Do Subjective Growth Expectations Matter for Asset Prices?

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Abstract

I quantify the causal impact of subjective cash flow growth expectations on asset prices. I develop a model of asset demand in which Bayesian investors update their priors over cash flow growth based on equity research analyst expectations. Given a panel of stock-level, analyst expected growth rates, I use tools from a branch of machine learning known as collaborative filtering to extract exogenous shocks to analyst expectations. High-frequency price reactions after analyst report releases and low-frequency changes in investor holdings reveal a 1% rise in investors’ annual expected cash flow growth raises stock price by 7 – 16 basis points, which is an order of magnitude less than in standard models. To reconcile this weak causal effect with the strong correlation of growth expectations and prices, I provide evidence of reverse causality: prices cause growth expectations. The small causal effect of growth expectations on prices is consistent with small price elasticities of demand and implies that biased beliefs have less impact on asset prices than standard models suggest.

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1 Introduction

This paper answers the following question: How much do asset prices rise in response to a 1% increase in investors’ annual subjective expected cash flow growth? In any standard model where cash flow shocks don’t impact discount rates or price-dividend ratios, a transient 1% growth shock raises price by 1% since it permanently raises the level of dividends by 1%. However, three stylized facts recently documented in the asset pricing literature cast doubt on this quantitative implication of standard models. First, surveyed measures of subjective beliefs — in particular, beliefs about future cash flows — correlate strongly, positively with asset prices.1 Second, investors exhibit a limited passthrough of beliefs to asset holdings.2 Third, asset demand in financial markets proves surprisingly inelastic.3 Standard models cannot replicate all three of these facts at the same time, which raises questions as to what role subjective beliefs can play in financial markets.

Does the limited passthrough of beliefs to holdings reduce the causal effect of beliefs on prices? Or does inelastic demand amplify the price impact of the small quantity responses to belief changes? Can a small causal effect of beliefs on prices be consistent with the strong, positive correlation between beliefs and prices? These are the questions I answer in this paper.

I document a small causal effect of subjective expected cash flow growth on asset prices in the cross section of equities. A 1% rise in investor annual expected cash flow growth raises price by only 7 – 16 basis points, which is an order of magnitude smaller than the 1% causal effect in standard models described above. I reconcile this small causal effect with the strong correlation of cash flow beliefs and prices by providing evidence of reverse causality: at least part of this correlation arises from a causal impact of prices on cash flow expectations. An exogenous 1% increase in price raises annual cash flow growth expectations by 32 basis points.

To measure the causal effect of prices on subjective cash flow expectations, I use the mutual fund flow-induced trading instrument of Lou (2012) to instrument for prices and examine how these exogenous price changes impact one-year earnings per share (EPS) growth forecasts from I/B/E/S analysts. A literature going back to Frazzini and Lamont (2008) finds that stock-level mutual fund trading induced by inflows and outflows is uninformed: mutual funds scale up or scale down their preexisting holdings proportionally. Thus, while flows may respond to aggregate shocks (i.e. an increase in risk aversion may lead to outflows), the stock-level trading induced by these flows is uninformed and orthogonal to these aggregate shocks. I find that a 1% exogenous (flow-driven) increase in price raises one-year analyst EPS growth expectations by 32 basis points.

Due to this reverse causality, OLS regressions of prices on cash flow expectations do not yield

1Greenwood and Shleifer (2014); Bordalo et al. (2019, 2020); Nagel and Xu (2021); De La O and Myers (2021)
2Merkle and Weber (2014); Meeuwis et al. (2018); Giglio et al. (2021a); Bacchetta, Tieche and Van Wincoop (2020); Giglio et al. (2021b); Beutel and Weber (2022)
3Shleifer (1986); Harris and Gurel (1986); Chang, Hong and Liskovich (2014); Pavlova and Sikorskaya (2020); Koijen and Yogo (2019); Gabaix and Koijen (2020b)
consistent estimates of the causal effect of cash flow expectations on prices. For this reason, I use the framework of asset demand to identify the causal effect of cash flow expectations on prices. I develop a model of asset demand in which Bayesian investors update their priors over cash flow growth based on equity research analyst expectations. Analyst expectations shift investor beliefs, which shift investor asset demand, which causes equilibrium prices to adjust to clear markets. There are two main identification problems. First, since analyst expectations themselves depend on prices, we need to isolate exogenous variation in analyst beliefs. Second, since we don’t observe investor expectations, we need to measure how much analyst beliefs influence investor beliefs.

To extract exogenous shocks to I/B/E/S analyst annual EPS growth expectations, I use tools from a branch of machine learning known as collaborative filtering. I model analyst beliefs as having a factor structure and use a latent factor model to extract idiosyncratic shocks to analyst growth expectations (e.g. private information garnered by the analyst) that are orthogonal to common factors (e.g. stock prices, public signals, firm characteristics, etc.). The triple panel structure of the expectations data (quarter × analyst institution × stock) and relatively small number of reported expectations per analyst institution in each period motivate the use of tools from collaborative filtering to efficiently estimate the latent factor model (Goldberg et al. (1992); Funk (2006); Koren and Bell (2015)).

To measure analyst influence on investor beliefs, I use an implication of Bayesian learning that imposes structure on how analyst influence varies in the cross section of equities. In particular, analyst influence is a function of the set of analysts who cover each stock. Due to signal averaging, the influence of each analyst declines with the number of analysts that issue expectations for a stock. Cross-sectional variation in the number of analysts that cover each stock identifies analyst influence on investor expectations.

Under the assumption that analyst influence and the sensitivity of asset demand to expected cash flow growth do not vary across investors, prices and beliefs data alone can identify the causal effect of investor cash flow expectations on price. High-frequency regressions of price changes shortly after analyst report releases on analyst idiosyncratic growth shocks and their interaction with the number of analysts covering each stock pin down both analyst influence and the causal effect of investor cash flow expectations on price. These regressions imply a 1% increase in annual investor expected cash flow growth raises stock price by 7 basis points.

Relaxing these homogeneity assumptions requires investor-level holdings data. To that end, I use institutional stock holdings data from SEC Form 13F. The SEC requires all institutional investors with at least $100 million in assets under management (AUM) to report itemized stock-level holdings at the quarterly frequency. After controlling for investor-specific price elasticities of demand (measured following the approach of Koijen and Yogo (2019)) and equilibrium price changes, low-frequency regressions of changes in investor holdings on analyst idiosyncratic growth shocks and their interaction with the number of analysts covering each stock pin down both analyst
influence and the causal effect of cash flow expectations on asset demand at the investor level. Aggregating the demand shift caused by cash flow expectations across investors and scaling by the aggregate price elasticity of demand identifies the causal effect of investor cash flow expectations on price under full investor heterogeneity. This procedure implies a 1% increase in annual investor expected cash flow growth raises stock price by 16 basis points.

This small causal effect of cash flow expectations on prices is consistent with low price elasticities of demand. Inelastic demand arises from a low sensitivity of demand to expected returns. When prices rise, expected returns fall, but quantity demanded does not adjust to the change in expected returns. A low sensitivity of demand to expected returns also implies changes in cash flow expectations cause only small demand curve shifts. Holding price fixed, increases in expected cash flow growth raise expected returns, but demand does not respond to that change in expected returns. Thus, the same mechanism that lowers price elasticity of demand also shrinks demand curve shifts caused by cash flow expectations. Lowering the sensitivity of demand to expected returns shrinks cash flow belief driven demand shifts more than it reduces the price elasticity. Hence, the price impact of cash flow belief shocks is small when price elasticity is small.

These results have important implications for asset pricing and macrofinance. A small causal impact of cash flow expectations on prices limits the role subjective beliefs can play in asset markets. If asset prices are insensitive to changes in cash flow beliefs, then extrapolative or overly optimistic expectations cannot quantitatively account for all price variation (e.g. in Bordalo et al. (2019, 2020); Nagel and Xu (2021)). However, since this small causal effect of cash flow expectations on prices is consistent with low price elasticities, it augments the importance of other demand shocks and so opens the door to other potential resolutions of asset pricing and macrofinance puzzles.

The remainder of the paper proceeds as follows. Section 1.1 reviews the related literature. Section 2 discusses the data I use. Section 3 presents evidence of reverse causality: a causal impact of prices on cash flow expectations. Section 4 presents a theoretical framework to highlight the structural parameter of interest. Section 5 uses price and beliefs data to identify the causal effect of growth expectations on prices under assumptions about investor homogeneity. Section 6 discusses how to use holdings data to relax these homogeneity assumptions and presents the associated estimates of the causal effect. Section 7 compares the estimates from these two approaches to each other as well as to related estimates in the previous literature. Lastly, Section 8 concludes.

### 1.1 Related Literature

This paper relates to four literatures: studies linking surveyed beliefs to asset prices, research on the passthrough of beliefs to asset holdings, recent developments measuring price elasticities of demand, and previous work at the intersection of analyst expectations and asset prices.

First, the past decade has seen a resurgence of interest in using surveys to measure beliefs
and in mapping these beliefs to asset prices. Greenwood and Shleifer (2014) assess extrapolation in surveyed expectations of market returns and the extent to which these beliefs correlate with aggregate market price levels and returns. Bordalo et al. (2019), Bordalo et al. (2020), and Nagel and Xu (2021) investigate the extent to which expectations about future cash flow growth correlate with cross-sectional and time-series variation in price levels. De La O and Myers (2021) find in a variance decomposition that subjective cash flow expectations correlate with price-dividend ratios more strongly than subjective expected returns do. While this literature documents important reduced-form facts, it does not quantify the causal impact of beliefs on asset prices. Expectations and prices are jointly determined in equilibrium and both are subject to other, potentially correlated shocks as well. For this reason, reduced-form correlations between beliefs and prices do not measure the causal effect of beliefs on prices; these correlations could be picking up reverse causality or omitted variable bias. In this paper I provide evidence of reverse causality: there is a causal effect of prices on growth expectations. In light of this endogeneity concern, I use the framework of asset demand to develop an empirical strategy to cleanly identify the causal effect of expected cash flow growth on asset prices.

Second, a large literature studies the passthrough of beliefs to asset holdings. This literature has found a limited sensitivity of demand to expected returns in both the cross section and time series. Cross-sectionally, investors who report higher expected returns for an asset hold only slightly larger portfolio weights in that asset as compared to their less bullish peers (Vissing-Jorgensen (2003); Dominitz and Manski (2007); Kézdi and Willis (2009); Hurd, Van Rooij and Winter (2011); Amromin and Sharpe (2014); Arrondel, Calvo Pardo and Tas (2014); Drerup, Enke and Von Gaudecker (2017); Giglio et al. (2021a); Ameriks et al. (2020); Andonov and Rauh (2020); Dahlquist and Ibert (2021)). In the time series, portfolio holdings respond very little to changes in expected returns (Giglio et al. (2021b); Merkle and Weber (2014); Meeuwis et al. (2018); Giglio et al. (2021a); Bacchetta, Tieche and Van Wincoop (2020); Beutel and Weber (2022)). This paper fills two gaps in this previous literature. First, whereas most of this literature focuses on household expectations and portfolio holdings, I find the limited passthrough of expectations to holdings is a marketwide phenomenon. Second, I document the asset pricing implications of this limited passthrough: the insensitivity of asset demand to expectations limits the price impact of subjective cash flow beliefs.

Third, a growing empirical literature seeks to measure price elasticities of demand in financial markets (Shleifer (1986); Harris and Gurel (1986); Chang, Hong and Liskovich (2014); Pavlova and Sikorskaya (2020); Koijen and Yogo (2019); Gabaix and Koijn (2020b); Schmickler and Tremacoldi-Rossi (2022)). This literature documents elasticities for individual stocks in the range of 0.1—2, which is several orders of magnitude smaller than what standard models suggest (Petajisto (2009)). The goal of this paper is not to measure price elasticities of demand. Instead, I investigate the

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4 Some previous work has examined certain types of institutional investors (Andonov and Rauh (2020); Bacchetta, Tieche and Van Wincoop (2020); Dahlquist and Ibert (2021)).
implications of inelasticity for the role beliefs can play in determining asset demand and prices. In particular, I find inelasticity does not amplify the price impact of subjective cash flow expectations.

Fourth, a large body of work examines the link between equity research analyst reports and asset prices. In particular, this literature finds directionally sensible price reactions for individual stocks at high frequency (i.e. over several days) upon the release of new analyst ratings, price targets, and earnings forecasts (Barber and Loeffler (1993); Francis and Soffer (1997); Park and Stice (2000); Barber et al. (2001); Brav and Lehavy (2003); Asquith, Mikhail and Au (2005); Kerl and Walter (2008); Ishigami and Takeda (2018)). Unlike this previous literature, I measure the causal effect of investor, not analyst, cash flow growth expectations. To that end, I use analyst reports as information shocks to investor cash flow growth expectations. That is, I am not directly concerned with analyst expectations; I simply use analyst expectations to instrument for investor beliefs.

2 Data

This paper uses three main sources of data: equity research analyst expected cash flow growth, stock prices, and institutional investor holdings.

I use I/B/E/S analyst earnings-per-share (EPS) forecasts to construct one-year cash flow growth expectations. I/B/E/S reports analyst EPS forecasts at the quarter $\times$ horizon $\times$ analyst institution $\times$ analyst $\times$ stock level. For example, we see the time series of Apple EPS forecasts issued by all equity research analysts at Goldman Sachs for multiple horizons. Forecast horizons range from one quarter up to ten years with various degrees of coverage. For each forecast horizon, I average EPS forecasts for each stock within each quarter at the level of their parent institution (e.g. I average the one-year EPS forecasts for Apple made by all Goldman Sachs analysts in the third quarter of 2022). I then interpolate among different horizons to construct fixed one-year horizon EPS forecasts. I scale by trailing one-year EPS to obtain annual EPS growth expectations and take quarter-over-quarter changes. Thus, I obtain a stock $\times$ analyst institution $\times$ quarter panel of quarterly changes in one-year EPS growth expectations.

I obtain stock price data from CRSP.

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5 Albert Jr and Smaby (1996); Fang and Yasuda (2014), and Jia, Wang and Xiong (2017) also document differential price reactions based on characteristics of the reporting analyst.

Davies and Canes (1978); Groth et al. (1979); Stickel (1995); Irvine (2003) discuss if these price reactions are with rational expectations (i.e. do price movements reflect “information” or “price pressure”) by examining if prices revert at longer horizons.

6 This interpolation proves necessary because analysts report EPS forecasts by fiscal year. For example, in June 2022 an analyst reports an EPS forecast for Apple for fiscal year 2022 and fiscal year 2023. To obtain the one-year EPS forecast from June 2022 to June 2023, I interpolate between the fiscal year 2022 and fiscal year 2023 EPS forecasts. De La O and Myers (2021) follow the same interpolation procedure.

7 I winsorize these final values at the 5% level to remove some extremely large outliers.
I use institutional holdings data from SEC Form 13F provided by Thomson Reuters via WRDS. The SEC requires all institutional investors with at least $100 million in assets under management (AUM) to report itemized stock-level holdings at the quarterly frequency. The 13F filings identify six types of institutions: banks, insurance companies, investment advisors (including hedge funds), mutual funds, pension funds, and other 13F institutions (i.e., endowments, foundations, and non-financial corporations). I allocate all remaining stock holdings to a residual “household” sector, which includes both direct stock holdings by households as well as those by non-13F institutions (i.e. institutions with less than $100 million in AUM).

The final dataset spans 1984-01:2021-12 and contains 2,173,492 unique quarterly changes in analyst-reported annual expected cash flow growth for 14,734 stocks and 1,150 equity research institutions, as well as 51,438,573 investor-stock-quarter holdings changes for 7,572 unique investors. The availability of the I/B/E/S EPS forecast data constrains the starting point of the time period.

3 Reverse Causality: Prices Cause Cash Flow Expectations

In this section I present evidence of reverse causality: a causal effect of prices on cash flow expectations. This evidence demonstrates why OLS regressions of prices on beliefs prove insufficient to identify the causal effect of beliefs on prices and why a more structured approach proves necessary.

The reverse causality concern is that prices and cash flow expectations are jointly determined in equilibrium, leading to the classic simultaneous equations problem (Koopmans (1949); Koopmans, Rubin and Leipnik (1950)). Let $\Delta G_{a,n,t}$ be the quarterly change in analyst institution $a$’s annual growth expectation for stock $n$ from quarter $t - 1$ to quarter $t$. Let $\Delta p_{a,n,t}$ be the price change between the release of analyst institution $a$’s growth expectations for stock $n$ in quarters $t - 1$ and $t$. We have the following system of simultaneous equations:

$$\Delta p_{a,n,t} = \beta \Delta G_{a,n,t} + M z_{a,n,t} + \epsilon_{a,n,t}$$

$$\Delta G_{a,n,t} = \alpha \Delta p_{a,n,t} + \nu_{a,n,t}. \quad (2)$$

Growth expectations have a causal effect on prices ($\beta$), and vice versa ($\alpha$). Both prices and growth expectations experience unobserved and possibly correlated shocks ($\epsilon_{a,n,t}$ and $\nu_{a,n,t}$, respectively).

I want to test for the presence of a causal effect of prices on growth expectations: $\alpha \neq 0$ in (2). Thus, I need some instrument $z_{a,n,t}$ that provides exogenous variation in prices. The instrument $z_{a,n,t}$ must satisfy:

1. (Relevance) $M \neq 0$ in (1): The instrument has an effect on price.

2. (Exclusion) $\mathbb{E}[z_{a,n,t} \nu_{a,n,t}] = 0$: The instrument affects growth expectations only through price.

The instrument is not correlated with other determinants of growth expectations.
I obtain exogenous price changes using the mutual fund flow-induced trading instrument (FIT) of Lou (2012). Section 3.1 justifies the FIT instrument and provides estimates of $\alpha$. Section 3.2 discusses potential threats to identification and why my identification strategy proves robust to them. To further address these identification concerns, Appendix A.2 uses a modified version of the FIT instrument that exploits within stock-quarter variation in the timing of analyst report releases. Both identification strategies yield quantitatively similar results.

### 3.1 Evidence from Lou (2012) FIT Instrument

I use the Lou (2012) mutual fund flow-induced trading instrument to obtain exogenous variation prices. A literature going back to Frazzini and Lamont (2008) finds that stock-level mutual fund trading induced by inflows and outflows is uninformed: mutual funds scale up or scale down their preexisting holdings proportionally. Thus, while flows may respond to aggregate shocks (i.e. an increase in risk aversion may lead to outflows), the stock-level trading induced by these flows is uninformed and orthogonal to these aggregate shocks (after removing time fixed effects). Since flow-induced trading is uninformed, it is uncorrelated with other determinants of growth expectations and so satisfies the exclusion restriction.

I calculate the quarterly flow to mutual fund $i$ as

$$\text{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \cdot (1 + \text{Ret}_{i,t})}{TNA_{i,t-1}}$$

where $TNA_{i,t}$ is the total net assets of mutual fund $i$ in quarter $t$ and $\text{Ret}_{i,t}$ is the mutual fund return from quarter $t-1$ to quarter $t$. The mechanical trading by fund $i$ in stock $n$ induced by this quarterly flow is then

$$\text{FIT}_{i,n,t} = \text{SharesHeld}_{n,i,t-1} \cdot \text{Flow}_{i,t}.$$ 

I aggregate this flow-induced trading in stock $n$ across all funds and scale by the total number of shares outstanding to obtain the flow-induced trading in stock $n$ in quarter $t$:\footnote{This specification is closer to that used by Li (2021) than to the original specification in Lou (2012). Lou (2012) multiplies the summand in the numerator by a “partial scaling factor” to reflect the fact that mutual funds may invest or sell less than one dollar in existing positions per dollar of flow they receive due to liquidity or other constraints. Table 2 in Lou (2012) suggests these constraints may bind when funds are investing inflows, but not when they are selling positions to meet outflows. Both Lou (2012) and Li (2021) state that the choice of partial scaling factor does not significantly affect the results of the regression of price changes on FIT. For this reason Li (2021) uses a partial scaling factor of one for both inflows and outflows, which I do as well.

One difference in my specification from that of Li (2021) is that he scales by the total number of shares held by all mutual funds in the previous quarter:

$$\text{FIT}_{n,t} = \frac{\sum_{\text{fund } i} \text{SharesHeld}_{n,i,t-1} \cdot \text{Flow}_{i,t}}{\sum_{\text{fund } i} \text{SharesHeld}_{n,i,t-1}}.$$}

I scale by the total number of shares outstanding so that $\text{FIT}_{n,t} = 0.01$ can be interpreted as buying or selling 1%
\[
\text{FIT}_{n,t} = \frac{\sum_{\text{fund } i} \text{SharesHeld}_{n,i,t-1} \cdot \text{Flow}_{i,t}}{\text{SharesOutstanding}_{n,t-1}}.
\]

Given this instrument, I run the following two-stage least-squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t}
\]

\[
\Delta G_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}.
\]

The first stage regresses price changes between analyst report releases (\(\Delta p_{a,n,t}\)) on the quarterly flow-induced trading instrument (\(\text{FIT}_{n,t}\)). The second stage regresses the change expected growth (\(\Delta G_{a,n,t}\)) on the instrumented price change (\(\Delta \hat{p}_{a,n,t}\)). \(X_{n,t}\) represents controls including stock and quarter fixed effects as well as one-quarter lagged stock characteristics motivated by Fama and French (2015) (log book equity, profitability, investment, market beta, and the ratio of dividend-to-book equity).\(^9\)

Table 1 displays the results of this regression. The OLS regressions of growth expectations on price in columns 1 and 2 display a strong correlation between these objects, as documented in previous work (Bordalo et al. (2019, 2020); Nagel and Xu (2021); De La O and Myers (2021)). The first stage regressions of price changes on the FIT instrument in columns 3 and 4 are strong with \(F\)-statistics of over 20 (partial \(F\)-statistics of 27 and 26, respectively). The reduced form regressions of growth expectations on the FIT instrument in columns 5 and 6 are also significant. The second-stage estimates of \(\alpha\) in column 7 and 8 reveal a statistically and economically significant causal effect of prices on growth expectations: an exogenous 1\% increase in price raises one-year expected cash flow growth by 32 basis points.\(^{10}\)

Thus, an OLS regression of prices on cash flow expectations proves insufficient to identify the causal impact of cash flow expectations on prices. Given this evidence of reverse causality, we could observe a strong positive correlation between beliefs and prices even if the causal effect of beliefs on prices is small. Identifying the causal effect of beliefs on prices, thus, requires more structure, which I impose starting in Section 4.

### 3.2 Potential Threats to Identification

1. **What if beliefs drive flows?** Previous work has documented correlations between fund flows and surveyed beliefs (Greenwood and Shleifer (2014)) as well as past performance (Ippolito of all shares of stock \(n\).

\(^9\) Appendix Figure A1 displays residualized binscatter plots for the first-stage and reduced-form regressions in (4).

\(^{10}\) Appendix Figure A2 illustrates these results prove robust to alternative specifications.

To address concerns about serial correlation in the FIT instrument, Appendix Figure A3 displays regression results using an FIT measure constructed from the residual flows remaining after removing the predictable component of flows from an AR(p) model. All results prove robust to using this alternative instrument.

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\(^9\) Appendix Figure A1 displays residualized binscatter plots for the first-stage and reduced-form regressions in (4).

\(^{10}\) Appendix Figure A2 illustrates these results prove robust to alternative specifications.
Table 1: Causal Effect of Prices on Earnings Growth Expectations

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<td>(0.0255)</td>
<td>(0.142)</td>
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<td>FIT$_{n,t}$</td>
<td>3.124***</td>
<td>3.046***</td>
<td>1.006**</td>
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<td>(0.594)</td>
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<td>F</td>
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<td>27.42</td>
<td>27.70</td>
<td>22.48</td>
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<tr>
<td>R-Squared</td>
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<td>0.0895</td>
<td>0.223</td>
<td>0.227</td>
<td>0.0751</td>
<td>0.0765</td>
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</table>

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays results for the following two-stage least squares regression:

\[
\begin{align*}
\Delta p_{a,n,t} &= a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t} \\
\Delta G_{a,n,t} &= b_0 + \alpha \hat{\Delta p}_{a,n,t} + X_{n,t} + e_{2,n,t}.
\end{align*}
\]

The first stage regresses percentage price changes between analyst institution $a$’s report releases for stock $n$ in consecutive quarters $t-1$ and $t$ ($\Delta p_{a,n,t}$) on the flow-induced trading instrument ($\text{FIT}_{n,t}$). The second stage regresses quarterly changes in one-year expected growth ($\Delta G_{a,n,t}$) on the instrumented price change ($\hat{\Delta p}_{a,n,t}$). Stock characteristics are log book equity, profitability, investment, market beta, and the dividend to book equity ratio. The time period is 1984-01:2021-12.
Chevalier and Ellison (1997); Sirri and Tufano (1998)). However, since mutual funds are diversified, stock-level beliefs cannot drive mutual fund flows even if beliefs about more aggregate quantities (e.g. the stock market, macroeconomy, etc.) do.

2. **What if cash flow expectations and flows are exposed to common factors?** For simplicity, consider a single common factor $f_t$. This situation gives rise to the following structure for fund flows, the FIT instrument, and cash flow expectations:

\[
\text{Flow}_{i,t} = c_i f_t + \varepsilon_{i,t} \tag{5}
\]
\[
\text{FIT}_{n,t} = \gamma_n f_t + e_{n,t} \tag{6}
\]
\[
\Delta G_{a,n,t} = \alpha \Delta p_{a,n,t} + \lambda a f_t + \nu_{a,n,t} \tag{7}
\]

(5) specifies that fund flows depend on fund-level characteristics $c_i$. For example, some mutual funds long value stocks and so receive more inflows if investors become more bullish about value. Since fund holdings correlate with stock characteristics (e.g. value funds hold high book-to-market stocks), (3) implies the stock-level FIT shock has stock-specific loadings on the common factor, as in (6). At the same time, analysts may update their cash flow expectations due to the common shock (e.g. analysts may become more bullish about value stocks as investors do), which implies $f_t$ affects $\Delta G_{a,n,t}$ as in (7). Controlling for stock characteristics in regression (4) absorbs the variation in the FIT instrument driven by the common shock ($\gamma_n f_t$). Moreover, controlling for stock characteristics barely changes the second-stage $\alpha$ estimates in Table 1, which suggests this source of endogeneity may not be a serious concern.

