2)}}_{t+1}\right) + \varepsilon^{\Delta\pi}_{j,t+1} \\
\sigma^2_{j,total} &= \underbrace{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + (\rho_{1,j}\mathcal{B}_{3,j})^2\sigma^2_{j,\mu} - 2\rho^2_{1,j}\mathcal{B}_{1,j}\mathcal{B}_{3,j}Cov(\varepsilon^{g}_{j,t+1}, \varepsilon^{\mu}_{j,t+1}) + \sigma^2_{j,\Delta\pi}}_{Idiosyncratic\ Component} \\
&\quad + \underbrace{(\rho_{1,j}\mathcal{B}_{1,j}\omega_{2,j})^2\sigma^2_{F^{(2)}} + (\rho_{1,j}\mathcal{B}_{3,j}\delta_{2,j})^2\sigma^2_{F^{(1)}} - 2\rho^2_{1,j}\mathcal{B}_{1,j}\mathcal{B}_{3,j}\omega_{2,j}\delta_{2,j}Cov(\varepsilon^{F^{(2)}}_{t+1}, \varepsilon^{F^{(1)}}_{t+1})}_{Systematic\ Component}
\end{aligned}
$$

The idiosyncratic cash flow news component of total unexpected return variance is:

$$
\sigma^2_{j,CFN} = (\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + \sigma^2_{j,\Delta\pi}.
$$

The share of cash flow news in total variation is:

$$\frac{\sigma^2_{j,CFN}}{\sigma^2_{j,Total}} = \frac{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + \sigma^2_{j,\Delta\pi}}{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + (\rho_{1,j}\mathcal{B}_{3,j})^2\sigma^2_{j,\mu} - 2\rho^2_{1,j}\mathcal{B}_{1,j}\mathcal{B}_{3,j}Cov(\varepsilon^g_{j,t+1},\varepsilon^\mu_{j,t+1}) + \sigma^2_{j,\Delta\pi} + S_j}$$

$$= \left[1 + \frac{(\rho_{1,j}\mathcal{B}_{3,j})^2\sigma^2_{j,\mu}}{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + \sigma^2_{j,\Delta\pi}} + \frac{S_j}{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + \sigma^2_{j,\Delta\pi}} - 2\frac{\rho^2_{1,j}\mathcal{B}_{1,j}\mathcal{B}_{3,j}Cov(\varepsilon^g_{j,t+1},\varepsilon^\mu_{j,t+1})}{(\rho_{1,j}\mathcal{B}_{1,j})^2\sigma^2_{j,g} + \sigma^2_{j,\Delta\pi}}\right]^{-1}$$

$$S_j = (\rho_{1,j}\mathcal{B}_{1,j}\omega_{2,j})^2\sigma^2_{F^{(2)}} + (\rho_{1,j}\mathcal{B}_{3,j}\delta_{2,j})^2\sigma^2_{F^{(1)}} - 2\rho^2_{1,j}\mathcal{B}_{1,j}\mathcal{B}_{3,j}\omega_{2,j}\delta_{2,j}Cov(\varepsilon^{F^{(2)}}_{t+1},\varepsilon^{F^{(1)}}_{t+1})$$

WLOG: $S_j = \sigma^2_{j,\Delta\pi} = 0$

$$\frac{\sigma^2_{j,CFN}}{\sigma^2_{j,Total}} = \left[1 + \frac{\mathcal{B}^2_{3,j}}{\mathcal{B}^2_{1,j}}\frac{\sigma^2_{j,\mu}}{\sigma^2_{j,g}} - 2\frac{\mathcal{B}_{3,j}}{\mathcal{B}_{1,j}}\frac{Cov(\varepsilon^g_{j,t+1},\varepsilon^\mu_{j,t+1})}{\sigma^2_{j,g}}\right]^{-1}$$

$$= \left[1 + \left(\frac{\mathcal{B}^2_{1,j}}{\mathcal{B}^2_{3,j}}\frac{\sigma^2_{j,g}}{\sigma^2_{j,\mu}}\right)^{-1} - 2\left(\frac{\mathcal{B}_{1,j}}{\mathcal{B}_{3,j}}\frac{\sigma^2_{j,g}}{Cov(\varepsilon^g_{j,t+1},\varepsilon^\mu_{j,t+1})}\right)^{-1}\right]^{-1}$$

$$\because \frac{\mathcal{B}_{1,j}}{\mathcal{B}_{3,j}} = \frac{1-\rho_{1,j}\delta_{1,j}}{1-\rho_{1,j}\omega_{1,j}}$$

$$= \mathcal{B}_{1,j} - \left(\frac{\rho_{1,j}(\delta_{1,j}-\omega_{1,j})}{1-\rho_{1,j}\omega_{1,j}} + \frac{\rho_{1,j}\omega_{1,j}}{1-\rho_{1,j}\omega_{1,j}}\right) = \mathcal{B}_{1,j} - (\rho_{1,j}\mathcal{B}_{1,j}(\delta_{1,j}-\omega_{1,j}) + \rho_{1,j}\mathcal{B}_{1,j}\omega_{1,j})$$

$$= \mathcal{B}_{1,j}\left[1-\rho_{1,j}(\delta_{1-j}-\omega_{1,j}) - \rho_{1,j}\omega_{1,j}\right]$$

$$= 1 - \rho_{1,j}\mathcal{B}_{1,j}(\delta_{1,j}-\omega_{1,j})$$

$$\therefore \frac{\sigma^2_{j,CFN}}{\sigma^2_{j,Total}} = \frac{1}{1 + \left[(1-\rho_{1,j}\mathcal{B}_{1,j}(\delta_{1,j}-\omega_{1,j}))^2\frac{\sigma^2_{j,g}}{\sigma^2_{j,\mu}}\right]^{-1} - 2\left[(1-\rho_{1,j}\mathcal{B}_{1,j}(\delta_{1,j}-\omega_{1,j})) - \rho_{1,j}\omega_{1,j})\frac{\sigma^2_{j,g}}{\sigma_{j,g\mu}}\right]^{-1}}$$

C Predictability of Cash Flows and Excess Returns

There is a very large literature on predictability of earnings or profits. Notable accounting literature includes Albrecht et al. (1977), Beaver (1970), Freeman et al. (1982), and Lev (1983). This literature is mostly concerned about the time series properties of earnings (mean reversion, stationarity), and use time series methods to predict earnings. Notable finance literature include Fama and French (2000), and Van Binsbergen et al. (2023). Fama and French (2000) uses methods developed in Fama and MacBeth (1973) to test for cointegration of profitability across firms. Van Binsbergen et al. (2023) take a different approach and models earnings per share using random forests to predict monthly firm-level earnings per share. In this section, I propose a direct approach to forecasting out of sample excess returns, profit growth, and price to profit growth. I start with the present value relationship derived in Section 2 and constrain the log-linearization constants $\rho_{1,j} = 1$ and $\rho_{2,j} = 0$[26], which gives the following relationship:

$$\begin{aligned} r_{j,t+1} &\approx \kappa_j + \Delta\pi_{j,t+1} - pe_{j,t} + \rho_{1,j} pe_{j,t+1} + \rho_{2,j} ev_{j,t+1} \\ &\approx \kappa_j + \Delta\pi_{j,t+1} + \Delta pe_{j,t+1}. \end{aligned} \tag{C.1}$$

This representation allows for the decomposition of realized returns into two components, profit growth ($\Delta\pi_{t+1}$) and price-to-profit growth (Δpe_{t+1}). I use 2 common factors extracted from profit growth and 2 common factors extracted from price-to-profit growth. I then turn equation (C.1) to a forecasting equation using the second lags of the factors and extend it with the second lags of observed profit growth and price to profit growth. Using the second lag instead of the first lag may seem unconventional at first. However, it is necessary to use second lags, because firm level accounting data is released with at least a quarter lag. Hence, in a scenario where an investor wants to forecast next quarter profits she can only use previous quarter's accounting data[27].

