Do Subjective Growth Expectations Matter for Asset Prices?

Aditya Chaudhry*

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Abstract

I find the causal effect of subjective growth expectations on asset prices is far smaller than suggested by standard models. To quantify this causal effect, I develop an asset demand model in which Bayesian investors learn from analysts and other signals. A 1% rise in annual investor growth expectations raises price only 7 to 16 basis points, an order of magnitude less than in standard models. This small causal effect arises from the limited passthrough of beliefs to asset demand and is consistent with small price elasticities of demand. To reconcile this small causal effect with the strong correlation of growth expectations and prices, I provide evidence of reverse causality. Using flow-induced trading to instrument for prices, I find prices cause growth expectations.

*University of Chicago, Booth School of Business. (aditya.chaudhry@chicagobooth.edu). First draft: June 2021. I thank Niels Gormsen, Lars Hansen, Ralph Koijen, and Stefan Nagel for their invaluable advice and generous help. For comments, I thank Alexandru Barbu, Francesca Bastianello, Valentin Haddad, Zhiguo He, John Heaton, Lubos Pastor, Yueran Ma, Aaron Pancost, Alp Simsek, Pietro Veronesi, Eric Zwick, and participants of the Chicago Booth Asset Pricing Working Group, Chicago Economic Dynamics Working Group, Chicago Booth Finance Brown Bag, Inter-Finance PhD Seminar, Chicago Joint Program Conference, SFS Cavalcade North America 2022, Transatlantic Doctoral Conference 2022, 14th Annual SoFiE Post-Conference, and the Machine Learning in Economics Summer Institute 2022. All errors are my own. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. DGE-1746045. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

1 Introduction

A long history of work appeals to subjective beliefs about fundamentals to explain important phenomena in asset pricing and macro-finance, such as excess volatility, asset bubbles, and credit cycles (Keynes (1937); Minsky (1977); Kindleberger (1978); Shiller (1981)). This view has recently experienced a resurgence of interest due to the increasing availability of survey measures of subjective beliefs. Since beliefs can be measured with survey data, subjective belief models offer an appealing alternative to the rational expectations paradigm, which attributes most price variation to "dark matter": unobservable shocks to preferences or risk (Chen, Dou and Kogan (2019)). Empirically, surveyed cash flow growth expectations correlate strongly with asset prices. This correlation motivates models that explain variation in asset prices with biased and excessively volatile cash flow growth expectations (Bordalo et al. (2019, 2022); Nagel and Xu (2021); De La O and Myers (2021)).

However, recent work raises doubts over the quantitative strength of the core mechanism in this class of subjective belief models: the causal impact of subjective growth expectations on prices. A growing literature finds that investors do not trade strongly on their beliefs, which suggests subjective growth expectations may have little impact on prices (Merkle and Weber (2014); Meeuwis et al. (2018); Giglio et al. (2021*a*,*b*); Bacchetta, Tieche and Van Wincoop (2020); Beutel and Weber (2022)). Moreover, while subjective belief models interpret the strong correlation of growth expectations with prices as evidence of a large causal effect, this correlation need not imply causation.

This paper answers two questions. Does the strong correlation of subjective growth expectations with prices imply a large causal effect of growth expectations on prices? If not, how large is the causal effect of subjective growth expectations on prices?

First, I provide evidence of reverse causality, which implies the correlation between subjective growth expectations and prices is not evidence of a large causal effect. Using several variations of flow induced trading to instrument for prices, I find prices cause growth expectations. Thus, quantifying the strength of the core mechanism in subjective belief models requires direct measurement of the causal effect of subjective growth expectations on prices.

Second, I find the causal effect of subjective growth expectations on prices is small. I develop an asset demand model in which Bayesian investors learn from analysts and other signals. Empirically, a 1% increase in investor annual growth expectations raises price only 7 to 16 basis points. This causal effect is an order of magnitude smaller than in leading rational (e.g. Campbell and Cochrane (1999); Bansal and Yaron (2004); Barro (2006); He and Krishnamurthy (2013)) and behavioral (e.g. Barberis et al. (2015); Nagel and Xu (2021); Bordalo et al. (2022)) models, which imply a transitory 1% increase in growth expectations (i.e. with no persistence) raises price by 1%. Any persistence in growth expectations shocks makes this benchmark value is even larger than 1%. Thus, if the only mechanism through which growth expectations impact prices is that featured in standard models, then subjective growth expectations matter far less for asset prices than suggested by these models.

This small causal effect arises from the limited passthrough of beliefs to asset demand and is consistent with small price elasticities of demand. Previous work documents a low sensitivity of demand to investors' expected returns. This low sensitivity generates both inelastic demand and small demand curve shifts due to growth expectations shocks. When price rises, expected return falls, but demand adjusts little to that change in expected return and so is inelastic. Holding price fixed, increases in growth expectations raise expected return, but demand curves shift little in response to that change in expected return. While lower price elasticities amplify price impact, smaller demand curve shifts dampen price impact. These channels do not offset. Theoretically and empirically the dampening of price impact due to small demand shifts dominates. As an extreme example, if demand curves do not shift at all due to growth expectations shocks, then these shocks have no price impact regardless of price elasticity. Similarly, small demand shifts due to growth expectations shocks cause only small price changes even though demand is inelastic. This result builds on the notion of "myopia" in inelastic markets introduced by Gabaix and Koijen (2020*b*).

The small causal effect of subjective growth expectations on prices raises the possibility that subjective growth expectations cannot quantitatively explain important phenomena in asset pricing and macro-finance. If asset prices are insensitive to growth expectations, then extrapolative or overly optimistic growth expectations cannot quantitatively explain all excess volatility (Bordalo et al. (2019); Nagel and Xu (2021); Bordalo et al. (2022)), asset bubbles (Bordalo et al. (2021)), or credit cycles (Bordalo, Gennaioli and Shleifer (2018); Farhi and Werning (2020); Maxted (2020); Bordalo et al. (2021)). However, since this small causal effect is consistent with low price elasticities, it augments the importance of other demand shocks and so opens the door to other resolutions of asset pricing and macro-finance puzzles.

If subjective growth expectations do significantly distort asset prices, this distortion must operate through dynamic amplification mechanisms outside existing models that use measured subjective growth expectations to match asset pricing moments. I find the standard mechanism through which subjective growth expectations distort asset prices is far weaker empirically than assumed in these models. Yet other mechanisms outside existing models could heighten the importance of subjective growth expectations at longer time horizons. My empirical results motivate augmenting existing models with these alternative mechanisms. Furthermore, my empirical methodology provides a general framework for using data on beliefs, prices, and holdings to assess these alternative mechanisms.

I begin by presenting evidence of reverse causality, which undermines the common interpretation of the correlation of subjective growth expectations with prices. Since prices and expectations are jointly determined, measuring the causal effect of prices on growth expectations requires exogenous variation in prices. To this end, I extend the mutual fund flow-induced trading instrument of Lou (2012) to instrument for stock prices and examine how these exogenous price changes impact one-year earnings per share (EPS) growth forecasts from I/B/E/S analysts. Stock-level mutual fund trading induced by inflows and outflows is uninformed: mutual funds tend to scale up or scale down their preexisting holdings proportionally. Flow-induced trading is a relevant instrument: this uninformed trading has a large impact on stock prices. Moreover, as a shift-share instrument, flow-induced trading does not require mutual fund flows to be exogenous. A sufficient condition for exogeneity is that the ex-ante mutual fund ownership shares do not correlate with other variables besides price that impact growth expectation updates. This assumption proves reasonable because expectation updates depend on new information. The ex-ante mutual fund ownership shares by construction do not depend on new ex-post information and so satisfy the exclusion restriction. To assuage any endogeneity concerns about the standard flow-induced trading instrument, I consider a series of robustness checks. I also consider several extensions that use within stock-quarter variation in the timing of analyst announcements to provide exogenous variation in prices. These alternate specifications yield similar results to the baseline specification.

Using the flow-induced trading instrument, I find an exogenous 1% increase in stock price raises one-year analyst EPS growth expectations by 41 basis points. Thus, the correlation of subjective growth expectations with prices cannot be interpreted as evidence of a large causal effect of growth expectations on prices. Testing the core mechanism in subjective belief models requires measuring this causal effect.

Next, I provide an asset demand framework to formally define the causal effect of subjective growth expectations on prices and motivate an empirical strategy to measure it. Changes in growth expectations shift asset demand curves and prices adjust to clear markets. This framework links this causal effect to previous work measuring the passthrough of subjective beliefs to asset demand and previous work measuring 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 Koijen (2020*b*); Schmickler and Tremacoldi-Rossi (2022)). Moreover, this framework motivates regressions of price changes and investor-level quantity changes on shocks to investor growth expectations to identify the causal effect of growth expectations on prices.

However, given the unavailability of investor-level subjective growth expectations, I use analyst growth expectations, which creates two empirical challenges. First, I must measure the passthrough of analyst beliefs to investor beliefs. Small price reactions to analyst growth expectations could arise if either 1) the causal effect of investor growth expectations on prices is small, or 2) analyst expectations are a poor proxy for investor growth expectations. Distinguishing these channels requires measurement of the passthrough of analyst beliefs to investor beliefs. Second, given the reverse causality result, I must extract exogenous shocks to observed analyst growth expectations not driven by price changes.

To solve the first challenge, I model investors as Bayesians who learn from analysts, as well as other signals, and measure analyst influence on investor beliefs. Bayesian learning imposes structure on how analyst influence varies in the cross section of equities. In particular, Bayesian learning implies signal averaging: the influence of each analyst declines with the number of analysts who cover a stock. This signal averaging mechanism appears in a large class of non-Bayesian learning models as well. Thus, cross-sectional variation in the number of analysts who cover each stock identifies analyst influence on investor expectations. This use of signal averaging is a novel method to identify analyst influence on investor beliefs without observing investor beliefs.

To solve the second challenge and extract exogenous shocks to analyst 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.). Stripping out these common factors yields exogenous variation in analyst beliefs uncorrelated with other sources of asset demand that impact prices. I use collaborative filtering to estimate the latent factor model (Goldberg et al. (1992); Funk (2006); Koren and Bell (2015)). This approach overcomes the limited efficiency of standard factor model estimation methods (e.g. PCA) in this setting where each analyst institution reports a relatively small number of expectations in each quarter.

Under some homogeneity assumptions, which I later relax, the causal effect of subjective growth expectations on prices can be identified in the cross section of equities from price and beliefs data alone. Specifically, the two homogeneity assumptions required are that analyst influence on investor beliefs and the sensitivity of asset demand to growth expectations do not vary across investors. Regressions of high-frequency price changes shortly after analyst report releases on idiosyncratic analyst growth expectations shocks and their interaction with the number of analysts covering each stock pin down both analyst influence and the causal effect of investor growth expectations on prices. These regressions imply that a 1% increase in annual investor growth expectations raises stock price by only 7 basis points.

The causal effect of subjective growth expectations on prices can be identified without these homogeneity assumptions using investor-level holdings data. To this end, I use institutional stock holdings data from SEC Form 13F. Controlling for investor-specific price elasticities of demand (measured following the approach of Koijen and Yogo (2019)) and equilibrium price changes allows for isolation of low-frequency (quarterly) demand curve shifts from the observed changes in equilibrium quantities demanded. In the cross section of each investor's holdings, regressions of these demand curve shifts on idiosyncratic analyst growth expectations shocks and their interaction with the number of analysts covering each stock pin down both analyst influence and the sensitivity of demand to investor growth expectations at the investor level. This analysis demonstrates the limited passthrough of beliefs to asset demand found in previous work for specific subsets of investors is actually a marketwide phenomenon. Aggregating the sensitivity of demand to investor growth expectations across investors and scaling by the aggregate price elasticity of demand identifies the causal effect of investor growth expectations on prices under full investor heterogeneity. This procedure finds that a 1% increase in annual investor growth expectations raises stock price by only 16 basis points. This paper represents the first use of subjective beliefs data in asset demand systems.

The remainder of this paper proceeds as follows. Section 1.1 reviews the related literature. Section 2 defines at at high level the two directions of causality quantified in this paper. Section 3 discusses the data I use. Section 4 presents evidence of reverse causality: a causal impact of prices on growth expectations. Section 5 presents a theoretical framework to formally define the causal effect of subjective growth expectations on prices. This section also explains how the low sensitivity of demand to expected return generates both inelastic demand and a small causal effect of growth expectations on prices. Section 6 uses price and beliefs data to identify the causal effect of growth expectations on prices under assumptions about investor homogeneity. Section 7 uses holdings data to relax these homogeneity assumptions and presents the associated estimates of the causal effect. 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 in 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 of 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 market price levels and returns. Bordalo et al. (2019), Nagel and Xu (2021), and Bordalo et al. (2022) investigate the extent to which long-term growth expectations correlate with cross-sectional and time-series variation in price levels. De La O and Myers (2021) find in a variance decomposition that subjective growth 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.[1] In light of this endogeneity concern, I use the demand-based asset pricing approach to develop an empirical strategy to cleanly identify the causal effect of subjective growth expectations on asset prices. Since this identification strategy uses cross-sectional variation across assets, I focus on the cross section of stocks (as in Bordalo et al. (2019)) instead of the time series of the equity market

[1] This reverse causality result also broadly relates to the corporate finance literature studying the dependence of managerial decisions on prices (e.g. Giammarino et al. (2004); Edmans, Goldstein and Jiang (2012)).

(as in Nagel and Xu (2021); De La O and Myers (2021); Bordalo et al. (2022)).

Second, a large literature studies the passthrough of beliefs to asset demand. This literature finds a limited sensitivity of demand to expected returns: investors do not trade aggressively based on their beliefs. 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. (2021*a*); Ameriks et al. (2020); Andonov and Rauh (2020); Dahlquist and Ibert (2021)). Additionally, investors adjust their portfolio weights little in response to changes in expected returns (Merkle and Weber (2014); Meeuwis et al. (2018); Giglio et al. (2021*a*); Bacchetta, Tieche and Van Wincoop (2020); Giglio et al. (2021*b*); Beutel and Weber (2022)). This paper fills three gaps in the previous literature. First and foremost, I focus on the asset pricing implications of the limited passthrough of beliefs to demand, which have not been studied in previous work. The insensitivity of asset demand to expectations limits the price impact of subjective growth expectations. Second, while most of this literature focuses on household expectations and holdings, I find the limited passthrough of expectations to holdings is a marketwide phenomenon.[2] Third, whereas previous work measures the passthrough of subjective expected returns to asset demand, this paper focuses on subjective growth expectations.

Third, a growing literature measures 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 Koijen (2020*b*); Haddad, Huebner and Loualiche (2021); Li (2021); 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 in standard models (Petajisto (2009)). The goal of this paper is not to measure price elasticities of demand. Instead, I investigate the implications of inelasticity for the role beliefs can play in determining asset demand and prices. In particular, inelastic demand driven by an insensitivity of demand to expected returns implies a small causal effect of subjective growth expectations on prices. This result builds on the notion of "myopia" in inelastic markets introduced by Gabaix and Koijen (2020*b*).