3. **What if the stock characteristics used don’t fully absorb variation in flows due to common factors?** Appendix A.2 uses a modified version of the FIT instrument that exploits within stock-quarter variation in the timing of analyst report releases. This within stock-quarter identification strategy allows for the use of stock-quarter fixed effects, which nonparametrically control for time-varying stock characteristics. The $\alpha$ estimate from this strategy (32 basis points in Table A1) is quantitatively similar to those in Table 1 (also 32 basis points), which again suggests that flow and belief exposure to common factors may not be a serious identification concern.

4. **What if long-term cash flow expectations don’t respond to price changes?** Appendix A.3 repeats two-stage least squares regression (4) using the long-term earnings growth (LTG) expectations focused on by Bordalo et al. (2019, 2020) and Nagel and Xu (2021). There is causal effect of prices on LTG expectations. An exogenous 1% increase in price raises LTG expectations by 12 basis points.
4 A Framework for Demand, Beliefs, and Prices

This section builds on the setup of Gabaix and Koijen (2020b) to present a theoretical framework for thinking about asset demand, beliefs, and prices in equilibrium in order to highlight the structural parameter of interest: the causal effect of cash flow expectations on prices. Sections 4.1 and 4.2 describe the structure I put on asset demand and beliefs (expected returns and expected cash flow growth). Section 4.3 characterizes the behavior of equilibrium prices and defines the the causal effect of cash flow expectations on prices. Section 4.4 presents the benchmark value for this causal effect in a standard model. These sections all consider a representative investor. Section 4.5 explains how the framework easily generalizes to multiple, heterogeneous investors.

4.1 Asset Demand

Assume there is a representative investor, $N$ stocks, and one outside asset (labelled $n = 0$). Time is indexed by quarter $t$ since I observe investor holdings quarterly.

Asset demand is a function of expected returns and other potentially-correlated sources of demand. In general, the investor demands portfolio weight in stock $n$ of $\theta_{n,t}$:

$$\theta_{n,t} = f_t \left( \mu_{n,t}, \epsilon_{n,t} \right),$$

(8)

where $\mu_{n,t}$ is the investor’s subjective excess expected return at time $t$ for stock $n$ and $\epsilon_{n,t}$ accounts for all other sources of asset demand. Any portfolio choice model admits this representation; (8) entails no loss of generalization. For example, in mean-variance portfolio choice $\epsilon_{n,t}$ captures asset $n$’s variance, its covariances with all other assets, and the expected returns on all other assets. More generally, $\epsilon_{n,t}$ can incorporate hedging demand (Merton (1973)), time-varying risk aversion (e.g. Campbell and Cochrane (1999)), higher moment risk (e.g. Barro (2006)), institutional frictions (e.g. He and Krishnamurthy (2013)), non-pecuniary preferences (e.g. Pástor, Stambaugh and Taylor (2021)), etc. In equilibrium, $\epsilon_{n,t}$ and $\mu_{n,t}$ are correlated through market clearing, as discussed in Section 4.3, since $\epsilon_{n,t}$ impacts price, which impacts expected return.

To match the empirical lognormal distribution of portfolio weights in the 13F data (Koijen and Yogo (2019)), I use the following functional form for $f_t$ motivated by Gabaix and Koijen (2020b):

$$\theta_{n,t} = \begin{cases} \frac{\hat{\theta}_{n,t}}{1 + \sum_{m=1}^{N} \hat{\theta}_{m,t}}, & n = 1, \ldots, N \\ \frac{1}{1 + \sum_{m=1}^{N} \hat{\theta}_{m,t}}, & n = 0 \end{cases}$$

where

$$\hat{\theta}_{n,t} = \exp \left[ \kappa \mu_{n,t} + \epsilon_{n,t} \right], n = 1, \ldots, N.$$
Thus,

\[ \theta_{n,t} = \exp \left[ \kappa \mu_{n,t} + \epsilon_{n,t} \right], \quad n = 1, \ldots, N \tag{9} \]

\[ \xi_t = -\log \left[ 1 + \sum_{m=1}^{N} \hat{\theta}_{m,t} \right]. \]

This exponential linear specification imposes that the semielasticity of portfolio weight demanded with respect to expected return

\[ \frac{\partial \log \theta_{n,t}}{\partial \mu_{n,t}} = \kappa \]

does not depend on the portfolio weight \((\theta_{n,t})\) and is constant over time and across stocks.

How do changes in expected return \((\mu_{n,t})\) and other sources of asset demand \((\epsilon_{n,t})\) affect the portfolio weight demanded? Say we start in equilibrium in subperiod \(t-\) and some shock occurs to \(\mu_{n,t}\) and \(\epsilon_{n,t}\) to bring us to a new equilibrium in subperiod \(t+\). Consider small percentage deviations in excess expected return \((\Delta \mu_{n,t} = \mu_{n,t+} - \mu_{n,t-})\), price \((\Delta p_{n,t} = p_{n,t+} - p_{n,t-})\), and other sources of asset demand \((\Delta \epsilon_{n,t} = \epsilon_{n,t+} - \epsilon_{n,t-})\) around the time \(t-\) quantities:

\[ \theta_{n,t+} = \theta_{n,t-} \exp [\kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}] . \]

Linearizing around \((\Delta \mu_{n,t}, \Delta p_{n,t}, \Delta \epsilon_{n,t}) = (0, 0, 0)\) yields percentage change in quantity of shares demanded (from \(t-\) to \(t+\))\(^{11}\):

\[ \Delta q_{n,t} \approx (\theta_{n,t-} - 1) \Delta p_{n,t} + \kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}. \tag{10} \]

See Appendix B.1 for a proof of this linearization.

\(^{11}\)Strictly speaking, \(\Delta \xi_t\) depends on \(\Delta \mu_{n,t}\) through \(\hat{\theta}_{n,t}\).

\[ \frac{\partial \xi_t}{\partial \mu_{n,t}} \bigg|_{\hat{\theta}_{m,t} = \theta_{m,t-}} = -\theta_{n,t-} \kappa. \]

Taking this dependence into account yields the following demand function

\[ \Delta q_{n,t} \approx (\theta_{n,t-} - 1) \Delta p_{n,t} + \kappa (1 - \theta_{n,t-}) \Delta \mu_{n,t} + \Delta \epsilon_{n,t}^{D} + \Delta \xi_{n,t}, \]

where \(\Delta \xi_{n,t} = \Delta \xi_t + \theta_{n,t-} \kappa \Delta \mu_{n,t}\). Since \(\theta_{n,t-}\) is small for individual stocks, I use the simpler approximation (10).
4.2 Beliefs

Sections 4.2.1 and 4.2.2 describe the structure I place on expected returns and expected cash flow growth, respectively.

4.2.1 Expected Returns

Letting $P_{n,t+1}$ be next period’s price, $D_{n,t+1}$ be next period’s dividend, and $R_f^t$ be the gross risk-free rate, the definition of excess expected return is for stock $n$ is

$$\mu_{n,t} = \frac{\tilde{E}_t[P_{n,t+1} + D_{n,t+1}]}{P_{n,t}} - R_f^t,$$

where $\tilde{E}_t$ is the conditional expectation under the investor’s subjective measure. Taking a first-order approximation around small percentage changes in

- Current price (i.e. from $P_{n,t}$ to $P_{n,t+1}$): $\Delta p_{n,t}$
- Expected next period price (i.e. from $\tilde{E}_t[P_{n,t+1}]$ to $\tilde{E}_t[P_{n,t+1}]$): $\Delta \tilde{p}_{n,t,1}$
- Expected next period dividend (i.e. from $\tilde{E}_t[D_{n,t+1}]$ to $\tilde{E}_t[D_{n,t+1}]$): $\Delta \tilde{d}_{n,t,1}$

yields:

$$\Delta \mu_{n,t} \approx (-1 - \delta)(1 + \tilde{g})\Delta p_{n,t} + \delta(1 + \tilde{g})\Delta \tilde{d}_{n,t,1} + (1 + \tilde{g})\Delta \tilde{p}_{n,t,1}.$$  \hspace{1cm} (11)

where $\delta$ is the average dividend-price ratio and $\tilde{g}$ is average dividend growth rate. See Appendix B.2 for a proof of this approximation.

This approximation places no restrictions on subjective expected returns. The investor can have rational expectations or exhibit behavioral biases.

4.2.2 Expected Cash Flow Growth

I model realized quarterly dividend growth $g_{n,t+1} \equiv \frac{D_{n,t+1}}{D_{n,t}} - 1$ as follows:

$$g_{n,t+1} = x_{n,t} + \epsilon^g_{n,t+1}; \quad \tilde{E}_t[\epsilon^g_{n,t+i}] = 0, \forall i > 0$$

$$x_{n,t+1} = \bar{x} + \rho(x_{n,t} - \bar{x}) + \epsilon^x_{n,t+1}; \quad \tilde{E}_t[\epsilon^x_{n,t+i}] = 0, \forall i > 0$$

(Non serial correlation in $\epsilon^g_{n,t}$)

$$\tilde{E}_t[\epsilon^g_{n,t+i}\epsilon^g_{n,t+j}] = 0, \forall i > 0, i \neq j,$$

(No serial correlation in $\epsilon^g_{n,t}$)

$$\tilde{E}_t[\epsilon^x_{n,t+i}\epsilon^x_{n,t+j}] = 0, \forall i > 0, i \neq j,$$

(No serial correlation in $\epsilon^x_{n,t}$)

$$\tilde{E}_t[\epsilon^g_{n,t+i}\epsilon^x_{n,t+j}] = 0, \forall i, j.$$ (No correlation between $\epsilon^g_{n,t}$ and $\epsilon^x_{n,t}$)
where \( x_{n,t} \) represents time-\( t \) conditional subjective expected dividend growth in period \( t+1 \) for stock \( n \). I model \( x_{n,t} \) as an AR(1) process with persistence \( \rho \). Average dividend growth is \( \bar{g} = \mathbb{E}[g_{n,t}] = \mathbb{E}[x_{n,t}] = \bar{x} \). Note that all expectations are taken under the investor’s subjective beliefs.

Crucially, \( x_{n,t} \) is not known with certainty. In period \( t \) the investor has Bayesian uncertainty over the expectation of next-period dividend growth. From subperiod \( t^- \) to \( t^+ \), the investor learns about \( x_{n,t} \). At \( t^- \) the investor has prior expectation \( \tilde{E}_{t^-}[x_{n,t}] \). After receiving new information, at \( t^+ \) he has posterior expectation \( \tilde{E}_{t^+}[x_{n,t}] \). The shock to the expected next-quarter growth rate is

\[
\Delta \nu_{n,t}^g = \tilde{E}_{t^+}[g_{n,t+1}] - \tilde{E}_{t^-}[g_{n,t+1}] = \tilde{E}_{t^+}[x_{n,t}] - \tilde{E}_{t^-}[x_{n,t}],
\]

(13)

since \( \epsilon_{t+1}^g \) has conditional expectation of zero.

Through the AR(1) dynamics, this shock also causes an update to future growth rate expectations\(^{12}\):

\[
\tilde{E}_{t^+}[g_{n,t+s+1}] - \tilde{E}_{t^-}[g_{n,t+s+1}] = \rho^s \Delta \nu_{n,t}^g.
\]

Appendix B.3 estimates \( \rho \) in the term structure of analyst growth expectations. Empirically, the persistence in expected quarterly earnings growth is \( \rho = 0.7 \).

Empirically I work with shocks to one-year expected cash flow growth. Let \( \Delta \nu_{n,t} \) be the shock to one-year expected cash flow growth. I assume this annual expectations shock is driven by a shock to expected quarterly dividend growth in quarter \( t+1 \) \((\Delta \nu_{n,t}^g)\).\(^{13}\)

\(^{12}\)You could consider an alternative specification where the investor learns about \( \epsilon_{n,t+1}^g \) instead of about \( x_{n,t} \). In this case the shock to the expected next-period growth rate is

\[
\Delta \nu_{n,t}^g = \tilde{E}_{t^+}[g_{n,t+1}] - \tilde{E}_{t^-}[g_{n,t+1}] = \tilde{E}_{t^+}[\epsilon_{n,t+1}^g] - \tilde{E}_{t^-}[\epsilon_{n,t}^g].
\]

The difference between learning about \( \epsilon_{n,t+1}^g \) instead of about \( x_{n,t} \) is that the former does not cause updates to future growth rate expectations:

\[
\tilde{E}_{t^+}[g_{n,t+s+1}] - \tilde{E}_{t^-}[g_{n,t+s+1}] = 0.
\]

For this reason, learning about \( x_{n,t} \) generally implies larger effects of changes in expected cash flow growth on demand and prices than learning about \( \epsilon_{n,t+1}^g \). How much larger these effects are depends on the persistence parameter \( \rho \). The conservative benchmark value of \( M_g = 1 \) I use in Section 4.4 assumes \( \rho = 0 \). If \( \rho = 0 \), then learning about \( \epsilon_{n,t+1}^g \) has the same price impact as learning about \( x_{n,t} \).

\(^{13}\)You could make alternative assumptions as well, such as the shock to annual expected cash flow growth \((\Delta \nu_{n,t})\) is driven by a shock to quarterly expected dividend growth in quarter \( t+4 \). For a fixed persistence \( \rho \), a larger shock to quarterly expected dividend growth is required in \( t+4 \) than in \( t \) to generate a fixed \( \Delta \nu_{n,t} \). For \( \rho = 0.7 \) a 1\% shock to quarterly expected dividend growth in quarter \( t+4 \) or a shock of \( \frac{1}{\rho^4+\rho^4+\rho^4+\rho^4} = 0.4\% \) in quarter \( t \) both generate an annual expected cash flow growth shock of \( \Delta \nu_{n,t} = 1\% \). Assuming the shock to quarterly expected cash flow growth occurs earlier in the year yields smaller (so more conservative) model-implied effects of annual cash flow expectations on demand and prices. The conservative benchmark value of \( M_g = 1 \) I use in Section 4.4 assumes \( \rho = 0 \). If \( \rho = 0 \), then 1\% shocks to quarterly expected dividend growth in both quarters \( t+1 \) and \( t+4 \) generate an annual expected cash flow growth shock of \( \Delta \nu_{n,t} = 1\% \). The only difference is that assuming the shock occurs one year in the future weakens the price impact today by a discount factor of slightly below one, so \( M_g \) is slightly less than 1 (e.g. 0.96 for a risk-free rate of 4\%).
4.3 The Causal Effect of Expected Cash Flow Growth on Price: $M_g$

Section 4.3.1 introduces the structural parameter of interest in this paper: the causal effect of expected cash flow growth on price, denoted $M_g$. Section 4.3.2 explains how $M_g$ depends on the primitives introduced in Sections 4.1 and 4.2. In particular, this section explains why inelastic demand does not amplify the price impact of cash flow expectations shocks.

4.3.1 Definition of $M_g$

Plugging the dividend growth dynamics from (12) into the expected return linearization (11), and the expected return linearization into the linearized demand function (10) yields the final demand function:

$$\Delta q_{n,t} = -\zeta \Delta p_{n,t} + \kappa^g \Delta \nu_{n,t} + \Delta \epsilon_{n,t}.$$  \hspace{1cm} (14)

- $\zeta$ is the price elasticity of demand (expressed as a positive number).
- $\kappa^g$ is the causal effect of cash flow growth expectations on asset demand. $\kappa^g$ represents how much the demand curve shifts in response to a 1% increase in one-year expected cash flow growth.
- $\Delta \epsilon_{n,t}$ is the residual demand shock; it comprises all sources of asset demand except changes in expected cash flow growth.

See Appendix B.4 for a derivation of this expression.

Assuming fixed supply ($\Delta q_{n,t} = 0$) and imposing market clearing yields the following change in equilibrium price from $t-$ to $t+$:

$$\Delta p_{n,t} = \frac{\kappa^g}{\zeta} \Delta \nu_{n,t} + \frac{1}{\zeta} \Delta \epsilon_{n,t}.$$  \hspace{1cm}

The structural parameter of interest in this paper is the causal effect of annual expected cash flow growth on price, denoted $M_g$:

$$M_g = \frac{\kappa^g}{\zeta}.$$  \hspace{1cm}

$M_g$ represents how much the equilibrium price must rise in response to a 1% rise in annual expected cash flow growth. Note that $M_g$ equals the demand shift induced by the change in expectations ($\kappa^g$) divided by the price elasticity of demand ($\zeta$). Figure 1 illustrates the graphical intuition for $M_g$. Assume the investor starts at equilibrium $A$ and receives new information that raises annual expected cash flow growth by 1%. The demand curve shifts right by $\kappa^g$ percent. The price must rise by $M_g = \kappa^g/\zeta$ percent to clear the market at the new equilibrium of $B$. 

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4.3.2 What does $M_g$ Depend On?

The parameters $\kappa^g, \zeta$, and $M_g$ are all functions of the underlying structural parameters $\kappa$ (the sensitivity of asset demand to expected return), $\delta$ (average dividend-price ratio), $\bar{g}$ (average dividend growth), $\rho$ (persistence of expected dividend growth), and $\theta_{n,t-}$ (ex-ante portfolio weight).

Proposition 1 describes the forms of $\kappa^g, \zeta$, and $M_g$ under the simplifying assumptions of zero persistence in expected cash flow growth $x_t$ ($\rho = 0$), zero average dividend growth ($\bar{g} = 0$), and small portfolio weights ($\theta_{n,t-} \approx 0$). These assumptions give rise to simple analytical expressions that clearly convey the intuition behind the first-order determinants of $\kappa^g, \zeta$, and $M_g$. Proposition 2 in Appendix B.3 describes the general forms of these parameters.

**Proposition 1 ($\kappa^g, \zeta$, and $M_g$ Under Simplifying Assumptions).** For zero persistence in expected cash flow growth $x_t$ ($\rho = 0$), zero average dividend growth ($\bar{g} = 0$), and small portfolio weights ($\theta_{n,t-} \approx 0$) we have:

$$\kappa^g = \kappa \delta$$  \hspace{1cm} (15)

$$\zeta = 1 + \kappa \delta$$  \hspace{1cm} (16)

$$M_g = \frac{\kappa^g}{\zeta} = \frac{\kappa \delta}{1 + \kappa \delta}.$$  \hspace{1cm} (17)

See Appendix B.3 for a proof of this proposition.

The intuition for these expressions is as follows:
• Holding price fixed, a 1% transient dividend growth shock (i.e. a permanent 1% increase in the level of dividends) raises expected return by $\delta\%$. The increase in asset demand due to this rise in expected return is $\kappa^g = \kappa \delta$ in (15) since $\kappa$ is the sensitivity of demand to expected return.

• The price elasticity has two components. When price rises 1%, the investor reduces quantity demanded by 1% to maintain the same portfolio weight, hence the leading 1 in (16). At the same time, a rise in price, holding fundamentals fixed, lowers expected return and so reduces the portfolio weight demanded. A 1% increase in price lowers expected return by $\delta\%$, which lowers asset demand by $\kappa \delta\%$, since $\kappa$ is the sensitivity of demand to expected return. As argued by Gabaix and Koijen (2020b), inelastic demand corresponds to low $\kappa$. When prices rise, expected returns fall, but quantities do not adjust because demand is insensitive to expected return.

• The equilibrium price change due to a shock to cash flow expectations is the demand shift $(\kappa^g)$ divided by the price elasticity ($\zeta$). Hence, $M_g = \frac{\kappa \delta}{1 + \kappa \delta}$ in (17).

Proposition 1 has two main takeaways.

1. Inelastic demand implies insensitivity of demand to cash flow expectations. Inelastic demand arises due to a low sensitivity of demand to expected return (low $\kappa$). Expected returns consist of three components: 1) this period’s price, 2) the expectation of next period’s dividend, and 3) the expectation of next period’s price (which itself depends on expectations of long-run dividends). A low $\kappa$ generates insensitivity of demand to all three components.

2. Inelastic demand does not amplify the price impact of cash flow expectations. $\kappa^g$, $\zeta$, and $M_g$ are all increasing functions of $\kappa$. Thus, insensitivity of demand to expected return (low $\kappa$) implies both inelastic demand (low $\zeta$) and a small causal effect of cash flow expectations on price (low $M_g$). The intuition for this result is that price elasticity in the denominator of $M_g$ has two components, only one of which depends on $\kappa$. The strength of the change in portfolio weight demanded when expected returns change due to price changes depends on $\kappa$. However, the mechanical selling of shares when price rises to maintain a constant portfolio share does not depend

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14To model investors who seek to maintain a constant number of shares instead of a constant portfolio weight when price changes (e.g. index funds), one can add a wedge $\psi$ to the demand function so that the elasticity is $\zeta = 1 - \psi + \kappa \delta$. For $\psi = 0$ and $\kappa = 0$, the investor reduces quantity of shares demanded by 1% in response to a 1% rise in price to maintain a constant portfolio weight. For $\psi = 1$ and $\kappa = 0$, the investor does not change his quantity of shares demanded in response to a 1% rise in price. See Appendix G.3. in Gabaix and Koijen (2020b) for further discussion. Bacchetta, Tieche and Van Wincoop (2020) find (in the context of international mutual funds) that investors’ desire to rebalance to ex-ante portfolio weights proves stronger than their desire to maintain a fixed number of shares.

15Note that $\frac{x}{1+x}$ is an increasing function of $x$, where $x = \kappa \delta$ in $M_g$. 

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on $\kappa$. For this reason, a 1% reduction in $\kappa$ in relative terms (e.g. from 10 to 9.9) reduces the demand shift due to cash flow belief shocks ($\kappa^g$ in the numerator) more than the price elasticity ($\zeta$ in the denominator):

$$\frac{0.99\kappa\delta}{1 + 0.99\kappa\delta} < \frac{\kappa\delta}{1 + \kappa\delta}. \quad (1.1)$$

Thus, $M_g$ falls as $\kappa$ falls and inelastic demand implies a small causal effect of cash flow expectations on price.

Proposition 2 in Appendix B.3 describes the general forms of $\kappa^g$, $\zeta$, and $M_g$. These general forms convey no essential intuition beyond Proposition 1. The only new dimension of note is that demand and prices respond more to cash flow shocks (i.e. $\kappa^g$ and $M_g$ are higher) when the persistence of expected cash flow growth ($\rho$) is higher.

### 4.4 Benchmark Value for $M_g$

The benchmark value I compare my empirical results against is $M_g = 1$.

In a standard model, 1% purely transient expected cash flow growth shock raises price by 1%. By “standard model,” I mean any asset pricing model in which fundamental information is fully incorporated into prices on impact. Any model that prices assets under a consumption-based stochastic discount factor satisfies this property. This set of models includes both rational expectations models (e.g. Campbell and Cochrane (1999); Bansal and Yaron (2004); Barro (2006); He and Krishnamurthy (2013)) and behavioral models (e.g. Barberis et al. (2015); Bordalo, Gennaioli and Shleifer (2018); Maxted (2020); Nagel and Xu (2021)). Dividend discount models also satisfy this property (e.g. Shiller (1981); Bordalo et al. (2020)).

The intuition for $M_g = 1$ is simple. A 1% purely transient increase in expected cash flow growth is a permanent 1% rise in the expected level of all future dividends. In any model where cash flow shocks do not impact discount rates (i.e. most asset pricing models), the price-dividend ratio does not change due to a purely transient expected cash flow growth shock.\(^{16}\) Thus, the 1% purely transient increase in expected cash flow growth raises price 1%. Appendix B.5 provides a simple consumption-based model (CRRA utility, i.i.d. consumption growth, potentially persistent dividend growth) to formalize this argument.\(^{17}\)

\(^{16}\)In particular, since my empirical setting is the cross section of equities, I assume the risk free rate is exogenous to stock-specific cash flow expectations shocks. In models that price consumption claims, the risk free rate is usually endogenous to growth shocks due to intertemporal substitution. I rule out those general equilibrium effects on the risk free rate.

\(^{17}\)A note about persistence: In most models, more persistent expected cash flow growth shocks have larger impacts on price. Since the I/B/E/S growth expectations exhibit some persistence ($\rho = 0.7$ in Appendix B.3), arguably I should use a larger benchmark value $M_g > 1$. I find $M_g \approx 1.3$ in the simple model in Appendix B.5 for persistence $\rho = 0.7$. Using $M_g = 1.3$ instead of $M_g = 1$ does not change my empirical conclusion: the causal impact of cash flow growth expectations on prices is about an order of magnitude smaller than in standard models. In fact, using the larger value of $M_g$ accounting for persistence strengthens this conclusion. Thus, to keep the benchmark value as simple as possible, I use the more conservative value of $M_g = 1$.  

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Note that, per the form of \( M_g \) in Proposition 1, \( M_g = 1 \) corresponds to \( \kappa = \infty \). That is, when asset demand is extremely sensitive to expected returns (and so also to expected cash flow growth), a 1% purely transient expected cash flow growth shock raises price by 1%.

### 4.5 Generalizing to Heterogeneous Agents

Generalizing the representative agent framework presented above to allow for heterogeneous investors proves simple. Following (14), investor \( i \) has the following percentage change in quantity of shares demanded for stock \( n \) in quarter \( t \):

\[
\Delta q_{i,n,t} = -\zeta_i \Delta p_{n,t} + \kappa^g_i \Delta \nu_{i,n,t} + \Delta \epsilon_{i,n,t},
\]

where \( \zeta_i \) and \( \kappa^g_i \) reflect heterogeneity in portfolio choice functions (9) (i.e. heterogeneous sensitivities of demand to expected return \( \kappa_i \)), \( \Delta \nu_{i,n,t} \) captures heterogeneous growth expectations, and \( \Delta \epsilon_{i,n,t} \) allows for heterogeneous demand shocks.

As discussed in Gabaix and Koijen (2020b), the correct way to aggregate percentage changes in shares demanded across investors is using ownership share weights \( S_{i,n,t} \):

\[
S_{i,n,t} = \frac{Q_{i,n,t}}{\sum_{j=1}^{\infty} Q_{j,n,t}},
\]

where \( Q_{i,n,t} \) is the ex-ante equilibrium (i.e. time \( t-\) ) quantity of shares owned by investor \( i \) in stock \( n \). Let subscript \( S \) denote an ownership share weighted average (e.g. \( \Delta q_{S,n,t} \equiv \sum_i S_{i,n,t} \Delta q_{i,n,t} \) is the aggregate change in quantity of shares demanded for stock \( n \)).