$$\begin{aligned} r_{j,t+1} &= c_j^{(r)} + \beta_{1,j}^{(r)} F_{1,t-1}^{\Delta\pi} + \beta_{2,j}^{(r)} F_{2,t-1}^{\Delta\pi} + \beta_{3,j}^{(r)} F_{1,t-1}^{\Delta pe} + \beta_{4,j}^{(r)} F_{2,t-1}^{\Delta pe} \\ &\quad + \beta_{5,j}^{(r)} \Delta\pi_{j,t-1} + \beta_{6,j}^{(r)} \Delta pe_{j,t-1} + \varepsilon_{j,t+1}^{(r)} \end{aligned} \tag{C.2}$$

$$\begin{aligned} \Delta\pi_{j,t+1} &= c_j^{(\Delta\pi)} + \beta_{1,j}^{(\Delta\pi)} F_{1,t-1}^{\Delta\pi} + \beta_{2,j}^{(\Delta\pi)} F_{2,t-1}^{\Delta\pi} + \beta_{3,j}^{(\Delta\pi)} F_{1,t-1}^{\Delta pe} + \beta_{4,j}^{(\Delta\pi)} F_{2,t-1}^{\Delta pe} \\ &\quad + \beta_{5,j}^{(\Delta\pi)} \Delta\pi_{j,t-1} + \beta_{6,j}^{(\Delta\pi)} \Delta pe_{j,t-1} + \varepsilon_{j,t+1}^{(\Delta\pi)} \end{aligned} \tag{C.3}$$

$$\begin{aligned} \Delta pe_{j,t+1} &= c_j^{(\Delta pe)} + \beta_{1,j}^{(\Delta pe)} F_{1,t-1}^{\Delta\pi} + \beta_{2,j}^{(\Delta pe)} F_{2,t-1}^{\Delta\pi} + \beta_{3,j}^{(\Delta pe)} F_{1,t-1}^{\Delta pe} + \beta_{4,j}^{(\Delta pe)} F_{2,t-1}^{\Delta pe} \\ &\quad + \beta_{5,j}^{(\Delta pe)} \Delta\pi_{j,t-1} + \beta_{6,j}^{(\Delta pe)} \Delta pe_{j,t-1} + \varepsilon_{j,t+1}^{(\Delta pe)} \end{aligned} \tag{C.4}$$

I estimate equations (C.2)-(C.4) using a pooled panel, and then industry wise regressions. Table E11 presents the pooled panel regression, and Figure E3 presents industry wise parameter estimates. For excess returns (equation (C.2)), all factors are statistically significant at the 5 percent level, with an in sample R^2 of approximately 5 percent. The coefficient on the second lag of the first factor extracted from gross profit growth is -0.35, which can interpreted as high current profit growth leads to lower expected returns. This interpretation is also valid for the coefficients of the factors extracted from price to profit growth, which are -0.58, and -1.43 respectively. For price-to-profit growth to increase, either prices need to increase, which would lead to lower expected returns, or an increase in profit which would also lead to lower expected returns. There is heterogeneity in the value of the coefficient across industries, however, almost all the industries have a negative loading the first factor extracted from profit growth, and the factors extracted from price to profit growth. Industries that have a positive loading on the first factor include, food, health, and telecom industries. These industries are in general highly concentrated and regulated. In equation (C.3), the significant coefficients that are the second lags of the first factor of profit growth, the second factor of price to profit growth, and industry profit and price to profit growth. Loadings on all the significant coefficients are positive with the largest being the first factor of profit growth at 0.92. Statistical significance of these coefficients imply cash flow predictability.

I test the out of sample performance of these forecasting models using the Campbell and Thompson (2008) Out of Sample R^2. As the benchmark I use the prevailing mean, which has the advantage of using data up to and including $T-1$. I estimate and generate out of sample forecasts using a panel LASSO covering the period starting in December 1999 and ending in December 2021. I use an expanding window

[26] These types of restrictions have been used in the literature, Ferreira and Santa-Clara (2011) and Pettenuzzo et al. (2020) restrict $\rho = 1$

[27] Gu et al. (2020) give a great discussion on accounting data availability. The main conclusion is that quarterly accounting data is available with a 4 month lag.

time series validation for the l1 penalty parameter, for which λ takes values between 0.0001 and 1. Table E12 presents the out of sampleR^2 values on the right panel. I obtain an average out of sample R^2 of 4.35 percent for excess returns, 6.05 percent for profit growth, and 6.77 percent for price to profit growth. For almost all industries cash flow and excess return out of sample R^2 values are positive (Figure E4).

D Mathematical Derivation for the GARCH Model

Suppose that cash flow news and discount rate news follow a GARCH(1,1):

$$\varepsilon^r_{j,t+1} \equiv -\rho_{1,j}\mathcal{B}_{3,j}\left(\varepsilon^\mu_{j,t+1} + \delta_{2,j}\varepsilon^{F^{(1)}}_{t+1}\right) + \rho_{1,j}\mathcal{B}_{1,j}\left(\varepsilon^g_{j,t+1} + \omega_{2,j}\varepsilon^{F^{(2)}}_{t+1}\right) \tag{D.1}$$

$$\sigma^r_{j,t+1}e^r_{j,t+1} = \left(\gamma_{j,CF}\sigma^g_{j,t+1} + \gamma_{j,CF}\omega_{2,j}\sigma^{F^{(2)}}_{t+1} - \gamma_{j,DR}\sigma^\mu_{j,t+1} - \gamma_{j,DR}\delta_{2,j}\sigma^{F^{(1)}}_{t+1}\right)\left(e^g_{j,t+1} + e^{F^{(2)}}_{t+1} + e^\mu_{j,t+1} + e^{F^{(1)}}_{t+1}\right),$$

where $\gamma_{j,CF} = \rho_{1,j}\mathcal{B}_{1,j}$, and $\gamma_{j,DR} = \rho_{1,j}\mathcal{B}_{3,j}$. Matching the left hand side and the right side:

$$\begin{aligned}
\sigma^r_{j,t+1} &= (\gamma_{j,CF}\sigma^g_{j,t+1} + \gamma_{j,CF}\omega_{2,j}\sigma^{F^{(2)}}_{t+1} - \gamma_{j,DR}\sigma^\mu_{j,t+1} - \gamma_{j,DR}\delta_{2,j}\sigma^{F^{(1)}}_{t+1})\\
e^r_{j,t+1} &= (e^g_{j,t+1} + e^{F^{(2)}}_{t+1} + e^\mu_{j,t+1} + e^{F^{(1)}}_{t+1}).
\end{aligned}$$