Fourth, a large body of work examines the link between equity research analyst reports and asset prices. This literature finds directionally sensible price reactions for individual stocks upon the release of new analyst ratings, price targets, and earnings forecasts (Davies and Canes (1978); Groth et al. (1979); Barber and Loeffler (1993); Stickel (1995); Albert Jr and Smaby (1996); Francis and Soffer (1997); Park and Stice (2000); Barber et al. (2001); Brav and Lehavy (2003); Irvine (2003); Asquith, Mikhail and Au (2005); Kerl and Walter (2008); Fang and Yasuda (2014); Ishigami and Takeda (2018)). Unlike this previous literature, I measure the causal effect of investor, not analyst,

[2] Some previous work has examined certain types of institutional investors (Andonov and Rauh (2020); Bacchetta, Tieche and Van Wincoop (2020); Dahlquist and Ibert (2021)).

growth expectations on prices. To that end, I use analyst reports as information shocks to investor growth expectations. Therefore, I am not directly concerned with analyst expectations; I simply use analyst expectations to instrument for investor beliefs.

2 Fixing Ideas: Two Directions of Causality

Contrary to the interpretation adopted by much of the beliefs literature, the strong correlation of surveyed growth expectations and asset prices may not imply a large causal effect of investor growth expectations on prices. First, two directions of causality could give rise to this strong correlation: 1) a causal effect of growth expectations on prices and 2) reverse causality, a causal effect of prices on growth expectations. Second, investors' true growth expectations may not align perfectly with surveyed growth expectations, which usually come from equity research analysts due to the lack of surveys on investor growth expectations.

The following system of simultaneous equations captures these two directions of causality and this growth expectations misalignment:

$$P = M_g G^I + \epsilon \tag{1}$$

$$G^I = \beta G^A + \nu \tag{2}$$

$$G^A = \alpha P + u, \tag{3}$$

where G^I and G^A are investor and analyst subjective growth expectations, respectively, and P is log price. For simplicity, assume ϵ, ν, and u are uncorrelated. I do not make this assumption empirically; much of the empirical strategy is dedicated to constructing exogenous price and growth expectation shifters. To convey the intuition, this section considers a representative investor whose growth expectations do not depend on prices. Section 5 relaxes these assumptions.

M_g represents the causal effect of investor subjective growth expectations on prices: how much would price rise due to a 1% rise in growth expectations via ν holding other determinants of prices fixed (e.g. a rise in growth expectations due to the "animal spirits" of Keynes (1937)).[3] β is the passthrough of analyst expectations to investor expectations and reflects potential misalignment between these expectations. α denotes the causal effect of prices on analyst growth expectations (i.e. reverse causality): how much would analyst growth expectations rise due to a 1% rise in price

[3] As discussed in Section 5, M_g does capture any amplification of price impact due to *investor* learning from prices (i.e. investor growth expectations rise, which raises price, which further raises investor growth expectations, etc.), e.g. as in Bastianello and Fontanier (2021*b*). M_g does not capture amplification of price impact due to *analyst* learning from prices (i.e. investor growth expectations rise, which raises price, which raises analyst growth expectations, which further raises investor growth expectations, etc.). The parameter that captures this amplification channel is $M_g/(1 - M_g\beta\alpha)$. However, this channel empirically is empirically weak. I find $M_g \approx 0.1, \beta = 0.06$, and $\alpha \approx 0.4$, and so this channel amplifies M_g by only a factor of 1.002.

via ϵ holding other determinants of growth expectations fixed (e.g. a rise in price due to exogenous supply shocks as in Grossman and Stiglitz (1980)).

The literature that explains variation in asset prices with measured subjective growth expectations (e.g. Bordalo et al. (2019, 2022); Nagel and Xu (2021); De La O and Myers (2021)) interprets the correlation of analyst growth expectations (G^A) and prices (P) as evidence of a large M_g. In particular, this literature uses analyst growth expectations as a proxy for the expectations of a representative investor. This interpretation assumes:

1. $\alpha = 0$: There is no causal effect of prices on analyst growth expectations. The class of models that uses measured subjective growth expectations to match asset pricing moments does not feature rational learning from prices (e.g. Grossman and Stiglitz (1980)) or price extrapolation.[4] However, these mechanisms raise the possibility that empirically $\alpha \neq 0$.

2. $\beta = 1$ and $\nu = 0$: Investor expectations are the same as analyst growth expectations. The class of models that uses measured subjective growth expectations to match asset pricing moments features a representative investor and so admits only one set of beliefs. However, a large literature finds evidence of belief heterogeneity[5], which raises the possibility that investors and analysts may disagree.

Under these two assumptions, the correlation of analyst growth expectations with prices *does* provide evidence of the core mechanism in subjective belief models: a large causal effect of investor growth expectations on prices (a large M_g). In this case, any behavioral biases observed in analyst growth expectations reflect biases in investor expectations and significantly distort asset prices. However, previous work has not justified these assumptions by quantifying α or β. If $\alpha > 0$, then analyst growth expectations could correlate strongly with prices even if M_g is small.

This paper empirically challenges the mechanism in subjective belief models. Using exogenous shocks to prices (ϵ in (1)), I find evidence of reverse causality ($\alpha > 0$). This reverse causality result necessitates direct measurement of M_g to quantify the strength of the mechanism in subjective belief models. Measuring M_g entails two empirical difficulties. First, since I only observe analyst, not investor, growth expectations, I must separately identify the passthrough of analyst expectations to investor expectations β. Second, the presence of reverse causality implies I must extract exogenous shocks to observed analyst growth expectations not driven by price changes (u in (3)). I find M_g is empirically an order of magnitude smaller than assumed in standard models. In this sense, subjective growth expectations matter far less for asset prices than assumed in these models.

[4] E.g. Hong and Stein (1999); Barberis et al. (2018); Bastianello and Fontanier (2021*a*); see Barberis (2018) for a survey

[5] Malmendier and Nagel (2016); Landvoigt (2017); Ben-David et al. (2018); Meeuwis et al. (2018); Bailey et al. (2019); D'Acunto et al. (2019); Giglio et al. (2021*a*); Das, Kuhnen and Nagel (2020); Leombroni et al. (2020); Kindermann et al. (2021); Weber, Gorodnichenko and Coibion (2022)

3 Data

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

I use I/B/E/S analyst earnings-per-share (EPS) forecasts to construct one-year growth expectations. I/B/E/S reports EPS forecasts at the quarter $\times$ horizon $\times$ analyst institution $\times$ analyst $\times$ stock level. For example, I 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 fiscal years ahead with varying 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 EPS forecasts for one fiscal year ahead 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.[6] I scale by trailing one-year EPS to obtain annual EPS growth expectations and take quarter-over-quarter changes.[7] Thus, I obtain a stock $\times$ analyst institution $\times$ quarter panel of quarterly changes in one-year EPS growth expectations.[8]

I obtain stock price data from CRSP.

I use institutional holdings data from two sources. First, to construct the flow-induced trading instrument of Lou (2012) I use mutual fund holdings from the Thomson Reuters S12 database and mutual fund flows from the CRSP Mutual Fund database. Second, to cover a broader set of investors 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 long holdings at the quarterly frequency.[9] 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 $2,173,492$ quarterly changes in analyst-reported annual growth expectations 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.

[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]If the trailing one-year EPS is negative I use its absolute value. All results prove robust to dropping firms with negative trailing one-year EPS.

[8]I winsorize these final values at the 5% level to remove some extremely large outliers.

[9]Short positions are not reported in the 13F data.

4 Reexamining Existing Evidence: Reverse Causality

This section presents evidence of reverse causality: a causal effect of prices on subjective growth expectations. This result undermines the interpretation of the correlation of growth expectations with prices as a evidence of the core mechanism in subjective beliefs models: a large causal effect of growth expectations on prices. Reverse causality also necessitates a more structured approach to measuring the causal effect of growth expectations on prices since OLS regressions will not yield consistent estimates.

As discussed in Section 2, the reverse causality concern is that prices and growth expectations are jointly determined in equilibrium, leading to the classic simultaneous equations problem. 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.[10] We have the following system of simultaneous equations:

$$\Delta p_{a,n,t} = C\Delta G_{a,n,t} + Mz_{a,n,t} + \epsilon_{a,n,t} \tag{4}$$

$$\Delta G_{a,n,t} = \alpha\Delta p_{a,n,t} + \nu_{a,n,t}. \tag{5}$$

Analyst growth expectations have a causal effect on prices (C), and vice versa (α). Note that C in (4) is the causal effect of *analyst* growth expectations on prices, not the causal effect of investor growth expectations on prices. In the notation from Section 2, $C = M_g\beta$. 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 (5). Thus, I need an instrument $z_{a,n,t}$ that provides exogenous variation in prices. This instrument must satisfy:

1. (Relevance) $M \neq 0$ in (4): 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 several instruments based on the mutual fund flow-induced trading (FIT) instrument of Lou (2012). Section 4.1 justifies the standard FIT instrument and Section 4.2 provides estimates of α. Section 4.3 then considers a series of robustness checks to address any endogeneity concerns about the standard FIT instrument. This section also introduces a modified version of the FIT instrument that exploits within stock-quarter variation in the timing of analyst report releases. These alternate specifications yield quantitatively similar results.

[10] If analyst institution a reports more than one growth expectation for stock n in each of quarter $t-1$ and quarter t (about 25% of (analyst institution, stock, quarter) observations fall into this category), I use the dates corresponding to the first announcement in $t-1$ and the last announcement in t to construct $\Delta p_{a,n,t}$.

4.1 Exogenous Price Variation: FIT Instrument

I use the Lou (2012) mutual fund flow-induced trading instrument to obtain the exogenous variation in prices needed to test for reverse causality. Section 4.3 considers refinements and extensions of this instrument.

Flow-induced trading (FIT) provides exogenous price variation in the cross section of stocks. 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 tend to scale up or scale down their preexisting holdings proportionally to their preexisting portfolio weights. For example, a \$1 inflow would induce an S&P 500 index fund to mechanically allocate about five additional cents to Apple (since the market cap weight of Apple in the S&P 500 is about 5%). Thus, this mechanical component of cross-sectional trading induced by flows is uninformed.

To construct the FIT instrument, I first calculate the quarterly flow to mutual fund i as

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

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 predicted mechanical trading by fund i in stock n induced by this quarterly flow is then[11]

$$\text{FIT}_{i,n,t}=\text{ SharesHeld }_{i,n,t-2}\cdot\text{ Flow }_{i,t}.$$

I aggregate this flow-induced trading in stock n across all funds and scale by the total number of shares outstanding to obtain the predicted flow-induced trading in stock n in quarter t[12]:

$$\text{FIT}_{n,t}=\frac{\sum_{\text{fund } i}\text{FIT}_{i,n,t}}{\text{SharesOutstanding}_{n,t-2}}. \tag{6}$$

As a shift-share instrument, the identifying variation in the FIT instrument comes from hetero-

[11]Note that it does not matter if the passthrough of flows to trading is not one-to-one. Let $\text{FIT}^{True}_{i,n,t}$ be the true, unobserved flow-induced trading by fund i in stock n due to flows in quarter t. Let $\text{FIT}^{True}_{i,n,t}=b\text{FIT}_{i,n,t}+e_{i,n,t}$. It doesn't matter if $b\neq 1$ or $e_{i,n,t}\neq 0$ as long as the relevance condition holds (the observed $\text{FIT}_{n,t}$ impacts price) and exclusion restriction $\mathbb{E}[\text{FIT}_{n,t}\nu_{a,n,t}]=0$ holds. That is, it doesn't matter if the observed FIT instrument is "measured with error" with respect to the true, unobserved FIT instrument. $b\neq 1$ or $e_{i,n,t}\neq 0$ will bias the estimate of the first-stage coefficient $M/(1-\alpha C)$ in (4), but will not affect the consistency of the second-stage estimate of α (since the reduced-form coefficient will be biased to exactly the same extent as the first-stage coefficient, and so the bias will cancel out when computing the second-stage α estimate).

[12]This specification is closer to that in Li (2021) than to the original specification in Lou (2012) in that I do not multiply the numerator summand by a "partial scaling factor" to reflect the fact that mutual funds may buy or sell less than one dollar in existing positions per dollar of flow they receive due to liquidity or other constraints. However, while Li (2021) scales by the total number of shares held by all mutual funds in the previous quarter, I scale by the number of shares outstanding so $\text{FIT}_{n,t}=0.01$ can be interpreted as buying 1% of stock n's shares.

geneous ownership shares (Goldsmith-Pinkham, Sorkin and Swift (2020)):

$$S_{i,n,t-2} = \frac{\text{SharesHeld }_{i,n,t-2}}{\text{SharesOutstanding}_{n,t-2}}.$$

$S_{n,i,t-2}$ represents the proportion of all shares of stock n owned by mutual fund i in quarter $t-2$. The identifying assumption is that these ex-ante ownership shares (from quarter $t-2$) do not correlate with non-price determinants of growth expectations updates (from quarter $t-1$ to t):

$$\mathbb{E}\left[S_{i,n,t-2}\nu_{a,n,t} \mid \text{Controls}\right] = 0, \tag{7}$$

where controls includes stock and quarter fixed effects as well as stock characteristics. (7) is a sufficient condition for $\mathbb{E}\left[\text{FIT}_{n,t}\nu_{a,n,t} \mid \text{Controls}\right] = 0$.[13] For example, in the cross section of stocks within each quarter, analyst growth expectation updates (from quarter $t-1$ to t) should not be more positive for stocks with larger Vanguard Explorer Fund ownership shares from quarter $t-2$.

Why is this assumption reasonable? Because changes in growth expectations depend on new information (in quarters $t-1$ or t), which by construction cannot affect the ex-ante ownership shares (from quarter $t-2$). Any information in the ex-ante ownership shares is already incorporated into the lagged expectation $G_{a,n,t-1}$, and so is differenced out in $\Delta G_{a,n,t}$. Old information (from quarter $t-2$) can correlate with old (from quarter $t-1$) and new (from quarter t) expectations. However, old information does not correlate with *changes* in expectations (from quarter $t-1$ to quarter t).

This identification strategy does *not* require mutual fund flows to be exogenous. Thus, while previous work documents correlations of flows with surveyed beliefs (Greenwood and Shleifer (2014)), past performance (Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998)), and past flows (Lou (2012)), none of these correlations threaten this strategy. I assume only that the ex-ante ownership shares do not correlate with non-price determinants of growth expectations.

4.2 Empirical Results

Using the FIT instrument, I run a two-stage least-squares regression and find $\alpha > 0$: there is a causal effect of prices on subjective growth expectations.

Specifically, I run the following two-stage least-squares regression:

$$\begin{aligned} \Delta p_{a,n,t} &= a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t} \\ \Delta G_{a,n,t} &= b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}. \end{aligned} \tag{8}$$

[13] The intuition for why exogeneity of the ex-ante ownership shares proves sufficient for $\mathbb{E}\left[\text{FIT}_{n,t}\nu_{a,n,t} \mid \text{Controls}\right] = 0$, is that using the actual FIT instrument is equivalent to using the ownership shares $S_{i,n,t-2}$ as instruments in an overidentified GMM system with a particular weighting matrix (Goldsmith-Pinkham, Sorkin and Swift (2020)). Appendix A.1 provides a simple one-period, one-analyst, two-fund example to illustrate this argument.