Assume all investors experience the same change in annual expected cash flow growth (\( \Delta \nu_{i,n,t} = \Delta \nu_{n,t}, \forall i \)). Market clearing under fixed supply (0 = \( \Delta q_{S,n,t} \)) implies

\[
\Delta p_{n,t} = \frac{\kappa^g_S}{\zeta_S} \Delta \nu_{n,t} + \frac{1}{\zeta_S} \Delta \epsilon_{S,n,t}.
\]

Thus, in general the causal effect of annual cash flow growth expectations on price is

\[
M_g = \frac{\kappa^g_S}{\zeta_S}.
\]

\( M_g \) is still the expectations-induced aggregate demand curve shift (\( \kappa^g_S \)) divided by the aggregate demand curve elasticity \( \zeta_S \).
5 Measuring $M_g$ under Investor Homogeneity

This section details my empirical strategy for identifying and presents estimates of $M_g$ from price and beliefs data alone under restrictions on investor heterogeneity. I develop a model in which Bayesian investors learn from analyst growth expectations. This update to growth expectations shifts asset demand and causes prices to change. While previous work has studied the price impact of analyst growth expectations, I seek to measure $M_g$: the price impact of investor growth expectations. Doing so requires measuring analyst “influence” on investor beliefs.

In this section I assume:

1. All investors have the same sensitivity of demand to cash flow expectations $\kappa_i$ and price elasticity $\zeta_i$.

2. Analyst influence on investor beliefs is the same for all investors.

Section 6 relaxes these homogeneity assumptions.

Section 5.1 presents an overview of the three main blocks of the empirical strategy: analyst expectation formation, investor learning and asset demand (analyst influence is defined here), and market clearing. Sections 5.2, 5.3, and 5.4 provides the details of each of these blocks. Section 5.5 presents the results of this empirical strategy.

5.1 Overview of Empirical Strategy

I present the three blocks of the empirical strategy and then discuss identification. All of the identification works within a quarter, so I suppress quarter $t$ subscripts. As discussed in Section 2, I group all analysts to their parent institution. Thus, any reference to “analysts” implicitly means “analyst institutions.” Figure 2 summarizes the timing of the model.

1. Analyst expectation formation. As demonstrated in Section 3, analyst growth expectations depend on prices. However, since analyst expectations don’t perfectly correlate with prices, they also contain some additional information. Thus, in general the quarter-over-quarter change in one-year analyst cash flow growth expectation for stock $n$ ($\Delta G^A_{a,n} \equiv G^A_{a,n} - G^{Log}_{a,n}$, where $G_{a,n}$ and $G^{Log}_{a,n}$
are the stock-\( n \) growth expectations analyst \( a \) reports in consecutive quarters) takes the following form:

\[
\Delta G_A^{a,n} = \phi_{a,n} \Delta p_n^- + \nu_A^{a,n},
\]

(21)

where \( \Delta p_n^- \) is the price change between analyst reports (i.e. in quarters \( t-1 \) and \( t \)) and \( \nu_A^{a,n} \) captures variation in analyst expectations not driven by price.

2. **Investor learning and asset demand.** Consider a high-frequency window (several days) immediately after the release of analyst \( a \)'s report for stock \( n \). From (18), the percentage change in quantity of shares demanded by investor \( i \) for stock \( n \) is:

\[
\Delta q_{i,a,n} = -\zeta \Delta p_{a,n}^+ + \kappa^g \Delta G_{i,a,n}^I + \Delta \epsilon_{i,a,n},
\]

where \( \Delta p_{a,n}^+ \) is the price change due to the analyst report release (the high-frequency price change after the announcement, not to be confused with the lagged, low-frequency price change \( \Delta p_n^- \) in (21)), \( \Delta G_{i,a,n}^I \) represents the shock to investor \( i \)'s one-year expected cash flow growth for stock \( n \), and \( \Delta \epsilon_{i,a,n} \) includes other high-frequency demand shocks. Superscript \( I \) distinguishes investor expectations from analyst expectations (identified by superscript \( A \)).

Since I do not observe investor expectations, I need to measure how analyst beliefs influence investor beliefs. Specifically, the update to investor expectations is:

\[
\Delta G_{i,a,n}^I = B_n (G_A^{a,n} - \bar{G}_{i,a,n}^I) + \nu_{i,a,n}^I,
\]

(22)

where \( \bar{G}_{i,a,n}^I \) is investor \( i \)'s prior growth expectation immediately before analyst \( a \)'s report release and \( \nu_{i,a,n}^I \) captures any other signals the investor contemporaneously learns from. \( B_n \) is analyst influence on investor expectations for stock \( n \).

3. **Market clearing.** From (19), the market clearing price change due to the analyst report release is:

\[
\Delta p_{a,n}^+ = M_g \Delta G_{S,a,n}^I + \frac{1}{\zeta} \Delta \epsilon_{S,a,n}
\]

\[
= M_g B_n \Delta G_A^{a,n} - M_g B_n (\bar{G}_{S,a,n}^I - G_{a,n}^{Log}) + M_g \nu_{S,a,n}^I + \frac{1}{\zeta} \Delta \epsilon_{S,a,n},
\]

(23)

where \( S \) denotes ownership-share weighted averages and \( G_{a,n}^{Log} \) is analyst \( a \)'s growth expectation for stock \( n \) reported last quarter. The high-frequency price change after the analyst report depends on: 1) the analyst-reported expectation \( (G_A^{a,n} = \Delta G_A^{a,n} + G_{a,n}^{Log}) \), 2) how much the analyst-reported expectation differs from investor prior expectations \( (\bar{G}_{S,a,n}^I) \), 3) any other contemporaneous signals investors learn from \( (\nu_{S,a,n}^I) \), and 4) any contemporaneous demand shocks \( (\Delta \epsilon_{S,a,n}) \). \( M_g B_n \) is analyst
price impact: the price rise due to a 1% higher reported analyst annual growth expectation.

**Identification** Identifying $M_g$ from (23) requires:

1. Exogenous variation in analyst expectations ($G_{a,n}^A$) to pin down analyst price impact ($M_g B_n$).
2. Measurement of analyst influence ($B_n$) to separately identify the investor price impact ($M_g$).

To obtain exogenous variation in analyst expectations, I impose a factor structure on their beliefs:

$$
\Delta G_{a,n}^A = \phi_{a,n} \Delta p_n^- + \lambda_a' \eta_n + u_{a,n} \tag{24}
$$

Quarterly analyst expectation updates ($\Delta G_{a,n}^A$) can depend on contemporaneous price changes ($\Delta p_n^-$) and stock characteristics ($\eta_n$, e.g. public signals), as well as uncorrelated idiosyncratic shocks ($u_{a,n}$). I view (24) as a latent factor model and use tools from a branch of machine learning known as collaborative filtering to efficiently estimate the factor model and isolate the idiosyncratic analyst growth shocks $u_{a,n}$. Section 5.2 details this procedure.

To measure analyst influence, I model investors as Bayesians who learn from analysts. With observed investor growth expectations, one could run a first-stage regression of investor expectations on analyst expectations to identify analyst influence. Unfortunately, I do not observe investor growth expectations, which necessitates a more structured approach. Bayesian learning implies that analyst influence $B_n$ varies in the cross section of equities: $B_n$ is smaller for stocks with more analysts due to signal averaging. The more signals (analyst expectations) a Bayesian learner observes, the less weight (influence) any particular signal receives in the posterior. Bayesian learning implies the following first-order approximation for analyst influence

$$
B_n = \beta - \beta^2 \tilde{A}_n, \tag{25}
$$

where $\beta$ is the average level of influence and $\tilde{A}_n$ is the demeaned number of analysts that rate stock $n$. Section 5.3 elaborates on this learning structure.

Plugging the factor structure (24) and the form of analyst influence (25) into the market-clearing price change (23) yields:
\[
\Delta p_{a,n}^+ = M_g \beta u_{a,n} - M_g \beta^2 u_{a,n} \tilde{A}_n \\
+ M_g \left( \beta - \beta^2 \tilde{A}_n \right) \left( \phi_{a,n} \Delta p_{a,n}^- + \lambda'_a \eta_a \right) \\
- M_g B_n \left( \tilde{G}_S, a, n - \tilde{G}_a, n \right) \\
+ M_g \nu_{S, a, n}^I + \frac{1}{\zeta} \Delta \epsilon_{S, a, n} \\
= M_g \beta u_{a,n} - M_g \beta^2 u_{a,n} \tilde{A}_n + e_{a,n}
\]

A regression of high-frequency price changes after analyst reports (\(\Delta p_{a,n}^+\)) on idiosyncratic growth shocks (\(u_{a,n}\)) and their interaction with the demeaned number of analysts (\(\tilde{A}_n\)) identifies both \(M_g\) and \(\beta\). The two moment conditions required for identification are:

\[
\mathbb{E} [u_{a,n} e_{a,n}] = 0 \quad (27) \\
\mathbb{E} [u_{a,n} \tilde{A}_n e_{a,n}] = 0. \quad (28)
\]

I have two instruments (\(u_{a,n}\) and \(u_{a,n} \tilde{A}_n\)), two moment conditions ((27) and (28)), and two structural parameters to identify (\(M_g\) and \(\beta\)). Exogenous variation in analyst expectations (\(u_{a,n}\)) pins down analyst price impact (\(M_g \beta\)). The interaction of \(u_{a,n}\) with cross-sectional variation in the number of analysts covering each stock (\(u_{a,n} \tilde{A}_n\)) pins down the decay rate of analyst price impact (\(M_g \beta^2\)), since analyst influence falls with the number of analysts. Bayesian learning links the level of influence with the decay rate of influence. Hence, from these two parameters (\(M_g \beta\) and \(M_g \beta^2\)), I obtain \(M_g\): the causal impact of investor annual growth expectations on price. Section 5.4 provides the details of how I use high-frequency panel regressions to estimate (26).

The identifying assumption is:

**Assumption 1 (Identifying Assumption).** Any common variation between analyst growth expectation updates (\(\Delta G_{a,n}^A\)) and

1. Investor prior expectations (\(\tilde{G}_S, a, n\))
2. Lagged analyst expectations (\(G_{a,n}^{Log}\))
3. Other contemporaneous signals (\(\nu_{S, a, n}^I\)), and
4. Other demand shocks (\(\Delta \epsilon_{S, a, n}\))
is spanned by stock-quarter characteristics.

If Assumption 1 holds, then the latent factor model strips out all common variation between \( \Delta G_{a,n}^A \) and both \( e_{a,n} \) and \( \tilde{A}_n \). In this case, both moment conditions (27) and (28) hold.

5.2 Analyst Expectation Formation

This section explains the nature of the idiosyncratic growth shocks \( u_{a,n} \) in (24) and explains how to empirically extract them.

I model quarterly changes\(^{18}\) in analyst annual growth expectations as having factor structure (24)
\[
\Delta G_{a,n}^A = (\phi_a + \phi_n) \Delta p_n^- + \lambda_a^t \eta_n + u_{a,n}.
\] (29)
Quarterly analyst expectation updates (\( \Delta G_{a,n}^A \)) can depend on contemporaneous price changes (\( \Delta p_n^- \)), stock characteristics (\( \eta_n \)), and uncorrelated idiosyncratic shocks (\( u_{a,n} \)). Stock characteristics may include public signals observed by all analysts and investors (e.g. firm \( n \)'s earnings surprise, monetary policy announcements, COVID news), firm characteristics, etc.\(^{19}\) I estimate factor model (29) within each quarter, so all factors, loadings, and idiosyncratic shocks vary over time.

What is an idiosyncratic expected analyst growth shock? The most natural candidate is private information obtained by analyst \( a \) about the future cash flows of stock \( n \).\(^{20}\) The lagged growth expectation (\( G_{a,n}^{Lag} \) in (26)) by definition does not reflect new information and so is uncorrelated with \( u_{a,n} \). This information may also have no bearing on other sources of asset demand (e.g. subjective risk perceptions, hedging demand, institutional mandates, non-pecuniary preferences, etc.) and so will be uncorrelated with other contemporaneous demand shocks (\( \Delta \epsilon_{S,a,n} \) in (26)). Moreover, information observed only by analyst \( a \) is uncorrelated with investor priors (\( \bar{G}_{I,a,n}^I \) in (26)) since investors cannot have not learned it and with other contemporaneous signals (\( \nu_{I,a,n}^I \) in (26)).

Extracting idiosyncratic variation with collaborative filtering. To operationalize factor model (29), I use tools from collaborative filtering, a branch of machine learning that learns models of individual-specific “preferences” over objects from reported preferences. The canonical example is Netflix learning models of individual-specific movie preferences from reported partial cross sections.

\(^{18}\)I use changes in instead of levels of analyst expected growth because changes should better isolate the new information in analyst reports and have been found to have greater price impact than the levels reported by analysts (e.g. Brav and Lehavy (2003)).

\(^{19}\)Factor structure (24) can also incorporate analyst or stock-specific biases (i.e. fixed effects). An analyst-quarter fixed effect is an element of \( \lambda_a \) constrained to load on a constant \( \eta_{n,f} = 1 \) and a stock-quarter fixed effect is an element of \( \eta_{n,t} \) constrained to be loaded on by \( \lambda_{a,f} = 1 \).

\(^{20}\)The notion that equity research analysts communicate private information to markets via their reports is well-established in the previous literature (e.g. Chen and Matsumoto (2006); Mayew, Sharp and Venkatachalam (2013)).
of ratings. In this setting, I seek to learn analyst-specific models of stock-level expected cash flow growth from partial cross sections of covered stocks.

I reexpress the structural factor model from (29) in reduced form as

$$\Delta G^A_{a,n} = \tilde{\lambda}_a^\top \tilde{\eta}_n + u_{a,n}. \quad (30)$$

Note that this representation subsumes the price term $(\phi_a + \phi_n)\Delta p_n^-$ from (29).\footnote{In this notation I’ve assumed all analysts learn from the same price change $\Delta p_n^-$ even if they report expectations at different times in each quarter. In this case, $(\phi_a + \phi_n)\Delta p_n^- = \phi_a \Delta p_n^- + \phi_n \Delta p_n^-$ so the first term is an analyst loading times a stock characteristic and the second term is one times a stock characteristic. $\tilde{\lambda}_a^\top \tilde{\eta}_n$ can absorb both of these terms.}

In reality, analysts may learn from slightly different price changes due to the staggered timing of analyst reports. In this case, we have the following structural factor model for $\Delta G^A_{a,n}$: $\Delta G^A_{a,n} = (\phi_a + \phi_n)\Delta p_n^- + \lambda_a \eta_n + u_{a,n}$. Let $\mathcal{D}_{a,n}$ be the set of days that elapse between the two quarterly report releases of $G^Lag_{a,n}$ last quarter and $G_{a,n}$ in the current quarter. If day $d$ occurs in at least two sets $\mathcal{D}_{a,n}$ and $\mathcal{D}_{b,n}$, the price change on day $d$ is a common factor that $\tilde{\eta}_n$ can capture. Let all such days belong to set $\mathcal{D}_n$. Then we can decompose $\Delta \tilde{p}_{a,n} = \lambda_{a,Timing} \Delta p_n^- + \Delta \tilde{p}_{a,n}$, where $\Delta p_n^-$ is the vector of price changes for days $d \in \mathcal{D}_n$ and $\Delta \tilde{p}_{a,n}$ is the sum of price changes over days in $\mathcal{D}_n \setminus \mathcal{D}_n$. Thus, $(\phi_a + \phi_n)\Delta p_{a,n}^- = \phi_a \lambda_{a,Timing} \Delta p_n^- + \lambda_{a,Timing} \phi_n \Delta p_n^-$, but not the second two terms $(\phi_a \lambda_{a,Timing} \Delta p_n^- + \lambda_{a,Timing} \phi_n \Delta p_n^-)$. Thus, the second two terms would appear in the estimated residual $\hat{u}_{a,n}$. These price changes prove unlikely to cause serious problems empirically for two reasons. First, only the first analyst to report in the previous quarter and the last analyst to report in the current quarter can have non-empty sets $\mathcal{D}_{a,n} \setminus \mathcal{D}_n$ and so non-zero $\Delta \tilde{p}_{a,n}$. Second, for these two analysts, $\Delta \tilde{p}_{a,n}$ proves unlikely to strongly correlate with $e_{a,n}$ in (26) because there is little high-frequency serial correlation in returns.

As an additional robustness check, one could also not include the analyst-stock pairs $(a, n)$ corresponding to the first analyst to report in the previous quarter or the last analyst to report in this quarter when estimating (26).\footnote{All results prove robust to using alternative numbers of latent factors, as discussed in Appendix G.1.}

5.3 Investor Learning and Asset Demand

This section derives the form of analyst influence (25) implied by Bayesian learning.

$$\mathbf{M} = \mathbf{A} \mathbf{H} + \mathbf{u}, \quad (31)$$

where $\mathbf{M}$ is the $A \times D$ matrix of reported expected cash flow growth for total number of analysts $A$ and number of stocks $D$, $\mathbf{A} \in \mathbb{R}^{A \times F}$ is the stacked matrix of institution-specific loading vectors $\lambda_a \in \mathbb{R}^F$, $\mathbf{H} \in \mathbb{R}^{F \times D}$ is the stacked matrix of stock-specific characteristic vectors $\eta_n \in \mathbb{R}^F$, and $\mathbf{u}$ is the $A \times D$ matrix of idiosyncratic analyst growth shocks. Here $F$ is the number of latent factors used. I fit latent factor model (31) quarter-by-quarter using the regularized singular value decomposition technique of Funk (2006). Given the sparsity of $\mathbf{M}$ (most analysts don’t report expectations for most stocks), I use regularization to more efficiently estimate the factor model. For the baseline estimation, I use five latent factors. Once $\mathbf{A}$ and $\mathbf{H}$ are estimated, one can recover empirical estimates of the factor model residuals $u_{a,n}$. Appendix C discusses some implementation details.
Right before analyst \( a \) releases a growth expectation for stock \( n \) (i.e. at \( t^{-} \) in Figure 2), investor \( i \) has the following prior distribution over the unknown stock-\( n \) annual growth expectation \( G_{n} \):

\[
G_{n} \sim N(\bar{G}_{i,a,n}, \bar{\tau}).
\]

Investor \( i \) views each analyst \( a \)'s expectation as a noisy signal of the true growth rate:

\[
G^{A}_{a,n} = G_{n} + \epsilon_{a,n}, \epsilon_{a,n} \sim N(0, \sigma^2).
\]

Let \( A_{n} \) be the number of analysts who report expectations for stock \( n \). The posterior precision after learning from \( A_{n} \) signals is \( \bar{\tau}^{-1} + A_{n}\sigma^{-2} \). Thus, the update to investor \( i \)'s prior mean for stock \( n \) due to analyst \( a \)'s signal is:

\[
\Delta G^{I}_{i,a,n} = \sigma^{-2} \bar{\tau}^{-1} + A_{n}\sigma^{-2} (G^{A}_{a,n} - \bar{G}^{I}_{i,a,n}).
\]

(32)

Analyst influence for stock \( n \) is

\[
B_{n} = \frac{\sigma^{-2}}{\bar{\tau}^{-1} + A_{n}\sigma^{-2}} \equiv \frac{\beta}{\bar{\tau}^{-1} + A_{n}\sigma^{-2}} \tilde{A}_{n},
\]

(33)

where the second line follows from a first-order approximation around the average number of analysts per stock in the current quarter (\( \bar{A} = \mathbb{E}[A_{n}] \)). \( \tilde{A}_{n} = A_{n} - A \) is the demeaned number of analysts that report expectations for stock \( n \). \( \beta \) is the level of influence for the average stock.\(^{24} \) \( \beta^2 \) represents how much influence declines per additional analyst added.\(^{25} \)

To build some intuition for this functional form, consider the flat prior case: \( \bar{\tau}^{-1} = 0 \). In this case, \( B_{n} = 1/A_{n} \), i.e. the investor takes an equal-weighted average of all analyst signals. For the

\(^{23}\)Assuming expectations are correlated across analysts \( a \) for stock \( n \) does not change the functional form of analyst influence \( B_{n} \) in (33) (if the signal correlation the same for each pair of analysts). Only the functional form of \( \beta \) changes, which does not affect my identification strategy. In particular, \( \beta \) becomes a function of not only the prior precision and the signal precision, but also the covariances across signals. The reduced-form interpretation of \( \beta \) remains the same: the level of analyst influence for the average stock.

\(^{24}\)In the baseline specification I assume homogeneous signal precisions for all analysts, which implies homogeneous analyst influence for all analysts in each stock \( n \) (i.e. \( \beta \) has no analyst \( a \) subscript). Appendix D.1 derives the general linearized form of \( B_{a,n} \) with heterogeneous signal precisions \( \sigma^{-2}_{a} \). All of the same intuition from (33) carries over to the general case. The full approximation simply adjusts (33) to account for the greater loss of influence involved when adding a highly influential (high signal precision) analyst to stock \( n \) versus when adding a non-influential (low signal precision) analyst.

\(^{25}\)Appendix D.3 describes an alternative specification for analyst influence that exploits variation in the order in which analysts report their expectations and explains how this alternative specification collapses to a functional form similar to (33) under some approximations.
average stock, $\beta = 1/A$, so influence is just one over the average number of analysts. Since the derivative of $1/x$ is $-1/x^2$, influence declines at a rate of $\beta^2 = 1/A^2$ per additional analyst.

The functional form of analyst influence in (33) proves robust to a wide range of deviations from Bayesian learning, as discussed in Appendix D.3.

### 5.4 Market Clearing

This section explains how I use high-frequency panel regressions to estimate $M_g$ and $\beta$ from (26).

I run the following high-frequency panel regression

$$
\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2\beta u_{a,n,t}A_{n,t-1} + X_{n,t} + e_{a,n,t}
$$

of price changes shortly after analyst $a$’s report release for stock $n$ in quarter $t$ (5 days in the baseline specification) on the idiosyncratic growth shock $u_{a,n,t}$ and its interaction with the demeaned number of analysts from the previous quarter $A_{n,t-1}$.\textsuperscript{26} I use the lagged demeaned number of analysts to avoid any potential endogeneity issues with analysts initiating coverage due to particularly bullish (or bearish) information.\textsuperscript{27} $X_{n,t}$ represents controls, including stock, quarter, and stock $\times$ quarter fixed effects. As described in Section 5.1, all of the identification occurs in the cross section of equities within a quarter. To obtain more power, I pool across all quarters.

Regression (34) estimates two reduced-form coefficients:

1. $c_1$ is analyst price impact for the average stock. A 1% higher reported analyst growth expectation raises price by $c_1\%$ for the average stock. Exogenous variation in analyst expectations ($u_{a,n}$) pins down $c_1$.

2. $c_2$ is the decay rate of analyst price impact as the number of analysts grows due to the corresponding decay in analyst influence. An additional analyst covering stock $n$ reduces analyst price impact by $c_2\%$ (in absolute terms). The interaction of $u_{a,n}$ with cross-sectional variation in the number of analysts pins down $c_2$.

The reduced-form coefficients $c_1$ and $c_2$ jointly identify analyst influence $\beta$ and the causal effect of investor annual expected cash flow growth on price $M_g$:

$$
\beta = \frac{c_2}{c_1}
$$

$$
M_g = \frac{c_1^2}{c_2}.
$$

\textsuperscript{26}Using alternative price reaction window lengths other than 5 days yields similar results. See Appendix G.2 for a full discussion.

\textsuperscript{27}Irvine (2003) discusses some of these concerns.
Table 2: $c_1$ and $c_2$ Estimates

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Quarter FE Y Y Y Y
Stock FE Y
Stock x Quarter FE Y
Quarter-Clustered SE
N 1530391 1530391 1530391 1530391
R-Squared 0.0000556 0.0218 0.0515 0.583

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays regression results for

$$\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2 u_{a,n,t} \tilde{A}_{n,t-1} + X_{n,t} + \epsilon_{a,n,t},$$

where $\Delta p_{a,n,t}^+$ is the price change 5 days after analyst institution $a$ reports an annual growth expectation for stock $n$ in quarter $t$, $u_{a,n,t}$ is the corresponding estimated idiosyncratic growth shock, and $\tilde{A}_{n,t-1}$ is the demeaned number of analysts that cover stock $n$ in the previous quarter $t-1$. $X_{n,t}$ represents controls, including stock, quarter, and stock x quarter fixed effects. All values are expressed in basis points (i.e. 1.0 is one basis point). The time period is 1984-01:2021-12.

### 5.5 Empirical Results

This section reports the $M_g$ and $\beta$ results from regression (34). Appendix Table E4 displays summary statistics for the data used in this analysis.

Table 2 reports the estimated reduced-form coefficients $c_1$ and $c_2$ from (34). Note that, across columns, the $c_1$ and $c_2$ results prove insensitive to the inclusion of stock, quarter, or stock x quarter fixed effects, which implies the latent factor model successfully removes variation in analyst growth expectations coming from these sources. The $c_1 = 0.457$ estimate in column 4 implies that a 1% higher analyst-reported annual growth expectation raises stock price by about 0.5 basis points. The $c_2 = 0.0282$ estimate implies that analyst price impact falls about 0.03 basis points (i.e. about 6% of the average price impact) per additional analyst who covers stock $n$.\(^{28}\)

Table 3 reports the $\beta$ and $M_g$ estimates implied by the estimated reduced-form coefficients $c_1$ and $c_2$ in Table 2. The analyst influence estimate $\beta = 0.06$ (robust to inclusion of various fixed effects across columns) is significantly positive, which means that investors do learn from analysts. The estimate of the causal impact of investor annual growth expectations on asset prices $M_g = 0.07$

\(^{28}\)As discussed in Appendix F, these values are broadly consistent with (if slightly smaller than) analyst price impact estimates from previous work.
Table 3: $M_g$ and $\beta$ Estimates Under Investor Homogeneity

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</tbody>
</table>

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays the $\beta$ and $M_g$ estimates implied by the regression

\[
\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2 u_{a,n,t} \hat{A}_{n,t-1} + X_{n,t} + e_{a,n,t}
\]

\[
\beta = \frac{c_2}{c_1}
\]

\[
M_g = \frac{c_2^2}{c_2}
\]

where $\Delta p_{a,n,t}^+$ is the price change 5 days after analyst institution $a$ reports an annual growth expectation for stock $n$ in quarter $t$, $u_{a,n,t}$ is the corresponding estimated idiosyncratic growth shock, and $\hat{A}_{n,t-1}$ is the demeaned number of analysts that report expectations for stock $n$ in quarter $t$. $X_{n,t}$ represents controls, including stock, quarter, and stock x quarter fixed effects. All values are expressed in percentage points (i.e. 1.0 is one percent). The time period is 1984-01:2021-12.