I substitute (D.1) into (D.2) and obtain:

$$r_{j,t+1} - \mu_{j,t+1} = \varepsilon^r_{j,t+1}$$

$$\varepsilon^r_{j,t+1} = \sigma^r_{j,t+1}e^r_{j,t+1} \tag{D.2}$$

$$\sigma^2_{r,j,t+1} = c^r_j + \alpha^r_j\varepsilon^2_{r,j,t} + \beta^r_j\sigma^2_{r,j,t} \tag{D.3}$$

$$\begin{aligned}
\sigma^2_{r,j,t+1} &= c^r_j + \alpha^r_j\left[\gamma_{j,CF}(\varepsilon^g_{j,t+1} + \omega_{2,j}\varepsilon^{F^{(2)}}_{j,t+1}) - \gamma_{j,DR}(\varepsilon^\mu_{j,t+1} + \delta_{2,j}\varepsilon^{F^{(1)}}_{j,t+1})\right]^2\\
&\quad + \beta^r_j\left[\gamma_{j,CF}(\sigma^g_{j,t+1} + \omega_{2,j}\sigma^{F^{(2)}}_{t+1}) - \gamma_{j,DR}\sigma^\mu_{j,t+1} + \delta_{2,j}\sigma^{F^{(1)}}_{t+1})\right]^2\\
\sigma^2_{r,j,t+1} &= c^r_j + \alpha^r_j\left[\gamma^2_{j,CF}\varepsilon^2_{j,g,t+1} - 2\gamma_{j,CF}\gamma_{j,DR}\varepsilon^g_{j,t+1}\varepsilon^\mu_{j,t+1} + \gamma^2_{j,DR}\varepsilon^2_{j,\mu,t+1}\right]\\
&\quad + \beta^r_j\left[\gamma^2_{j,CF}\sigma^2_{j,g,t+1} - 2\gamma_{j,CF}\gamma_{j,DR}\sigma^g_{j,t+1}\sigma^\mu_{j,t+1} + \gamma^2_{j,DR}\sigma^2_{j,\mu,t+1}\right]\\
&\quad + \alpha^r_j\left[\gamma^2_{j,CF}\omega^2_{2,j}\varepsilon^2_{F^{(2)},t+1} - 2\gamma_{j,CF}\gamma_{j,DR}\omega_{2,j}\delta_{2,j}\varepsilon^{F^{(2)}}_{t+1}\varepsilon^{F^{(1)}}_{t+1} + \gamma^2_{j,DR}\delta^2_{2,j}\varepsilon^2_{F^{(1)},t+1}\right]\\
&\quad + \beta^r_j\left[\gamma^2_{j,CF}\omega^2_{2,j}\sigma^2_{F^{(2)},t+1} - 2\gamma_{j,CF}\gamma_{j,DR}\omega_{2,j}\delta_{2,j}\sigma^{F^{(2)}}_{t+1}\sigma^{F^{(1)}}_{t+1} + \gamma^2_{j,DR}\delta^2_{2,j}\sigma^2_{F^{(1)},t+1}\right].
\end{aligned} \tag{D.4}$$

Under the assumptions that cash flow news and discount rate news follows a GARCH(1,1) process, equation D.4 shows that the volatility process of industry returns can be expressed as a Scalar BEKK.

D.1 DCC-GARCH Details

$$
\begin{aligned}
\mathcal{J}_{j,t+1} &= D^J_{j,t+1} R^J_{j,t+1} D^J_{j,t+1}, \text{ where } D^J_{j,t+1} = \begin{bmatrix} \gamma_{j,CF}\sigma^g_{j,t+1} & 0 \\ 0 & \gamma_{j,DR}\sigma^\mu_{j,t+1} \end{bmatrix} \\
(D^J_{j,t+1})^2 &= \begin{bmatrix} C_{j,CF} & 0 \\ 0 & C_{j,DR} \end{bmatrix} + \begin{bmatrix} \alpha^r_{j,cf} & 0 \\ 0 & \alpha^r_{j,dr} \end{bmatrix} \odot \left[\begin{pmatrix} \gamma_{j,CF}\varepsilon^g_{j,t} \\ \gamma_{j,DR}\varepsilon^\mu_{j,t} \end{pmatrix} \begin{pmatrix} \gamma_{j,CF}\varepsilon^g_{j,t} \\ \gamma_{j,DR}\varepsilon^\mu_{j,t} \end{pmatrix}' \right] \\
&\quad + \begin{bmatrix} \beta^r_{j,cf} & 0 \\ 0 & \beta^r_{j,dr} \end{bmatrix} \odot (D^J_{j,t})^2 \qquad \text{(D.5)} \\
\nu^J_{j,t+1} &= (D^J_{j,t+1})^{-1} \begin{pmatrix} \gamma_{j,CF}\varepsilon^g_{j,t+1} \\ \gamma_{j,DR}\varepsilon^\mu_{j,t+1} \end{pmatrix}, \\
\mathcal{Q}^J_{j,t+1} &= W^J_j(1-\alpha_{j,dcc}-\beta_{j,dcc}) + \alpha_{j,dcc}\left(\nu^J_{j,t}(\nu^J_{j,t})'\right) + \beta_{j,dcc}\mathcal{Q}^J_{j,t}, \qquad \text{(D.6)} \\
R^J_{j,t+1} &= diag\{\mathcal{Q}^J_{j,t+1}\}^{-1}\mathcal{Q}^J_{j,t+1} diag\{\mathcal{Q}^J_{j,t+1}\}^{-1} \qquad \text{(D.7)}
\end{aligned}
$$

Equation (D.5), in which $\odot$ indicates the Hadamard product, is a GARCH(1,1) representation for cash flow news and discount rate news. Equation (D.6) is the dynamic conditional correlation model, in which W^J_j is the unconditional correlation matrix of cash flow shocks and discount rate shocks. Note that for $\alpha_{j,dcc} = \beta_{j,dcc} = 0$, $\mathcal{Q}^J_{j,t+1} = R^J_{j,t+1} = W^J_j$, which is the Bollerslev (1990) constant conditional correlation model. I estimate $\mathcal{S}_{t+1}$ using the methodology described in equations (D.5)-(D.7).

E Tables

	Profits		Dividends
σ_π^2	0.06 (0.084)	σ_d^2	0.04 (0.006)
σ_g^2	0.04 (0.190)	σ_g^2	0.02 (0.004)
σ_μ^2	0.05 (0.238)	σ_μ^2	0.14 (0.630)
$\sigma_{\mu g}$	0.74 (0.790)	$\sigma_{\mu g}$	-0.78 (1.514)
$\mathcal{A}$	4.42 (0.977)	$\mathcal{A}$	5.46 (1.033)
$\mathcal{B}_1^M$	10.94 (1.069)	$\mathcal{B}_1^M$	11.00 (2.290)
$\mathcal{B}_2^M$	4.29 (1.230)	$\mathcal{B}_2^M$	1.54 (1.163)
δ_0	0.01 (0.767)	δ_0	0.05 (0.242)
δ_1	0.98 (0.071)	δ_1	0.95 (0.265)
ω_0	0.10 (0.208)	ω_0	0.03 (0.047)
ω_1	0.75 (0.506)	ω_1	0.25 (0.065)
ρ	0.98	ρ	0.99

Table E1: **Estimation output of the Van Binsbergen and Koijen (2010) model using 2 different cash flow proxies: profits and dividends**. Bootstrapped standard errors are in parentheses.