The first stage regresses price changes between analyst reports ($\Delta p_{a,n,t}$) on the FIT instrument ($\text{FIT}_{n,t}$). The second stage regresses analyst growth expectations changes ($\Delta G_{a,n,t}$) on instrumented price changes ($\Delta \hat{p}_{a,n,t}$). $X_{n,t}$ represents controls including stock and quarter fixed effects as well as one-quarter lagged (i.e. from quarter $t-1$) stock characteristics motivated by Fama and French (2015) and used by Koijen and Yogo (2019): log book equity, profitability, investment, market beta, and the dividend-to-book equity ratio (instead of the market-to book equity ratio, which would contain price).[14]

Table 1 displays the regression results. The OLS regressions of growth expectations on prices in columns 1 and 2 display a strong correlation between these objects, as documented in previous work (Bordalo et al. (2019, 2022); Nagel and Xu (2021); De La O and Myers (2021)). The first stage regressions in columns 3 and 4 are strong with F-statistics of over 15 (partial F-statistics of 16 and 15, respectively). The reduced form regressions of expectations changes on the FIT instrument in columns 5 and 6 are also significant. The second-stage α estimates in columns 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 growth expectations by 41 basis points.[15]

Appendix A.3 repeats two-stage least squares regression (8) using the long-term earnings growth (LTG) expectations focused on by Bordalo et al. (2019, 2022) and Nagel and Xu (2021). There is causal effect of prices on LTG expectations. An exogenous 1% increase in price raises LTG expectations by 16 basis points.

This reverse causality result undermines the common interpretation of the correlation of growth expectations with prices. This correlation does *not* provide evidence of the core mechanism in subjective belief models: a large causal effect of growth expectations on prices. Quantifying the strength of that mechanism requires direct measurement of this causal effect. However, measuring this causal effect demands a more structured approach since OLS regressions of prices on growth expectations will not yield consistent estimates due to reverse causality.

There are multiple potential mechanisms that may underlie this causal effect of prices on analyst growth expectations. For example, analysts may learn from prices because they believe prices reflect private information known to investors, as in Grossman and Stiglitz (1980). Analysts may also extrapolate fundamentals from prices.[16] Alternatively, analysts may simply adjust their growth expectations to justify prevailing stock prices. I do not take a stance on the mechanism in this paper. Regardless of the mechanism, this reverse causality result undermines the interpretation of the correlation of subjective growth expectations with prices in much of the beliefs literature.

[14] Appendix Figure A1 displays binscatter plots for the first-stage and reduced-form regressions in (8).

[15] Appendix Figure A2 illustrates these results prove robust to alternative specifications.

To determine if the effect of prices on growth expectations reverts at longer horizons, I add lagged price changes to (8). I find no significant evidence of reversal, as displayed in Appendix Table A1.

[16] Note behavioral models where prices affect expectations typically involve expectations in the current period that depend on *past* price changes (e.g. Hong and Stein (1999) or Barberis et al. (2018); see Barberis (2018) for a survey). Fontanier (2021) features fundamental extrapolation from the current price.

Table 1: Causal Effect of Prices on Growth Expectations

	(1) OLS	(2) OLS	(3) First Stage	(4) First Stage	(5) Reduced Form	(6) Reduced Form	(7) 2SLS	(8) 2SLS
$\Delta p_{a,n,t}$	0.365***	0.303***					0.417**	0.411**
	(0.0475)	(0.0250)					(0.169)	(0.172)
$\text{FIT}_{n,t}$			2.449***	2.397***	1.021**	0.985**		
			(0.620)	(0.607)	(0.459)	(0.456)		
Stock Characteristics		Y		Y		Y		Y
Quarter FE		Y	Y	Y	Y	Y	Y	Y
Stock FE		Y	Y	Y	Y	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
N	1311394	1311394	1311394	1311394	1311394	1311394	1311394	1311394
F	58.97	27.65	15.60	19.57	4.952	4.255	6.066	4.519
R-Squared	0.0245	0.0909	0.226	0.230	0.0767	0.0780		

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:

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

The first stage regresses 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 annual growth expectations ($\Delta G_{a,n,t}$) on the instrumented price changes ($\Delta \hat{p}_{a,n,t}$). 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.

4.3 Refining the Instrument

This section discusses robustness checks and extensions of the standard FIT instrument that I use to assuage endogeneity concerns.

The key threat to identification is the possibility that analyst expectation updates depend on lagged information. This situation can only arise if analysts fail to incorporate all available information from quarter $t-2$ into growth expectations in quarter $t-1$. For example, ex-ante ownership shares may depend on ex-ante stock characteristics:

$$S_{i,n,t-2} = \boldsymbol{b}_i^{'}\boldsymbol{X}_{n,t-2} + \tilde{S}_{i,n,t-2}.$$

At the same time, if analysts form expectations suboptimally (i.e. in a non-Bayesian manner), then analyst expectation updates may also depend on lagged stock characteristics

$$\Delta G_{a,n,t} = \alpha\Delta p_{a,n,t} + \underbrace{\boldsymbol{\lambda}^{'}\boldsymbol{X}_{n,t-2} + \tilde{\nu}_{a,n,t}}_{\equiv \nu_{a,n,t}}, \tag{9}$$

because analysts did not fully incorporate this information in $G_{a,n,t-1}$. In this situation, the exclusion restriction is violated: $\mathbb{E}\left[S_{i,n,t-2}\nu_{a,n,t}\right] \neq 0$.

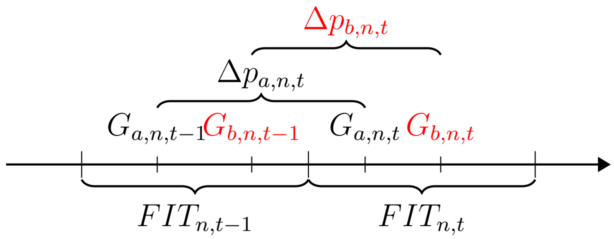
The next two sections consider robustness checks and extensions to address this concern.

4.3.1 Robustness Checks for Standard FIT Instrument

First, I control for stock characteristics in regression (8). As Table 1 exhibits, controlling for characteristics from quarter $t-1$ does not change the second-stage α estimate. Table A.2 in Appendix A2 additionally controls for characteristics (log book equity, profitability, investment, market beta, and dividend-to-book equity ratio) from quarter $t-2$, which absorbs the variation in expectation updates driven by the lagged characteristics ($\boldsymbol{\lambda}^{'}\boldsymbol{X}_{n,t-2}$) in (9). Doing so yields essentially the same second-stage α estimate as in Table 1 (42 basis points instead of the baseline 41 basis points), which suggests endogeneity due to sluggish updating may not be a serious concern.

Second, in Appendix A.2 I construct the FIT instrument using earlier lags of the ownership shares. Whereas the baseline specification finds $\alpha = 41$ basis points using ownership shares lagged by two quarters, Table A3 demonstrates that lagging the ownership shares as far back as four quarters delivers similar α estimates (41 to 44 basis points). The similarity of the second-stage α estimates across lags also suggests that endogeneity due to sluggish updating may not be a serious concern.

Figure 1: Within Stock-Quarter Timeline



Staggered timing of expectation releases for two analyst institutions a and b for stock-quarter pair (n, t). Institution b reports expectations for stock n later than institution a in both $t-1$ and t, so $\Delta p_{b,n,t}$ is more exposed to $\text{FIT}_{n,t}$ and less exposed to $\text{FIT}_{n,t-1}$ than $\Delta p_{a,n,t}$.

4.3.2 Alternate Instrument Using Within Stock-Quarter Variation

I develop a modified version of the FIT instrument that exploits within stock-quarter variation in the timing of analyst report releases. This strategy allows for the use of stock-quarter fixed effects, which absorb any variation in expectation updates driven by stock characteristics (lagged and contemporaneous) in (9). This section outlines this strategy. See Appendix A.4 for details.

Multiple analyst institutions issue growth expectations for each stock in each quarter and generally not on the same day. Consider the timing in Figure 1. Institution b reports expectations for stock n later than institution a in quarters $t-1$ and t. Thus, b's inter-announcement price change $\Delta p_{b,n,t}$ is more exposed to $\text{FIT}_{n,t}$ and less exposed to $\text{FIT}_{n,t-1}$ than $\Delta p_{a,n,t}$. This variation in analyst report timing allows construction of an analyst-stock-quarter specific instrument[17]:

$$\text{FIT}_{a,n,t} = \underbrace{\frac{\#\text{ days elapsed in } t-1 \text{ since } G_{a,n,t-1}}{92}}_{\equiv w^1_{a,n,t}} \cdot \text{FIT}_{n,t-1} + \underbrace{\frac{\#\text{ days elapsed in } t \text{ until } G_{a,n,t}}{92}}_{\equiv w^2_{a,n,t}} \cdot \text{FIT}_{n,t}.$$

As a shift-share instrument, the identifying variation in $\text{FIT}_{a,n,t}$ comes from within stock-quarter variation in the timing weights $w^1_{a,n,t}$ and $w^2_{a,n,t}$ across analysts. The identifying assumption is that the within stock-quarter analyst timing is not correlated with non-price determinants of expectation updates:

$$\mathbb{E}\left[w^1_{a,n,t}\nu_{a,n,t} \mid \text{Fixed Effect}_{n,t}\right] = \mathbb{E}_{n,t}\left[w^2_{a,n,t}\nu_{a,n,t} \mid \text{Fixed Effect}_{n,t}\right] = 0,$$

[17] In this section I construct $\text{FIT}_{n,t}$ using ownership share weights from quarter $t-1$ ($S_{i,n,t-1}$) instead of those from $t-2$ ($S_{i,n,t-2}$) as in Section 4.1. Doing so improves power. Using $S_{i,n,t-1}$ in Section 4.1 would potentially violate the exclusion restriction there because $S_{i,n,t-1}$ (measured at the end of quarter $t-1$) occurs in the middle of the expectation update from quarter $t-1$ to quarter t. In this section, however, the endogeneity of $S_{i,n,t-1}$ is not a problem: the identifying assumption is now $\mathbb{E}_{n,t}[w_{a,n,t-1}\nu_{a,n,t}] = \mathbb{E}_{n,t}[w_{a,n,t}\nu_{a,n,t}] = 0$, not $\mathbb{E}_{n,t}[S_{i,n,t-1}\nu_{a,n,t}] = 0$.

For example, Goldman Sachs reporting expectations for Apple before J.P. Morgan does must not predict these institutions' non-price determinants of growth expectations. If institutions pick announcement dates ex-ante (e.g. in the previous quarter) and do not deviate from that preset schedule based on new information that affects growth expectations, then this assumption is satisfied.

The α estimates from this strategy (30 to 31 basis points in Appendix Table A5) are quantitatively similar to those in Table 1 (41 basis points), which again suggests the dependence of growth expectation updates on lagged information may not be a serious identification concern.

To address any concerns about the endogeneity of analyst report timing in this within stock-quarter strategy, I also conduct a version of this strategy using only ex-ante predictable variation in the timing of analyst reports in Appendix A.4.1. This strategy also yields significantly positive α estimates ($\alpha = 99$ to 110 basis points, although these point estimates are not statistically distinguishable from 41 basis points at the 95% confidence level).

5 A Framework for Demand, Beliefs, and Prices

This section presents a theoretical framework for thinking about asset demand, beliefs, and prices in equilibrium in order to formally define the parameter of interest: the causal effect of subjective growth expectations on prices. At a high level, shocks to growth expectations shift asset demand curves and prices must adjust to clear markets. This framework motivates the empirical strategies I use to measure this causal effect in Sections 6 and 7.

This section proceeds as follows. Before introducing the causal effect of subjective growth expectations on prices, I must first define asset demand (Section 5.1) and shocks to growth expectations (Section 5.2). Section 5.3 defines the the causal effect of subjective growth expectations on prices. Section 5.4 explains how insensitivity of demand to expected returns generates both inelastic demand and a small causal effect of growth expectations on prices. Section 5.5 presents the benchmark value for this causal effect in standard models. These sections all consider a representative investor. Section 5.6 explains how the framework easily generalizes to multiple, heterogeneous investors.

5.1 Asset Demand

This section builds on the setup of Gabaix and Koijen (2020*b*) to present a tractable asset demand system. This framework explains how beliefs shift asset demand and so lays the groundwork for defining the causal effect of subjective growth expectations on prices in Section 5.3.

Assume there is a representative investor, N stocks, and one outside asset (labeled $n = 0$). Time is indexed by quarter t since I observe investor holdings quarterly. The investor demands portfolio weight in stock n of $\theta_{n,t}$.

To match the empirical lognormal distribution of portfolio weights in the 13F data (Koijen and

Yogo (2019)), I use the following functional form for the portfolio weight demand function motivated by Gabaix and Koijen (2020*b*):

$$\theta_{n,t} = \begin{cases} \frac{\hat{\theta}_{n,t}}{1+\sum_{m=1}^{N}\hat{\theta}_{m,t}}, & n = 1,\ldots,N \\ \frac{1}{1+\sum_{m=1}^{N}\hat{\theta}_{m,t}}, & n = 0 \end{cases}$$
$$\hat{\theta}_{n,t} = \exp\left[\kappa\mu_{n,t} + \epsilon^{D}_{n,t}\right], n = 1,\ldots,N.$$

$\mu_{n,t}$ is the quarterly subjective excess expected return at time t for stock n. $\epsilon^{D}_{n,t}$ accounts for all other sources of asset demand (e.g. risk, risk aversion, nonpecuniary preferences, etc.).[18] Thus,

$$\theta_{n,t} = \exp\left[\kappa\mu_{n,t} + \underbrace{\epsilon_{n,t}}_{\equiv\epsilon^{D}_{n,t}+\xi_t}\right], n = 1,\ldots,N \tag{10}$$
$$\xi_t = -\log\left[1 + \sum_{m=1}^{N}\hat{\theta}_{m,t}\right].$$

Current price and growth expectations enter portfolio weight demanded through the expected return. 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 for stock n is

$$\mu_{n,t} = \frac{\tilde{\mathbb{E}}_t[P_{n,t+1} + D_{n,t+1}]}{P_{n,t}} - R^f_t. \tag{11}$$

$\tilde{\mathbb{E}}_t$ is the conditional expectation under the investor's subjective measure. I place no restrictions on subjective beliefs. The investor can have rational expectations or exhibit behavioral biases.

κ is the sensitivity (i.e. semi-elasticity) of asset demand to expected return

$$\frac{\partial\log\theta_{n,t}}{\partial\mu_{n,t}} = \kappa.$$

κ represents the percentage change in demand (e.g. $\theta_{n,t} = 0.1$ to $\theta_{n,t} = 0.101$ would be 1%) due to a one percentage point rise in expected return (e.g. from $\mu_{n,t} = 4\%$ to $\mu_{n,t} = 5\%$). Since, growth expectations enter demand through expected return, κ plays a key role in defining the causal effect of subjective growth expectations on prices in Section 5.3.

[18] For example, in mean-variance portfolio choice $\epsilon^{D}_{n,t}$ captures asset n's variance, its covariances with all other assets, and the expected returns on all other assets. More generally, $\epsilon^{D}_{i,n,t}$ can incorporate hedging demand (Merton (1973)), time-varying risk aversion (e.g. Campbell and Cochrane (1999)), time-varying risk (e.g. Bansal and Yaron (2004); Wachter (2013)), institutional frictions (e.g. He and Krishnamurthy (2013)), non-pecuniary preferences (e.g. Pástor, Stambaugh and Taylor (2021)), etc.