(Also robust to inclusion of various fixed effects across columns) implies that a 1% rise in one-year investor (not analyst) expected cash flow growth raises price by only 7 basis points. This empirical estimate of $M_g = 0.07$ is an order of magnitude smaller than the benchmark value of $M_g = 1$ from Section 4.4. Thus, the causal effect of subjective cash flow growth expectations on asset prices is far smaller than suggested by standard models.

As explained in 4.3.2, this small causal effect of growth expectations on prices is consistent with low price elasticities of demand. Section 7 discusses how this small causal effect of growth expectations on prices is quantitatively consistent with the small sensitivities of asset demand to subjective beliefs documented in previous work using matched expectations and holdings data.

Appendix A.3 repeats this analysis using the long-term earnings growth (LTG) expectations focused on by Bordalo et al. (2019, 2020) and Nagel and Xu (2021) and finds quantitatively consistent results.\(^{29}\)

\(^{29}\)LTG expectations represent the analyst’s forecast for average EPS growth over the next 3–5 years. Thus, the price impact of investor “long-term” (3–5 year) cash flow growth expectations should be roughly 3–5 times as
6 Measuring $M_g$ with General Investor Heterogeneity

This section relaxes the homogeneity assumptions in Section 5. I detail my empirical strategy and present the empirical results for identifying $M_g$ from price, beliefs, and holdings data under general investor heterogeneity.

Specifically, I allow for heterogeneous price elasticities ($\zeta_i$) and sensitivities of demand to expected cash flow growth ($\kappa^g_i$), as well as for heterogeneous analyst influence across investors ($\beta^I_i$).

Section 6.1 explains the new identification problem introduced by investor heterogeneity and why holdings data prove necessary to identify $M_g$. Section 6.2 details the empirical strategy. Section 6.3 provides estimation details. Section 6.4 presents the empirical results.

6.1 Identification Problem Created by Investor Heterogeneity

Relaxing the homogeneity assumptions in Section 5 only changes the second block of the empirical strategy in Section 5.1: investor learning and asset demand. The investor-level demand function becomes

$$\Delta q_{i,a,n} = -\zeta_i \Delta p^+_{a,n} + \kappa^g_i \Delta G^I_{i,a,n} + \Delta \epsilon_{i,a,n},$$

and the update to beliefs becomes

$$\Delta G^I_{i,a,n} = B_{i,n} (G^A_{a,n} - \bar{G}^I_{i,a,n}) + \nu^I_{i,a,n}.$$

Note that $\zeta_i, \kappa^g_i$, and $B_{i,n}$ all have investor $i$ subscripts now. Substituting in the factor structure for analyst expectations from (24) and the Bayesian learning form of analyst influence from (25), aggregating across investors using ownership share weights, and imposing fixed aggregate supply yields the following market clearing price change (analogous to (26))\(^{30}\):

$$\Delta p^+_{a,n} = \frac{(\kappa^g \beta^I)}{\zeta_s} \sum_{c_1} u_{a,n} \bar{A}_n + \epsilon_{a,n},$$

where subscript $S$ denotes the ownership-share weighted average, $u_{a,n}$ are the idiosyncratic analyst growth shocks, and $\bar{A}_n$ is the demeaned number of analysts that cover stock $n$, as in Section 5.1.

Reduced-form parameters $c_1$ and $c_2$ still represent average analyst price impact and how analyst large as the price impact of annual growth expectations (see Appendix G.3.1 for a full discussion). Appendix G.3.2 finds a 1% rise in investor long-term cash flow growth expectations raises price by about 23 basis points, which is $3 - 4$ times the $M_g = 0.07$ estimate in Table 3.

\(^{30}\)The market-clearing price change before these substitutions (analogous to (23)) is:

$$\Delta p^+_{a,n} = \frac{(\kappa^g B_{a,n})}{\zeta_s} \sum_{c_1} \Delta G^A_{a,n} - \frac{(\kappa^g \beta^I)}{\zeta_s} \sum_{c_2} \frac{(\kappa^g \nu^I_{a,n})}{\zeta_s} + \frac{1}{\zeta_s} \Delta \epsilon_{S,a,n}.$$
price impact declines as the number of analysts rises. However, now ratios of \( c_1 \) and \( c_2 \) do not identify \( M_g = \kappa_S^2 / \zeta_s \) (from (20)) or \( \beta_S \). Thus, identifying \( M_g \) requires separately identifying \( \kappa_S^2 \) and \( \zeta_s \) and taking their ratio.

To this end, I measure both the sensitivity of demand to expected cash flow growth \( \kappa_i^g \) and the price elasticity \( \zeta_i \) at the investor level. Measuring these quantities requires investor-level holdings data: investor-level demand shifts and price elasticities cannot be identified from equilibrium price changes alone.

### 6.2 Empirical Strategy

All of the identification works within a quarter, so I suppress quarter \( t \) subscripts.

Starting with the investor demand curve

\[
\Delta q_{i,n} = -\zeta_i \Delta p_n + \kappa_i^g \Delta G_{i,n} + \Delta \epsilon_{i,n},
\]

I want to identify \( \kappa_i^g \) and \( \zeta_i \). Since I observe investor holdings at the quarterly frequency, all of these objects are quarterly changes (as opposed to the high-frequency analysis in Section 5.1).

The key identification problem is both the low-frequency change in investor growth expectations \( \Delta G_{i,n} \) and the low-frequency demand shock \( \Delta \epsilon_{i,n} \) are correlated with the low-frequency price change \( \Delta p_n \) through market clearing.\(^{31}\) As discussed in Section 5.1, the idiosyncratic analyst growth shocks \( u_{a,n} \) and Bayesian learning form of analyst influence \( B_{i,n} = \beta_i - \beta_i^2 \bar{A}_n \) provide an instrument for investor growth expectations. The first block below (“Low-frequency investor expectation formation”) details how investor learning from analysts operates at low frequency. In addition, we must now also control for the quarterly price change and the price elasticity of demand. The second block below (“Price elasticity and low-frequency price change”) explains how I do so by using the approach of Koijen and Yogo (2019) to measure investor price elasticities. Given these two blocks, I then discuss how the identification of \( \kappa_i^g \) and \( \zeta_i \) works.

1. **Low-frequency investor expectation formation.** From (22), the high-frequency update to investor \( i \)'s growth expectations around the release of analyst \( a \)'s report is

\[
\Delta G_{i,a,n}^I = B_{i,n} (G_{a,n}^A - \bar{G}_{i,a,n}^I) + \nu_{i,a,n}^I,
\]

where \( \bar{G}_{i,a,n}^I \) is investor \( i \)'s prior growth expectation immediately before analyst \( a \)'s report release and \( \nu_{i,a,n}^I \) captures any other signals the investor contemporaneously learns from.

\(^{31}\)The causal effect of prices on growth expectations discussed in Section 3 also induces a correlation between \( \Delta G_{i,n} \) and \( \Delta p_n \).
Over the whole quarter, the low-frequency update to \( i \)'s growth expectation is

\[
\Delta G_{i,n}^I = B_{i,n} \sum_{a \in A_n} \left( G_{a,n}^A - \bar{G}_{i,a,n}^I \right) + \nu_{i,n}^I \\
= \beta_i \sum_{a \in A_n} u_{a,n} - \beta_i^2 \sum_{a \in A_n} u_{a,n} \bar{A}_n \\
+ \left( \beta_i - \beta_i^2 \bar{A}_n \right) \sum_{a \in A_n} \left( \frac{G_{i,a,n}^I \lambda_{a,n}^I + \lambda_{a,n}^I}{\text{Other Determinants of Analyst Expectations}} \right) \\
- \left( \beta_i - \beta_i^2 \bar{A}_n \right) \sum_{a \in A_n} \left( \frac{G_{i,a,n}^I}{\text{Investor Prior Expectations}} - \frac{G_{a,n}^{\text{Log}}}{\text{Lagged Analyst Expectation}} \right) \\
+ \sum_{a \in A_n} \nu_{i,a,n}^I \quad + \quad \nu_{i,n}^I \quad + \quad \nu_{i,n}^I \quad + \\
\sum_{a \in A_n} \nu_{i,a,n}^I \quad + \quad \nu_{i,n}^I \quad + \quad \nu_{i,n}^I \\
= \beta_i \sum_{a \in A_n} u_{a,n} - \beta_i^2 \sum_{a \in A_n} u_{a,n} \bar{A}_n + e_{i,n}^G \\
\text{(37)}
\]

where \( A_n \) is the set of analysts who cover stock \( n \) and \( \nu_{i,n}^I \) captures any other signals the investor learns from. The second line follows from plugging in the factor structure for analyst expectations from (24) and the Bayesian learning form of analyst influence from (25).

2. Price elasticity and low-frequency price change. To deal with the correlation of growth expectations updates (\( \Delta G_{i,n} \)) and quarterly price changes \( \Delta p_n \), I measure each investor’s elasticity \( \zeta_i \) and remove the price term from the equilibrium quantity change:

\[
\Delta q_{i,n} + \zeta_i \Delta p_n = \kappa_i^G \Delta G_{i,n}^I + \Delta \epsilon_{i,n}. \\
\text{(38)}
\]

The left-hand side (\( \Delta q_{i,n} + \zeta_i \Delta p_n \)) is investor \( i \)’s quarterly demand curve shift: the equilibrium change in quantity demanded minus movement along the demand curve. The right-hand side decomposes this demand shift into the part due to the growth expectation update (\( \kappa_i^G \Delta G_{i,n} \)) and other (unobserved) demand shocks (\( \Delta \epsilon_{i,n} \)).

Identification  Plugging in the low-frequency investor expectation update (37) into the quarterly demand curve shift (38) yields

$$\Delta q_{i,n} + \zeta_i \Delta p_n = \kappa^g_i \beta_i S_n - \kappa^g_i \beta_i^2 S_n \bar{A}_n + \kappa^g_i \epsilon_{i,n}^G + \Delta \epsilon_{i,n},$$  (39)

where $S_n = \sum_{a \in A_n} u_{a,n}$ is the sum of the analyst idiosyncratic growth shocks for stock $n$.

Every term on the left-hand side of (39) is either observed ($\Delta q_{i,n}$ and $\Delta p_n$) or estimated ($\zeta_i$). The first two terms on the right-hand side ($\kappa^g_i \beta_i S_n$ and $\kappa^g_i \beta_i^2 S_n \bar{A}_n$) represent the demand shift due to learning from the idiosyncratic components of analyst expectations. This demand shift depends on both investor $i$’s sensitivity of demand to cash flow expectations ($\kappa^g_i$) and analyst influence on investor $i$ ($\beta_i$). The unobserved error term $\epsilon_{i,n}$ captures other demand shocks ($\Delta \epsilon_{i,n}$) and learning from other sources ($\epsilon_{G_{i,n}}^G$ includes other components of analyst expectations and non-analyst signals).

Thus, a regression of the quarterly demand shift ($\Delta q_{i,n} + \zeta_i \Delta p_n$) on the sum of idiosyncratic analyst growth shocks ($S_n$) and its interaction with the demeaned number of analysts ($\bar{A}_n$) identifies both $\kappa^g_i$ and $\beta_i$. The moment conditions for identifying $\kappa^g_i$ and $\beta_i$ in regression (39) are

$$\mathbb{E} [S_n \epsilon_{i,n}] = 0$$  (40)

$$\mathbb{E} [S_n \bar{A}_n \epsilon_{i,n}] = 0$$  (41)

I have two instruments ($S_n$ and $S_n \bar{A}_n$), two moment conditions ((40) and (41)), and two structural parameters to identify ($\kappa^g_i$ and $\beta_i$). Exogenous variation in analyst expectations ($S_n$) pins down analyst impact on demand for the average stock ($\kappa^g_i \beta_i$). The interaction of $S_n$ with cross-sectional variation in the number of analysts covering each stock ($S_n \bar{A}_n$) pins down the decay rate of analyst demand impact ($\kappa^g_i \beta_i^2$). From these two parameters, I obtain $\kappa^g_i$: the sensitivity of demand to investor annual growth expectations.

The identifying assumption is:

**Assumption 2 (Identifying Assumption).** Any common variation between analyst growth expectation updates ($\Delta G_{a,n}^A$) and

1. Investor prior expectations ($\bar{G}_{i,a,n}$)
2. Other contemporaneous signals at low ($\nu_{i,n}^L$) and high frequencies ($\nu_{i,a,n}^H$), and
3. Other demand shocks ($\Delta \epsilon_{i,n}$)

is spanned by stock-quarter characteristics.

If Assumption 2 holds, then the latent factor model strips out all common variation between $\Delta G_{a,n}^A$ and both $\epsilon_{i,n}$ and $\bar{A}_n$ in (39). In this case, both moment conditions (40) and (41) hold.
Unfortunately, regression (39) lacks power since the holdings data are noisy. To improve precision, I pool the estimation across all quarters (even though the identification requires only cross-sectional variation) and employ L2 regularization. Section 6.3 discusses these estimation details.

Given $\kappa^g_i$ and $\zeta_i$ at the investor level, the causal effect of annual expected cash flow growth on price is

$$M_g = \frac{\kappa^g_i}{\zeta_S}.$$

I also calculate the ownership share weighted average analyst influence: $\beta_S$.

### 6.3 Estimation Details

This section provides details of how I estimate $\kappa^g_i$ and $\beta_i$ from holdings regression (39).

Although the identification of $\kappa^g_i$ and $\beta_i$ in (39) requires only variation in analyst reports and stocks within an (investor, quarter) pair, the regression lacks power.

To improve precision, I run one constrained regression pooled across all investors and quarters:\[^32]\)

\[
\Delta \hat{q}_{i,n,t} = b_{1,i} S_{n,t} - b_{2,i} S_{n,t} \cdot \bar{A}_{n,t-1} + X_{n,t} + FE_{i,t} + e_{i,n,t} \\
s.t. \quad \Delta \hat{q}_{i,n,t} = \Delta q_{i,n,t} + \zeta_i \Delta p_n \\
\quad 0 \leq b_{2,i} \leq b_{1,i} \quad (\text{enforces } \beta_i \leq 1) \\
\quad b_{1,S} = c_1 \zeta_S \quad (\text{definition of } c_1) \\
\quad b_{2,S} = c_2 \zeta_S \quad (\text{definition of } c_2),
\]

where subscript $S$ denotes ownership-share weighted averages.\[^33]\) $X_{n,t}$ represents one-quarter lagged stock characteristics motivated by Fama and French (2015) and used by Koijen and Yogo (2019) (log book equity, profitability, investment, market beta, and the ratio of dividend to book equity). These controls soak up residual variation and provide more power. $FE_{i,t}$ is an investor-quarter fixed effect.\[^34]\)

\[^32\)To raise the volatility of $S_{n,t}$ and gain more power, I don’t use the sum of idiosyncratic shocks for all analyst institutions in $A_{n,t}$. Instead I use the sum of idiosyncratic shocks to the 5 largest institutions, ranked by number of expectations reported in the quarter. All results are robust to using other numbers of institutions. See Appendix I.2 for details.

\[^33\)I use the average AUM-share distribution over investors (averaging across quarters) to proxy for the ownership-share distribution for the average stock in the average quarter.

\[^34\)Empirically I work with the following calculation of the percentage change in quantity of shares held

\[
\Delta q_{i,n,t} = \max \left\{ -1, \frac{\hat{Q}_{i,n,t} - \hat{Q}_{i,n,t-1}}{\frac{1}{2}(\hat{Q}_{i,n,t} + \hat{Q}_{i,n,t-1})} \right\}
\]

where $\hat{Q}_{i,n,t-1} = H_{i,n,t-1}$ is the dollar holdings of investor $i$ in stock $n$ in the previous period $t - 1$ and $\hat{Q}_{i,n,t} = \frac{H_{i,n,t}}{1 + R_{n,t-1-t}}$ is the dollar holdings of investor $i$ in stock $n$ in this period $t$ adjusted for the ex-dividend return (i.e.
The reduced-form coefficients $b_{1,i}$ and $b_{2,i}$ have the following structural form:

\[ b_{1,i} = \kappa_i^g \beta_i \]
\[ b_{2,i} = \kappa_i^g \beta_i^2. \]

Thus, constraint (43) enforces $0 \leq \beta_i \leq 1$, as implied by the definition of $\beta_i$ from Bayesian learning (33).

From the market clearing expression (35) in Section 6.1, the analyst price impact coefficients $c_1$ and $c_2$ have the following relationship to the reduced-form demand shift coefficients $b_{1,i}$ and $b_{2,i}$:

\[ c_1 = \frac{b_{1,S}}{\zeta_S} \]
\[ c_2 = \frac{b_{2,S}}{\zeta_S}. \]

Constraints (44) and (45) enforce these market clearing restrictions.

Lastly, to further improve precision I apply an L2 penalty to $b_{1,i}$ and $b_{2,i}$ to shrink these coefficients toward $b_{1,S} = c_1 \zeta_S$ and $b_{2,S} = c_2 \zeta_S$, respectively. I choose the regularization parameter via cross validation to allow for the maximum amount of heterogeneity in $b_{1,i}$ and $b_{2,i}$ supported by the data.\(^{35}\)

\[ b_{1,i} \text{ and } b_{2,i} \text{ jointly identify } \beta_i \text{ and } \kappa_i^g: \]
\[ \beta_i = \frac{b_{2,i}}{b_{1,i}} \]
\[ \kappa_i^g = \frac{b_{1,i}^2}{b_{2,i}}. \]

Appendix I provides further estimation details.

### 6.4 Empirical Results

Table 4 displays the estimated $\kappa_S^g$, $\beta_S$, and $M_g$ from regression (42). While these results differ from those estimated assuming investor heterogeneity in Table 3, the conclusions drawn from both sets of results remain the same. Appendix Table E4 displays summary statistics for the data used in

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\(^{35}\)Koijen, Richmond and Yogo (2020) follow a similar regularization approach in a different setting.
Table 4: $c_1$ and $c_2$ Estimates

<table>
<thead>
<tr>
<th></th>
<th>$\beta_S$</th>
<th>$\kappa_S$</th>
<th>$M_g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Point Estimate</td>
<td>0.0982***</td>
<td>0.062***</td>
<td>0.163***</td>
</tr>
<tr>
<td>95% Confidence Interval</td>
<td>(0.086, 0.121)</td>
<td>(0.043, 0.245)</td>
<td>(0.114, 0.634)</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01

This table displays the estimated $\kappa_S^g$, $\beta_S$, and $M_g$ from (42). Point estimates are the medians of the bootstrapped sampling distributions. Confidence intervals are bootstrapped (see Appendix I.3 for details). The time period is 1984-01:2021-12.

The ownership-share weighted average analyst influence is $\beta_S = 0.10$, which is larger than the $\beta = 0.06$ from Table 3 estimated assuming investor heterogeneity. Both sets of estimates imply that investors do learn from analysts.

The weighted average sensitivity of demand to expected cash flow growth is $\kappa_S^g = 0.06$, which means a 1% increase in one-year expected cash flow growth raises the average investor’s quantity demanded by 6 basis points. Section 7 explains how this low sensitivity of demand to expected cash flow growth is consistent with the small sensitivities of asset demand to subjective beliefs documented in previous work using matched expectations and holdings data.

The causal effect of one-year expected cash flow growth on price is $M_g = 0.16$, which means a 1% increase in one-year expected cash flow growth raises price by 16 basis points. While this estimate proves larger than that from Table 3 assuming investor heterogeneity ($M_g = 0.07$), $M_g = 0.16$ is still far smaller than the benchmark value of $M_g = 1$ from Section 4.4. Thus, these results support the conclusion that the causal effect of subjective cash flow growth expectations on asset prices is far smaller than suggested by standard models. Section 7 explains why allowing for investor heterogeneity can raise the estimate of $M_g$.

7 Discussion

7.1 How does $M_g$ compare to previous work on beliefs and holdings?

The small causal effect of expected cash flow growth on prices proves quantitatively consistent with the limited passthrough of beliefs to holdings documented by previous work.36

Recall from Proposition 1 that under simplifying assumptions, $\kappa^g$ and $M_g$ take the following

36 Vissing-Jorgensen (2003); Dominitz and Manski (2007); Kézdi and Willis (2009); Hurd, Van Rooij and Winter (2011); Amromin and Sharpe (2014); Arrondel, Calvo Pardo and Tas (2014); Merkle and Weber (2014); Drerup, Enke and Von Gaudecker (2017); Meeuwis et al. (2018); Giglio et al. (2021a); Ameriks et al. (2020); Andonov and Rauh (2020); Giglio et al. (2021b); Bacchetta, Tieche and Van Wincoop (2020); Dahlquist and Ibert (2021); Beutel and Weber (2022)
\[
k^g = \kappa \delta \\
M_g = \frac{\kappa^g}{\zeta},
\]

where \(\kappa\) is the sensitivity (semi-elasticity) of asset demand to expected return and \(\delta\) is the average dividend-price ratio. The previous literature has focused on measuring \(\kappa\) instead of \(\kappa^g\) or \(M_g\). For this reason, I compare previous estimates of \(\kappa\) to the values of \(\kappa^g\) implied by my estimated \(M_g = 0.07\) assuming investor homogeneity from Table 3 and my estimated \(M_g = 0.16\) allowing for heterogeneity from Table 4.

Calibrate \(\delta = 0.01\) to match the historical average quarterly dividend-price ratio for the aggregate equity market and \(\zeta = 0.38\) to match the average stock-level, ownership-share weighted price elasticity of demand using the estimated investor price elasticities from Koijen and Yogo (2019). My estimate of \(M_g = 0.07\) then implies \(\kappa \approx 3\). My estimate of \(M_g = 0.16\) implies \(\kappa \approx 6\). These estimates imply a one percentage point rise in expected return raises quantity demanded by 3% and 6%, respectively. As illustrated by Figure 3, both of these \(\kappa\) values fall within the range of estimates from previous work.\(^{37}\) Thus, as explained in Section 4, the small causal effect of expected cash flow growth on prices is consistent with the limited passthrough of beliefs to holdings.

### 7.2 Why is \(M_g\) bigger when accounting for investor heterogeneity?

As noted in \((35)\), the analyst price impact coefficients \(c_1\) and \(c_2\) take the following forms when allowing for investor heterogeneity:

\[
c_1 = \frac{(\kappa^g \beta)_S}{\zeta_S} = \frac{\kappa^g \beta_S + \text{Cov}_S(\kappa^g, \beta_i)}{\zeta_S} \\
c_2 = \frac{(\kappa^g \beta^2)_S}{\zeta_S} = \frac{\kappa^g (\beta^2_S + \text{Var}_S[\beta_i]) + \text{Cov}_S(\kappa^g, \beta^2_i)}{\zeta_S},
\]

where the subscript \(S\) indicates variances and covariances are being taken in the cross section of investors under the ownership share weighted measure. Thus, taking the ratio

\[
\frac{c_1^2}{c_2} = \frac{(\kappa^g \beta_S + \text{Cov}_S(\kappa^g, \beta_i))^2}{\kappa^g (\beta^2_S + \text{Var}_S[\beta_i]) + \text{Cov}_S(\kappa^g, \beta^2_i)} \frac{1}{\zeta_S},
\]

only identifies \(M_g = \kappa^g_S / \zeta_S\) if analysts have the same influence on all investors so \(\text{Var}[\beta_i] = \text{Cov}(\kappa^g, \beta_i) = 0.\ heartbreaking

\(^{37}\)Previous work usually regresses portfolio weights (\(\theta\)) on expected returns (\(\mu\)) and so measures \(\partial \theta / \partial \mu\). However, \(\kappa = \partial \log \theta / \partial \mu = \partial \theta / \partial \mu \cdot 1/\theta\) in \((9)\). Appendix J details the assumptions about average portfolio weights I use to convert estimates of \(\partial \theta / \partial \mu\) to estimates of \(\kappa = \partial \log \theta / \partial \mu\) for each of the papers in Figure 3.
Figure 3: Comparison of $M_g$-Implied $\kappa$ Estimates to Previous Literature

Graphical comparison of the sensitivity of demand to expected return ($\kappa$) implied by the estimates $M_g = 0.07$ (without heterogeneity) and $M_g = 0.16$ (with heterogeneity) to values found in previous work.
If the covariance terms are small so
\[
\frac{c_1^2}{c_2} \approx \frac{\beta_3^2}{\beta_S^2 + \nabla_S[\beta_i]} \frac{\kappa_S^2}{\zeta_S} \leq \frac{\kappa_S^2}{\zeta_S},
\]
then heterogeneity in analyst influence across investors (i.e. \( \nabla[\beta_i] > 0 \)) implies the estimator for \( M_g \) assuming homogeneity (\( \hat{M}_g = c_1^2/c_2 \)) underestimates the true parameter.

Thus, heterogeneity in analyst influence represents one potential reason why the \( M_g = 0.07 \) estimated from price and beliefs data assuming homogeneity is smaller than the \( M_g = 0.16 \) estimated from holdings data allowing for full heterogeneity. Additionally, since I observe investors holdings quarterly, the \( M_g = 0.16 \) estimated from holdings data may also capture lower-frequency demand adjustment missed by the high-frequency strategy used to estimate \( M_g = 0.07 \) from price and beliefs data alone.

8 Conclusion

I quantify the causal impact of subjective expected cash flow growth on asset prices. A 1% rise in annual investor expected cash flow growth raises price by 7 to 16 basis points. This price impact is an order of magnitude smaller than in standard models.