	Consumer	Manufacturing	Technology	Health	Other
σ_d^2	0.882 (0.2815)	0.021 (0.0119)	0.000 (0.0110)	0.016 (0.0799)	0.037 (0.0845)
σ_g^2	0.050 (0.0664)	0.000 (0.0100)	0.014 (0.0177)	0.008 (0.0086)	0.018 (0.0223)
σ_μ^2	2.838 (0.1636)	0.273 (0.0325)	1.209 (0.0312)	0.096 (0.0429)	0.060 (0.0246)
$\rho_{\mu d}$	2.854 (0.1262)	-1.162 (0.1957)	-0.591 (0.1993)	0.12 (0.2214)	0.090 (0.1953)
$\rho_{\mu g}$	-1.348 (0.8301)	0.013 (1.2436)	-0.179 (0.9593)	-3.738 (0.6753)	-0.134 (0.8165)
$\mathcal{A}$	1.873 (0.0052)	1.244 (0.0049)	0.817 (0.0036)	-0.088 (0.0011)	1.658 (0.0035)
$\mathcal{B}_1$	5.231 (0.0272)	12.822 (0.0515)	43.018 (0.0402)	12.287 (0.028)	7.234 (0.0339)
$\mathcal{B}_2$	0.870 (0.1880)	0.008 (0.3454)	0.856 (0.2682)	2.067 (0.1895)	1.204 (0.2284)
δ_0	0.016 (0.0011)	0.054 (0.0009)	0.062 (0.0007)	0.000 (0.0002)	0.017 (0.0007)
δ_1	0.798 (0.0024)	0.973 (0.0025)	0.976 (0.0016)	0.901 (0.0002)	0.863 (0.0018)
γ_0	0.009 (0.0162)	0.010 (0.0180)	0.066 (0.0164)	0.003 (0.0165)	0.025 (0.0198)
γ_1	0.659 (0.1726)	0.901 (0.3736)	0.191 (0.3047)	0.336 (0.3162)	0.074 (0.3444)

Table E2: **Estimation of the Van Binsbergen and Koijen (2010) model using dividends as cash flow proxy for the Fama-French 5 industries**. The quarterly data is seasonally adjusted. The standard errors are bootstrapped standard errors with 1000 draws. All standard errors are in parentheses.

Cash Flow Proxy:	Discount Rate News	Cash Flow News	Covariance
Dividends	97.1	0.3	2.7
Profits	91.1	11.5	-2.6

Table E3: **Variance decomposition of quarterly unexpected market returns using profits and dividends as cash flow proxies**. This table presents the variance decomposition of unexpected market returns using equation (A.1). The first row presents the share of discount rate news, cash flow news, and the covariance in the variance of unexpected returns using dividends as cash flow proxy. The second row reports the results for unexpected returns using profits as cash flow proxy. All rows add up to 100.

	Diagonal BEKK(1,1) Market Estimates	
	A) CF:Profits	B) CF:Dividends
c_{11}	**0.01** (0.004)	**0.04** (0.004)
c_{12}	**-0.02** (0.009)	**-0.07** (0.016)
c_{22}	**0.03** (0.011)	0.03 (0.039)
α_{11}^r	**0.41** (0.086)	**0.60** (0.081)
α_{22}^r	**0.57** (0.175)	**0.64** (0.096)
β_{11}^r	**0.89** (0.035)	0.24 (0.166)
β_{22}^r	**0.59** (0.271)	**0.61** (0.206)

Table E4: **Diagonal BEKK(1,1) estimates of unexpected market returns with different cash flow proxies (equation (A.2))**. Panel A of the table presents coefficients estimates for unexpected market returns using profits as cash flow proxy, and panel B presents coefficients estimates for unexpected market returns using dividends as cash flow proxy. Robust standard errors are in parentheses, boldface coefficients are significant at the 5 percent level.

	Mkt-RF	HML	SMB	RMW	CMA
Gross Profit	0.31	0.58	0.14	0.34	0.08
Operating Profit	0.27	0.55	0.34	0.32	0.27
Earnings	0.25	-0.09	-0.02	0.23	0.00

Table E5: **Correlation of risk factor loadings between excess returns and profitability measures**. We calculate the correlation coefficient between risk factor loadings of the Fama-French 5 factor regression where the dependent variable excess returns and profitability measures.

	Gross Profits	Operating Profits	Earnings
	$H0$: Industry fixed effects are zero		
F-Stat	65.177	11.145	25.408
P-Value	0.0000	0.0000	0.0000

Table E6: **Significance test of industry fixed effects**. This table presents three test results in which industry fixed effects are tested against a pooled alternative. The F statistic is obtained as $F = \frac{(RSS_{pool} - RSS_{panel})/(df_{pool} - df_{panel})}{RSS_{effect}/df_{effect}}$, where the RSS is the sum of squared residuals, and df indicates the degree of freedom.

Industry	Gross Profits	Operating Profits	Earnings
Autos	0.75 (0.397)	**0.64** (9.141)	0.77 (-0.24)
Beer	**0.19** (-2.795)	**0.00** (-2.419)	0.77 (-0.245)
Books	**0.31** (-2.083)	0.04 (-1.803)	0.68 (-0.426)
BusEq.	0.46 (-1.242)	0.05 (-1.656)	0.86 (-0.047)
Carry	**0.08** (-3.377)	0.08 (-0.986)	0.91 (0.051)
Chemicals	0.41 (-1.559)	**0.03** (-1.989)	0.82 (-0.146)
Clothes	**0.31** (-2.113)	0.09 (-0.955)	0.73 (-0.333)
Coal	**0.22** (-2.578)	0.22 (1.539)	0.22 (-1.387)
Const	**0.12** (-3.159)	0.07 (-1.184)	0.79 (-0.199)
ElcEq	**0.06** (-3.505)	**-0.05** (-3.364)	0.51 (-0.78)
FabProd	**0.17** (-2.862)	0.1 (-0.647)	0.87 (-0.035)
Food	**0.17** (-2.871)	**0.03** (-2.021)	0.80 (-0.176)
Games	**0.08** (-3.364)	**0.00** (-2.561)	0.72 (-0.353)
Health	0.48 (-1.171)	**0.02** (-2.169)	0.76 (-0.272)
Hshld	**0.16** (-2.92)	**0.01** (-2.35)	0.80 (-0.184)
Meals	**0.27** (-2.317)	0.16 (0.345)	0.84 (-0.085)
Mines	0.51 (-0.987)	**0.49** (6.45)	0.55 (-0.71)
Oil	0.67 (-0.056)	**0.59** (8.156)	0.90 (0.029)
Other	0.47 (-1.222)	**0.33** (3.397)	0.92 (0.068)
Paper	**0.14** (-3.038)	**0.03** (-1.961)	0.85 (-0.065)
Real Estate	0.50 (-1.052)	**0.48** (6.246)	0.71 (-0.369)
Retail	**0.17** (-2.882)	0.04 (-1.808)	0.82 (-0.133)
Services	0.67 (-0.054)	0.17 (0.517)	0.81 (-0.148)
Steel	0.40 (-1.567)	**0.37** (4.13)	0.68 (-0.432)
Telecom	0.75 (0.367)	**0.33** (3.427)	0.87 (-0.041)
Textiles	**0.12** (-3.162)	0.03 (-1.878)	0.60 (-0.606)
Transport	**0.32** (-2.028)	0.21 (1.226)	0.72 (-0.344)
Wholesale	**0.04** (-3.613)	**0.01** (-2.383)	0.85 (-0.065)
Market	**0.68** (12.982)	**0.14** (3.905)	**0.89** (19.212)

Table E7: **Mean reversion coefficients by industry**. This table shows the mean reversion coefficient of an AR(1) regression. The columns indicate the different definitions of profits. Values in parentheses represent test result of the difference between pooled and industry specific mean reversion coefficient. Coefficients that are significantly different than the pooled coefficient are shown in bold font. The row named "Pooled" presents the pooled mean reversion coefficient, and robust t-values are in parentheses.

	Gross Profits		Operating Profits		Earnings	
	Competitive	Concentrated	Competitive	Concentrated	Competitive	Concentrated
Long Run Profits	0.080	0.057	0.026	0.023	0.042	0.052
Adjustment Speed	0.259	0.183	0.577	0.538	0.068	0.186

Table E8: **Long run mean and speed of adjustment by HHI class**. We define two classifications for the HHI index: HHI $<= 1500$: Competitive, and HHI > 1500 : Concentrated. The row named 'Long Run Profits" indicate the long-run mean computed as $\mu = \frac{\alpha}{1-\phi}$, where α is the constant from the AR(1) regression and ϕ is the mean reversion coefficient. Row named "Adjustment Speed " indicate the estimated speed of adjustment, and are calculated as $1 - \phi$, where ϕ is the mean reversion coefficient estimated using an AR(1) regression.