5.2 Subjective Growth Expectations

This section defines a "shock to subjective growth expectations." I divide the current period t into two subperiods: $t-$ and $t+$. The investor starts in the ex-ante equilibrium at $t-$ and then receives new information at $t+$ that shocks his growth expectations. Empirically this new information will be analyst-reported growth expectations. As a result, demand shifts and prices adjust to clear markets, as discussed in the next section. Since I am considering a representative investor here, I do not allow the investor to learn from prices. Section 5.6 relaxes this assumption.

In subperiod $t-$, the investor believes realized quarterly dividend growth $g_{n,t+1} \equiv \frac{D_{n,t+1}}{D_{n,t}} - 1$ has the following dynamics[19]:

$$
\begin{aligned}
g_{n,t+1} &= x_{n,t-} + \epsilon^g_{n,t+1} \\
x_{n,(t+1)-} &= \bar{x} + \rho(x_{n,t-} - \bar{x}) + \epsilon^x_{n,t+1}
\end{aligned}
\tag{12}
$$

where $x_{n,t-}$ represents time-$t-$ conditional subjective growth expectation for quarter $t+1$ and stock n. I model $x_{n,t-}$ as an AR(1) process with persistence ρ. Appendix B.1 estimates ρ in the term structure of analyst growth expectations and finds a quarterly persistence of $\rho = 0.7$.

At $t+$, the investor obtains new information (i.e. the analyst expectation) and updates his subjective growth expectation for quarter $t+1$:

$$x_{n,t+} = x_{n,t-} + \Delta x_t.$$

Both $\epsilon^g_{n,t+1}$ and $\epsilon^x_{n,t+1}$ have conditional expectations of zero at $t-$ and $t+$.[20] As a result, the investor now believes realized quarterly dividend growth has the following dynamics:

$$
\begin{aligned}
g_{n,t+1} &= x_{n,t+} + \epsilon^g_{n,t+1} \\
x_{n,(t+1)+} &= \bar{x} + \rho(x_{n,t+} - \bar{x}) + \epsilon^x_{n,t+1}.
\end{aligned}
$$

Empirically I work with shocks to one-year growth expectations since the one-year horizon has better coverage in I/B/E/S than the one-quarter horizon. Denote annual realized dividend growth from quarter $t+1$ to $t+4$ as $G_{n,t+4} = \Pi_{s=1}^4(1+g_{t+s}) - 1$. The shock to the investor's one-year

[19] I assume $\tilde{\mathbb{E}}_t[\epsilon^g_{n,t+s}] = 0, \forall s > 0$, $\tilde{\mathbb{E}}_t[\epsilon^g_{n,t}\epsilon^g_{n,t+s}] = 0, \forall s \neq 0$, $\tilde{\mathbb{E}}_t[\epsilon^x_{n,t}\epsilon^x_{n,t+j}] = 0, \forall j \neq 0$, and $\tilde{\mathbb{E}}_t[\epsilon^g_{n,t+s}\epsilon^x_{n,t+s'}] = 0, \forall s, s'$. Note that all expectations are taken under the investor's subjective beliefs.

[20] You could consider an alternative specification where the investor learns about $\epsilon^g_{n,t+1}$ instead of about $x_{n,t}$. The difference is learning about $\epsilon^g_{n,t+1}$ does not cause updates to future growth expectations. Thus, learning about $x_{n,t}$ generally implies larger effects of growth expectations on demand and prices. How much larger these effects are depends on the persistence ρ. The conservative benchmark value of $M_g = 1$ I use in Section 5.5 assumes $\rho = 0$. If $\rho = 0$, then learning about $\epsilon^g_{n,t+1}$ has the same price impact as learning about $x_{n,t}$.

subjective growth expectation due to Δx_t is:

$$\Delta G^e_{n,t} = \tilde{\mathbb{E}}_{t+} \left[G_{n,t+4} \right] - \tilde{\mathbb{E}}_{t-} \left[G_{n,t+4} \right] \approx \left(1 + \rho + \rho^2 + \rho^3 \right) \Delta x_t, \tag{13}$$

where the approximation follows from $\log(1 + a) \approx a$.[21]

5.3 Causal Effect of Subjective Growth Expectations on Prices: M_g

This section formally defines the causal effect of subjective growth expectations on prices. This definition motivates the regressions used to identify this causal effect in Section 6, where I assume homogeneous demand functions across investors.

The shock to subjective growth expectations shifts the investor's asset demand curve. Appendix B.2 linearizes portfolio weight demand function (10) (around small changes in price, expected return, and other asset demand shocks from $t-$ to $t+$) and plugs in the dividend growth dynamics from (12) to obtain the following demand function for stock n:

$$\Delta q_{n,t} = -\zeta \Delta p_{n,t} + \kappa^g \Delta G^e_{n,t} + \Delta \epsilon_{n,t}. \tag{14}$$

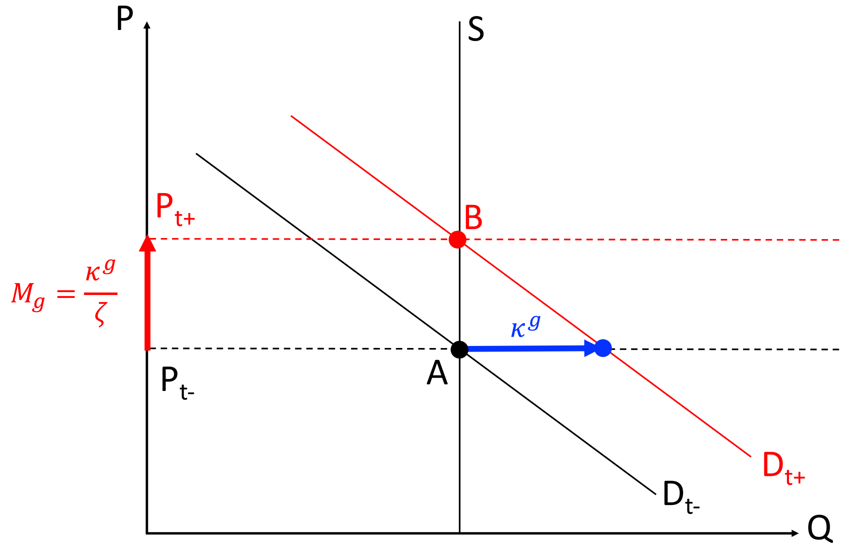
$\Delta q_{n,t}$ and $\Delta p_{n,t}$ are the percentage changes in quantity of shares demanded and price (pinned down by market clearing). $\Delta G_{n,t}$ is the annual growth expectation shock from Section 5.2. ζ is the price elasticity of demand (expressed as a positive number). κ^g is the causal effect subjective growth expectations on asset demand; it represents how much the demand curve shifts in response to a 1% increase in one-year growth expectation. $\Delta \epsilon_{n,t}$ is the residual demand shock; it comprises all sources of asset demand except changes in growth expectations.

Parameters κ^g and M_g are functions of the structural parameters κ (demand sensitivity to expected return), $\bar{g}$ (average dividend growth), ρ (subjective growth expectation persistence), and $\theta_{n,t-}$ (ex-ante portfolio weight). Proposition 1 in the next section discusses these functional forms.

The demand curve shift caused by the subjective growth expectations shock induces a market-clearing price change. Assume fixed supply, which means $\Delta q_{n,t} = 0$ since there is a representative

[21] I assume this annual growth expectation shock is driven by a shock to the growth expectation for quarter $t+1$ (Δx_t). You could make alternative assumptions, such as the shock to annual growth expectation is driven by a shock to the growth expectation for quarter $t+4$. For a fixed persistence ρ, a larger shock to quarterly growth expectations is required in $t+4$ than in t to generate a fixed $\Delta G^e_{n,t}$. For $\rho = 0.7$ a 1% shock to quarterly growth expectation in quarter $t+4$ or a shock of $\frac{1}{1+\rho+\rho^2+\rho^3} = 0.4\%$ in quarter $t+1$ both generate an annual growth expectation shock of $\Delta G^e_{n,t} = 1\%$. Assuming the shock to quarterly growth expectations occurs earlier in the year yields smaller (more conservative) model-implied effects of annual growth expectations on prices. The conservative benchmark value of $M_g = 1$ I use in Section 5.5 assumes $\rho = 0$. If $\rho = 0$, then 1% quarterly growth expectations shocks in both quarters $t+1$ and $t+4$ generate an annual growth expectations shock of $\Delta G^e_{n,t} = 1\%$. 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%).

Figure 2: Equilibrium Price Change due to Subjective Growth Expectations Shock



Graphical illustration of demand shift and price change caused by a subjective growth expectations shock. The investor starts at equilibrium A at $t-$ and receives new information that raises his annual growth expectation by 1%. The demand curve shifts right by κ^g percent. The price must rise by $M_g = \kappa^g/\zeta$ percent to clear the market at the new equilibrium of B at $t+$.

investor. Solving for the market clearing price change from $t-$ to $t+$ yields:

$$\Delta p_{n,t} = \frac{\kappa^g}{\zeta}\Delta G^e_{n,t} + \frac{1}{\zeta}\Delta \epsilon_{n,t}. \tag{15}$$

The causal effect of subjective growth expectations on prices, denoted M_g, is thus:

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

M_g represents how much the equilibrium price rises in response to a 1% rise in annual subjective growth expectation. M_g equals the demand shift caused by the change in expectations (κ^g) divided by the price elasticity of demand (ζ). Figure 2 illustrates the graphical intuition for M_g.

5.4 Inelastic Demand and Small M_g

This section explains how the low sensitivity of asset demand to expected returns found in previous work generates both inelastic demand and a small causal effect of subjective growth expectations on prices. This result is closely related to the notion of "myopia" in inelastic markets introduced by Gabaix and Koijen (2020*b*).

I express sensitivity of demand to growth expectations (κ^g), price elasticity (ζ), and the effect of growth expectations on prices (M_g) as functions of the sensitivity of demand to expected return (κ). Proposition 1 (proved in Appendix B.1) describes these functions under some simplifying assumptions that yield simple analytical expressions. Proposition 2 in Appendix B.1 relaxes these assumptions and describes the general functions, which convey no essential additional intuition.[22]

Proposition 1 (κ^g, ζ, and M_g Under Simplifying Assumptions). *For zero persistence in growth expectation x_t ($\rho = 0$), zero average dividend growth ($\bar{g} = 0$), and small portfolio weights ($\theta_{n,t-} \approx 0$):*

$$\kappa^g = \kappa\delta \tag{16}$$

$$\zeta = 1 + \kappa\delta \tag{17}$$

$$M_g = \frac{\kappa^g}{\zeta} = \frac{\kappa\delta}{1+\kappa\delta}, \tag{18}$$

where δ is the average dividend-price ratio.

Per (16), demand shifts due to growth expectations shocks (κ^g) are small when κ is small. Holding price fixed, a 1% transitory (zero persistence) growth expectations shock (i.e. a permanent 1% increase in the level of expected dividends) raises expected return by δ%. Asset demand rises by $\kappa^g = \kappa\delta$ in (16) since κ is the sensitivity of demand to expected return.

Per (17), demand is inelastic (ζ is small) when κ is small (as argued by Gabaix and Koijen (2020*b*)). When price rises 1%, the investor reduces quantity demanded by 1% to maintain the same portfolio weight, hence the leading 1 in (17).[23] 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 δ%, which lowers asset demand by $\kappa\delta$%.

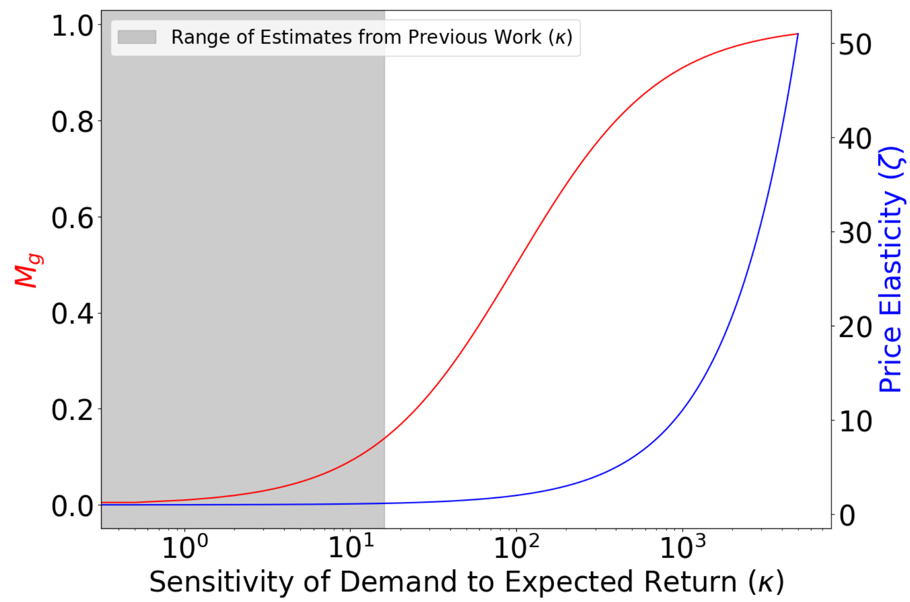
Per (18), the causal effect of subjective growth expectations on prices (M_g) is small when κ is small since $M_g = \kappa\delta/(1+\kappa\delta)$ is an increasing function of κ. Insensitivity of demand to expected returns generates 1) small demand shifts due to growth expectations shocks, which dampen price impact, and 2) inelastic demand, which augments price impact. However, these channels do not cancel out because the demand shift (κ^g) is more sensitive to κ than the elasticity (ζ) is.[24] Intuitively, if demand is perfectly insensitive to expected return ($\kappa = 0$), then growth expectations shocks do

[22]The only new dimension of note is that demand and prices respond more to growth expectations shocks (i.e. κ^g and M_g are higher) when the persistence of growth expectations (ρ) is higher.

[23]To 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 ψ 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 (2020*b*) 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, which suggests a relatively small ψ.

[24]As κ falls, demand shift κ^g shrinks faster than price elasticity ζ. The intuition is that price elasticity in the denominator of M_g has two components, only one of which depends on κ. The strength of the change in portfolio weight demanded when expected returns change due to price changes depends on κ. However, the mechanical selling

Figure 3: M_g and ζ as a Function of κ



Plot of M_g and ζ values implied by Proposition 1 as a function of κ, calibrating average quarterly dividend-price ratio $\delta = 0.01$ to match the historical average for the aggregate equity market. The gray shaded area indicates the range of κ estimates found in previous work (see Appendix J for details).

not shift the demand curve at all ($\kappa^g = 0$) and have zero price impact ($M_g = 0$), in spite of demand being very inelastic ($\zeta = 1$). If κ is positive but small, then growth expectations shocks induce small demand curve shifts, which have only small price impact.