This small price impact of cash flow beliefs reconciles with the previously documented limited passthrough of beliefs to holdings and small price elasticities of demand. A low sensitivity of demand to expected return implies a low sensitivity of demand to expected cash flow growth since cash flow beliefs appear in the definition of expected return. The same low sensitivity of demand to expected return creates inelasticity: when price rises expected return falls, but quantity demanded responds little to the change in expected return. However, as the sensitivity of demand to expected return falls, the demand shift induced by cash flow beliefs shrinks faster than the price elasticity. Thus, inelastic demand implies a small causal effect of subjective cash flow expectations on price.

In light of the small causal effect of cash flow expectations on prices, I demonstrate the strong correlation of cash flow expectations with prices arises in part due to reverse causality. An exogenous 1% increase in price raises one-year expected cash flow growth by 32 basis points.

These results pose significant implications for asset pricing and macrofinance. The small causal effect of cash flow expectations on prices implies biased beliefs have smaller impacts on asset prices and the real economy than standard models suggest. Yet this small causal effect proves consistent with inelastic demand, which amplifies the importance of other demand shocks (e.g. shocks to risk aversion, intermediary leverage, higher moment beliefs, nonpecuniary preferences, etc.). Thus, while my empirical results suggest that subjective cash flow beliefs cannot quantitatively resolve all asset pricing and macrofinance puzzles alone, they open the door to other channels. If biased beliefs about cash flows cannot quantitatively explain all excess price volatility, perhaps inelasticity-amplified
shocks to higher moment beliefs or nonpecuniary preferences can. If extrapolative expectations about fundamentals cannot quantitatively explain stylized facts about credit cycles, perhaps acknowledging the inelastic demand of constrained intermediaries can. These possibilities and others like them represent promising directions for future work.

Additionally, further work is required to pin down the sources of the low sensitivity of demand to expectations that underlies both the small causal effect of cash flow beliefs on prices and inelastic demand. Do investors not respond to expectations due to inattention, constraints, transactions costs (both physical and psychological), ambiguity aversion, or some other reason? The mechanism for this low sensitivity will shed light on what shocks do matter for asset demand and prices. Empirically disentangling these channels, therefore, represents an important avenue for future research.
References


Appendix

Aditya Chaudhry

September 12, 2022
A Reverse Causality Supplements

A.1 Supplements to Baseline Specification

Figure A1: Binscatter Plots for First Stage and Reduced Form of Baseline Specification

This figure displays binscatter plots for the following first-stage and reduced-form regressions:

\[ \Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t} \]
\[ \Delta G_{a,n,t} = b_0 + b_1 \text{FIT}_{n,t} + X_{n,t} + e_{2,n,t}. \]

The first stage regresses quarterly percent price changes (\(\Delta p_{a,n,t}\)) on the flow-induced trading instrument (FIT\(_{n,t}\)). The reduced form regresses quarterly changes in average one-year expected growth (\(\Delta G_{a,n,t}\)) on the flow-induced trading instrument (FIT\(_{n,t}\)). X\(_{n,t}\) includes stock and quarter fixed effects as well as the following stock characteristics: log book equity, profitability, investment, market beta, and the dividend to book equity ratio. The time period is 1984-01:2021-12.
This figure displays results for different specifications of the following two-stage least squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{t} + e_{1,n,t}
\]
\[
\Delta G_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{t} + e_{2,n,t}.
\]

The first stage regresses quarterly percent price changes (\(\Delta p_{a,n,t}\)) on the flow-induced trading instrument (FIT\(_{n,t}\)). The second stage regresses quarterly changes in average one-year expected growth (\(\Delta G_{a,n,t}\)) on the instrumented price change (\(\Delta \hat{p}_{a,n,t}\)). Stock characteristics are log book equity, profitability, investment, market beta, and the dividend to book equity ratio. The time period is 1984-01:2021-12.
This figure displays results for the following two-stage least squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_n,t + X_{n,t} + e_{1,n,t}
\]
\[
\Delta G_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t},
\]

where \( \text{FIT}_{n,t} \) has been constructed from the residual flows remaining after applying an AR(p) model to flows:

\[
\text{Flow}_{i,t} = \rho_0 + \sum_{l=1}^{p} \rho_l \text{ Flow}_{i,t-l} + \epsilon_{i,t}^{\text{flow}}
\]
\[
\text{FIT}_{n,t} = \frac{\sum_{\text{fund }i} \text{ SharesHeld}_{n,i,t-1} \cdot \epsilon_{i,t}^{\text{flow}}}{\text{SharesOutstanding}_{n,t-1}}.
\]

The first stage regresses quarterly percent price changes \( (\Delta p_{a,n,t}) \) on the flow-induced trading instrument \( (\text{FIT}_{n,t}) \). The second stage regresses quarterly changes in average one-year expected growth \( (\Delta G_{a,n,t}) \) on the instrumented price change \( (\Delta \hat{p}_{a,n,t}) \). \( X_{n,t} \) includes stock and quarter fixed effects as well as the following stock characteristics: log book equity, profitability, investment, market beta, and the ratio of dividend to book equity. The top and bottom figures display the first and second-stage coefficients, respectively, with 95% confidence intervals for different values of the AR model lag \( p \). The time period is 1984-01:2021-12.
Illustration of staggered timing of analyst expectation releases for two analysts $a$ and $b$ for the same stock $n$ and quarter $t$.

A.2 Exploiting Within Stock-Quarter Variation

I construct an analyst-stock-quarter specific FIT measure, as opposed to the standard stock-quarter specific FIT measure in Section 3.1. Multiple analyst institutions issue cash flow expectations for each stock in each quarter and generally not on the same day. Thus, the timing of analyst report releases creates variation in exposure to the FIT instrument.

Consider the timing illustrated in Figure A4. Analyst institutions $a$ and $b$ both report expectations for stock $n$ in quarters $t-1$ and $t$. Analyst institution $b$ reports later than $a$ in both quarters. Thus, $b$’s inter-announcement price change ($\Delta p_{b,n,t}$) is more exposed to $FIT_{n,t}$ and less exposed to $FIT_{n,t-1}$ than that of analyst institution $a$. This variation in analyst report timing allows us to construct an analyst-stock-quarter specific FIT measure:

$$FIT_{a,n,t} = \frac{\text{# days elapsed in } t-1}{91} \cdot FIT_{n,t-1} + \frac{\text{# days elapsed in } t}{91} \cdot FIT_{n,t}. $$

This measure allows exploitation of within stock-quarter variation. For example, assume for a fixed stock $n$ and quarter $t$ $FIT_{n,t} > FIT_{n,t-1}$, i.e. there is more flow-induced price pressure in quarter $t$ than in $t-1$. Analyst institutions that report later in quarter $t$ (e.g. $b$ in Figure A4) are exposed to more flow-induced price pressure than those that report earlier. This within stock-quarter variation across analysts allows for cleaner identification of the causal effect of prices on growth expectations $\alpha$.

Returning to the system of simultaneous equations (1) and (2), the exclusion restriction is $E_{n,t} [FIT_{a,n,t}v_{a,n,t}] = 0$, where $E_{n,t}$ denotes the expectation taken across analysts $a$ within stock-
quarter pair \((n, t)\). A sufficient condition for the exclusion restriction to hold is:

\[
\mathbb{E}_{n,t}[w_{a,n,t-1}\nu_{a,n,t}] = \mathbb{E}_{n,t}[w_{a,n,t}\nu_{a,n,t}] = 0.
\]

That is, the timing of analyst report releases is not correlated with belief formation.

Table A1 displays the results of the following two-stage least-squares regression:

\[
\begin{align*}
\Delta p_{a,n,t} &= a_0 + a_1\text{FIT}_{a,n,t} + X_{a,n,t} + e_{1,n,t} \\
\Delta G_{a,n,t} &= b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{a,n,t} + e_{2,n,t},
\end{align*}
\]

where \(X_{a,n,t}\) represents controls, including saturated fixed effects. The first stage regression of price changes on the FIT instrument in column 3 is strong with an \(F\)-statistic of over 26 (partial \(F\)-statistic of 24). The reduced form regression of growth expectations on the FIT instrument in column 4 is also strong. The second-stage estimate of \(\alpha\) in column 5 is the same as that in Table 1: a 1\% increase in price raises one-year expected cash flow growth by 32 basis points. Note that this within stock-quarter specification has more power than the within quarter specification (the second-stage coefficient standard errors are 0.07 and 0.14, respectively) since the saturated fixed effects here soak up much more residual variation than the stock and quarter fixed effects in Table 1. Figure A5 displays residualized binscatter plots for the first-stage and reduced-form regressions.

The quantitative similarity of the \(\alpha\) estimates from the within quarter specification in Table 1 and the within-stock quarter specification in Table A1 assuage concerns about the potential threats to identification laid out in Section 3.2.
Table A1: Causal Effect of Prices on Earnings Growth Expectations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>First Stage</td>
<td>Reduced Form</td>
<td>2SLS</td>
</tr>
<tr>
<td>$\Delta p_{a,n,t}$</td>
<td>0.371***</td>
<td>0.157***</td>
<td>0.323***</td>
<td>(0.0487)</td>
<td>(0.0105)</td>
</tr>
<tr>
<td>$FIT_{a,n,t}$</td>
<td></td>
<td></td>
<td>5.123***</td>
<td>1.657***</td>
<td>(0.999)</td>
</tr>
<tr>
<td>Stock x Quarter FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Analyst Instit. x Quarter FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Stock x Analyst Instit. FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Quarter-Clustered SE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1282391</td>
<td>1282391</td>
<td>1282391</td>
<td>1282391</td>
<td>1282391</td>
</tr>
<tr>
<td>F</td>
<td>58.04</td>
<td>224.2</td>
<td>26.29</td>
<td>15.75</td>
<td>24.29</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.0249</td>
<td>0.841</td>
<td>0.871</td>
<td>0.841</td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays results for the following two-stage least squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1 FIT_{a,n,t} + X_{n,t} + e_{1,n,t}
\]
\[
\Delta G_{a,n,t} = b_0 + \alpha \hat{\Delta p}_{a,n,t} + X_{n,t} + e_{2,n,t}.
\]

The first stage regresses percent price changes between analyst reports ($\Delta p_{a,n,t}$) on the analyst-specific flow-induced trading instrument ($FIT_{a,n,t}$). The second stage regresses quarterly changes in average one-year expected growth ($\Delta G_{a,n,t}$) on the instrumented price change ($\hat{\Delta p}_{a,n,t}$). The time period is 1984-01:2021-12.
Figure A5: Binscatter Plots for First Stage and Reduced Form of Within Stock-Quarter Specification

This figure displays binscatter plots for the following first-stage and reduced-form regressions:

\[
\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{a,n,t} + X_{n,t} + e_{1,n,t},
\]
\[
\Delta G_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}.
\]

The first stage regresses percent price changes between analyst reports (\(\Delta p_{a,n,t}\)) on the analyst-specific flow-induced trading instrument (\(\text{FIT}_{a,n,t}\)). The reduced form regresses quarterly changes in average one-year expected growth (\(\Delta G_{a,n,t}\)) on the analyst-specific flow-induced trading instrument (\(\text{FIT}_{a,n,t}\)). \(X_{n,t}\) includes stock-quarter, analyst-quarter, and stock-analyst fixed effects. The time period is 1984-01:2021-12.
A.3 LTG Results

I replicate the baseline analysis using the I/B/E/S long-term earnings growth (LTG) expectations used by Bordalo et al. (2019, 2020) and Nagel and Xu (2021). The LTG expectations reflect analysts’ average annual EPS growth expectations for the next 3 – 5 years.

Using the standard FIT instrument discussed in Section 3.1, I run the following two-stage least squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t} \\
\Delta \text{LTG}_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t},
\]

where \(\Delta \text{LTG}_{a,n,t}\) is the quarter-over-quarter change in LTG expectation reported by analyst institution \(a\) for stock \(n\) in quarter \(t\) and \(\Delta p_{a,n,t}\) is the price change that occurs between these two reports in quarters \(t - 1\) and \(t\). The first stage regresses price changes between analyst report releases (\(\Delta p_{a,n,t}\)) on the quarterly flow-induced trading instrument (\(\text{FIT}_{n,t}\)). The second stage regresses the change in LTG expectations (\(\Delta \text{LTG}_{a,n,t}\)) on the instrumented price change (\(\Delta \hat{p}_{a,n,t}\)). \(X_{n,t}\) represents controls including stock and quarter fixed effects as well as one-quarter lagged stock characteristics motivated by Fama and French (2015) (log book equity, profitability, investment, market beta, and the ratio of dividend-to-book equity).38

Table A2 displays the results of this regression. The OLS regressions of LTG expectations on price in columns 1 and 2 display a strong correlation between these objects, as documented in previous work (Bordalo et al. (2019, 2020); Nagel and Xu (2021)). The first stage regressions of price changes on the FIT instrument in columns 3 and 4 are strong with \(F\)-statistics of over 10 (partial \(F\)-statistics of 23 and 17, respectively). The reduced form regressions of LTG expectations on the FIT instrument in columns 5 and 6 are also significant. The second-stage estimates of \(\alpha\) in column 7 and 8 reveal a statistically and economically significant causal effect of prices on LTG expectations: a 1% increase in price raises LTG expectations by 12 basis points. Thus, the reverse causality issue raised in Section 3 exists in the LTG expectations data as well.

38Appendix Figure A6 displays residualized binscatter plots for the first-stage and reduced-form regressions in (46).
Table A2: Causal Effect of Prices on LTG Expectations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(5)</th>
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<td>OLS</td>
<td>OLS</td>
<td>First Stage</td>
<td>First Stage</td>
<td>Reduced Form</td>
<td>Reduced Form</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>(\Delta p_{a,n,t})</td>
<td>0.0628***</td>
<td>0.0434***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.121***</td>
<td>0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.00845)</td>
<td>(0.00326)</td>
<td>(0.0387)</td>
<td>(0.0394)</td>
<td></td>
<td></td>
<td>(0.0387)</td>
<td>(0.0394)</td>
</tr>
<tr>
<td>(FIT_{n,t})</td>
<td></td>
<td>3.342***</td>
<td>3.279***</td>
<td>0.405**</td>
<td>0.392**</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.695)</td>
<td>(0.693)</td>
<td>(0.176)</td>
<td>(0.174)</td>
<td></td>
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<td>Stock Characteristics</td>
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<td>Quarter FE</td>
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<tr>
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<td></td>
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</tr>
<tr>
<td>Quarter-Clustered SE</td>
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<td>Y</td>
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<td>227598</td>
</tr>
<tr>
<td>F</td>
<td>55.11</td>
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<td>23.08</td>
<td>14.57</td>
<td>5.303</td>
<td>11.87</td>
<td>9.764</td>
<td>10.93</td>
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<tr>
<td>R-Squared</td>
<td>0.0182</td>
<td>0.117</td>
<td>0.229</td>
<td>0.231</td>
<td>0.108</td>
<td>0.111</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays results for the following two-stage least squares regression:

\[
\Delta p_{a,n,t} = a_0 + a_1FIT_{n,t} + X_{n,t} + e_{1,n,t}
\]
\[
\Delta LTG_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}.
\]

The first stage regresses percent price changes between analyst reports (\(\Delta p_{a,n,t}\)) on the analyst-specific flow-induced trading instrument (FIT\(_{a,n,t}\)). The second stage regresses quarterly changes in LTG expectations (\(\Delta LTG_{a,n,t}\)) on the instrumented price change (\(\Delta \hat{p}_{a,n,t}\)). The time period is 1982-04:2021-12.
Figure A6: Binscatter Plots for First Stage and Reduced Form of LTG Specification

This figure displays binscatter plots for the following first-stage and reduced-form regressions:

\[ \Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t}, \]
\[ \Delta \text{LTG}_{a,n,t} = b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}, \]

The first stage regresses percent price changes between analyst reports (\(\Delta p_{a,n,t}\)) on the analyst-specific flow-induced trading instrument (\(\text{FIT}_{a,n,t}\)). The reduced form regresses quarterly changes in LTG expectations (\(\Delta \text{LTG}_{a,n,t}\)) on the analyst-specific flow-induced trading instrument (\(\text{FIT}_{a,n,t}\)). \(X_{n,t}\) includes stock-quarter, analyst-quarter, and stock-analyst fixed effects. The time period is 1982-04:2021-12.
B  Section 4 Supplementary Material

B.1 Linearized Demand Function Derivation

The true percentage change in quantity of shares demanded is

$$
\Delta q_{D,nt} = \frac{Q_{n,t+}}{Q_{n,t-}} - 1
$$

$$
= \frac{W_{i,t+} - \theta_{n,t+}}{W_{i,t-} - \theta_{n,t-}} - 1
$$

$$
= \frac{W_{i,t+} - \theta_{n,t+}}{W_{i,t-} - \theta_{n,t-}} \exp[\kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}] - 1
$$

$$
= \frac{1 + \Delta w_t}{1 + \Delta p_{n,t}} \exp[\kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}^D] - 1.
$$

Linearizing the last equation around $(\Delta w_t, \Delta p_{n,t}, \Delta \mu_{n,t}, \Delta \epsilon_{n,t}^D) = (0, 0, 0, 0)$ yields:

$$
\Delta q_{n,t}^D \approx \Delta w_t - \Delta p_{n,t} + \kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}^D.
$$

(47)

Note that the change in wealth is

$$
W_{t+} - W_{t-} = (P_{n,t+} - P_{n,t-})Q_{n,t-}^D.
$$

so

$$
\Delta w_t = \frac{W_{i,t+} - W_{t-}}{W_{t-}} = \frac{(P_{n,t+} - P_{n,t-})Q_{n,t-}^D}{W_{t-}} = \frac{(P_{n,t+} - P_{n,t-}) \theta_{n,t-} - W_{t-}}{P_{n,t-}} = \theta_{n,t-} \Delta p_{n,t}.
$$

(48)

where the third equality follows since the equilibrium quantity of shares demanded is

$$
Q_{n,t-}^D = \frac{\theta_{n,t-} - W_{t-}}{P_{n,t-}}.
$$

Plugging this expression for $\Delta w_t$ into (47) yields

$$
\Delta q_{n,t}^D \approx \theta_{n,t-} - 1 \Delta p_{n,t} + \kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}
$$

$$
= (\theta_{n,t-} - 1) \Delta p_{n,t} + \kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}.
$$
B.2 Proof of (11) from Gabaix and Koijen (2020b)

Proof. The definition of the expected return is

$$\mu_{n,t} = \frac{\tilde{E}_t[P_{n,t+1} + D_{n,t+1}]}{P_{n,t}} - R^f_t.$$ 

So at time $t-$ we have

$$\mu_{n,t-} = \frac{\tilde{E}_{t-}[P_{n,t+1} + D_{n,t+1}]}{P_{n,t-}} - R^f_t,$$

and at time $t+$ we have

$$\mu_{n,t+} = \frac{\tilde{E}_{t+}[P_{n,t+1} + D_{n,t+1}]}{P_{n,t+}} - R^f_t.$$

Rewriting definition of the expected return in terms of deviations from the equilibrium yields:

$$R^f_t + \mu_{n,t-} + \Delta \mu_{n,t-} = \frac{\tilde{E}_t-[P_{n,t+1}](1 + \Delta \tilde{p}_{n,t,1}) + \tilde{E}_t-[D_{n,t+1}](1 + \Delta \tilde{d}_{n,t,1})}{P_{n,t-}(1 + \Delta p_{n,t})},$$

(49)

where $\Delta p_{n,t}$, $\Delta \tilde{p}_{n,t,1}$, and $\Delta \tilde{d}_{n,t,1}$ represent percentage deviations from the time-$t-$ equilibrium:

$\Delta p_{n,t}$ is the percentage deviation in current price: $\Delta p_{n,t} = \frac{P_{n,t+}}{P_{n,t-}} - 1$

$\Delta \tilde{p}_{n,t,1}$ is the percentage deviation in expected next period price: $\Delta \tilde{p}_{n,t,1} = \frac{\tilde{E}_{t+}[P_{n,t+1}]}{\tilde{E}_{t-}[P_{n,t+1}]} - 1$

$\Delta \tilde{d}_{n,t,1}$ is the percentage deviation in expected next period dividend: $\Delta \tilde{d}_{n,t,1} = \frac{\tilde{E}_{t+}[D_{n,t+1}]}{\tilde{E}_{t-}[D_{n,t+1}]} - 1$

Now linearize the right-hand side of (49) around $(\Delta p_{n,t}, \Delta \tilde{p}_{n,t,1}, \Delta \tilde{d}_{n,t,1}) = (0, 0, 0)$:

$$R^f_t + \mu_{n,t-} + \Delta \mu_{n,t-} \approx \frac{\tilde{E}_{t-}[P_{n,t+1}]}{P_{n,t-}}(1 + \Delta \tilde{p}_{n,t,1} - \Delta p_{n,t}) + \frac{\tilde{E}_{t-}[D_{n,t+1}]}{D_{n,t}}\frac{D_{n,t}}{P_{n,t-}}(1 + \Delta \tilde{d}_{n,t,1} - \Delta p_{n,t})$$

$$= (1 + \bar{g})(1 + \Delta \tilde{p}_{n,t,1} - \Delta p_{n,t}) + (1 + \bar{g})\delta(1 + \Delta \tilde{d}_{n,t,1} - \Delta p_{n,t}),$$

where $(1 + \bar{g}) = \frac{\tilde{E}_{t-}[D_{n,t+1}]}{D_{n,t}}$, so $\bar{g}$ is the average equilibrium growth rate of dividends (i.e. in equilibrium $\frac{\tilde{E}_{t-}[P_{n,t+1}]}{P_{n,t-}} = (1 + \bar{g})$ under the assumption that the discount rate doesn’t change), and $\delta = \frac{\tilde{E}_{t-}[D_{n,t+1}]}{P_{n,t-}}$ is the equilibrium dividend-price ratio.

Now linearize again around $(\Delta p_{n,t}, \Delta \tilde{p}_{n,t,1}, \Delta \tilde{d}_{n,t,1}) = (0, 0, 0)$:

$$R^f_t + \mu_{n,t-} + \Delta \mu_{n,t} \approx (1 + \bar{g})(1 + \delta) + (1 + \bar{g})\left[\Delta \tilde{p}_{n,t,1} - \Delta p_{n,t} + \delta(\Delta \tilde{d}_{n,t,1} - \Delta p_{n,t})\right].$$

(50)

As noted by Gabaix and Koijen (2020b), the first right-hand-side term (zeroth order term) gives the Gordon growth formula:

$$R^f_t + \mu_{n,t-} = (1 + \bar{g})(1 + \delta) \leftrightarrow (R^f_t - 1) + \mu_{n,t-} - \bar{g} = (1 + \bar{g})\delta = \frac{\tilde{E}_{t-}[D_{n,t+1}]}{P_{n,t-}}.$$
Thus, from (50) we obtain:

\[ \Delta \mu_{n,t} \approx (-1 - \delta)(1 + \tilde{g})\Delta p_{n,t} + \delta(1 + \tilde{g})\Delta \tilde{d}_{n,t,1} + (1 + \tilde{g})\Delta \tilde{p}_{n,t,1}, \]

as desired.

\[ \square \]

### B.3 Measuring Persistence in I/B/E/S Expectations

Let \( G^h_{n,t} \) represent one-year dividend growth starting \( h \) years from quarter \( t \) so that \( 1 + G^h_{n,t+1} = \prod_{s=1}^{4}(1 + g_{n,t+4(h-1)+s}) \). For example, \( G^1_{n,t+1} \) is the growth rate over the next year starting next quarter, \( G^2_{n,t+1} \) is the growth rate in the year after that, and so on.

I measure \( \rho \) by running the following regression using the I/B/E/S analyst EPS forecasts:

\[
G^h_{a,n,t+1} = \rho^{\text{annual}} G^{h-1}_{a,n,t+1} + X_{n,t} + \epsilon^h_{a,n,t+1},
\]

\( \tilde{G}^h_{a,n,t+1} \) is analyst \( a \)'s expectation of \( G^h_{n,t+1} \). That is, within the term structure of growth forecasts made by analyst \( a \) for stock \( n \) in quarter \( t \), I regress consecutive annual growth forecasts. For example, for \( h = 2 \) I would regress analyst \( a \)'s annual expected growth rate starting one year from now (i.e. from quarter \( t + 5 \) to quarter \( t + 8 \)) on the annual expected growth rate for the next year (i.e. from quarter \( t + 1 \) to quarter \( t + 4 \)). \( X_{n,t} \) includes stock and/or time fixed effects.

Table B3 displays the results of this regression. I am currently using the \( \rho \) estimate without the stock fixed effects: \( \rho^{\text{annual}} \approx 0.24 \). I then convert \( \rho^{\text{annual}} \) into a quarterly persistence \( \rho \):

\[ \rho^{\text{annual}} = \rho^4, \]

which yields \( \rho = 0.7 \).

| \( \rho^{\text{annual}} \) Estimates |
|-----------------|------|------|------|
| \( \rho^{\text{annual}} \) | (1) | (2) | (3) | (4) |
| \( \rho^{\text{annual}} \) | 0.238*** | 0.244*** | 0.141*** | 0.143*** |
| | (0.00625) | (0.00561) | (0.00565) | (0.00502) |
| Quarter FE | Y | Y | Y | Y |
| Stock FE | | | | |
| Quarter-Clustered SE | Y | Y | Y | Y |
| Stock-Clustered SE | Y | Y | Y | Y |
| \( N \) | 2374716 | 2374715 | 2373814 | 2373813 |
| R-Squared | 0.117 | 0.133 | 0.331 | 0.340 |

Standard errors in parentheses

* \( p<0.10 \), ** \( p<0.05 \), *** \( p<0.01 \)
B.4 Derivation of Expressions and Propositions in Section 4.3

This Appendix derives (14)

$$\Delta q_{n,t} = -\zeta \Delta p_{n,t} + \kappa^g \Delta \nu_{n,t} + \Delta \epsilon_{n,t},$$

as well as the structural forms of $\zeta, \kappa^g$, and their ratio $M_g = \kappa^g / \zeta$.

The proof uses the following lemma, which I prove in Appendix B.4.1.