	Gross Profits	Operating Profits	Earnings
Autos	0.75 (0.397)	**0.64** (9.141)	0.77 (-0.240)
Beer	0.19 (-2.795)	0.00 (-2.419)	0.77 (-0.245)
Books	0.31 (-2.083)	0.04 (-1.803)	0.68 (-0.426)
BusEq.	0.46 (-1.242)	0.05 (-1.656)	0.86 (-0.047)
Carry	**0.08** (-3.377)	0.08 (-0.986)	0.91 (0.051)
Chemicals	0.41 (-1.559)	0.03 (-1.989)	0.82 (-0.146)
Clothes	0.31 (-2.113)	0.09 (-0.955)	0.73 (-0.333)
Coal	0.22 (-2.578)	0.22 (1.539)	0.22 (-1.387)
Const	**0.12** (-3.159)	0.07 (-1.184)	0.79 (-0.199)
ElcEq	**0.06** (-3.505)	**-0.05** (-3.364)	0.51 (-0.78)
FabProd	0.17 (-2.862)	0.10 (-0.647)	0.87 (-0.035)
Food	0.17 (-2.871)	0.03 (-2.021)	0.80 (-0.176)
Games	**0.08** (-3.364)	-0.00 (-2.561)	0.72 (-0.353)
Health	0.48 (-1.171)	0.02 (-2.169)	0.76 (-0.272)
Hshld	0.16 (-2.92)	0.01 (-2.35)	0.80 (-0.184)
Meals	0.27 (-2.317)	0.16 (0.345)	0.84 (-0.085)
Mines	0.51 (-0.987)	**0.49** (6.45)	0.55 (-0.71)
Oil	0.67 (-0.056)	**0.59** (8.156)	0.90 (0.029)
Other	0.47 (-1.222)	**0.33** (3.397)	0.92 (0.068)
Paper	0.14 (-3.038)	0.03 (-1.961)	0.85 (-0.065)
Real Estate	0.50 (-1.052)	**0.48** (6.246)	0.71 (-0.369)
Retail	0.17 (-2.882)	0.04 (-1.808)	0.82 (-0.133)
Services	0.67 (-0.054)	0.17 (0.517)	0.81 (-0.148)
Steel	0.40 (-1.567)	**0.37** (4.13)	0.68 (-0.432)
Telecom	0.75 (0.367)	**0.33** (3.427)	0.87 (-0.041)
Textiles	**0.12** (-3.162)	0.03 (-1.878)	0.60 (-0.606)
Transport	0.32 (-2.028)	0.21 (1.226)	0.72 (-0.344)
Wholesale	**0.04** (-3.613)	0.01 (-2.383)	0.85 (-0.065)
Market	**0.68** (12.982)	**0.14** (3.905)	**0.89** (19.212)

Table E9: **Mean reversion coefficients by industry with Bonferroni p-value adjustment**. This table shows the mean reversion coefficient of an AR(1) regression. The columns indicate the different definitions of profits. Values in parentheses represent test result of the difference between pooled and industry specific mean reversion coefficient. Coefficients that are significantly different than the pooled coefficient are shown in bold font. The row named "Pooled" presents the pooled mean reversion coefficient, and robust t-values are in parentheses.

	Excess Returns			$\Delta\pi$			Δpe		
	Gross Profits	Oper. Profits	Earnings	Gross Profits	Oper. Profits	Earnings	Gross Profits	Oper. Profits	Earnings
Intercept	**1.59**	**1.57**	**1.51**	**1.16**	**1.09**	**1.47**	**0.57**	**0.81**	0.53
	(0.106)	(0.106)	(0.113)	(0.206)	(0.228)	(0.275)	(0.263)	(0.282)	(0.312)
$F^{\Delta\pi}_{1,t-1}$	**-1.17**	**-1.16**	**-0.51**	**1.76**	0.63	**1.28**	**-3.56**	**-2.22**	**-2.40**
	(0.145)	(0.156)	(0.141)	(0.309)	(0.356)	(0.316)	(0.383)	(0.423)	(0.384)
$F^{\Delta\pi}_{2,t-1}$	**-0.41**	0.17	-0.22	-0.03	-0.35	-0.39	**-0.77**	**0.84**	0.52
	(0.096)	(0.143)	(0.155)	(0.212)	(0.321)	(0.342)	(0.277)	(0.370)	(0.390)
$F^{\Delta pe}_{1,t-1}$	**-1.00**	**-0.80**	**-0.69**	0.34	-0.07	0.28	-0.53	0.42	0.40
	(0.194)	(0.183)	(0.171)	(0.349)	(0.406)	(0.419)	(0.461)	(0.510)	(0.526)
$F^{\Delta pe}_{2,t-1}$	**-0.30**	**0.42**	**0.49**	**0.36**	**-1.05**	0.49	**-0.87**	**1.69**	-0.50
	(0.102)	(0.181)	(0.192)	(0.148)	(0.377)	(0.405)	(0.246)	(0.451)	(0.441)
$\Delta\pi_{t-1}$	-0.00	-0.02	-0.01	**0.24**	**0.38**	**0.14**	**-0.14**	**-0.38**	**-0.16**
	(0.017)	(0.018)	(0.019)	(0.056)	(0.062)	(0.056)	(0.062)	(0.069)	(0.057)
Δpe_{t-1}	-0.02	-0.03	-0.02	**0.07**	**0.08**	0.02	-0.00	-0.08	-0.05
	(0.016)	(0.017)	(0.018)	(0.033)	(0.037)	(0.051)	(0.040)	(0.045)	(0.055)
R^2	3.77	3.90	2.50	6.68	11.51	2.21	6.74	11.24	3.62
Intercept	**1.59**	**1.61**	**1.56**	**1.21**	**1.38**	**1.43**	0.43	0.58	0.61
	(0.103)	(0.105)	(0.113)	(0.209)	(0.264)	(0.296)	(0.254)	(0.303)	(0.323)
$F^{\Delta\pi}_{1,t-2}$	**-0.35**	-0.20	-0.06	**0.92**	0.08	0.02	**-3.34**	**-1.78**	-0.70
	(0.121)	(0.127)	(0.143)	(0.260)	(0.358)	(0.330)	(0.295)	(0.413)	(0.378)
$F^{\Delta\pi}_{2,t-2}$	**0.56**	-0.23	**0.91**	-0.14	-0.20	-0.39	**0.97**	-0.08	**1.60**
	(0.095)	(0.140)	(0.131)	(0.205)	(0.330)	(0.379)	(0.248)	(0.379)	(0.397)
$F^{\Delta pe}_{1,t-2}$	**-0.58**	-0.23	-0.15	-0.58	-0.56	-0.50	**-1.33**	0.06	0.46
	(0.194)	(0.178)	(0.185)	(0.525)	(0.326)	(0.415)	(0.510)	(0.429)	(0.477)
$F^{\Delta pe}_{2,t-2}$	**-1.43**	**0.98**	**-0.37**	**0.69**	**-0.85**	0.44	**-2.82**	**2.05**	-0.24
	(0.136)	(0.150)	(0.150)	(0.212)	(0.373)	(0.471)	(0.280)	(0.428)	(0.469)
$\Delta\pi_{t-2}$	-0.01	-0.03	-0.04	**0.16**	**0.15**	**0.14**	-0.03	**-0.15**	**-0.18**
	(0.018)	(0.019)	(0.020)	(0.058)	(0.046)	(0.045)	(0.047)	(0.055)	(0.050)
Δpe_{t-2}	-0.01	-0.03	-0.03	**0.24**	**0.23**	**0.17**	**-0.12**	**-0.22**	**-0.19**
	(0.017)	(0.018)	(0.018)	(0.051)	(0.031)	(0.041)	(0.047)	(0.039)	(0.048)
R^2	4.99	2.27	1.97	5.13	3.83	1.02	6.15	3.90	1.92
Obs.	4680	3780	3420	4680	3780	3420	4680	3780	3420

Table E10: **Pooled panel regressions of lagged factors and cash flow variables on excess returns, cash flow, and price to earnings**. Bold face coefficients are significant at the 5 percent level. Heteroskedasticity robust standard errors are in parentheses.