To illustrate this point graphically, Figure 3 plots both the causal effect of subjective growth expectations on prices (M_g) and price elasticity (ζ) as functions of the the sensitivity of demand to expected return (κ). The range of κ estimates found in previous work using matched expectations and holdings data ($\kappa \in [0, 16]$, see Appendix J for details) implies both realistically inelastic demand ($\zeta \approx 1$, consistent with previous estimates[25]) and a small M_g.[26] For this range of κ, the model-implied M_g is in the range of about $[0, 0.2]$, which is far smaller than the benchmark $M_g = 1$ discussed in the next section. This model-implied range of $[0, 0.2]$ is consistent with the empirical range of $M_g \in [0.07, 0.16]$ I find in Sections 6 and 7.

of shares when price rises to maintain a constant portfolio weight does not depend on κ. For this reason, a 1% reduction in κ in relative terms (e.g. from 10 to 9.9) reduces the demand shift due to the growth expectations shocks (κ^g in the numerator) by more than the price elasticity (ζ in the denominator): $0.99\kappa\delta/(1 + 0.99\kappa\delta) < \kappa\delta/(1 + \kappa\delta)$.

[25] Chang, Hong and Liskovich (2014); Pavlova and Sikorskaya (2020); Koijen and Yogo (2019); Gabaix and Koijen (2020*b*); Schmickler and Tremacoldi-Rossi (2022)

[26] Previous work usually regresses portfolio weights (θ) on expected returns (μ) and so measures $\partial\theta/\partial\mu$. However, $\kappa = \partial \log \theta / \partial \mu = \partial\theta/\partial\mu \cdot 1/\theta$ in (10). 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 used to establish the gray shaded range in Figure 3.

5.5 Benchmark Value for M_g

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

Consider a standard consumption CAPM model. The representative investor has CRRA utility over consumption:

$$U(C_t) = \frac{{C_t}^{1-\gamma}}{1-\gamma}.$$

Quarterly consumption growth is i.i.d. Quarterly dividend growth dynamics for stock n are as described in Section 5.2. Assume both dividend and consumption growth are normally distributed.

The price of stock n satisfies:

$$P_{n,t} = \mathbb{E}_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}(P_{n,t+1} + D_{n,t+1})\right], \tag{19}$$

To convey the intuition, I consider the case of zero persistence in subjective growth expectation x_t ($\rho = 0$), which provides a conservative benchmark value for M_g, as discussed below. Since the only state variable in this economy x_t, one can easily show the log price-dividend ratio takes the following form (as proven in Appendix B.4):

$$\log\left(P_{n,t}/D_{n,t}\right) = A_0 + x_t,$$

for some constant A_0. Thus, the percentage change in price from $t-$ to $t+$ due to an annual growth expectation shock of $\Delta G^e_{n,t} = \Delta x_t$ (following (13)) is

$$\Delta p_{n,t} = \Delta G^e_{n,t},$$

so $M_g = 1$.

The intuition for $M_g = 1$ is simple. Since the purely transitory growth expectation shock does not alter discount rates, it does not impact the forward price-dividend ratio ($P_{n,t}/\mathbb{E}_t[D_{n,t+1}]$).[27] A 1% purely transitory growth expectation shock raises the expected *level* of all future dividends by 1%. Thus, the 1% purely transitory increase in growth expectation raises price 1%.

Since adding additional state variables to the economy does not alter this logic, most leading asset pricing models imply $M_g = 1$, including 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); Nagel and Xu (2021); Bordalo et al. (2022)).

Persistence in growth expectations ($\rho > 0$) raises M_g. Appendix B.4 demonstrates $M_g = 1.3$ in this model for the empirical persistence of $\rho = 0.7$ in the I/B/E/S growth expectations data (see

[27] Since my empirical setting is the cross section of equities, I assume the risk free rate is exogenous to stock-specific growth expectations shocks. In models that price consumption claims, the risk-free rate is usually endogenous to growth expectations shocks due to intertemporal substitution. I rule out these general equilibrium effects.

Appendix B.1). Using $M_g = 1.3$ instead of $M_g = 1$ does not change my empirical conclusion that the causal effect of subjective growth expectations on prices is an order of magnitude smaller than in standard models. Thus, I use the more conservative and simpler benchmark value of $M_g = 1$.

5.6 Generalizing to Heterogeneous Agents

The representative agent framework presented above easily generalizes to heterogeneous investors. With heterogeneous investors, M_g is the weighted-average demand shift due to the growth expectations shock divided by the weighted average price elasticity (weighted by ownership shares). This generalization motivates the regressions used to identify M_g in Section 7, where I allow for heterogeneous demand functions across investors. For simplicity, I assume investors do not learn from prices in this section. However, this assumption does not impact the empirical strategy, as discussed in Appendix B.5. Learning from prices changes the functional form of the investor's price elasticity of demand, but does not alter the form of the demand curve or the definition of M_g.

Consider the following generalization of demand function (14):

$$\Delta q_{i,n,t} = -\zeta_i \Delta p_{n,t} + \kappa_i^g \Delta G^e_{i,n,t} + \Delta \epsilon_{i,n,t}, \tag{20}$$

with heterogeneous price elasticities (ζ_i) and sensitivities of demand to growth expectations (κ_i^g) across investors. $\Delta G^e_{i,n,t}$ captures heterogeneous changes in growth expectations. $\Delta \epsilon_{i,n,t}$ allows for heterogeneous demand shocks. The aggregate change in quantity of shares demanded is

$$\Delta q_{S,n,t} \equiv \sum_i S_{i,n,t} \Delta q_{i,n,t}$$
$$S_{i,n,t} \equiv \frac{Q_{i,n,t-}}{\sum_{j=1} Q_{j,n,t-}}.$$

$Q_{i,n,t-}$ is the ex-ante (time $t-$) quantity of shares owned by investor i in stock n and $S_{i,n,t}$ is the ex-ante ownership-share weight.

As in the representative agent case, the aggregate demand curve shift due to the shock to subjective growth expectations induces a market-clearing price change. Assume all investors experience the same growth expectations shock ($\Delta G^e_{i,n,t} = \Delta G^e_{n,t}, \forall i$). Market clearing under fixed supply ($\Delta q_{S,n,t} = 0$) implies

$$\Delta p_{n,t} = \frac{\kappa_S^g}{\zeta_S} \Delta G^e_{n,t} + \frac{1}{\zeta_S} \Delta \epsilon_{S,n,t}, \tag{21}$$

where S denotes the ownership-share weighted average (e.g. $\kappa_S^g \equiv \sum_i S_{i,n,t} \kappa_i^g$).

Thus, in general the causal effect of subjective growth expectations on prices is:

$$M_g = \frac{\kappa_S^g}{\zeta_S}. \tag{22}$$

M_g is still the aggregate demand curve shift (κ_S^g) divided by the aggregate price elasticity (ζ_S).

6 Effect of Growth Expectations on Prices: Homogeneity

This section measures the causal effect of subjective growth expectations on prices (M_g) under two assumptions about investor homogeneity:

1. All investors have the same demand sensitivity to growth expectations κ_i^g and price elasticity ζ_i.
2. Analyst influence on investor beliefs is the same for all investors.

These homogeneity assumptions allow identification of M_g from price and beliefs data alone. Section 7 relaxes these assumptions and measures M_g under full investor heterogeneity using holdings data. I find M_g is small. A one percent rise in investor annual growth expectations raises price only 7 basis points – an order of magnitude less than the benchmark of 1%. Thus, the core mechanism in subjective belief models is far weaker empirically than assumed by these models.

As discussed in Section 2, measuring M_g requires solutions to two problems:

1. Measuring the passthrough of analyst influence to investor beliefs.
2. Extracting exogenous variation in observed analyst growth expectations.

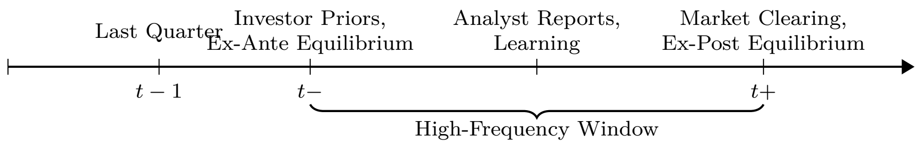
First, I measure analyst influence on investor beliefs by modeling investors as Bayesians who learn from analysts. Bayesian learning implies signal averaging, which allows identification of analyst influence using cross-sectional variation in the number of analysts who cover each stock. This signal averaging mechanism appears in a large class of non-Bayesian learning models as well. Second, I isolate exogenous variation in observed analyst growth expectations by using collaborative filtering to fit a latent factor model to the within-quarter analyst institution $\times$ stock panel of growth expectations. I extract the factor model residuals as exogenous shocks to analyst expectations.

Section 6.1 overviews the timing of the empirical strategy. Section 6.2 explains how Bayesian learning enables identification of analyst influence. Section 6.3 details the latent factor model I fit to analyst expectations. Section 6.4 uses market clearing to motivate the high-frequency panel regressions I use to measure M_g. Section 6.5 presents the empirical results.

6.1 Timing and Notation

My empirical strategy uses high-frequency windows around analyst growth expectation announcements. Let t denote the current quarter. Following Section 5.2, $t-$ is the ex-ante equilibrium right before an analyst announcement and $t+$ is the ex-post equilibrium after investors learn the new

Figure 4: Model Timeline



Timeline of high-frequency identification strategy.

information, demand shifts, and prices adjust to clear markets. Since all of the identification works within a quarter, I suppress quarter t subscripts. As discussed in Section 3, I group analysts to their parent institution. Thus, any reference to "analyst" means "analyst institution."

As displayed in Figure 4, the timing of the empirical strategy involves four steps:

1. In the previous quarter $t-1$, analyst a reported a growth expectation for stock n: $G_{a,n,}^{A,lag}$ (superscript A denotes analyst expectations). Denote the price change from that announcement until $t-$ as Δp_n^- , which is the price change that may affect analyst a's quarter-over-quarter expectation update (consistent with the reverse causality evidence in Section 4).

2. At the ex-ante equilibrium $t-$, investors have priors over annual growth expectations for stock n. Let $\bar{G}_{S,a,n}^I$ be the ownership-share weighted average prior mean growth expectation before the announcement by analyst a (superscript I denotes investor expectations).

3. The information shock is the announcement of analyst a's growth expectation in the current quarter t: $G_{a,n,}^A$.

4. Investors update their priors over annual growth expectations for stock n. Asset demand curves shift and prices adjust to clear markets. $\Delta q_{i,a,n}^+$ and $\Delta p_{a,n}^+$ are the equilibrium changes in quantity demanded by investor i and price in a high-frequency window (several days) after analyst a's announcement that engender the ex-post equilibrium at $t+$.

6.2 Measuring Analyst Influence: Bayesian Learning

This section explains how the signal averaging mechanism implied by Bayesian learning enables identification of analyst influence on investor beliefs in the cross section of stocks. This section assumes homogeneous analyst influence across investors; Section 7 relaxes this assumption. This section also assumes homogeneous influence across analysts; Section 6.6.1 relaxes this assumption. All of the identification occurs within a quarter, so I omit quarter t subscripts.

Prior to the analyst a's announcement (i.e. at $t-$), each investor i has the following prior distribution over the unknown stock-n annual expected growth rate G_n^e:

$$G_n^e \sim N(\bar{G}_{i,a,n}^I, \bar{\tau}).$$

Investors view analyst a's announced growth expectation $G_{a,n}^A$ as a noisy signal of G_n^e[28]:

$$G_{a,n}^A = G_n^e + \epsilon_{a,n}, \epsilon_{a,n} \sim N(0, \sigma^2).$$

The Bayesian learning update to investor i's prior mean for stock n due to analyst a's signal is:

$$\Delta G_{i,a,n}^I = \underbrace{\frac{\sigma^{-2}}{\tau^{-1} + A_n \sigma^{-2}}}_{\equiv B_n} \left(G_{a,n}^A - \bar{G}_{i,a,n}^I \right) + \nu_{i,a,n}^I. \tag{23}$$

$\nu_{i,a,n}^I$ captures any other growth signals investor i learns from in the high-frequency window after analyst a's announcement. B_n represents analyst influence on investor beliefs for stock n: the weight each analyst's expectation receives in each investor's posterior. As usual with Gaussian priors and signals, this posterior weight is the ratio of the signal precision (σ^{-2}) to the posterior precision ($\tau^{-1} + A_n \sigma^{-2}$, where $\tau^{-1} = \bar{\tau}^{-1} + \sigma_\nu^{-2}$ includes the signal precision of $\nu_{i,a,n}^I$).

To elucidate the identifying variation, I linearize analyst influence B_n around the average number of analysts per stock in the current quarter ($A = \mathbb{E}[A_n]$):

$$B_n \approx \underbrace{\beta}_{\equiv \frac{\sigma^{-2}}{\tau^{-1} + A\sigma^{-2}}} - \beta^2 \underbrace{\tilde{A}_n}_{A_n - A}. \tag{24}$$

$\tilde{A}_n = A_n - A$ is the demeaned number of analysts who cover stock n. β is the level of influence for the average stock. β^2 represents how much influence shrinks per additional analyst added.[29]

The functional form for analyst influence (24) allows identification of β in the cross section of stocks. Bayesian learning implies signal averaging. The more signals (analyst expectations) a Bayesian learner observes, the less weight (influence) any particular signal receives in the posterior, which is why B_n is decreasing in $\tilde{A}_n$ in (24). Moreover, signal averaging links the level of influence (β) with how much influence shrinks as additional signals are added (β^2).

For example, consider the flat prior (and no other signals) case: $\tau^{-1} = 0$. In this case, $B_n = 1/A_n$: investors take an equal-weighted average of all analyst signals. For the average stock, $B_n = \beta = 1/A$: influence is one over the average number of analysts. Since the derivative of $1/x$ is $-1/x^2$, influence

[28] As written, investors view analyst expectations as uncorrelated signals. However, allowing analyst expectations to be correlated across analysts does not change the functional form of influence in (24).

[29] Appendix C.2 describes an alternative specification for analyst influence that exploits variation in the order of analyst report releases. This specification collapses to a functional form similar to (24) under some approximations.

shrinks at a rate of $\beta^2 = 1/A^2$ per additional analyst.

The functional form of analyst influence in (24) proves robust to a wide range of deviations from Bayesian learning, as discussed in Appendix C.3.

6.3 Exogenous Variation in Analyst Expectations: Latent Factor Model

This section explains how I extract exogenous variation in analyst expectations by using collaborative filtering to fit a latent factor model to the within-quarter analyst $\times$ stock panel of growth expectation updates. All of the identification occurs within a quarter, so I omit quarter t subscripts.

I model quarterly changes[30] in annual analyst growth expectations as having a factor structure:

$$\Delta G^A_{a,n} = (\alpha_a + \alpha_n)\Delta p^-_n + \boldsymbol{\lambda}'_a \boldsymbol{\eta}_n + u_{a,n}. \tag{25}$$

Quarterly analyst expectation updates ($\Delta G^A_{a,n} = G^A_{a,n} - G^{A,lag}_{a,n}$) can depend on:

1. Contemporaneous price changes: Δp^-_n (consistent with the reverse causality evidence from Section 4). Note that both $\Delta G^A_{a,n}$ and Δp^-_n are changes from quarter $t-1$ to quarter t.

2. Stock characteristics: $\boldsymbol{\eta}_n$. Characteristics may include public signals (e.g. earnings surprises, monetary policy announcements, COVID news), firm characteristics, etc.[31]

3. Uncorrelated idiosyncratic shocks: $u_{a,n}$.

The idiosyncratic shocks $u_{a,n}$ capture within stock-quarter variation in growth expectations across analysts and so provide exogenous variation in analyst expectations. I assume $u_{a,n}$ are uncorrelated across analysts and stocks. I estimate factor model (25) within each quarter: all factors, loadings, and idiosyncratic shocks vary over time.