**Lemma 1** (Quarterly Expected Dividend Growth Shock Price Expectation Impact). A shock to annual expected dividend growth of $\Delta \nu_{n,t}$ induces the following contemporaneous price change in the expectation of next period’s price:

$$\Delta \tilde{p}_{n,t,1} = \Delta p_{n,t} + M_{\mu} \rho \frac{1}{1 - M_{\mu} \rho} \frac{1}{1 + \rho + \rho^2 + \rho^3} \Delta \nu_{n,t},$$

where

$$M_{\mu} = \frac{\kappa(1 + \bar{g})}{\zeta + \kappa(1 + \bar{g})} = \frac{\kappa(1 + \bar{g})}{1 - \theta_{n,t-} + \kappa(1 + \delta)(1 + \bar{g})}.$$

In deriving (14), I also prove the following proposition, which provides the general expressions for $\zeta$ and $\kappa^g$. At the end of the proof, I specialize to the case of zero persistence in expected cash flow growth $x_t$ ($\rho = 0$), zero average dividend growth ($\bar{g} = 0$), and small portfolio weights ($\theta_{n,t-} \approx 0$), which provides the expressions in Proposition 1.

**Proposition 2** ($\kappa^g, \zeta$, and $M_g$ in General). In general, we have:

$$\kappa^g = \kappa(1 + \bar{g}) \delta \left[ 1 + \frac{M_{\mu} \rho}{1 - \rho M_{\mu}} \right] \frac{1}{1 + \rho + \rho^2 + \rho^3}$$

$$\zeta = 1 - \theta_{n,t-} + \kappa(1 + \bar{g}) \delta$$

$$M_g = \frac{\kappa^g}{\zeta}$$

*Proof of Proposition 2 and derivation of (14).* Plugging the expected return linearization (11) into the linearized demand function (10) yields the following demand function:

$$\Delta q_{n,t} = (\theta_{n,t-} - 1 - \kappa(1 + \delta)(1 + \bar{g})) \Delta p_{n,t} + \kappa(1 + \bar{g}) \left[ \delta \Delta \tilde{d}_{n,t,1} + \Delta \tilde{p}_{n,t,1} \right] + \Delta \epsilon_{n,t}. \quad (51)$$

We need to substitute for $\Delta \tilde{d}_{n,t,1}$ and $\Delta \tilde{p}_{n,t,1}$. Since the shock to annual growth expectations at quarter $t$ is assumed to be driven by a shock to expected dividend growth in quarter $t + 1$, we have

$$\Delta \tilde{d}_{n,t,1} = \Delta \nu_{n,t}.$$
The shock to dividend growth also changes the expectation of next period price. By Lemma 1, the change in expectation of next period’s price driven by $\Delta \nu_{n,t}$ is

$$
\Delta p_{n,t} + M_\mu \delta \frac{\rho}{1 - M_\mu \rho} \frac{1}{1 + \rho + \rho^2 + \rho^3} \Delta \nu_{n,t}. 
$$

(52)

Plugging this last expression into the demand function (51) yields

$$
\Delta q_{n,t} = \left( \theta_{n,t} - \kappa (1 + \bar{g}) \delta \right) \Delta p_{n,t} + \kappa (1 + \bar{g}) \delta \left[ \frac{1}{1 - \rho M_\mu} \right] \frac{1}{1 + \rho + \rho^2 + \rho^3} \Delta \nu_{n,t} + \Delta \epsilon_{n,t},
$$

(53)

as desired.

For the special case of $\rho = \bar{g} = \theta_{n,t} = 0$, we have

$$
\zeta = 1 + \kappa \delta \\
\kappa^g = \kappa \delta,
$$

as desired for Proposition 1.

**B.4.1 Proof of Lemma 1**

The proof uses the following present value relation, which I prove in Appendix B.4.2.

**Lemma 2** (Present Value Relation). Let $\Delta \tilde{d}_{n,t,s} = \frac{\mathbb{E}_{t+}[D_{n,t+s}]}{\mathbb{E}_{t-}[D_{n,t+s}]} - 1$ represent the percentage change between $t-$ and $t+$ in the expectation of the dividend in period $t+s$ and $\Delta \tilde{\epsilon}_{n,t,s} = \mathbb{E}_{t+}[\mathcal{E}_{n,t+s} + \xi_{t+s}] - \mathbb{E}_{t-}[[\mathcal{D}_{n,t+s} + \xi_{t+s}]]$ represent change between $t-$ and $t+$ in the expectation of the residual demand shock in period $t+s$. We have the following expression for price change today ($\Delta p_{n,t}$) as a function of changes in long-run expected dividends and demand shocks:

$$
\Delta p_{n,t} = M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \Delta \tilde{d}_{n,t,s+1} + \sum_{s=0}^{\infty} M_\mu^s \frac{1}{\zeta + \kappa (1 + \bar{g})} \Delta \tilde{\epsilon}_{n,t,s},
$$

(54)

where

$$
M_\mu = \frac{\kappa (1 + \bar{g})}{\zeta + \kappa (1 + \bar{g})} = \frac{\kappa (1 + \bar{g})}{1 - \theta_{n,t} - \kappa (1 + \delta) (1 + \bar{g})}.
$$

The proof also uses the following lemma, which I prove in Appendix B.4.3.

**Lemma 3** (Quarterly Expected Dividend Growth Shock Price Impact). A shock of $\Delta \nu_{n,t}$ to annual expected dividend growth requires a shock of $\Delta \nu_{n,t}^g$ to quarterly expected dividend growth, where:

$$
\Delta \nu_{n,t}^g \equiv \frac{\Delta \nu_{n,t}}{1 + \rho + \rho^2 + \rho^3}.
$$
Proof of Lemma 1. First I derive the price impact of a quarterly dividend growth shock, as defined in (13) from Section 4.2.2:

\[ \Delta \nu_{n,t}^g \equiv \tilde{E}_{t+} [g_{n,t+1}] - \tilde{E}_{t-} [g_{n,t+1}] . \]

At the end I plug in the quarterly dividend growth shock implied by an annual dividend growth shock from Lemma 3:

\[ \Delta \nu_{n,t}^g = \frac{\Delta \nu_{n,t}}{1 + \rho + \rho^2 + \rho^3} . \]

Let \( g_{n,t+s} = \tilde{E}_{t-} [g_{t+s}] \). The percentage increase in the expected level of next period’s dividend is:

\[ \Delta \tilde{d}_{n,t,1} = \frac{1 + g_{n,t+1} + \Delta \nu_{n,t}^g}{1 + g_{n,t+1}} - 1 . \]

The percentage increase in the expected level of dividend two periods from now is:

\[ \Delta \tilde{d}_{n,t,2} = \frac{(1 + g_{n,t+1} + \Delta \nu_{n,t}^g)(1 + g_{n,t+2} + \rho \Delta \nu_{n,t}^g)}{(1 + g_{n,t+1})(1 + g_{n,t+2})} - 1 . \]

For \( s + 1 \) periods from now we have

\[
1 + \Delta \tilde{d}_{n,t,s+1} = \frac{\prod_{j=0}^{s} \left( 1 + g_{n,t+j+1} + \rho^j \Delta \nu_{n,t}^g \right)}{\prod_{j=0}^{s} \left( 1 + g_{n,t+j+1} \right)}
\]

\[
\rightarrow \Delta \tilde{d}_{n,t,s+1} \approx \log \left( 1 + \Delta \tilde{d}_{n,t,s+1} \right) = \sum_{j=0}^{s} \log \left( 1 + g_{n,t+j+1} + \rho^j \Delta \nu_{n,t}^g \right) - \sum_{j=0}^{s} \log \left( 1 + g_{n,t+j+1} \right)
\]

\[
\approx \sum_{j=0}^{s} \rho^j \Delta \nu_{n,t}^g
\]

\[
= \frac{1 - \rho^{s+1}}{1 - \rho} \Delta \nu_{n,t}^g
\]

(55)

Plugging this last result (55) into the present-value identity from Lemma 2 (and setting all other
demand shocks $\Delta \tilde{\epsilon}_{n,t,s} = 0$ for brevity) yields the following market-clearing price change:\footnote{This framework can handle non-zero demand shocks $\Delta \tilde{\epsilon}_{n,t,s}$ as well. If the residual demand shock in period $t$ ($\Delta \epsilon_{n,t} \equiv \Delta \epsilon^D_{n,t} + \xi_t$) is permanent (i.e. $\Delta \tilde{\epsilon}_{n,t,s} = \Delta \epsilon_{n,t}$, $\forall s > 0$), then the result of this lemma (58) holds exactly. If the residual demand shock today has some persistence or reversion, then (58) will have an additional term that is a function of $\Delta \epsilon_{n,t}$. Denote this additional term as $\omega_{n,t}$. In this case, an additional term of $\kappa(1 + \bar{g})\omega_{n,t}$ will appear in the final demand curve (14):

$$\Delta q_{n,t} = -\zeta \Delta p_{n,t} + \kappa \Delta \nu_{n,t} + \Delta \epsilon_{n,t} + \kappa(1 + \bar{g})\omega_{n,t}.$$}

$$\Delta p_{n,t} = M_{\mu} \delta \sum_{s=0}^{\infty} M_{\mu}^s \Delta \tilde{d}_{n,t,s+1}$$

$$= M_{\mu} \delta \sum_{s=0}^{\infty} M_{\mu}^s \left[ \frac{1 - \rho^{s+1}}{1 - \rho} \right] \Delta \nu_{n,t}^g$$

$$= M_{\mu} \frac{\delta}{1 - \rho} \left[ \frac{1}{1 - M_{\mu}} - \frac{\rho}{1 - \rho M_{\mu}} \right] \Delta \nu_{n,t}^g. \quad (56)$$

Now plug in the quarterly dividend growth shock implied by an annual dividend growth shock from Lemma 3

$$\Delta \nu_{n,t}^g = \frac{\Delta \nu_{n,t}}{1 + \rho + \rho^2 + \rho^3},$$

to obtain

$$\Delta p_{n,t} = M_{\mu} \frac{\delta}{1 - \rho} \left[ \frac{1}{1 - M_{\mu}} - \frac{\rho}{1 - \rho M_{\mu}} \right] \frac{1}{1 + \rho + \rho^2 + \rho^3} \Delta \nu_{n,t}.$$
the change in expected next period price is:

\[
\Delta \tilde{p}_{n,t,1} = \delta \sum_{s=1}^{\infty} M_{\mu}^{s} \Delta \tilde{d}_{n,t,s+1} \\
= \delta \sum_{s=1}^{\infty} M_{\mu}^{s} \frac{1 - \rho^{s+1}}{1 - \rho} \Delta \nu_{n,t}^{g} \\
= \delta M_{\mu} \sum_{s=0}^{\infty} M_{\mu}^{s} \frac{1 - \rho^{s+2}}{1 - \rho} \Delta \nu_{n,t}^{g} \\
= M_{\mu} \frac{\delta}{1 - \rho} \left[ \frac{1}{1 - M_{\mu}} - \frac{\rho^{2}}{1 - \rho M_{\mu}} \right] \Delta \nu_{n,t}^{g} \\
= \Delta p_{n,t} + \left[ M_{\mu} \frac{\delta}{1 - \rho} \frac{\rho}{1 - \rho M_{\mu}} - M_{\mu} \frac{\delta}{1 - \rho} \frac{\rho^{2}}{1 - \rho M_{\mu}} \right] \Delta \nu_{n,t}^{g} \\
= \Delta p_{n,t} + M_{\mu} \frac{\delta}{1 - \rho} \frac{\rho}{1 - \rho M_{\mu}} \Delta \nu_{n,t}^{g} \\
= \Delta p_{n,t} + M_{\mu} \frac{\delta}{1 - \rho} \frac{\rho}{1 - \rho M_{\mu}} \frac{1}{1 + \rho^{2} + \rho^{3}} \Delta \nu_{n,t}^{g},
\]

(57)

where (57) follows from (56). The last line follows from plugging in the quarterly dividend growth shock implied by an annual dividend growth shock: \(\Delta \nu_{n,t}^{g} = \frac{\Delta \nu_{n,t}}{1 + \rho^{2} + \rho^{3}}\) from Lemma 3.

B.4.2 Proof of Lemma 2

Proof. In general, I use \(\Delta \tilde{d}_{n,t,s}\) to denote the percentage change between \(\tilde{E}_{t-}[D_{n,t+s}]\) and \(\tilde{E}_{t+}[D_{n,t+s}]\). Similarly, I use \(\Delta \tilde{p}_{n,t,s}\) to denote the percentage change between \(\tilde{E}_{t-}[P_{n,t+s}]\) and \(\tilde{E}_{t+}[P_{n,t+s}]\). \(\Delta \tilde{\epsilon}_{n,t,s}\) is the change between \(t-\) and \(t+\) in the expectation of the residual demand shock in period \(t+s\).

Plugging the expected return linearization (11) into the linearized demand function (10) yields the following demand function:

\[
\Delta q_{n,t} = (\theta_{n,t-} - 1 - \kappa(1 + \delta)(1 + \bar{g})) \Delta p_{n,t} + \kappa(1 + \bar{g}) \left[ \delta \Delta \tilde{d}_{n,t,1} + \Delta \tilde{p}_{n,t,1} \right] + \Delta \epsilon_{n,t}.
\]

Market clearing under fixed supply (\(\Delta q_{n,t} = 0\)) implies:

\[
\Delta p_{n,t} = \frac{\kappa(1 + \bar{g})}{1 - \theta_{n,t-} + \kappa(1 + \delta)(1 + \bar{g})} \left( \delta \Delta \tilde{d}_{n,t,1} + \Delta \tilde{p}_{n,t,1} \right) + \frac{1}{1 - \theta_{n,t-} + \kappa(1 + \delta)(1 + \bar{g})} \Delta \epsilon_{n,t}.
\]

(59)

Note that

\[
\frac{1}{1 - \theta_{n,t-} + \kappa(1 + \delta)(1 + \bar{g})} = \frac{1}{\zeta + \kappa(1 + \bar{g})},
\]

for \(\zeta\) as defined in Proposition 2.
Rolling (59) one period forward, we see next period’s actual price change $\Delta p_{n,t+1}$ can be written as:

$$\Delta p_{n,t+1} = M\mu \left( \delta \Delta \tilde{d}_{n,t+1,1} + \Delta \tilde{p}_{n,t+1,1} \right) + \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t+1},$$

where $\tilde{d}_{n,t+1,1}$ and $\Delta \tilde{p}_{n,t+1,1}$ are the changes in expected dividend and price two periods from now (at $t+2$) that occur one period from now (at $t+1$) and $\Delta \epsilon_{n,t+1}$ is the residual demand shock one period from now (at $t+1$).

Thus, the change in tomorrow’s (i.e. period $t+1$) expected price that occurs today is:

$$\Delta \tilde{p}_{n,t,1} = M\mu \left( \delta \Delta \tilde{d}_{n,t,2} + \Delta \tilde{p}_{n,t,2} \right) + \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,1},$$

by the law of iterated expectations.

Iterating this process forward, we see

$$\Delta \tilde{p}_{n,t,1} = \delta M\mu \Delta \tilde{d}_{n,t,2} + \delta M^2\mu \Delta \tilde{d}_{n,t,3} + \delta M^3\mu \Delta \tilde{d}_{n,t,4} + \ldots$$

$$+ \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,1} + M\mu \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,2} + \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,3} + \ldots, \quad (60)$$

$$= \delta \sum_{s=0}^{\infty} M^s\mu \Delta \tilde{d}_{n,t,s+1} + \sum_{s=0}^{\infty} M^s\mu \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,s+1}. \quad (61)$$

Thus, we have

$$\delta \Delta \tilde{d}_{n,t,1} + \Delta \tilde{p}_{n,t,1} = \delta \sum_{s=0}^{\infty} M^s\mu \Delta \tilde{d}_{n,t,s+1} + \sum_{s=0}^{\infty} M^s\mu \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,s+1}. \quad (62)$$

So the change in price today from (59) becomes:

$$\Delta p_{n,t} = M\mu \delta \sum_{s=0}^{\infty} M^s\mu \Delta \tilde{d}_{n,t,s+1} + \sum_{s=0}^{\infty} M^s\mu \frac{1}{\zeta + \kappa(1+\bar{g})} \Delta \epsilon_{n,t,s}, \quad (63)$$

as desired.

**B.4.3 Proof of Lemma 3**

*Proof.* Starting with the definition of annual dividend growth, we have

$$1 + G_{n,t+1} = \prod_{s=1}^{4} (1 + g_{n,t+s})$$

$$\leftrightarrow G_{n,t+1} \approx \sum_{s=1}^{4} g_{n,t+s},$$

21
using \( \log(1 + x) \approx x \) for small \( x \). Now plug in the dynamics for quarterly dividend growth \( g_{n,t} \) from (12) into the second expression:

\[
G_{n,t+1} \approx \sum_{s=1}^{4} g_{n,t+s} = \sum_{s=1}^{4} x_{n,t+s-1} + \sum_{s=1}^{4} \epsilon_{n,t+s}^g.
\]

Thus,

\[
\tilde{E}_t [G_{n,t+1}] = \sum_{s=1}^{4} \tilde{E}_t [x_{n,t+s-1}] + \sum_{s=1}^{4} \tilde{E}_t [\epsilon_{n,t+s}^g] = \sum_{s=1}^{4} \tilde{E}_t [x_{n,t+s-1}].
\]

Note that

\[
x_{n,t+s-1} = \bar{x} + \rho(x_{n,t+s-2} - \bar{x}) + \epsilon_{n,t+s-1}^x
\]

\[
= \bar{x}(1 - \rho) \sum_{j=1}^{s-2} \rho^j + \rho^{s-1}x_{n,t} + \sum_{j=1}^{s-1} \rho^{s-1-j} \epsilon_{n,t+s-1}^x.
\]

Therefore,

\[
\tilde{E}_t [G_{n,t+1}] = \tilde{E}_t [x_{n,t}] (1 + \rho + \rho^2 + \rho^3) + \bar{x}(1 - \rho) \left[ 1 + (1 + \rho) + (1 + \rho + \rho^2) \right]
\]

\[
\rightarrow \Delta \nu_{n,t} \equiv \tilde{E}_t^+ [G_{n,t+1}] - \tilde{E}_t^- [G_{n,t+1}] = \left( \tilde{E}_t^+ [x_{n,t}] - \tilde{E}_t^- [x_{n,t}] \right) (1 + \rho + \rho^2 + \rho^3)
\]

\[
= \Delta \nu_{n,t}^g (1 + \rho + \rho^2 + \rho^3)
\]

\[
\leftrightarrow \Delta \nu_{n,t}^g = \frac{1}{1 + \rho + \rho^2 + \rho^3},
\]

as desired.

\[\square\]

### B.5 \( M_g \) in a Standard Model

There is one risky asset and a representative investor with CRRA utility over consumption:

\[
U(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}.
\]
Log consumption growth is i.i.d.

\[ \Delta c_{t+1} = \mu_c + \epsilon^c_{t+1}. \]

To match the setup in Section 4.2.2, realized (quarterly) log dividend growth has the following dynamics:

\[ \Delta d_{t+1} = x_t + \epsilon^d_{t+1}, \]

\[ x_{t+1} = \bar{x} + \rho (x_t - \bar{x}) + \epsilon^x_{t+1}, \]

i.e. expected dividend growth \( x_t \) is an AR(1) process. \( \epsilon^c_{t+1} \) and \( \epsilon^d_{t+1} \) are arbitrarily correlated but \( \epsilon^x_{t+1} \) is uncorrelated with both.

The representative investor’s stochastic discount factor (SDF) is:

\[ M_{t+1} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \] (64)

\[ \leftrightarrow m_{t+1} = \log M_{t+1} = \log \beta - \gamma \Delta c_{t+1}, \]

for subjective discount factor \( \beta \).

Gross returns \( R_{t+1} \) for the asset that pays out dividends \( D_t \) must satisfy

\[ \mathbb{E}_t \left[ \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} R_{t+1} \right] = 1. \] (65)

I derive an approximate log-linearized solution using the decomposition of Campbell and Shiller (1988), under which log returns have the following form:

\[ r_{t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta d_{t+1}, \] (66)

where \( r_{t+1} = \log R_{t+1}, z_t = \log (P_t/D_t) \), and \( \kappa_1 = \frac{1}{1+\exp[-z_t]} \) and \( \kappa_0 = -\log \kappa_1 + (1-\kappa_1) \log \left( \frac{1}{\kappa_1} - 1 \right) \) are constants that depend only on the average level of \( z_t \).

I solve the model by guess and verify. I conjecture the following form for \( z_t \):

\[ z_t = A_0 + A_1 x_t. \]

Plugging this expression into

\[ \mathbb{E}_t \left[ \exp [m_{t+1} + r_{t+1}] \right] = 1 \] (67)
yields
\[ A_1 = \frac{1}{1 - \kappa_1 \rho} \]
\[ A_0 = \frac{1}{1 - \kappa_1} \left[ \log \beta - \gamma \mu_c + \kappa_0 + A_1 \kappa_1 \bar{x}(1 - \rho) + \mathbb{V} \left[ \kappa_1 A_1 \epsilon_t^{x_{t+1}} + \epsilon_t^{y_{t+1}} - \gamma \epsilon_t^{c_{t+1}} \right] \right]. \]

The part of return expression (66) that accounts for price appreciation (as opposed to the realized dividend yield) is:

\[ \kappa_0 + \kappa_1 z_{t+1} = \kappa_0 + \kappa_1 (A_0 + A_1 x_{t+1}) \]
\[ = \kappa_0 + A_0 \kappa_1 + A_1 \kappa_1 \bar{x}(1 - \rho) + \kappa_1 A_1 \rho x_t + \kappa_1 A_1 \epsilon_t^{x_{t+1}}. \]

\[ \bar{M}_g = \kappa_1 A_1 \] is close to the causal impact of quarterly growth expectations on price. \( \bar{M}_g = \kappa_1 A_1 \) is the percent price change in \( t+1 \) from the cum-dividend price (i.e. the price at the end of \( t \) before the dividend has been paid in \( t+1 \)) induced by a 1% increase in expected cash flow growth \((\epsilon_t^{x_{t+1}} = 1\%)\). \( M_g \) as defined in Section 4.3.1 is the percent change in price in \( t+1 \) from the ex-dividend price (i.e. the price in \( t+1 \) after the dividend has been paid in \( t+1 \)).

To obtain \( M_g \), I adjust \( \bar{M}_g \) to express the change in price caused by the 1% increase in expected cash flow growth \((\epsilon_t^{x_{t+1}} = 1\%)\) as a percentage in terms of the ex-dividend price. Let \( P_t \) be the ex-dividend price in period \( t \). Then the cum-dividend price in \( t \) is

\[ P_t + D_t = P_t (1 + D_t/P_t) = P_t (1 + \exp[-z_t]). \]

So adjusting \( \bar{M}_g = \kappa_1 A_1 \) we have

\[ M_g^{\text{quarterly}} = \frac{\bar{M}_g P_t + D_t}{P_t} = \kappa_1 A_1 (1 + \exp[-z_t]). \]

To obtain \( M_g \), we must multiply \( M_g^{\text{quarterly}} \) by the shock to quarterly expected cash flow growth that induces a 1% rise in annual expected cash flow growth (see Lemma 3 in Appendix B.4.1):

\[ \frac{1}{1 + \rho + \rho^2 + \rho^3}. \]

Thus,

\[ M_g = \kappa_1 A_1 (1 + \exp[-z_t]) \frac{1}{1 + \rho + \rho^2 + \rho^3}. \]

Consider the following two cases:

1. **No persistence** \((\rho = 0)\): In this case, the price dividend ratio is constant. Recall that
\[ \kappa_1 = \frac{1}{1 + \exp[-z_t]} \] and so \[ \kappa_1 = \frac{1}{1 + \exp[-z]} \] since \( z_t = z, \forall t \). Thus,

\[
M_g = \kappa_1 A_1 (1 + \exp[-z_t]) \frac{1}{1 + \rho + \rho^2 + \rho^3}.
\]

\[
= 1,
\]

since \( A_1 = 1 \) for \( \rho = 0 \)

2. **General persistence:** In this case we have:

\[
M_g = \kappa_1 A_1 (1 + \exp[-z_t]) \frac{1}{1 + \rho + \rho^2 + \rho^3}.
\]

\[
= \frac{1 + \exp[-z_t]}{1 + \exp[E[-z_t]]} \frac{1}{1 - \kappa_1 \rho} \frac{1 + \rho + \rho^2 + \rho^3}{1 + \rho + \rho^2 + \rho^3}.
\]

Quarterly dividend-price ratios are small (e.g. on the order of 0.01 for the equity market). So the leading coefficient

\[
\frac{1 + \exp[-z_t]}{1 + \exp[E[-z_t]]} \approx 1.
\]

So

\[
M_g \approx \frac{1}{1 - \kappa_1 \rho} \frac{1 + \rho + \rho^2 + \rho^3}{1 + \rho + \rho^2 + \rho^3},
\]

which is generally increasing in \( \rho \) for \( \rho > 0 \).\(^{40}\) For the estimated \( \rho = 0.7 \) in the I/B/E/S data (see Appendix B.3), the implied causal effect of growth expectations on prices in this standard model is

\[
M_g \approx 1.3.
\]

Since \( M_g = 1.3 \) for the estimate \( \rho = 0.7 \) is not enormously different than \( M_g = 1 \) for \( \rho = 0 \), I use the latter as a simpler and more conservative benchmark.

In the case of zero persistence (\( \rho = 0 \)), \( M_g = 1 \) is an unavoidable implication of the fundamental pricing equation (65). Pinning down equilibrium expected returns by this equation necessarily means a transient 1% dividend growth shock (i.e. a permanent 1% increase in the level of dividends)

\(^{40}\)This function for \( M_g \) can be very slightly decreasing for small values of \( \rho \) (e.g. \( 0, \rho < .152 \) for \( \kappa_1 = 0.99 \)) due to approximation error that arises over the course of the linearizations, but not to an extent that could be seen in a plot \( M_g \) of as a function of \( \rho \) for \( 0 < \rho < 1 \).
raises price by 1%. Since the pure cash flow shock doesn’t impact the expected return pinned down by this equation, the price-dividend ratio doesn’t change, and so the price change equals the change in the level of dividends. Intuitively, if price rises by less than 1%, price-dividend ratio will fall and expected return will rise. So expected return would be greater than it “should” be under (65). The representative investor’s demand rises as much as is necessary to push price up to lower expected return until (65) is satisfied.