	Panel A: 1976Q3 - 2021Q4		
	$\text{Returns}_{j,t}$	$\Delta\pi_{j,t}$	$\Delta pe_{j,t}$
Intercept	**1.59**	**1.21**	0.43
	(0.103)	(0.209)	(0.254)
$F^{\Delta\pi}_{1,t-2}$	**-0.35**	**0.92**	**-3.34**
	(0.121)	(0.260)	(0.295)
$F^{\Delta\pi}_{2,t-2}$	**0.56**	-0.14	**0.97**
	(0.095)	(0.205)	(0.248)
$F^{\Delta pe}_{1,t-2}$	**-0.58**	-0.58	**-1.33**
	(0.194)	(0.525)	(0.51)
$F^{\Delta pe}_{2,t-2}$	**-1.43**	**0.69**	**-2.82**
	(0.136)	(0.212)	(0.28)
$\Delta\pi_{t-2}$	-0.01	**0.16**	-0.03
	(0.018)	(0.058)	(0.047)
Δpe_{t-2}	-0.01	**0.24**	**-0.12**
	(0.017)	(0.051)	(0.047)
R^2	4.99	5.13	6.15
Obs.	4680	4680	4680
	Panel B: 1976Q3 - 2019Q4		
Intercept	**1.55**	**1.24**	0.34
	(0.103)	(0.214)	(0.263)
$F^{\Delta\pi}_{1,t-2}$	**-0.25**	**0.8**	**-2.99**
	(0.126)	(0.279)	(0.312)
$F^{\Delta\pi}_{2,t-2}$	**0.51**	-0.01	**0.98**
	(0.098)	(0.215)	(0.256)
$F^{\Delta pe}_{1,t-2}$	**-0.74**	-0.74	**-1.37**
	(0.205)	(0.556)	(0.537)
$F^{\Delta pe}_{2,t-2}$	**-1.52**	**0.67**	**-2.95**
	(0.138)	(0.216)	(0.283)
$\Delta\pi_{t-2}$	-0.01	**0.13**	-0.01
	(0.018)	(0.065)	(0.051)
Δpe_{t-2}	-0.01	**0.23**	**-0.12**
	(0.018)	(0.056)	(0.051)
R^2	6.33	4.67	6.25
Obs.	4368	4368	4368

Table E11: **Pooled panel regressions of lagged factors and cash flow variables on excess returns, gross profit growth, and price to gross profits**. Bold face coefficients are significant at the 5 percent level. Heteroskedasticity robust standard errors are in parentheses.

	In Sample R^2			Out of Sample R^2		
Industry	Excess Returns	$\Delta\pi$	Δpe	Excess Returns	$\Delta\pi$	Δpe
Benchmark				Prevail.Mean	Prevail.Mean	Prevail.Mean
Autos	10.07	9.20	9.24	4.39	2.13	3.95
Beer	5.24	12.73	10.48	-1.53	2.86	3.94
Books	11.18	2.78	12.16	9.70	1.52	0.51
BusEq.	7.90	15.28	12.74	-0.34	4.22	9.36
Carry	9.32	4.76	12.56	7.04	-1.21	8.84
Chemicals	5.37	5.16	9.68	4.85	6.35	11.26
Clothes	7.17	13.25	20.39	-2.54	-10.50	7.99
Coal	2.03	14.15	3.83	-3.24	10.58	0.55
Const	10.15	7.18	14.00	9.63	-1.25	14.79
ElcEq	7.49	4.01	11.46	6.73	6.57	13.27
FabProd	9.69	5.75	13.46	2.93	19.63	17.60
Food	3.72	2.61	5.97	0.85	5.61	3.64
Games	13.33	5.63	11.04	6.31	3.37	7.16
Health	1.85	14.50	3.99	-7.95	5.29	2.09
Hshld	1.93	11.81	11.95	2.16	-5.21	9.76
Meals	4.98	14.69	13.59	4.60	4.07	8.24
Oil	2.71	11.45	8.49	-1.11	4.10	4.96
Paper	13.20	5.31	12.30	12.37	-11.72	10.21
Real Estate	10.15	16.43	13.69	10.08	2.22	5.84
Retail	11.58	0.68	4.10	-6.65	-14.39	8.67
Services	6.76	2.70	3.48	-2.42	2.39	15.36
Steel	8.54	23.49	22.57	4.76	7.77	9.17
Telecom	7.31	13.76	5.78	6.49	0.44	8.91
Textiles	16.68	9.59	11.85	9.70	-11.92	10.51
Transport	9.77	9.10	10.21	6.99	14.28	10.71
Wholesale	9.60	5.13	8.76	7.73	5.78	12.67
Pooled	4.99	5.13	6.15	4.35	6.05	6.77

Table E12: **In sample and out of sample R^2 values for excess returns, profit growth, and price to profit growth**. Industry wise in sample R^2 are obtained by estimating equations (C.2)-(C.4) for each industry separately, the pooled R^2 values are from the pooled panel estimation. Out of sample R^2 values are from the panel LASSO forecasting model, where the benchmark is the prevailing mean for excess returns, profit growth, and price to profit growth.