What is an idiosyncratic analyst growth expectation shock? A natural candidate is private information obtained by analyst a about the future cash flows of stock n.[32] This information need not have any bearing on other sources of demand (e.g. subjective risk perceptions, hedging demand, non-pecuniary preferences, etc.) and so will be uncorrelated with other contemporaneous demand shocks. Moreover, information observed only by analyst a is uncorrelated with investor priors (since investors cannot yet have not learned it) and with other contemporaneous growth signals.

[30] Changes (vs. levels) better isolate new information and have greater price impact (e.g. Brav and Lehavy (2003)).

[31] Factor structure (25) can also incorporate analyst or stock-specific biases (i.e. fixed effects). An analyst-quarter fixed effect is an element of $\boldsymbol{\lambda}_a$ constrained to load on a constant $\eta_{n,f} = 1$ and a stock-quarter fixed effect is an element of $\boldsymbol{\eta}_{n,t}$ constrained to be loaded on by $\lambda_{a,f} = 1$.

[32] 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)).

Extracting idiosyncratic shocks with collaborative filtering. I operationalize factor model (25) with 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 individual-specific models of movie preferences from partial cross sections of ratings. I learn analyst-specific models of growth expectations from partial cross sections of covered stocks.

To fit the factor model, I reexpress structural factor model (25) in reduced form as

$$\Delta G^A_{a,n} = \tilde{\boldsymbol{\lambda}}_a^\top \tilde{\boldsymbol{\eta}}_n + u_{a,n}. \tag{26}$$

This representation subsumes the price term $(\phi_a + \phi_n)\Delta p^-_n$ from (25).[33] I fit latent factor model (26) quarter-by-quarter using the regularized singular value decomposition technique of Funk (2006). This method decomposes the analyst-by-stock matrix of growth expectation updates ($\mathbf{G} = \left[\Delta G^A_{a,n}\right]_{a,n}$) into the product of a matrix of factor loadings ($\Lambda = [\boldsymbol{\lambda}_a]_a$) with a matrix of factors ($\mathbf{H} = [\tilde{\boldsymbol{\eta}}_n]_n$). Given the sparsity of the data (most analysts don't cover most stocks), I use L2 (i.e. ridge) regularization to more efficiently estimate the factor model. Regularization biases the factor and loading estimates toward zero in order to reduce the variance of these estimates. The baseline specification uses five latent factors, but all results prove robust to using alternative numbers of factors (see Section 6.6.2). After estimating the factors ($\tilde{\boldsymbol{\eta}}_n$) and loadings ($\tilde{\boldsymbol{\lambda}}_a$), one can recover estimates of the factor model residuals $u_{a,n}$. Figure 5 plots the histogram of idiosyncratic analyst growth expectations shocks across all analyst institutions, stocks, and quarters.[34] Appendix D discusses implementation details.

6.4 Identifying M_g: Market Clearing

This section explains how I use high-frequency panel regressions to estimate M_g given the form of analyst influence from Section 6.2 and exogenous variation in analyst expectations from Section 6.3.

The information shock from the analyst announcement shifts investors' demand curves. From (20), the percentage change in quantity of shares demanded by investor i for stock n in the high-frequency window after analyst a's announcement is:

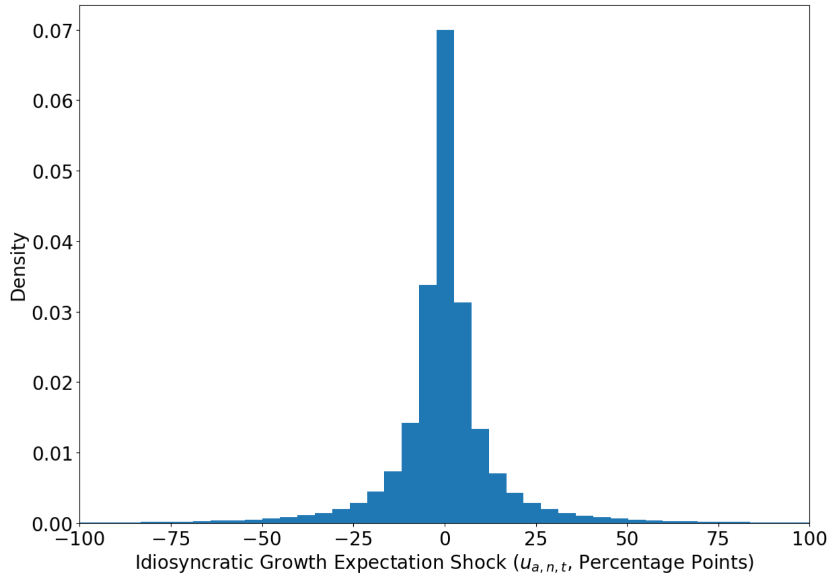
$$\Delta q^+_{i,a,n} = -\zeta \Delta p^+_{a,n} + \kappa^g \Delta G^I_{i.a,n} + \Delta \epsilon_{i,a,n}. \tag{27}$$

$\Delta p^+_{a,n}$ is the price change in the high-frequency window (not to be confused with the lagged, low-frequency price change Δp^-_n in (25)), $\Delta G^I_{i.a,n}$ represents the shock to investor i's annual growth expectation for stock n, and $\Delta \epsilon_{i,a,n}$ includes other high-frequency demand shocks.

[33]This notation assumes all analysts learn from the same price change Δp^-_n even if they report expectations at different times in each quarter. Analysts may learn from slightly different price changes due to the staggered timing of analyst reports. However this scenario does not pose significant challenges. See Appendix D.1 for a full discussion.

[34]For clarity I truncate the histogram range to $[-100\%, 100\%]$, which contains over 99.5% of the observations.

Figure 5: Histogram of Idiosyncratic Analyst Growth Expectations Shocks



Histogram of estimated idiosyncratic analyst growth expectations shocks.

Aggregating the change in demand across investors and imposing fixed supply ($\Delta q^{+}_{S,a,n} = 0$) yields the market-clearing price change in this window ($\Delta p^{+}_{a,n}$) from (21):

$$\Delta p^{+}_{a,n} = M_g \Delta G^{I}_{S,a,n} + \frac{1}{\zeta}\Delta\epsilon_{S,a,n} \qquad \text{(Market Clearing)}$$

$$\Delta G^{I}_{S,a,n} = B_n\left(G^{A}_{a,n} - \bar{G}^{I}_{S,a,n}\right) + \nu^{I}_{S,a,n} \qquad \text{(Bayesian Update)}$$

$$B_n = \beta - \beta^2 \tilde{A}_n \qquad \text{(Bayesian Analyst Influence)}$$

$$\Delta G^{A}_{a,n} = (\alpha_a + \alpha_n)\Delta p^{-}_{n} + \boldsymbol{\lambda}^{'}_{a}\boldsymbol{\eta}_n + u_{a,n} \qquad \text{(Analyst Factor Structure)}$$

where S denotes ownership-share weighted averages. Plugging in the Bayesian-learning implied investor growth expectation update from (23), the Bayesian-learning form of analyst influence from (24), and the factor structure on analyst expectations from (25) yields:

$$\Delta p^{+}_{a,n} = M_g \beta u_{a,n} - M_g \beta^2 u_{a,n}\tilde{A}_n + e_{a,n}. \tag{28}$$

The structural error term $e_{a,n}$ comprises five components: 1) other determinants of analyst expectations, 2) investors prior expectations, 3) lagged analyst growth expectations, 4) other contemporaneous growth signals investors learn from, and 5) other demand shocks (see E.1 for details).

Although all identification occurs in the cross section of stocks within a quarter, I pool across all quarters to obtain more power. Thus, I run the following panel regression motivated by market-clearing expression (28) (I add the time t subscripts to emphasize that I pool across quarters):

$$\Delta p^{+}_{a,n,t} = \underbrace{c_1}_{\equiv M_g \beta} u_{a,n,t} - \underbrace{c_2}_{\equiv M_g \beta^2} u_{a,n,t} \tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t}. \tag{29}$$

The left-hand side is the price change shortly after analyst a's announcement for stock n in quarter t (5 days in the baseline specification, but Section 6.6.3 finds similar results using alternative window lengths).[35] The right-hand side includes the idiosyncratic analyst growth expectation shock $u_{a,n,t}$ and its interaction with the lagged demeaned number of analysts $\tilde{A}_{n,t-1}$.[36] $X_{n,t}$ includes stock, quarter, and stock-quarter fixed effects.

Regression (29) estimates two reduced-form coefficients, which jointly pin down the causal effect of investor subjective growth expectations on prices (M_g).

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

2. c_2 is the shrinkage rate of analyst price impact as the number of analysts grows and influence shrinks. Adding an analyst to stock n reduces 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 β and the causal effect of investor growth expectations on prices M_g:

$$\beta = \frac{c_2}{c_1}$$
$$M_g = \frac{c_1}{\beta} = \frac{c_1^2}{c_2}. \tag{30}$$

The intuition is that signal averaging links the level of analyst price impact (c_1) and the shrinkage rate of price impact as the number of analysts grows (c_2): $c_2 = \beta c_1$. This link arises from the link between the the level of influence (β) and how much influence shrinks with additional analysts (β^2).

The two moment conditions required to identify c_1 and c_2 are:

$$\mathbb{E}\left[u_{a,n} e_{a,n}\right] = 0 \tag{31}$$
$$\mathbb{E}\left[u_{a,n} \tilde{A}_n e_{a,n}\right] = 0. \tag{32}$$

[35] If analyst institution a reports multiple expectations for stock n in quarter t ($\approx$ 25% of (institution, stock, quarter) observations are in this category, though some of these still occur on the same day), I use the first announcement in quarter t as the first day in $\Delta p^{+}_{a,n,t}$. Using the first announcement for each (institution, stock, quarter) yields the largest analyst price impact estimates. (Other options include using the price change after the last or median announcement, or using the sum, mean, or median of price changes after all announcements for this (institution, stock, quarter)).

[36] I use the lagged demeaned number of analysts to avoid any potential endogeneity issues with analysts initiating (or ending) coverage due to particularly good (or bad) information. Irvine (2003) discusses some of these concerns.

Table 2: Summary Statistics

	$\Delta p^{+}_{a,n,t}$	$A_{n,t}$	$\Delta G^{A}_{a,n,t}$	$u_{a,n,t}$	$\Delta q_{i,n,t}$
Count	2145713	2173492	2173492	2173492	51438573
Mean	0.00	10.03	-0.01	0.00	0.02
Std. Dev.	0.09	7.23	0.53	0.18	0.67
Min	-0.99	1.00	-4.43	-4.89	-1.00
25th Percentile	-0.04	4.00	-0.12	-0.04	-0.15
Median	0.00	8.00	0.00	0.00	-0.00
75th Percentile	0.04	14.00	0.11	0.04	0.08
Max	11.00	49.00	3.63	4.65	2.00

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 annual analyst growth expectations ($\Delta G^{A}_{a,n,t}$), the idiosyncratic analyst growth expectations shocks ($u_{a,n,t}$), and quarterly percentage changes in quantity of shares held by investor i in stock n ($\Delta q_{i,n,t}$). $\Delta p^{+}_{a,n,t}, \Delta G^{A}_{a,n,t}, u_{a,n,t}$, 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.

I have two instruments ($u_{a,n}$ and $u_{a,n}\tilde{A}_n$), two moment conditions ((31) and (32)), and two structural parameters to identify (M_g and β). The identifying assumption is:

Assumption 1 (Identifying Assumption for Price Regression)**.** *Any common variation between analyst growth expectation updates ($\Delta G^{A}_{a,n}$) and 1) investor prior expectations ($\bar{G}^{I}_{S,a,n}$), 2) lagged analyst expectations ($G^{Lag}_{a,n}$), 3) other contemporaneous signals ($\nu^{I}_{S,a,n}$), 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 $\Delta G^{A}_{a,n}$ and both $e_{a,n}$ and $\tilde{A}_n$. In this case, both moment conditions (31) and (32) hold.

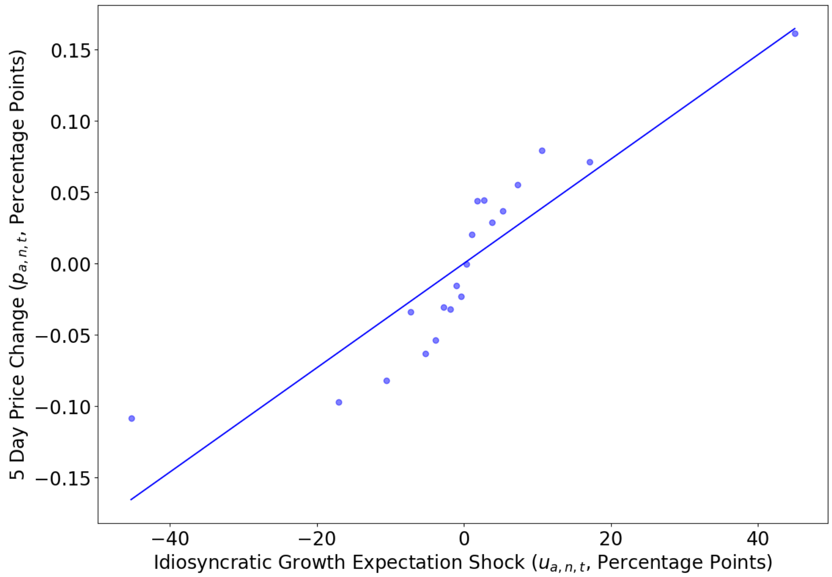
6.5 Empirical Results

This section reports estimates for the causal effect of subjective growth expectations on prices (M_g) under assumptions about investor homogeneity. M_g is small, an order of magnitude smaller than the benchmark $M_g = 1$. Table 2 displays summary statistics for the data used in this analysis.

I first provide reduced-form results to justify the model structure. Figure 6 displays the binscatter plot of five-day post announcement price changes versus idiosyncratic analyst growth expectations shocks. Prices respond to exogenous variation in analyst expectations, which immediately implies analysts do influence investor beliefs ($\beta \neq 0$).

Figure 7 displays overlapping binscatter plots of five-day post announcement price changes versus idiosyncratic analyst growth expectations shocks. The red binscatter represents analyst-stock-quarter observations (a, n, t) where the demeaned number of analysts covering stock n in the previous quarter ($\tilde{A}_{n,t-1}$) is in the bottom quintile. Similarly, the blue binscatter represents

Figure 6: High-Frequency Price Changes vs. Idiosyncratic Analyst Growth Expectations Shocks



Binscatter of five-day post announcement price changes ($\Delta p^{+}_{a,n,t}$) versus idiosyncratic analyst growth expectations shocks ($u_{a,n,t}$).

observations where the demeaned number of analysts is in the top quintile. Analyst price impact is positive for both quintiles, but is much smaller for the top quintile: analysts impact prices less for stocks covered by more analysts. Appendix Figure G8 demonstrates that analyst price impact is monotonically decreasing in the quintile of the demeaned number of analysts. These results are consistent with the signal averaging mechanism detailed in Section 6.2.