For the price impact of a transient 1% growth shock to be anything other than 1%, the price dividend ratio must change, which means expected return must change. For $M_g$ to be less than 1, the representative investor’s demand must not respond strongly enough to push price up and expected return down until (65) is satisfied. That is, the investor must be willing to leave the higher expected return “on the table.” In that case, the equilibrium expected return is not pinned down by the fundamental pricing equation using the consumption-based SDF.\footnote{Since there is no violation of the law of one price here, there will be some SDF that satisfies (65). However, the consumption-based SDF of the representative investor in (64) will not. Gabaix and Koijen (2020b) provide a concrete example of how to construct an admissible SDF in a setting similar to that describe in Section 4.} The theoretical framework in Section 4 pins down equilibrium prices — and so expected returns — using a different approach: by equating investor asset demand with supply.
C Singular Value Decomposition Implementation Details

In this appendix, I discuss some implementation details involved in applying the Funk (2006) singular value decomposition to the latent factor model

\[ M_t = \Lambda_t H_t + u_t, \]

where \( M_t \) is the \( A \times D \) matrix of reported expected returns for number of analyst institutions \( A \) and number of stocks \( D \), \( \Lambda_t \in \mathbb{R}^{A \times F} \) is the stacked matrix of institution-specific loading vectors \( \tilde{\lambda}_{a,t} \in \mathbb{R}^F \), \( H_t \in \mathbb{R}^{F \times D} \) is the stacked matrix of stock-specific characteristic vectors \( \tilde{\eta}_{n,t} \in \mathbb{R}^F \), and \( u_t \) is the \( A \times D \) matrix of idiosyncratic residual expected return shocks.

One can estimate matrices \( \Lambda_t \) and \( H_t \) as the minimizers of the following loss function

\[
\begin{align*}
\min_{\Lambda_t, H_t} \sum_{a,n} \left( \Delta G^A_{a,n,t} - \hat{G}^A_{a,n,t} \right)^2 \\
\text{s.t.} \quad \hat{G}^A_{a,n,t} = \tilde{\lambda}_{a,t}^\top \tilde{\eta}_{n,t} = b_{a,t} + c_{n,t} + \lambda_{a,t}^\top \eta_{n,t},
\end{align*}
\]

where \( \lambda_{a,t} \) and \( \eta_{n,t} \) are the unconstrained components of \( \tilde{\lambda}_{a,t} \) and \( \tilde{\eta}_{n,t} \), while \( b_{a,t} \) is the element of \( \tilde{\lambda}_{a,t} \) constrained to load on a constant \( \tilde{\eta}_{n,t,f} = 1 \) and \( c_{n,t} \) is the element of \( \tilde{\eta}_{n,t} \) constrained to be loaded on by \( \tilde{\lambda}_{a,t,f} = 1 \).

Empirically, each institution only covers a small subset of stocks in each quarter (on average, roughly 2\% of the entries in \( M_t \) are filled). For this reason, we can attain more efficient estimates of \( \Lambda_t \) and \( H_t \) by adding L2 penalties to the least-squares loss function (Funk (2006); Bai and Ng (2019)):

\[
\begin{align*}
\min_{\Lambda_t, H_t} \sum_{a,n} \left( \Delta G^A_{a,n,t} - \hat{G}^A_{a,n,t} \right)^2 + \sum_{a,n} \gamma_1 \lambda_{a,t}^2 + \gamma_2 c_{n,t}^2 + \gamma_3 \lambda_{a,t}^2 + \gamma_4 \eta_{n,t}^2 \\
\text{s.t.} \quad \hat{G}^A_{a,n,t} = b_{a,t} + c_{n,t} + \lambda_{a,t}^\top \eta_{n,t},
\end{align*}
\]

In the baseline analysis, I use five latent factors. Since I fit the factor model quarter by quarter, all regularization parameters can vary over time. I conduct three-fold cross-validation within each quarter to choose regularization parameters \( \gamma_{3,t} \) and \( \gamma_{4,t} \). Since the fixed effects \( b_{a,t} \) and (especially) \( c_{n,t} \) are responsible for absorbing the price terms in the \( \Delta \hat{G}^A_{a,n,t} \), I do not regularize them (\( \gamma_{1,t} = \gamma_{2,t} = 0 \)) in order to avoid biasing the estimated fixed effects toward zero and thereby leaving some price variation in the estimated residuals \( \hat{u}_{a,n,t} \).

However, since the fixed effects \( b_{a,t} \) and \( c_{n,t} \) are jointly estimated with the factors \( \eta_{n,t} \) and loadings \( \lambda_{a,t} \), regularizing \( \eta_{n,t} \) and \( \lambda_{a,t} \) will somewhat affect the estimates of \( b_{a,t} \) and \( c_{n,t} \). To avoid this issue, one could remove

---

\(^{42}\)Nevertheless, since the fixed effects \( b_{a,t} \) and \( c_{n,t} \) are jointly estimated with the factors \( \eta_{n,t} \) and loadings \( \lambda_{a,t} \), regularizing \( \eta_{n,t} \) and \( \lambda_{a,t} \) will somewhat affect the estimates of \( b_{a,t} \) and \( c_{n,t} \). To avoid this issue, one could remove
D Alternative Learning Specifications

D.1 General Linearization of Analyst Influence $B_{i,a,n}$ with Analyst and Investor Heterogeneity

In this appendix I derive the general form of analyst influence $B_{i,a,n}$ under investor and analyst heterogeneity. With this heterogeneity, (32) becomes

$$B_{i,a,n} = \frac{\sigma_{i,a}^{-2}}{\tau_i^{-1} + \sum_{a' \in A_n} \sigma_{i,a'}^{-2}},$$

where $\sigma_{i,a}^{-2}$ is the signal precision of analyst $a$’s growth expectation as perceived by investor $i$ and $A_n$ is the set of analysts who issue expectations for stock $n$. Rewrite this equation in reduced form as:

$$B_{i,a,n} = \frac{\sigma_{i,a}^{-2}}{\tau_i^{-1} + \sum_{a' \in A_n} \sigma_{i,a'}^{-2}} \cdot \frac{x_{i,a}}{1 + \sum_{a' \in A_n} x_{i,a'}},$$

where $x_{i,a} \equiv \sigma_{i,a}^{-2}/\tau_i^{-1}$ is the scaled signal precision of analyst $a$ as perceived by investor $i$. Let $A_n = |A_n|$ represent the number of analysts that rate stock $n$. Linearizing the last equation around the average scaled signal precision $x_{i,a} = x_i$ and the average number of analysts to rate a stock $A_n = A$ yields

$$B_{i,a,n} \approx \left[ \beta_i \cdot \frac{y_{i,a}}{x_{i,a} - x_i} - \beta_i \sum_{a' \in A_n} y_{i,a'} \right] \left( 1 - \beta_i \cdot \frac{\tilde{A_n}}{A_n - A} \right).$$

(68)

Note that analyst influence depends on:

1. $\beta_i$ — The average analyst influence on investor $i$ across all analysts $a$ and stocks $n$.

2. $y_{i,a}$ — The gap between analyst $a$’s influence on investor $i$ and the average influence level $\beta_i$ for the average stock.

3. $A_n$ — The set of analysts that rate stock $n$. $A_n$ enters (68) in two places:

   (a) $1 - \beta_i \cdot \tilde{A_n}$ — Each additional analyst added to the rating set reduces the influence of analyst $a$. $\tilde{A_n}$ is the demeaned number of analysts in $A_n$.

   (b) $-\beta_i \sum_{a' \in A_n} y_{i,a'}$ — Analyst $a$’s influence falls by more when higher-influence analysts (higher $y_{i,a}$) enter $A_n$.

The special case with no heterogeneity in scaled signal precisions across analysts follows from setting $y_{i,a} = 0, \forall a$;

analyst-quarter and stock-quarter fixed effects from $\Delta G_{a,n,t}^A$ before running the factor model.
Further restricting all investors to agree on a single analyst signal precision yields the baseline specification (25):

\[ B_{i,a,n} = B_{i,n} \approx \beta_i - \beta_i^2 \tilde{A}_n. \]

(68) can be taken to the data. In general, \( \beta_i \) and all \( y_{i,a} \) can be identified using beliefs, price, and holdings data. If we suppress investor-level heterogeneity, \( \beta \) and all \( y_a \) can be identified from beliefs and price data. The baseline specification (26) uses only idiosyncratic growth shocks and their interaction with the demeaned number of analysts. To allow for heterogeneous influence across analysts, you would need to also include interactions with analyst-specific indicators.

### D.2 General Linearization of Analyst Influence \( B_{i,a,n} \) with Analyst and Investor Heterogeneity

In this appendix I derive the general form of analyst influence \( B_{i,a,n} \) under investor and analyst heterogeneity. With this heterogeneity, (32) becomes

\[ B_{i,a,n} = \frac{\sigma^{-2}_{i,a}}{\tau_i^{-1} + \sum_{a' \in A_n} \sigma^{-2}_{i,a'}}, \]

where \( \sigma^{-2}_{i,a} \) is the signal precision of analyst \( a \)'s growth expectation as perceived by investor \( i \) and \( A_n \) is the set of analysts who issue expectations for stock \( n \). Rewrite this equation in reduced form as:

\[ B_{i,a,n} = \frac{\sigma^{-2}_{i,a}}{\tau_i^{-1} + \sum_{a' \in A_n} \sigma^{-2}_{i,a'}} = \frac{x_{i,a}}{1 + \sum_{a' \in A_n} x_{i,a'}}, \]

where \( x_{i,a} \equiv \sigma^{-2}_{i,a}/\tau_i^{-1} \) is the scaled signal precision of analyst \( a \) as perceived by investor \( i \). Let \( A_n = |A_n| \) represent the number of analysts that rate stock \( n \). Linearizing the last equation around the average scaled signal precision \( x_{i,a} = x_i \) and the average number of analysts to rate a stock \( A_n = A \) yields

\[ B_{i,a,n} \approx \left[ \beta_i + y_{i,a} - \beta_i \sum_{a' \in A_n} y_{i,a'} \right] \left( 1 - \frac{\tilde{A}_n}{A_n - A} \right). \]  

(69)

Note that analyst influence depends on:

1. \( \beta_i \) — The average analyst influence on investor \( i \) across all analysts \( a \) and stocks \( n \).
2. \( y_{i,a} \) — The gap between analyst \( a \)'s influence on investor \( i \) and the average influence level \( \beta_i \) for the average stock.
3. \( A_n \) — The set of analysts that rate stock \( n \). \( A_n \) enters (69) in two places:

(a) \( 1 - \beta_i \tilde{A}_n \) — Each additional analyst added to the rating set reduces the influence of analyst \( a \). \( \tilde{A}_n \) is the demeaned number of analysts in \( A_n \).

(b) \( -\beta_i \sum_{a' \in A_n} y_{i,a'} \) — Analyst \( a \)'s influence falls by more when higher-influence analysts (higher \( y_{i,a} \)) enter \( A_n \).

The special case with no heterogeneity in scaled signal precisions across analysts follows from setting \( y_{i,a} = 0, \forall a \):

\[
B_{i,a,n} = B_{i,n} \approx \beta_i - \beta_i^2 \tilde{A}_n.
\]

Further restricting all investors to agree on a single analyst signal precision yields the baseline specification (25):

\[
B_{i,a,n} = B_n \approx \beta - \beta^2 \tilde{A}_n.
\]

(69) can be taken to the data. In general, \( \beta_i \) and all \( y_{i,a} \) can be identified using beliefs, price, and holdings data. If we suppress investor-level heterogeneity, \( \beta \) and all \( y_a \) can be identified from beliefs and price data. The baseline specification (26) uses only idiosyncratic growth shocks and their interaction with the demeaned number of analysts. To allow for heterogeneous influence across analysts, you would need to also include interactions with analyst-specific indicators.

### D.3 Deviations from Bayesian Learning

I consider a general class of deviations from Bayesian learning using the conceptual framework of Benjamin (2019).

In the notation from Section 5.3, Benjamin (2019) use the following specification of the posterior distribution for the unknown growth rate \( G_n \) that investor \( i \) is learning about:

\[
\mathbb{P}(G_n | \{G_{a,n}\}_{a \in A_n}) = \frac{\mathbb{P}(\{G_{a,n}^A\}_{a \in A_n} | G_n)^c \mathbb{P}(G_n | \tilde{G}_{i,a,n}^I)^d}{\int_{G_n} \mathbb{P}(\{G_{a,n}^A\}_{a \in A_n} | G_n')^c \mathbb{P}(G_n' | \tilde{G}_{i,a,n}^I)^d}.
\]

Parameters \( c \) and \( d \) capture over or underweighting of signals and the prior, respectively.

- Bayesian learning corresponds to the special case where \( c = d = 1 \).
- \( c < 1 \) represents “underinference” —the learner puts less weight on signals than a Bayesian would.
- \( c > 1 \) represents “overinference” —the learner puts more weight on signals than a Bayesian would.
• $d < 1$ represents “base-rate neglect” —the learner puts less weight on the prior than a Bayesian would.

• $d < 1$ represents “base-rate over-use” —the learner puts more weight on the prior than a Bayesian would.

Thus, this specification of the posterior captures wide range of deviations from Bayesian learning.

Given the Gaussian prior and signal structure in Section 5.3, one can easily show that the posterior mean growth expectation after learning from $A_n$ analysts is

$$
\frac{c\sigma^{-2}}{c\sigma^{-2}A_n + d\tau - 1} \sum_{a \in A_n} G_{a,n}^A + \frac{d\tau - 1}{c\sigma^{-2}A_n + d\tau - 1} \bar{G}_{i,a,n}^{I},
$$

and so the update to mean growth expectation is

$$
\frac{c\sigma^{-2}}{c\sigma^{-2}A_n + d\tau - 1} \sum_{a \in A_n} \left( G_{a,n}^A - \bar{G}_{i,a,n}^{I} \right).
$$

Thus we have analyst influence

$$
B_n = \frac{c\sigma^{-2}}{c\sigma^{-2}A_n + d\tau - 1} \approx \beta - \beta^2 (A_n - A)
$$

$$
\beta = \frac{c\sigma^{-2}}{c\sigma^{-2}A + d\tau - 1},
$$

where $A = \mathbb{E}[A_n]$ is the average number of analyst institutions that cover each stock. We get the same functional form for $B_n$ as in (33) in Section 5.3. The underlying structure of average influence $\beta$ has changed. However, the way analyst influence $B_n$ varies in the cross section of equities has not changed.

Thus, my identification strategy does not rely on investors acting as perfect Bayesian learners. They may exhibit any of the wide range of behavioral biases listed above. The functional form of analyst influence ($B_n = \beta - \beta^2 (A_n - A)$) proves robust to these deviations from Bayesian learning.
### Summary Statistics

Table E4: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>$\Delta p_{a,n,t}^+$</th>
<th>$A_{n,t}$</th>
<th>$\Delta G_{A,a,n,t}^A$</th>
<th>$u_{a,n,t}$</th>
<th>$\Delta q_{i,n,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>2066042</td>
<td>2173221</td>
<td>2173221</td>
<td>2173221</td>
<td>51438199</td>
</tr>
<tr>
<td>Mean</td>
<td>0.002</td>
<td>10.031</td>
<td>-0.008</td>
<td>-0.0</td>
<td>0.022</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.09</td>
<td>7.234</td>
<td>0.534</td>
<td>0.184</td>
<td>0.672</td>
</tr>
<tr>
<td>Min</td>
<td>-0.985</td>
<td>1.0</td>
<td>-4.434</td>
<td>-4.887</td>
<td>-1.0</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>-0.035</td>
<td>4.0</td>
<td>-0.118</td>
<td>-0.044</td>
<td>-0.152</td>
</tr>
<tr>
<td>Median</td>
<td>0.001</td>
<td>8.0</td>
<td>-0.003</td>
<td>0.0</td>
<td>-0.0</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>0.038</td>
<td>14.0</td>
<td>0.109</td>
<td>0.044</td>
<td>0.082</td>
</tr>
<tr>
<td>Max</td>
<td>11.0</td>
<td>49.0</td>
<td>3.627</td>
<td>4.653</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Summary statistics for price changes five days after analyst report releases ($\Delta p_{a,n,t}^+$), the number of analyst institutions who cover each stock ($A_{n,t}$), the quarter-over-quarter change in analyst annual expected EPS growth ($\Delta G_{A,a,n,t}^A$), the idiosyncratic analyst growth shocks ($u_{a,n,t}$), and quarterly percentage changes in quantity of shares held by investor $i$ in stock $n$ ($\Delta q_{i,n,t}$). $\Delta p_{a,n,t}^+$, $\Delta G_{A,a,n,t}^A$, $u_{a,n,t}$, and $\Delta q_{i,n,t}$ are all expressed in absolute terms (i.e. 0.01 is 1%). The time period is 1984-01:2021-12.
Analyst Price Impact Estimates from Previous Work

Figure F7 graphically compares my analyst price impact estimate $c_1 \approx 0.5$ basis points to values found in previous work. Table F5 provides details of estimates from previous work.

My analyst price impact estimate is slightly smaller than what the previous literature has found. I offer four potential reasons to reconcile these estimates:

1. The previous literature uses a different specification than this paper. This paper focuses on how cash flow growth expectations impact prices, so I scale analyst fixed one-year horizon EPS forecasts by the trailing level of EPS to obtain EPS growth forecasts and take quarterly differences. The previous literature uses the percentage change in EPS forecasts for the current fiscal year. So both the measure and horizon used by the previous literature are different. If the percentage change in fixed-year (instead of fixed-horizon) EPS forecast has more influence on investor expectations (i.e. higher $\beta$), this measure will have greater price impact than my $c_1 \approx 0.5$. This scenario does not change the interpretation of my $M_g$ estimate. The $\beta$ I estimate is the analyst influence of a particular piece of information in analyst reports. Other pieces of information having different $\beta$ values (e.g. due to different perceived signal precisions) does not invalidate the $\beta$ I measure. For this reason, the $M_g$ I measure is unaffected. I prefer my empirical measure of fixed-horizon EPS growth forecasts since it proves closer to the theoretical framework in Section 4.

2. Analyst influence $\beta$ may be lower in my sample than in previous work. Much of the previous literature studies analyst price impact prior to the introduction of the SEC Regulation Fair Disclosure (“Red FD”) in 2000, which limited the ability of firm managers to disclose information solely to particular analysts before revealing that information publicly. My sample extends through 2021. Thus, to the extent that analyst influence $\beta$ is lower after the introduction of Red FD because the perceived signal precision of analyst expectations has fallen, analyst price impact will also be lower post-2000.

3. $M_g$ may be lower in my sample than in previous work. Koijen and Yogo (2019) document that price elasticities of demand have fallen over time (e.g. due to the rise of passive investing). As discussed in Section 4.3.2, the price impact of investor beliefs $M_g$ is low when price elasticity is low. Thus, to the extent that $M_g$ is lower in my sample than in previous work, my analyst price impact estimate will also be lower.

4. Statistically, my estimate proves consistent with the smaller estimates from the previous literature. The 95% lower bound for the analyst price impact estimate from Park and Stice (2000) is about 0.6 basis points. The lower estimate of 2 basis points from Asquith, Mikhail and Au (2005) is not statistically significant.
Figure F7: Comparison of $M_g$-Implied $\kappa$ to Previous Literature

Graphical comparison of my analyst price impact estimate ($c_1 \approx 0.5$ basis points from Table 2) to values found in previous work.
Table F5: Details of Recovering $\kappa$ Estimates from Previous Work

<table>
<thead>
<tr>
<th>Paper</th>
<th>Raw Estimates</th>
<th>My Assumptions</th>
<th>Converted Estimates</th>
<th>Empirical Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Francis &amp; Soffer</td>
<td>Table 3: Regression of 3-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.10-0.12</td>
<td>None</td>
<td>10-12 bps</td>
<td>Percentage change in current fiscal year EPS forecast.</td>
</tr>
<tr>
<td>(1997)</td>
<td>Table 2: Regression of 3-day return (centered window) on change in EPS forecast implied earnings yield has coefficient 0.13.</td>
<td>Multiply by average P/E for S&amp;P 500 from Robert Shiller’s data library (16) and divide by 100 to convert to a percentage change in EPS forecast.</td>
<td>2 bps</td>
<td>Change in EPS forecast implied earnings yield.</td>
</tr>
<tr>
<td>Park &amp; Stice (2000)</td>
<td>Table 3: Regression of 5-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.08</td>
<td>None</td>
<td>2-8 bps</td>
<td>Percentage change in current fiscal year EPS forecast.</td>
</tr>
<tr>
<td>Asquith, Mikhail &amp; Au</td>
<td>Table 8: After adding controls, coefficient drops to 0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2005)</td>
<td>Table 3: Regression of 5-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.06-0.16</td>
<td>None</td>
<td>6-16 bps</td>
<td>Percentage change in current fiscal year EPS forecast.</td>
</tr>
<tr>
<td>Kerl &amp; Walter (2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
G Supplements to Empirical Results in Section 5.5

G.1 Alternative Numbers of Latent Factors

The baseline specification in Section 5.5 uses 5 latent factors. Figures G11 and G12 display estimates for reduced-form coefficients $c_1$ and $c_2$ as well as structural parameters $\beta$ and $M_g$. All results prove robust to using alternative numbers of latent factors.

Figure G10 displays the cumulative percentage variation in $\Delta G_{a,n,t}^A$ explained as a function of the number of latent factors. The first 5 latent factors (along with stock-quarter and analyst-quarter fixed effects) explain 88% of the variation in $\Delta G_{a,n,t}^A$. Adding more factors explains only marginally more variation: 5 more factors (for a total of 10) explain less than 1% additional variation in $\Delta G_{a,n,t}^A$. 
Estimates of reduced-form parameters $c_1$ and $c_2$ from the following regression:

$$\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2 u_{a,n,t} A_{n,t-1} + F E_{a,t} + F E_{n,t} + e_{a,n,t},$$

where $\Delta p_{a,n,t}^+$ is measured over different windows from 1 to 10 days. Zero factors corresponds to using the full analyst growth expectation update $\Delta G_{a,n,t}^A$. 
Estimates of implied structural parameters $\beta$ and $M_g$ from the following regression:

$$
\Delta p_{a,n,t}^+ = \underbrace{c_1 u_{a,n,t}}_{=M_g \beta} - \underbrace{c_2 u_{a,n,t} \tilde{A}_{n,t-1}}_{=M_g \beta^2} + F E_{a,t} + F E_{n,t} + X_{n,t} + \epsilon_{a,n,t},
$$

where $\Delta p_{a,n,t}^+$ is measured over different windows from 1 to 10 days. Zero factors corresponds to using the full analyst growth expectation update $\Delta G_{a,n,t}^A$. 

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Percentage variation in $\Delta G^A_{a,n,t}$ explained as a function of the number of latent factors. Zero factors corresponds to the percentage variation explained by just stock-quarter and analyst-quarter fixed effects.

G.2 Alternative Price Reaction Windows

The baseline specification in Section 5.5 uses the 5-day return following an analyst report to measure the high-frequency price change $\Delta p^+_{a,n,t}$. Figures G11 and G12 display estimates for reduced-form coefficients $c_1$ and $c_2$ as well as structural parameters $\beta$ and $M_g$ using reaction windows of different lengths. The $M_g$ results for windows of 1−5 days prove similar and all are roughly within the range of 7 − 16 basis points that I argue for, especially after accounting for standard errors.

I use 5-days for the baseline specification to account for the possibility of a delayed investor reaction to analyst reports. Ideally, I would like to go out further than 5 days but, as Figures G11 and G12 exhibit, past 5 days regression (34) lacks power. In particular, the estimate of analyst price impact for the average stock ($c_1$) lacks power. The intuition for this decay in power is that the regression uses within stock-quarter variation in analyst expectations to identify $c_1$. When constructing the idiosyncratic analyst growth shocks $u_{a,n}$, the factor model removes analyst-quarter and stock-quarter fixed effects. Thus, the high-frequency price reactions $\Delta p^+_{a,n,t}$ need to vary across analysts $a$ within the (stock $n$, quarter $t$) pair. For example, if all analysts reported on the same day so $\Delta p^+_{a,n,t} = \Delta p^+_{n,t}, \forall a$, then the regression

$$\Delta p^+_{n,t} = c_1 u_{a,n,t} + c_2 u_{a,n,t} \tilde{A}_{n,t} + e_{a,n,t}$$

would not be able to identify $c_1$. Essentially, this regression would be trying to explain a constant
(within stock-quarter) constant on the left-hand side since the latent factor model removes all stock-quarter variation from $u_{a,n,t}$. $u_{a,n,t}\tilde{A}_{n,t}$, on the other hand, does have stock-quarter variation, which is presumably why the $c_2$ estimates in Figure G11 vary less as the window expands.

For short windows, $\Delta p^+_{a,n,t}$ has variation across analysts $a$ within the (stock $n$, quarter $t$) pair. However, as the window expands, the post-report price changes $\Delta p^+_{a,n,t}$ overlap significantly across analysts, since analyst reports tend to cluster temporally within a quarter. For a 10-day window, stock-quarter fixed effects explain 63% of the variation in $\Delta p^+_{a,n,t}$. The remaining variation proves insufficient to pin down $c_1$. 
Estimates of reduced-form parameters $c_1$ and $c_2$ from the following regression:

$$\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2 u_{a,n,t} \tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},$$

where $\Delta p_{a,n,t}^+$ is measured over different windows from 1 to 10 days.
Figure G12: \( \beta \) and \( M_g \) Results for Different Price Reaction Windows

Estimates of implied structural parameters \( \beta \) and \( M_g \) from the following regression:

\[
\Delta p_{a,n,t}^+ = \frac{c_1}{M_g \beta} u_{a,n,t} - \frac{c_2}{M_g \beta^2} \tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},
\]

where \( \Delta p_{a,n,t}^+ \) is measured over different windows from 1 to 10 days.