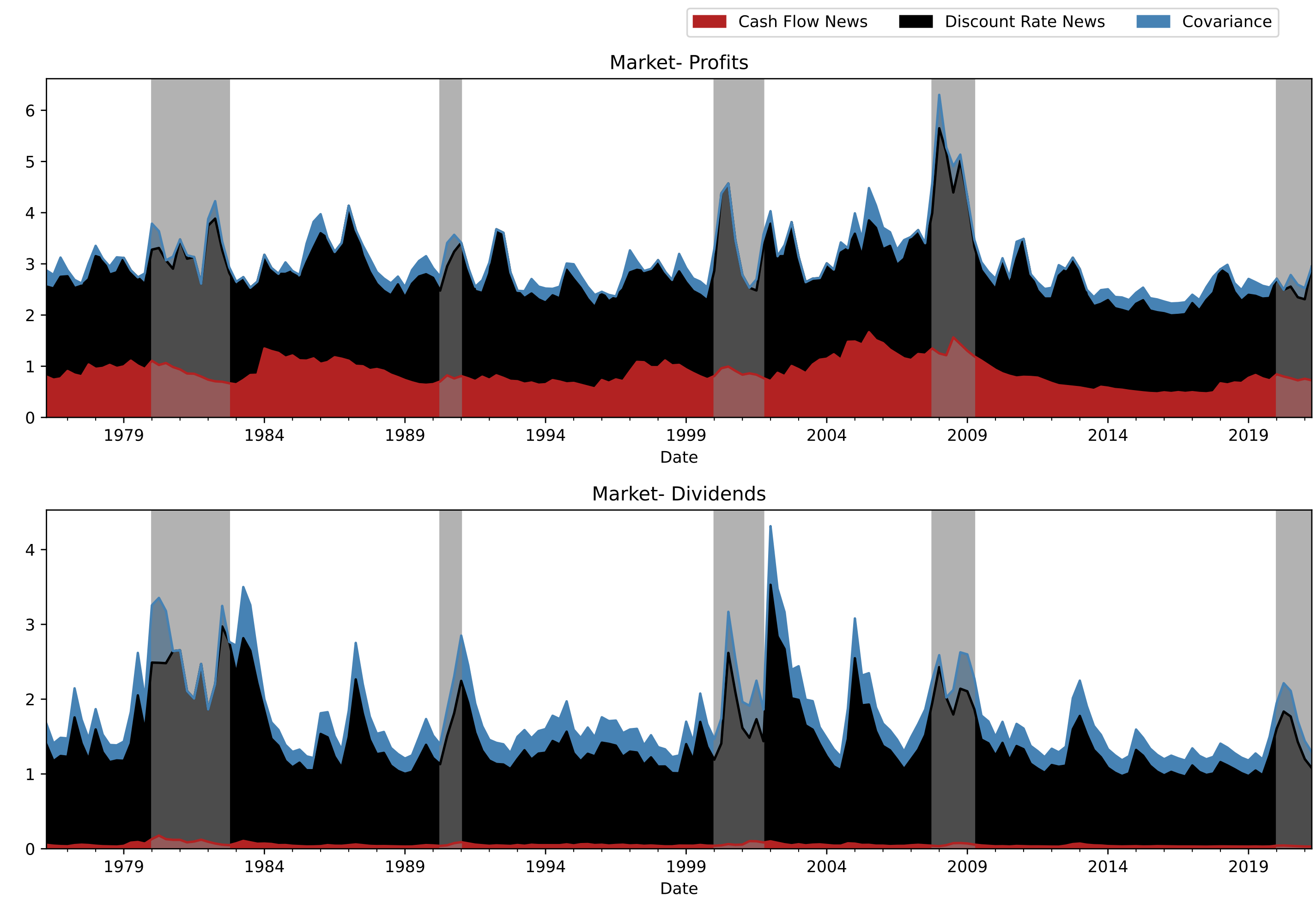

Figure E1: **Conditional time varying volatility of unexpected market returns' components**. The top panel shows unexpected market returns where the cash flow proxy is profits, the bottom panel shows the time series evolution of unexpected market returns for the model using dividends as cash flow proxy. Shaded grey areas indicate NBER recessions. Shaded red regions indicate cash flow news contribution to total volatility, shaded black regions indicate discount rate news contribution to total volatility, and shaded blue regions indicate the contribution of the covariance between cash flow news and discount rate news.

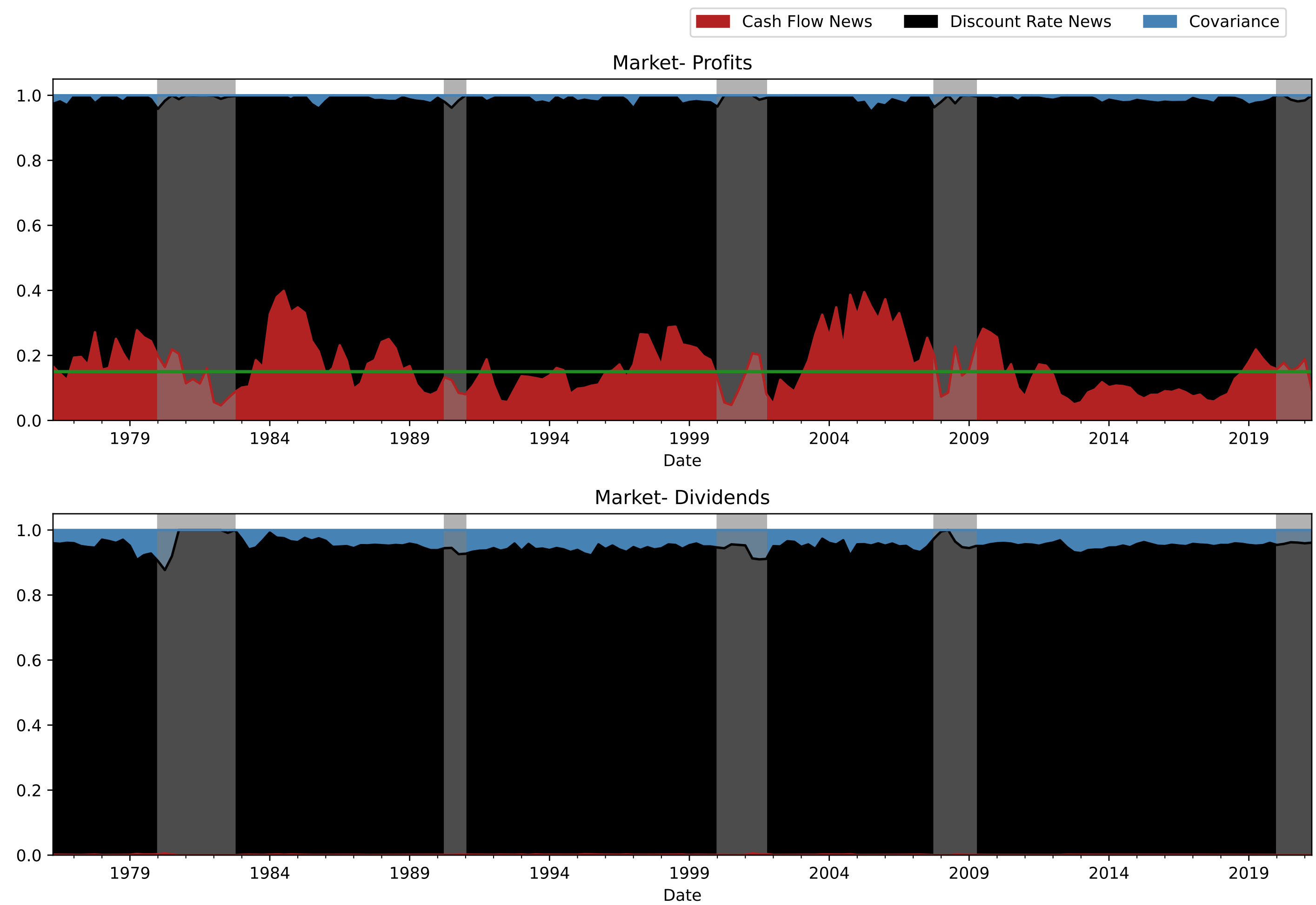

Figure E2: **Decomposition of conditional time varying volatility of unexpected market returns**. The top panel shows the decomposition of unexpected market returns where the cash flow proxy is profits. The green line indicates the average cash flow news contribution to unexpected market returns. The bottom panel shows the decomposition for the model using dividends as cash flow proxy. Shaded grey areas indicate NBER recessions. Shaded red regions indicate cash flow news contribution to total volatility, shaded black regions indicate discount rate news contribution to total volatility, and shaded blue regions indicate the contribution of the covariance between cash flow news and discount rate news.Components of unexpected returns sum to 1.