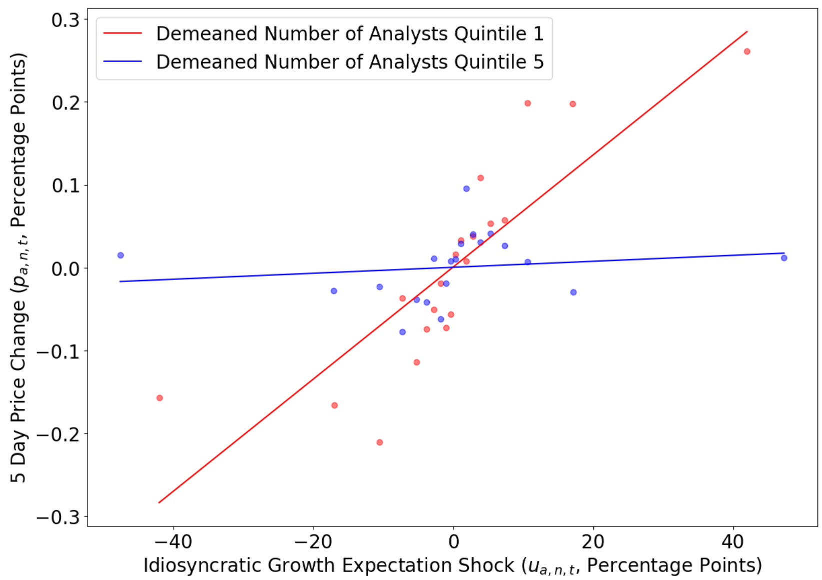
Table 3 reports the estimated reduced-form coefficients c_1 and c_2 from (29). Note that, across columns, c_1 and c_2 prove insensitive to the inclusion of stock, quarter, and stock $\times$ quarter fixed effects, which implies the latent factor model successfully removes variation in analyst growth 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.[37]

Table 4 reports the β and M_g estimates implied by the c_1 and c_2 estimates in Table 3. 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. A 1% higher analyst-reported annual growth expectation raises investor growth expectations by 6 basis points.

The causal effect of investor subjective growth expectations on prices is $M_g = 0.07$ (robust to inclusion of various fixed effects across columns). This estimate implies a 1% rise in one-year investor

[37]These values are broadly consistent with (if slightly smaller than) analyst price impact estimates from previous work (details in Appendix F).

Figure 7: Analyst Price Impact for Top and Bottom Quintiles of Number of Analysts



Binscatters of five-day post announcement price changes ($\Delta p^+_{a,n,t}$) versus idiosyncratic analyst growth expectations shocks ($u_{a,n,t}$) for analyst-stock-quarter observations (a, n, t) in the top (blue) and bottom (red) quintile based on the demeaned number of analysts covering stock n in quarter $t-1$ ($\tilde{A}_{n,t-1}$).

Table 3: c_1 and c_2 Estimates

	(1)	(2)	(3)	(4)
c_1	0.458***	0.459***	0.457***	0.457***
	(0.0534)	(0.0545)	(0.0546)	(0.0549)
c_2	0.0287***	0.0287***	0.0286***	0.0282***
	(0.00408)	(0.00411)	(0.00411)	(0.00406)
Quarter FE		Y	Y	
Stock FE			Y	
Stock x Quarter FE				Y
Quarter-Clustered SE	Y	Y	Y	Y
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

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

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 idiosyncratic analyst growth expectation shock, and $\tilde{A}_{n,t-1}$ is the demeaned number of analyst institutions that cover stock n in the previous quarter $t-1$. $X_{n,t}$ represents various fixed effects. All estimates represent the marginal effect in basis points of a 1 percentage point increase in analyst growth expectations. The time period is 1984-01:2021-12.

Table 4: M_g and β Estimates Under Investor Homogeneity

	(1)	(2)	(3)	(4)
β	0.0626***	0.0625***	0.0625***	0.0616***
	(0.00719)	(0.00717)	(0.00721)	(0.00724)
M_g	0.0731***	0.0734***	0.0732***	0.0741***
	(0.0133)	(0.0135)	(0.0136)	(0.0140)
Quarter FE		Y	Y	
Stock FE			Y	
Stock x Quarter FE				Y
Quarter-Clustered SE	Y	Y	Y	Y
N	1530391	1530391	1530391	1530391

Standard errors in parentheses

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

This table displays the β and M_g estimates implied by the regression

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

$$\beta = \frac{c_2}{c_1} \text{ and } M_g = \frac{c_1^2}{c_2},$$

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 idiosyncratic growth expectation shock, and $\tilde{A}_{n,t-1}$ is the demeaned number of analyst institutions that cover stock n in quarter t. $X_{n,t}$ represents various fixed effects. All estimates represent the marginal effect in percentage points of a 1 percentage point increase in growth expectations (analyst expectations for β and investor expectations for M_g). The time period is 1984-01:2021-12.

(not analyst) growth expectations raises price only 7 basis points. This estimate of $M_g = 0.07$ is an order of magnitude smaller than the benchmark value of $M_g = 1$ from Section 5.5.

Thus, the causal effect of subjective growth expectations on prices is far smaller than suggested by standard models. The core mechanism in subjective belief models is far weaker empirically than assumed by these models. As Section 5.4 discusses, this small causal effect is quantitatively consistent with the low sensitivities of demand to expected returns and the small price elasticities of demand found in previous work.

6.6 Robustness

This section summarizes the robustness checks I conduct for the baseline results in Tables 3 and 4.

6.6.1 Allowing for Analyst Heterogeneity

Appendix G.4 relaxes the assumption of homogeneous influence for all analyst institutions and finds similar results. I derive the general linearized form of analyst influence $B_{a,n}$ with heterogeneous signal precisions σ_a^{-2}. All of the intuition from Section 6.2 carries over. The full approximation simply adjusts (24) to account for the greater loss of influence due to adding a highly influential (high signal precision) analyst to stock n versus adding a non-influential (low signal precision) analyst. Thus, identifying heterogeneous influence requires cross-sectional variation in the set — not the number — of analysts who cover each stock (e.g. Goldman Sachs and J.P. Morgan cover Apple while Goldman Sachs and Morgan Stanley cover Google). This analysis finds $M_g = 0.05$, which is close to the baseline $M_g = 0.07$.

6.6.2 Alternative Numbers of Latent Factors

Appendix G.2 conducts this analysis with alternative numbers of latent factors and finds similar results. The largest M_g estimate among these alternative numbers of latent factors is $M_g = 0.08$, which is close to the baseline $M_g = 0.07$.

6.6.3 Alternative Post-Announcement Window Lengths

Appendix G.3 runs this analysis with alternative post-announcement window lengths other than 5 days and finds similar results. The largest M_g estimate among these alternative window lengths is $M_g = 0.21$, which is still far smaller than the benchmark of $M_g = 1$ and statistically indistinguishable from the upper end of the range I argue for ($M_g \in [0.07, 0.16]$). Unfortunately the post-announcement window cannot be lengthened far beyond five days in this empirical strategy. The idiosyncratic growth expectations shocks ($u_{a,n,t}$) represent within stock-quarter variation in analyst expectations. For long horizons, there is no variation in post-announcement price changes across analysts within stock-quarter. For example, the one-year post-announcement price changes for two analysts who report expectations one week apart for Apple in quarter t are virtually the same. Thus at longer horizons, regression (29) cannot identify c_1 (or M_g) because it features essentially a within stock-quarter constant on the left hand side. See Appendix G.3 for a full discussion. The empirical strategy in Section 7 operates at a lower frequency (quarterly) and finds similar results to those in Table 4.

6.6.4 LTG expectations

Appendix G.5 finds consistent results using the long-term earnings growth (LTG) expectations focused on by Bordalo et al. (2019, 2022) and Nagel and Xu (2021). Since LTG expectations represent the analyst's forecast for average EPS growth over the next $3-5$ years, the price impact of investor "long-term" growth expectations should be roughly $3-5$ times as large as the price impact of annual growth expectations (see Appendix G.5.1 for a full discussion). Appendix G.5.2 finds a 1% rise in investor long-term growth expectations raises price by about 23 basis points, which is $3-4$ times the $M_g = 0.07$ estimate in Table 4 and an order of magnitude smaller than the benchmark price impact of investor long-term growth expectations. Since the number of analyst institutions that issue LTG expectations does not vary that much across stocks, I cannot obtain a precise estimate of c_2 in regression (29) and so I cannot measure analyst influence on investor beliefs (β) for LTG expectations. Instead, I estimate average analyst price impact for LTG expectations (c_1) and scale by the baseline $\beta = 0.06$ estimate from Table 4 (see Appendix G.5.2 for details).

7 Effect of Growth Expectations on Prices: Heterogeneity

This section relaxes the homogeneity assumptions in Section 6 and measures the the causal effect of subjective growth expectations on prices (M_g) under investor heterogeneity. I allow investor heterogeneity in price elasticities (ζ_i), sensitivities of demand to growth expectations (κ_i^g), and analyst influence (β_i), which necessitates the use of investor-level holdings data. As in Section 6, I find M_g is small. A one percent rise in investor annual growth expectations raises price only 16 basis points – an order of magnitude less than the benchmark of 1%. Thus, the core mechanism in subjective belief models is far weaker empirically than assumed by these models.

Section 7.1 explains the new identification problem introduced by investor heterogeneity and why holdings data prove necessary to identify M_g. Section 7.2 details the empirical strategy for measuring M_g while allowing for investor heterogeneity. Section 7.3 presents the empirical results.

7.1 New Identification Problem Created by Investor Heterogeneity

I allow heterogeneous price elasticities (ζ_i), sensitivities of demand to growth expectations (κ_i^g), and analyst influence (β_i) . I suppress quarter t subscripts because all identification occurs within a quarter. The high-frequency investor-level demand curve from (27) becomes:

$$\begin{aligned}
\Delta q^+_{i,a,n} &= -\zeta_i \Delta p^+_{a,n} + \kappa_i^g \Delta G^I_{i.a,n} + \Delta \epsilon_{i,a,n} \\
\Delta G^I_{i,a,n} &= B_{i,n}(G^A_{a,n} - \bar{G}^I_{i,a,n}) + \nu^I_{i,a,n} \\
B_{i,n} &= \beta_i - \beta_i^2 \tilde{A}_n.
\end{aligned}$$

This heterogeneity yields a slightly different market-clearing expression (analogous to (28)):

$$\Delta p^+_{a,n} = \underbrace{\frac{(\kappa^g_\cdot \beta_\cdot)_S}{\zeta_S}}_{\equiv c_1} u_{a,n} - \underbrace{\frac{(\kappa^g_\cdot \beta^2_\cdot)_S}{\zeta_S}}_{\equiv c_2} u_{a,n} \tilde{A}_n + e_{a,n}, \tag{33}$$

where subscript S indicates the ownership-share weighted average. c_1 and c_2 still represent analyst price impact for the average stock and the shrinkage rate of analyst price impact. However, now ratios of c_1 and c_2 do not identify $M_g = \kappa^g_S/\zeta_s$ (from (22)) or β_S.

Moreover, assuming homogeneity in the presence of heterogeneity may bias the estimate of M_g

downward. With heterogeneity, the estimator for M_g assuming homogeneity from (30) is:

$$\hat{M}_g = \frac{c_1^2}{c_2} = \frac{\left(\kappa_S^g \beta_S + Cov_S(\kappa_i^g, \beta_i)\right)^2}{\kappa_S^g \left(\beta_S^2 + \mathbb{V}_S[\beta_i]\right) + Cov_S(\kappa_i^g, \beta_i^2)} \frac{1}{\zeta_S},$$

where the subscript S indicates variances and covariances are being taken in the cross section of investors under the ownership-share weighted measure. $\hat{M}_g$ only identifies M_g if analysts have the same influence on all investors so $\mathbb{V}_S[\beta_i] = Cov_S(\kappa_i^g, \beta_i) = 0$. If the covariance terms are small, then

$$\frac{c_1^2}{c_2} \approx \frac{\beta_S^2}{\beta_S^2 + \mathbb{V}_S[\beta_i]} \frac{\kappa_S^g}{\zeta_S} \leq \frac{\kappa_S^g}{\zeta_S}.$$

In this case, heterogeneity in analyst influence across investors (i.e. $\mathbb{V}_S[\beta_i] > 0$) implies the estimator for M_g assuming homogeneity ($\hat{M}_g = c_1^2/c_2$) underestimates the true parameter.

Thus, to identify M_g under investor heterogeneity, I separately identify κ_S^g and ζ_s and take their ratio. To this end, I measure both κ_i^g and ζ_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.

7.2 Empirical Strategy

This section explains how I identify M_g accounting for investor heterogeneity. Specifically, I use holdings data to identify both the sensitivity of demand to growth expectations κ_i^g and the price elasticity ζ_i at the investor level. M_g is the ratio of the ownership-share weighted averages of these quantities. All of the identification works within a quarter, so I suppress quarter t subscripts.

To identify κ_i^g and ζ_i, I use the following low-frequency (quarterly) demand curve:

$$\Delta q_{i,n} = -\zeta_i \Delta p_n + \kappa_i^g \Delta G_{i,n}^I + \Delta \epsilon_{i,n}, \tag{34}$$

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 6). $\Delta q_{i,n}$ is the quarterly percentage change in quantity of shares demanded by investor i for stock n. $\Delta G_{i,n}^I$ is the quarterly shock to annual investor growth expectations. $\Delta \epsilon_{i,n}$ accounts for (unobserved) demand shocks in the quarter.

Identifying κ_i^g and ζ_i requires two steps. The key identification problem is that both the low-frequency growth expectations shock ($\Delta G_{i,n}^I$) and the low-frequency demand shock ($\Delta \epsilon_{i,n}$) are correlated with the low-frequency price change (Δp_n) through market clearing. Thus, step one (detailed in Section 7.2.1) is to isolate the quarterly demand curve shift ($\Delta q_{i,n} + \zeta_i \Delta p_n$) from the equilibrium change in quantity demanded ($\Delta q_{i,n}$). Doing so requires estimates of investor-level price elasticities ζ_i, which I obtain from the approach of Koijen and Yogo (2019). Step two (detailed in Section 7.2.2) is then to substitute the Bayesian learning form of analyst influence (from Section

6.2) and the analyst expectations factor structure (from Section 6.3) into the unobserved investor growth expectations shock $\Delta G_{i,n}$, as in Section 6. Doing so allows identification of κ_i^g (detailed in Section 7.2.3). Given κ_i^g and ζ_i at the investor level, M_g is the ratio of the ownership-share weighted averages of these quantities: $M_g = \kappa_S^g/\zeta_S$. Section 7.2.4 discusses some estimation details.

7.2.1 Isolating Demand Curve Shifts from Equilibrium Changes in Quantities

To address the correlation of growth expectations shocks $\Delta G_{i,n}$ with price changes Δp_n, I measure each investor's elasticity (ζ_i) and remove the price term from the equilibrium quantity change:

$$\Delta q_{i,n} + \zeta_i \Delta p_n = \kappa_i^g \Delta G_{i,n}^I + \Delta \epsilon_{i,n}. \tag{35}$$

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 ($\Delta q_{i,n}$) minus movement along the demand curve ($-\zeta_i \Delta p_n$). The right-hand side decomposes this demand shift into the part due to growth expectation shocks ($\kappa_i^g \Delta G_{i,n}$) and the part due to other (unobserved) demand shocks ($\Delta \epsilon_{i,n}$).