To provide further evidence that the within stock-quarter lack of variation in \( \Delta p_{a,n,t}^+ \) is the problem (as opposed to price reversal at longer horizons or some other reason), I run the following regression:

\[
\Delta p_{a,n,t}^+ = c_1 \Delta G_{a,n,t} + c_2 \Delta G_{a,n,t} \tilde{A}_{n,t} + F_{E_n} + F_{E_t} + e_{a,n,t}.
\] (70)
Figures G13 and G14 display the regression results for price reaction windows of 1 to 10 days. This regression uses the entire analyst update $\Delta G_{a,n,t}$ instead of just the idiosyncratic analyst growth shock $u_{a,n,t}$. Unlike $u_{a,n,t}$, $\Delta G_{a,n,t}$ has within-quarter variation across stocks. Thus, even if for longer windows $\Delta p_{a,n,t}^{+}$ does not have much variation across analysts within stock-quarter, regression (70) can still estimate $c_1$. For this reason, the $c_1$ estimates in Figure G13 are all significant stable across window lengths.\footnote{If ex-post reversal explained the insignificance of the $c_1$ estimates from the baseline regression (34), we would not see stable $c_1$ estimates across window lengths from regression (70).}

Of course, $\hat{c}_1$ and $\hat{c}_2$ from (70) are not consistent estimates of the parameters $c_1$ and $c_2$ because $\Delta G_{a,n,t}$ likely does not satisfy moment conditions (27) and (28):

\[ \mathbb{E}[\Delta G_{a,n,t}e_{a,n}] \neq 0 \]  \hfill (71)
\[ \mathbb{E}[\Delta G_{a,n,t}\tilde{A}_ne_{a,n}] \neq 0. \]  \hfill (72)

Nevertheless, the $M_g$ estimates implied by $\hat{c}_1$ and $\hat{c}_2$ from (70) actually prove broadly consistent (if slightly larger) with those from the baseline regression (34). The $M_g$ estimates in Figure G14 range from 20 to 27 basis points, and so are roughly in line with the range of 7 – 16 basis points that I argue for, especially after accounting for standard errors.
Estimates of reduced-form parameters $c_1$ and $c_2$:

$$\Delta p_{a,n,t}^+ = c_1 \Delta G_{a,n,t} + \underbrace{c_2 \Delta G_{a,n,t} \bar{A}_{n,t}}_{\equiv M_g \beta^2} + FE_n + FE_t + e_{a,n,t}.$$

where $\Delta p_{a,n,t}^+$ is measured over different windows from 1 to 10 days.
Estimates of reduced-form parameters implied structural parameters $\beta$ and $M_g$ from the following regression:

$$\Delta p_{a,n,t}^+ = \underbrace{c_1}_{\equiv M_g \beta} \Delta G_{a,n,t} + \underbrace{c_2}_{\equiv M_g \beta^2} \Delta G_{a,n,t} \bar{A}_{n,t} + FE_n + FE_t + e_{a,n,t}.$$

where $\Delta p_{a,n,t}^+$ is measured over different windows from 1 to 10 days.

**G.3 Evidence from LTG Expectations**

This appendix extends the baseline analysis in Section 5 to measure the causal effect of long-term (as opposed to one-year) cash flow growth expectations on prices using the I/B/E/S long-term
earnings growth (LTG) expectations. The results of this analysis prove quantitatively consistent with those from Section 5.5. Appendix G.3.1 provides a simple benchmark range for the causal effect of long-term cash flow growth expectations on price (Appendix G.3.3 considers alternative benchmark ranges). Appendix G.3.2 presents the empirical results.

G.3.1 Benchmark Price Impact with Long-Term Growth Expectations

The benchmark range for the price impact of long-term growth expectations, denoted $M_{LTG}$, is

$$M_{LTG} \in [3, 5].$$

LTG expectations represent the analyst’s forecast for average EPS growth over the next 3 – 5 years. For example, an LTG expectation of 5% represents a forecast of 5% annual EPS growth in the average year over the next 3 – 5 years. So a 1% increase in LTG expectation represents a 1% higher forecasted annual EPS growth for the average year over the next 3 – 5 years.

How much price rises today in response to a change in 3 – 5 year expected cash flow growth depends (somewhat) on the timing of the quarterly growth shocks over that time period. The simplest assumption is that the entire increase in average forecasted growth is driven by a higher expected growth rate in the next quarter. For example, if LTG expectations represent 3 year average growth expectations, the assumption is a 1% increase in LTG captures a 3% increase in next-quarter expected growth and zero change is growth expectations thereafter. In this case, the price impact of long-term growth expectations, denoted $M_{LTG}$, is just

$$M_{LTG} = H \cdot M_g,$$

where $M_g$ is still the price impact of one-year growth expectations and $H$ is the horizon of the long-term growth expectations (so empirically $H \in [3, 5]$ years). Thus, under this assumption we have a benchmark range for $M_{LTG}$ of between 3 and 5, since we have a benchmark $M_g = 1$ from Section 4.4.

Other timing assumptions do not significantly alter this benchmark range, as discussed in Appendix G.3.3 below. The minimum possible benchmark range for $M_{LTG}$ is

$$M_{LTG} \in [2.7, 4.1],$$

which corresponds to the entire change in average expected over the next $H$ years being driven by a shock to quarterly expected growth in the last quarter of that time period (i.e. quarter $t + 4H$).
G.3.2 Empirical Results

The key empirical challenge raised by the LTG expectations is the lack of coverage. Specifically, the baseline analysis in Section 5.5 crucially relies on observing growth expectations from multiple analyst institutions for the same (stock, quarter) pair for two reasons:

1. To remove time-varying stock characteristics $\eta_n$ in the latent factor model (29) when extracting the idiosyncratic analyst growth shocks $u_{a,n}$.

2. To pin down the decay rate of analyst price impact as the number of analysts rises ($c_2$ in regression (34)) using the instrument $u_{a,n} \tilde{A}_n$, where $\tilde{A}_n$ is the demeaned number of analysts that rate stock $n$.

As displayed in Table E4, the average stock in the average quarter has one-year growth expectations from 10 analyst institutions with a standard deviation of 7 institutions. On the other hand, the average stock in the average quarter has LTG expectations from only 2 analyst institutions with a standard deviation of 1 institution. For this reason, extracting exogenous variation in LTG expectations and separately identifying $M_g$ from $\beta$ (which requires a precise estimate of $c_2$) prove difficult using the LTG expectations.

Thus, I measure $c_1 = M_{LTG}\beta$ using the same regression as in Section 5:

$$
\Delta p_{a,n,t}^+ = c_1 \Delta LTG_{a,n,t} - c_2 \Delta LTG_{a,n,t} \tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},
$$

where $\Delta LTG_{a,n,t}$ the full LTG expectation update. Since the $c_2$ estimate will not be significant (due to lack of variation in $\tilde{A}_{n,t-1}$), I use the estimated analyst influence $\beta = 0.06$ from Table 3 to back out $M_{LTG}$ from $c_1$.

Table G6 displays the regression results. The specification in column 4 proves most likely to satisfy moment conditions (27) and (28) since it includes stock-quarter fixed effects. The $c_1 = 1.4$ estimate implies a 1% higher analyst-reported LTG expectation raises price 1.4 basis points. Dividing $c_1 = 1.41$ by the estimated $\beta = 0.06$ from Table 3 (and dividing again by 100 to convert from basis points to percentages) yields

$$
M_{LTG} = 0.23.
$$

A 1% rise in investor long-term cash flow growth expectations raises price by 23 basis points, which is an order of magnitude smaller than the benchmark range $M_{LTG} \in [3, 5]$. Thus, using the LTG expectations data I again find the causal effect of investor growth expectations on prices proves far smaller than suggested by standard models.

In fact, $M_{LTG} = 0.23$ is a little more than three times as large as $M_g = 0.07$ from Table 3, which
is consistent with investors interpreting analyst LTG expectations as 3–4 year cash flow growth expectations, as discussed in Appendix G.3.1.

Since $\Delta LTG_{a,n,t}$ likely does not satisfy moment conditions (27) and (28):

$$\mathbb{E} [\Delta LTG_{a,n,t}e_{a,n}] \neq 0$$
$$\mathbb{E} [\Delta LTG_{a,n,t}\tilde{A}_{n,t}e_{a,n}] \neq 0,$$

I run the same regression using the idiosyncratic LTG shock $u_{a,n,t}$ extracted from factor model (29) using 5 latent factors. Table G7 reports the regression results. This regression has less power than that using the full LTG expectation update due to the difficulty in estimating the factor model discussed above. Nevertheless, the $c_1$ point estimates are similar to that reported column 4 of in Table G6, which includes stock-quarter fixed effects. The $c_1 = 1.7$ estimate in column 4 and $\beta = 0.07$ implies

$$M_{LTG} = 0.28,$$

which is still an order of magnitude smaller than the benchmark range $M_{LTG} \in [3, 5]$.

<table>
<thead>
<tr>
<th>Table G6: $c_1$ and $c_2$ Estimates Using Full LTG Updates</th>
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<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>$c_1$</td>
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<tr>
<td></td>
</tr>
<tr>
<td>$c_2$</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Quarter FE</td>
</tr>
<tr>
<td>Stock FE</td>
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<tr>
<td>Stock x Quarter FE</td>
</tr>
<tr>
<td>Quarter-Clustered SE</td>
</tr>
<tr>
<td>N</td>
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<tr>
<td>R-Squared</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

This table displays regression results for

$$\Delta p_{a,n,t}^+ = c_1 \Delta LTG_{a,n,t} - c_2 \Delta LTG_{a,n,t}\tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},$$

where $\Delta p_{a,n,t}^+$ is the price change 5 days after analyst institution $a$ reports an LTG expectation for stock $n$ in quarter $t$, $\Delta LTG_{a,n,t}$ is the corresponding quarter-over-quarter change in LTG expectation, and $\tilde{A}_{n,t-1}$ is the demeaned number of analysts that cover stock $n$ in the previous quarter $t-1$. $X_{n,t}$ represents controls, including stock, quarter, and stock × quarter fixed effects. All values are expressed in basis points (i.e. 1.0 is one basis point). The time period is 1982-01:2021-12.
Table G7: \(c_1\) and \(c_2\) Estimates Using Idiosyncratic LTG Shocks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_1)</td>
<td>1.81*</td>
<td>1.81*</td>
<td>1.81*</td>
<td>1.68*</td>
</tr>
<tr>
<td></td>
<td>(0.986)</td>
<td>(0.985)</td>
<td>(1.00)</td>
<td>(0.971)</td>
</tr>
<tr>
<td>(c_2)</td>
<td>-0.926</td>
<td>-0.923</td>
<td>-0.921</td>
<td>-0.876</td>
</tr>
<tr>
<td></td>
<td>(0.601)</td>
<td>(0.601)</td>
<td>(0.614)</td>
<td>(0.608)</td>
</tr>
</tbody>
</table>

Quarter FE Y Y Y Y
Stock FE Y
Stock x Quarter FE Y
Quarter-Clustered SE Y Y Y Y
N 65428 65428 65428 65428
R-Squared 0.0000415 0.0221 0.102 0.615

Standard errors in parentheses
* \(p<0.10\), ** \(p<0.05\), *** \(p<0.01\)

This table displays regression results for

\[
\Delta p_{a,n,t}^+ = c_1 u_{a,n,t} - c_2 u_{a,n,t} \tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},
\]

where \(\Delta p_{a,n,t}^+\) is the price change 5 days after analyst institution \(a\) reports an LTG expectation for stock \(n\) in quarter \(t\), \(u_{a,n,t}\) is the corresponding estimated idiosyncratic LTG shock, and \(\tilde{A}_{n,t-1}\) is the demeaned number of analysts that cover stock \(n\) in the previous quarter \(t-1\). \(X_{n,t}\) represents controls, including stock, quarter, and stock \(\times\) quarter fixed effects. All values are expressed in basis points (i.e. 1.0 is one basis point). The time period is 1982-01:2021-12.

G.3.3 Other Benchmark Ranges for \(M_{LTG}\)

From the present-value identity in Lemma 2 in Appendix B.4.1, the general price impact of a change in expected future dividends is:

\[
\Delta p_{n,t} = M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \Delta \tilde{d}_{n,t,s+1},
\]

where \(\Delta \tilde{d}_{n,t,s+1}\) is the percentage change in the expected dividend level in period \(t+s+1\) and the benchmark value of \(M_\mu\) is\(^{44}\)

\[
M_\mu = \frac{1}{1 + \delta},
\]

\(^{44}\text{From Lemma 2, we have}

\[
M_\mu = \frac{\kappa(1 + \bar{g})}{1 - \theta_{n,t-} + \kappa(1 + \delta)(1 + \bar{g})}.
\]

As discussed in Section 4.4, the benchmark case corresponds to \(\kappa = \infty\), in which case

\[
M_\mu = \frac{1}{1 + \delta}.
\]
for average dividend-price ratio $\delta$.

Since $M_\mu < 1$, the smallest price impact occurs when the long-term expected growth shock is driven by quarterly expected growth shocks as far into the future as possible. Generating a 1% increase in average expected growth over the next $H$ years requires a quarterly expected growth shock of $H\%$ (assuming no persistence in expected dividend growth). Thus, the smallest possible value of $M_{LTG}$ corresponds to an $H\%$ increase in expected dividend growth in quarter $t + 4H$ and no change in expected dividend growth in any other quarter. This shock proves the same as $H\%$ increase in the expected dividend level in every quarter starting in $t + 4H$:

$$\Delta \tilde{d}_{n,t,s} = 0\%, 1 \leq s < 4H$$
$$\Delta \tilde{d}_{n,t,s} = H\%, s \geq 4H.$$

The price impact of this shock is

$$M_{LTG} = M_\mu \delta \sum_{s=4H-1}^{\infty} M_\mu^s H$$
$$= M_\mu^{4H} \delta \sum_{s=0}^{\infty} M_\mu^s H$$
$$= M_\mu^{4H} \frac{\delta}{1 - M_\mu - H}$$
$$= M_\mu^{4H}(1 + \delta) H.$$

Calibrating $\delta = 0.01$ to match the historical average quarterly dividend-price ratio for the aggregate equity market yields:

$$M_{LTG} = \begin{cases} 
2.7, & H = 3 \text{ years} \\
4.1, & H = 5 \text{ years}
\end{cases}$$
Details of Koijen and Yogo (2019) Price Elasticity of Demand Measurement

To measure price elasticities of demand at the investor level, I follow the approach of Koijen and Yogo (2019). Since all of the identification happens in the cross section of equities, I drop all quarter subscripts. The estimated price elasticities vary by investor, stock, and quarter: \( \zeta_{i,n,t} \).

Koijen and Yogo (2019) place additional structure on the asset demand function from (9) and model the portfolio weight demanded in stock \( n \) as a function of stock characteristics, including the market equity (i.e. price, denoted \( m_{e,n} \)) of the stock:

$$
\log \theta_{i,n} = \alpha_{0,i} m_{e,n} + \sum_{k=1}^{K-1} \alpha_{k,i} x_{k,n} + FE_i + \epsilon_{i,n}^D,
$$

where \( x_{k,n} \) are stock characteristics (log book equity, profitability, investment, dividends to book equity, and market beta). The coefficient on market equity (\( \alpha_{0,i} \)) maps directly into the price elasticity of demand. However, since other asset demand shocks (\( \epsilon_{i,n}^D \)) are correlated with equilibrium prices, we need exogenous cross-sectional variation in market equity to consistently estimate \( \alpha_{0,i} \).

To this end, Koijen and Yogo (2019) construct an instrument for market equity based on cross-sectional variation in which investors’ investment universes stock \( n \) falls into. Specifically, the instrument is

$$
\bar{m}_{e,i,n} = \log \left( \sum_{j \neq i} A_j \frac{1_j(n)}{1 + \sum_{m=1}^{N} 1_j(m)} \right),
$$

where \( 1_j(n) \) is an indicator for if stock \( n \) falls into the investment universe of investor \( j \) and \( A_j \) is the assets under management of investor \( i \). One can interpret this instrument as the counterfactual market equity of stock \( n \) if all investors held an equal-weighted portfolio of the stocks in their investment universe. This instrument exploits only the wealth distribution and the investment universes of other investors, both of which I take as exogenous. This assumption proves reasonable because investment universes are defined by investment mandates, which are predetermined rules that don’t change in response to current demand shocks (\( \epsilon_{i,n}^D \)). Thus, if stock \( n \) exogenously falls into the investment universe of more or larger investors, it will face greater demand and will have greater market equity. Koijen and Yogo (2019) measure the investment universe of investor \( i \) as the set of all stocks this investor currently holds or has ever held in the previous eleven quarters.

One can estimate \( \alpha_{0,i} \), and the other \( \alpha_{k,i} \) coefficients, via GMM using the following moment condition:

$$
\mathbb{E} \left[ \epsilon_{i,n}^D \mid \bar{m}_{e,i,n}, \mathbf{x}_n \right] = 0.
$$

The price elasticities of demand for investor \( i \) (\( \zeta_i \)) can then be computed as the diagonal elements...
of
\[ \frac{\partial q_i}{\partial p} = -I + \alpha_{0,i} (\text{diag} \theta_i)^{-1} (\text{diag} \theta_i - \theta_i \theta_i') , \] (74)

where \( q_i \) is the vector of log shares held, \( p \) is the vector of log prices, and \( \theta_i \) is the vector of log portfolio weights.\(^{45}\)

\(^{45}\)Strictly speaking, the price elasticities from (74) vary by investor and stock (i.e. \( \zeta_{i,n} \)) since portfolio weights differ across stocks \( n \) for each investor \( i \). In practice, since individual stock portfolio weights are small, \( \zeta_{i,n} \) does not vary much across stocks \( n \) for each investor \( i \). Empirically I use the corresponding \( \zeta_{i,n,t} \) for each stock \( n \).
I Holdings Regression Estimation Details

This appendix provides details of estimating holdings regression (42).

I.1 Optimization Problem

I solve the following optimization problem:

\[
\min_{\{b_{1,i}, b_{2,i}\}, i, n} \sum_{i, n} \left[ \Delta \tilde{q}_{i,n,t} - (b_{1,i}S_{n,t} - b_{2,i}S_{n,t} \cdot \tilde{A}_{n,t-1}) \right]^2 + \lambda \sum_{i} \left( \left( \frac{b_{1,i} - b_{1,S}}{b_{1,S}} \right)^2 + \left( \frac{b_{2,i} - b_{2,S}}{b_{2,S}} \right)^2 \right) 
\] (75)

s.t. \( \tilde{q}_{i,n,t} = q_{i,n,t} + \zeta_{i,n,t} \left( c_1 S_{n,t} - c_2 S_{n,t} \tilde{A}_{n,t-1} \right) \)

\( b_{2,i} \leq b_{1,i} \) (enforces \( \beta_i \leq 1 \))

\( b_{1,S} = c_1 \zeta_S \) (definition of \( c_1 \))

\( b_{2,S} = c_2 \zeta_S \) (definition of \( c_2 \))

The first term in (75) is the standard least-squares loss function. The second term is the L2 penalty. I regularize deviations of \( b_{1,i} \) and \( b_{2,i} \) from their ownership-share weighted averages \( b_{1,S} = c_1 \zeta_S \) and \( b_{2,S} = c_2 \zeta_S \) to enable more efficient estimation. In particular, I regularize percentage deviations of \( b_{1,i} \) and \( b_{2,i} \) from \( b_{1,S} \) and \( b_{2,S} \). L2 regularization is scale-dependent: it penalizes larger coefficients to a greater extent than smaller coefficients. This asymmetric shrinkage would cause problems since \( b_{1,i} \) is larger in magnitude than \( b_{2,i} \) (since \( b_{2,i} = \beta_i b_{1,i} \) and \( \beta_i < 1 \)) and I want to take ratios of these coefficients. Thus, I express the penalty in terms of percentage deviations from \( b_{1,S} \) and \( b_{2,S} \) to ensure both \( b_{1,i} \) and \( b_{2,i} \) are penalized to the same extent.

I choose the regularization parameter \( \lambda \) via 10-fold cross-validation. In this way, I use the level of heterogeneity in \( b_{1,i} \) and \( b_{2,i} \) that best fits the data.

This optimization can be solved efficiently as a quadratic program with linear constraints using OSQP (Stellato et al. (2020)).

I use \( \zeta_S = 0.38 \), the average stock-level, ownership-share weighted price elasticity of demand in my sample using the estimated investor price elasticities from the approach of Koijen and Yogo (2019).

I.2 Subset of Analyst Institutions

While I use all institutions in each quarter to estimate factor model (24) and to estimate the analyst price impact panel regression (34), to estimate the investor-level regression (42) I retain only the idiosyncratic expected growth shocks associated with the 5 largest (by number of expectations
issued) analyst institutions in each quarter. Since, as discussed in Appendix C, I remove stock-
quarter and analyst institution-quarter fixed effects when estimating the idiosyncratic shocks $u_{a,n}$,
the sum of all $u_{a,n}$ would be zero by construction. Dropping smaller institutions, therefore, raises
the volatility of $S_n$ and so provides more power when estimating $\kappa^g_i$ and $\beta_i$. Using 5 analysts
maximizes power. As displayed in Figure I15, the results prove robust to using other numbers of
analyst institutions.

Retaining only the idiosyncratic growth shocks of the largest analyst institutions has a flavor of
the granular instrument variable estimator of Gabaix and Koijen (2020a).
This figure displays the estimated $\kappa_S^g$, $\beta_S$, and $M_g$ from (42) using different numbers of analyst institutions. Point estimates are the medians of the bootstrapped sampling distributions. 95% confidence intervals are bootstrapped (see Appendix I.3 for details). The time period is 1984-01:2021-12.
I.3 Bootstrapped Standard Errors

I compute bootstrapped confidence intervals for \( \kappa_S^g, \beta_S, \) and \( M_g \) as follows.

Let \( N_t \) be the number of unique stocks in quarter \( t \). In each quarter \( t \):

1. Pick a stock \( n \)

2. For each investor \( i \), collect all holdings changes \( \Delta q_{i,n,t} \) for that stock \( n \).

3. Repeat steps 1 and 2 a total of \( N_t \) times.

I compute regression (42) on this bootstrapped dataset and calculate \( \kappa_S^g, \beta_S \), and \( M_g \) from the estimated \( \kappa_i^g \) and \( \beta_i \). I repeat this process 500 times and report the mean as well as 2.5th, 50th, and 97.5th percentile estimates of each parameter.
<table>
<thead>
<tr>
<th>Paper</th>
<th>Table 2: Regression of portfolio weight on dummies for if expected return is in 0%-5%, 10%-15%, 20%+ (omitted category is expected return &lt;= 0%). Dummy coefficients: 2.7, 4.6, 10.2, 10.2, 5</th>
<th>1. Expected return of &lt;= 0 corresponds to 0 portfolio weight. 2. Average portfolio share of about 50% (constant in regression). 3. Calculate ( \kappa = (\text{Dummy Coefficient} - 0) / (\text{Expected Return Bin Midpoint} - 0) \times 1 / 0.5 )</th>
<th>Households, Aggregate Equity, Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vissing-Jorgensen (2003)</td>
<td>Table 1: Mean 10-year expected return is 10% (so 1% of this 10% is 0.1%). Mean portfolio share is 37%. 2. For log-log specification calculate ( \kappa = 0.05 / 0.1 \times 1 / 0.37 ). 3. For level-level specification calculate ( \kappa = 0.3 / 0.37 ).</td>
<td>1. Table 1: Average portfolio share is 70%. 2. For all specifications, calculate ( \kappa = \text{coefficient} / 0.7 ).</td>
<td>Households, Aggregate Equity, Market</td>
</tr>
<tr>
<td>Amronin &amp; Sharpe (2014)</td>
<td>Table 8: Regression of log portfolio weight on log 10-year expected return has coefficient 0.05. Regression of portfolio weight on 10-year expected return has coefficient 0.3.</td>
<td>Table 3: Regression of portfolio weight on 1-year expected return has coefficient 0.05.</td>
<td>Households, Aggregate Equity, Market</td>
</tr>
<tr>
<td>Ameriks, Kezdi, Lee &amp; Shapiro (2020)</td>
<td>Table 5: Cross-sectional regression of portfolio weight on 1-year expected return has coefficient of 0.7-1.2 depending on specification. Accounting for heterogeneity, above coefficient can rise to 3.5.</td>
<td>1. Table 1: Average portfolio share is 70%. 2. For all specifications, calculate ( \kappa = \text{coefficient} / 0.2 ).</td>
<td>Households, Aggregate Equity, Market</td>
</tr>
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<td>Giglio, Maggiori, Strobel &amp; Utkus (2021)</td>
<td>Table 4: Accounting for heterogeneity, above coefficient can rise to 3.5.</td>
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<td>Paper</td>
<td>Raw Estimates</td>
<td>My Assumptions</td>
<td>Converted Estimates</td>
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<tr>
<td><strong>Beutel &amp; Weber (2022)</strong></td>
<td>Table 4: 1% Regression of portfolio weight on expected return has coefficient</td>
<td>1. Table A.4.: Mean survey respondent has 33% of portfolio in stocks (21581 euros in stocks/65907 total wealth) 2. Calculate kappa = coefficient / .33 1. As suggested by the authors on page 23, I divide the regression coefficient by 12 to convert to a passthrough with respect to annual expected returns.</td>
<td>4-8.5</td>
</tr>
<tr>
<td></td>
<td>of 1.3% (OLS) - 2.8% (2SLS)</td>
<td></td>
<td></td>
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<tr>
<td><strong>Bacchetta, Tieche &amp; Van Wincoop (2020)</strong></td>
<td>Table 3: Regression of portfolio weight on long-run expected return (see paper for more details) has coefficient of 8-10</td>
<td>2. Median portfolio weight is 6%. 3. Calculate kappa = coefficient / 12 * 1 /0.06</td>
<td>11-14</td>
</tr>
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<td>Tables 4, 5, 6: Regressions of portfolio weights on 1-year expected return have</td>
<td>1. Table 1: Mean equity portfolio share is 33%. 2. Calculate kappa = coefficient / .33</td>
<td>3-12</td>
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<tr>
<td></td>
<td>coefficients of 2-4, 1-2, and 2-4, respectively</td>
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<td><strong>Dahlquist &amp; Ibert (2022)</strong></td>
<td>Table 9: Regression of portfolio weight on annual risk premium has coefficient</td>
<td>1. Table 1: Average risky asset portfolio share is 99%, equity share is 47%, real asset share is 11%, and private equity share 8% 2. Calculate kappa = coefficient / corresponding average portfolio share.</td>
<td>1-6</td>
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<td>of 1 (for all risky assets), 3.1 (for equity), 0.6 (for real assets), and 0.2 (for private equity)</td>
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