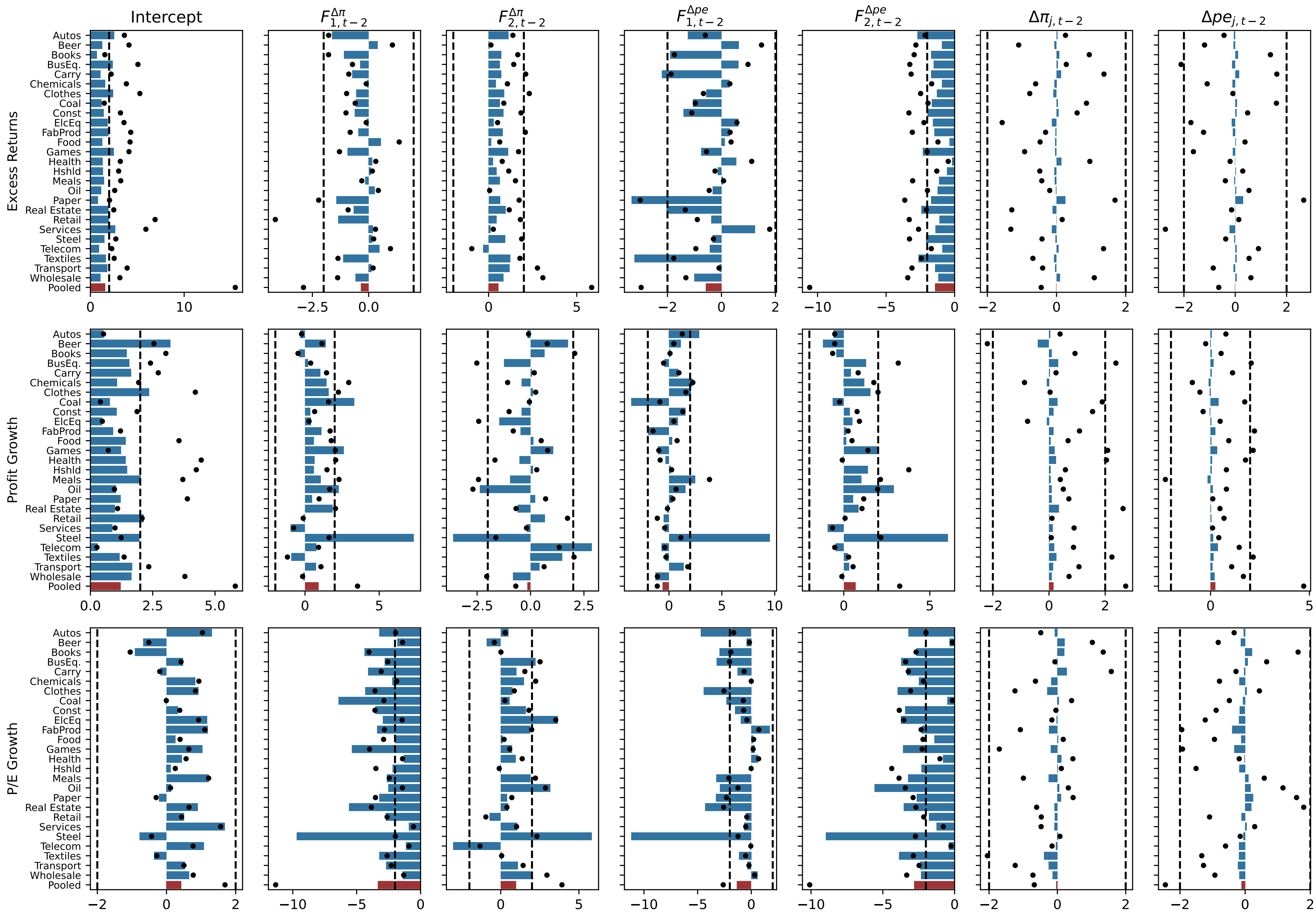

Figure E3: **Industry wise parameter estimates of equations** (C.2)-(C.4). The blue bars indicate the parameter estimates for each variable included in the regression, the red bar indicates the pooled parameter estimate. The black dots indicate t-statistics adjusted for heteroskedasticity, and the dotted black line indicates the (-2,2) t-stat region. All industries have 180 observations.

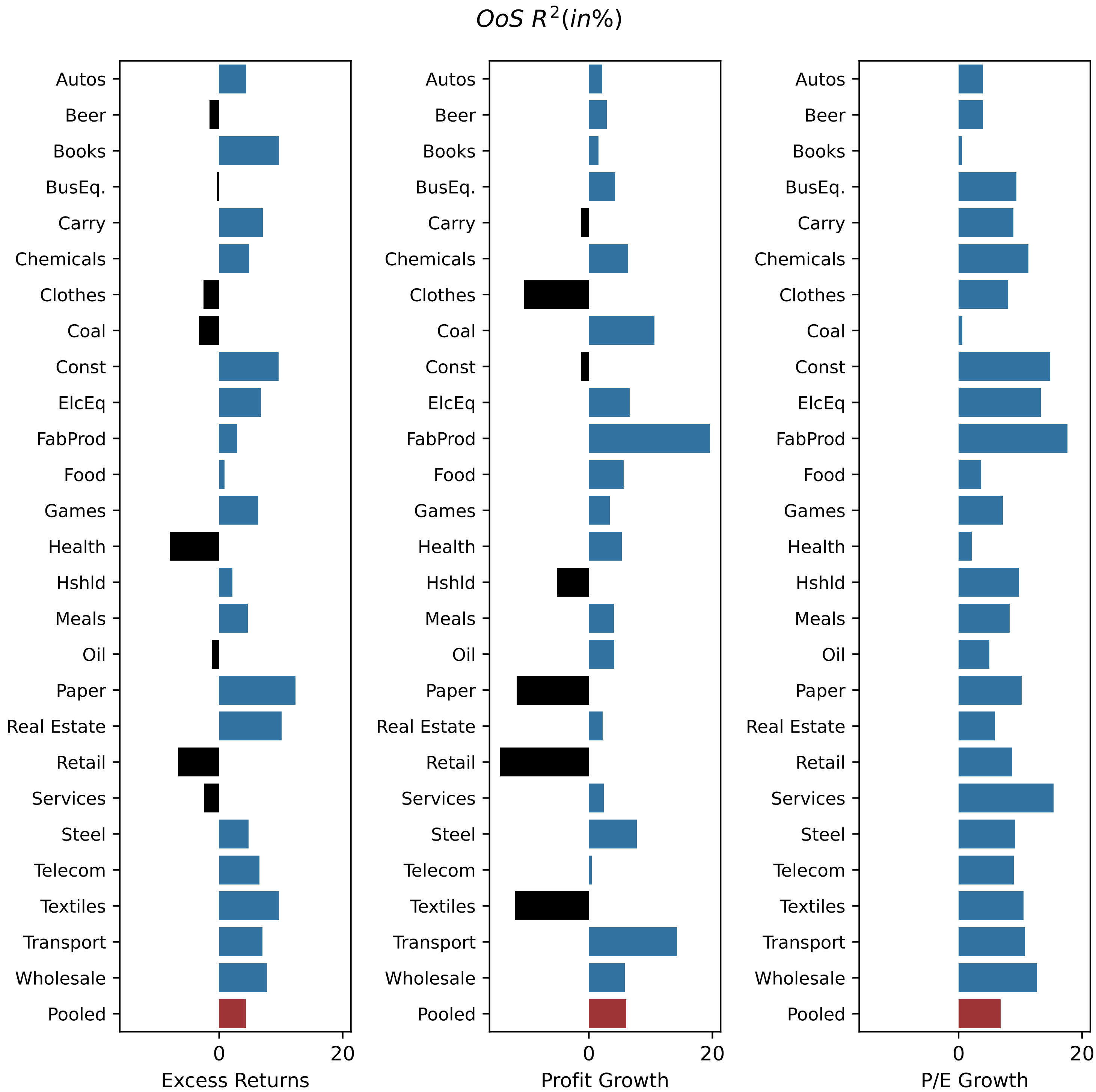

Figure E4: **Out of Sample R^2 of the panel LASSO model across all industries**. The red bars indicate the pooled out of sample R^2, blue bars indicate positive out of sample R^2, and black bars indicate negative out of sample R^2. We use the prevailing mean to compute the out of sample R^2 statistic for excess returns (left panel), profit growth (middle panel), price to profit growth (right panel).