I follow the approach of Koijen and Yogo (2019) to measure investor-specific price elasticities of demand ζ_i. Koijen and Yogo (2019) use cross-sectional variation in investment mandates across investors to obtain exogenous variation in price levels, which allows identification of price elasticities from portfolio weight levels. Appendix H provides the details of this procedure.

Given price elasticity estimates, the demand shift $\Delta q_{i,n} + \zeta_i \Delta p_n$ can be calculated using observed changes in equilibrium quantities $\Delta q_{i,n}$ (from investor holdings data) and prices Δp_n.

7.2.2 Substitute for Unobserved Investor Growth Expectation Shock

From (23), 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.

Over the whole quarter, the low-frequency update to i's growth expectation ($\Delta G_{i,n}^I$) is the sum of the high-frequency updates ($\Delta G_{i,a,n}^I$) plus any updates due to other signals:

$$\Delta G_{i,n}^I = \beta_i \sum_{a \in \mathcal{A}_n} u_{a,n} - \beta_i^2 \sum_{a \in \mathcal{A}_n} u_{a,n} \tilde{A}_n + e_{i,n}^G, \tag{36}$$

where $\mathcal{A}_n$ is the set of analysts who cover stock n. This equation follows from plugging in the Bayesian learning form of analyst influence from (24) and the factor structure for analyst expectations from (25). The structural error term $e_{i,n}^G$ comprises four components: 1) other determinants of analyst expectations, 2) investors prior expectations, 3) lagged analyst expectations, and 4) other signals investors learn from (see E.2 for details).

7.2.3 Identifying κ_i^g

I identify κ_i^g from regressions of quarterly demand shifts on the idiosyncratic analyst growth expectations shocks and their interaction with the demeaned number of analysts. All identification works in the cross section of holdings within an (investor, quarter) pair.

The expressions for the demand curve shift and the substituted investor growth expectation shock motivate a low-frequency holdings regression. Plugging in the low-frequency investor expectation update (36) into the quarterly demand curve shift (35) yields

$$\Delta q_{i,n} + \zeta_i \Delta p_n = \underbrace{b_{1,i}}_{\equiv \kappa_i^g \beta_i} S_n - \underbrace{b_{2,i}}_{\equiv \kappa_i^g \beta_i^2} S_n \tilde{A}_n + \underbrace{\kappa_i^g e_{i,n}^G + \Delta \epsilon_{i,n}}_{\equiv \varepsilon_{i,n}}. \tag{37}$$

$S_n = \sum_{a \in \mathcal{A}_n} u_{a,n}$ is the sum of the idiosyncratic analyst growth expectations shocks for stock n.

(37) identifies two reduced-form coefficients, which jointly pin down the sensitivity of demand to growth expectations κ_i^g:

1. $b_{1,i}$ is average analyst demand impact. A 1% higher analyst expectation raises demand $b_{1,i}$% for the average stock. Exogenous variation in analyst beliefs (S_n) pins down $b_{1,i}$.

2. $b_{2,i}$ is the shrinkage rate of analyst demand impact as the number of analysts grows due to the corresponding shrinkage in analyst influence. An additional analyst covering stock n reduces analyst demand impact by $b_{2,i}$% (in absolute terms). The interaction of S_n with cross-sectional variation in the number of analysts pins down $b_{2,i}$.

$b_{1,i}$ and $b_{2,i}$ jointly identify β_i and κ_i^g:

$$\beta_i = \frac{b_{2,i}}{b_{1,i}}$$
$$\kappa_i^g = \frac{b_{1,i}^2}{b_{2,i}}.$$

Thus, a regression of the quarterly demand shift ($\Delta q_{i,n} + \zeta_i \Delta p_n$) on the sum of idiosyncratic analyst growth expectations shocks (S_n) and its interaction with the demeaned number of analysts ($\tilde{A}_n$) identifies both κ_i^g and β_i. The moment conditions for identifying κ_i^g and β_i in regression (37) are

$$\mathbb{E}\left[S_n \varepsilon_{i,n}\right] = 0 \tag{38}$$
$$\mathbb{E}\left[S_n \tilde{A}_n \varepsilon_{i,n}\right] = 0 \tag{39}$$

I have two instruments (S_n and $S_n\tilde{A}_n$), two moment conditions ((38) and (39)), and two structural parameters to identify (κ_i^g and β_i). The identifying assumption is:

Assumption 2 (Identifying Assumption for Holdings Regression)**.** *Any common variation between analyst growth expectation updates ($\Delta G_{a,n}^A$) and 1) investor prior expectations, 2) other contemporaneous signals at low and high frequencies, and 3) other demand shocks, 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 $\varepsilon_{i,n}$ and $\tilde{A}_n$ in (37). In this case, both moment conditions (38) and (39) hold.

The investor-level κ_i^g and ζ_i identify the causal effect of investor annual growth expectations on prices $M_g = \kappa_S^g/\zeta_S$. I also calculate the ownership-share weighted average analyst influence: β_S.

7.2.4 Estimation Details

Although (37) identifies κ_i^g and β_i within an (investor, quarter) pair, the regression lacks power since the holdings data are noisy. To improve precision, I run one constrained regression pooled across all investors and quarters[38]:

$$\Delta\hat{q}_{i,n,t} = b_{1,i}S_{n,t} - b_{2,i}S_{n,t}\cdot\tilde{A}_{n,t-1} + X_{n,t} + FE_{i,t} + e_{i,n,t} \tag{40}$$

$$\text{s.t. } \Delta\hat{q}_{i,n,t} = \Delta q_{i,n,t} + \zeta_i\Delta p_n$$

$$0 \le b_{2,i} \le b_{1,i} \text{ (enforces } 0 \le \beta_i \le 1) \tag{41}$$

$$b_{1,S} = c_1\zeta_S \text{ (definition of } c_1) \tag{42}$$

$$b_{2,S} = c_2\zeta_S \text{ (definition of } c_2), \tag{43}$$

where subscript S denotes ownership-share weighted averages.[39] $X_{n,t}$ 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 dividend-to-book equity ratio). These controls absorb residual variation and increase power. $FE_{i,t}$ is an investor-quarter fixed effect.[40]

The three constraints further improve estimation efficiency. Constraint (41) enforces $0 \le \beta_i \le 1$, as implied by the definition of β_i from Bayesian learning (24) (since $b_{1,i} = \kappa_i^g\beta_i$ and $b_{2,i} = \kappa_i^g\beta_i^2$).

[38] To raise the volatility of $S_{n,t}$ and gain more power, I use the sum of idiosyncratic shocks to the 5 largest institutions, ranked by number of expectations reported in the quarter, instead of the sum of shocks for all institutions in $\mathcal{A}_{n,t}$. All results are robust to using other numbers of institutions. See Appendix I.2 for details.

[39] 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.

[40] Empirically I work with the following calculation of the percentage change in quantity of shares held

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

Table 5: Estimation Results Allowing for Investor Heterogeneity

	β_S	κ_S^g	M_g
Point Estimate	0.0982***	0.062***	0.163***
95% Confidence Interval	(0.086, 0.121)	(0.043, 0.245)	(0.114, 0.634)

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

This table displays the estimated κ_S^g, β_S, and M_g from (40). Point estimates are bootstrapped sampling distribution medians. Confidence intervals are bootstrapped (see Appendix I.3 for details). All estimates represent the marginal effect in percentage points of a 1 percentage point increase in growth expectations (analyst expectations for β_S, investor expectations for κ_S^g and M_g). The time period is 1984-01:2021-12.

Constraints (42) and (43) enforce market clearing. From the market clearing expression (33) in Section 7.1, the analyst price impact coefficients c_1 and c_2 have the following relationship to the reduced-form analyst demand impact coefficients $b_{1,i}$ and $b_{2,i}$:

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

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.[41]

Appendix I provides further estimation details.

7.3 Empirical Results

This section reports estimates for the causal effect of subjective growth expectations on prices (M_g) allowing for investor heterogeneity. M_g is small, an order of magnitude smaller than the benchmark $M_g = 1$. Table 2 displays summary statistics for the data used in this analysis.

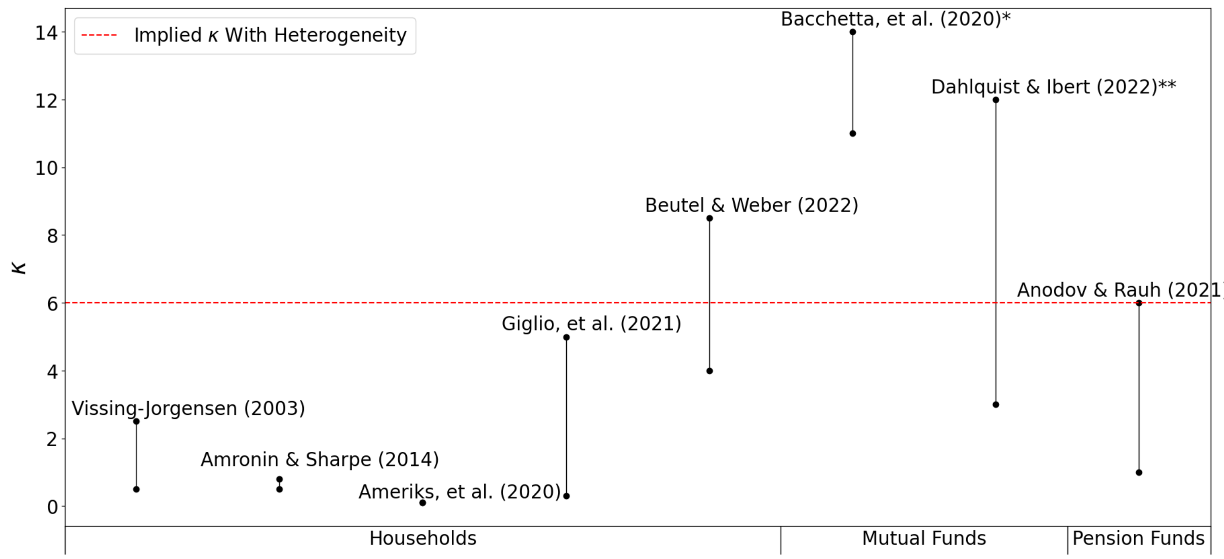
Table 5 displays the estimated κ_S^g, β_S, and M_g from regression (40). While these results differ from those estimated assuming investor homogeneity in Table 4, the economic conclusions drawn from both sets of results are the same.

The ownership-share weighted average analyst influence is $\beta_S = 0.10$, which implies a 1% higher

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 quarter $t-1$ and $\hat{Q}_{i,n,t} = H_{i,n,t}/(1+R^X_{n,t-1\to t})$ is the *dollar* holdings of investor i in stock n in this quarter t adjusted for the ex-dividend return (i.e. the price change) since last period $R^X_{n,t-1\to t}$. The denominator maps the expression into the range $[-2, 2]$. Since a holdings change of less than -100% has no economic meaning, I censor changes at -100%. The motivation for this calculation is that the 13F filings available from Thomson Reuters via WRDS contain some measurement error (i.e. data entry errors) in the number of shares (e.g. failure to adjust for stock splits, etc.). Using dollar holdings circumvents these issues. Adjusting the denominator essentially winsorizes large positive percentage changes.

[41] Koijen, Richmond and Yogo (2020) follow a similar regularization approach in a different setting.

Figure 8: Comparison of κ Implied by κ_S^g to Previous Literature



Comparison of the sensitivity of demand to expected return (κ) implied by the estimate $\kappa_S^g = 0.06$ to values found in previous work (see Appendix J for details, including discussions of the interpretation of the results from Bacchetta, Tieche and Van Wincoop (2020) and Dahlquist and Ibert (2021)).

analyst-reported annual growth expectation raises the average investor's growth expectation by 10 basis points. While this estimate proves larger than the $\beta = 0.06$ estimate under investor homogeneity from Table 4, both sets of estimates imply that investors do learn from analysts.

The weighted average sensitivity of demand to growth expectations is $\kappa_S^g = 0.06$, which means a 1% increase in annual investor growth expectation raises the average investor's quantity demanded by 6 basis points. Figure 8 illustrates that this sensitivity of demand to growth expectations is quantitatively consistent with the small sensitivities of demand to expected returns documented in previous work, including work using matched expectations and holdings data. Recall from Proposition 1 in Section 5.4 the structural form of $\kappa^g = \kappa\delta$, where κ is the sensitivity of demand to expected return and δ is the average dividend-price ratio. Calibrating average quarterly dividend-price ratio $\delta = 0.01$ to match the historical average for the aggregate equity market implies $\kappa = 6$, which is in line with previous estimates.[42]

The causal effect of subjective growth expectations on prices is $M_g = 0.16$, which means a 1% increase in investors' annual growth expectations raises price by 16 basis points. While this estimate proves larger than that from Table 4 assuming investor homogeneity ($M_g = 0.07$), $M_g = 0.16$ is still an order of magnitude smaller than the benchmark value of $M_g = 1$ from Section 5.5. Thus, these results support the conclusion that the causal effect of subjective growth expectations on prices is

[42] Previous work usually regresses portfolio weights (θ) on expected returns (μ) and so measures $\partial\theta/\partial\mu$. However, $\kappa = \partial \log \theta/\partial\mu = \partial\theta/\partial\mu \cdot 1/\theta$ in (10). 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 8.

empirically far smaller than assumed in subjective belief models.

8 Conclusion

Subjective belief models assume a large causal effect of subjective growth expectations on prices and use the strong correlation of analyst growth expectations with prices as evidence of this causal effect. However, reverse causality contaminates this interpretation of the correlation of growth expectations with prices: prices cause growth expectations. A 1% rise in price raises annual growth expectations 41 basis points. The true causal effect of subjective growth expectations on prices is an order of magnitude smaller than assumed in subjective belief models. A 1% rise in annual investor growth expectations raises price only 7 to 16 basis points compared to the benchmark of 1%. Hence, the core mechanism in subjective belief models is far weaker empirically than assumed by these models. In this sense, subjective growth expectations matter far less for asset prices than suggested by standard models.

This small causal effect of subjective growth expectations on prices arises due to the low sensitivity of demand to expected return and is consistent with inelastic demand. A low sensitivity of demand to expected return implies both small demand curve shifts due to growth expectations shocks, and inelastic demand. These small demand curve shifts due to growth expectations shocks have only a small impact on price, even though demand is inelastic.

These results pose significant implications for asset pricing and macro-finance. The small causal effect of subjective growth expectations on prices raises the possibility that biased beliefs have limited impact on asset prices and the real economy. 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 raise the possibility that subjective growth expectations cannot quantitatively resolve asset pricing and macro-finance puzzles, they open the door to other channels. If biased growth expectations cannot quantitatively explain 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.

If subjective growth expectations do significantly distort asset prices, this distortion must operate through dynamic amplification mechanisms outside existing models. The empirical analysis in this paper quantifies the standard mechanism through which subjective growth expectations distort asset prices and finds it is far weaker empirically than assumed in standard models. Yet there could be other mechanisms that existing models and this analysis do not address. For example, growth expectations may only strongly impact asset demand, and so prices, at substantial lags.

My empirical results motivate augmenting existing models with these alternative mechanisms. The empirical methodology developed in this paper offers a general framework for using data on beliefs, prices, and holdings to tackle these possibilities and shed new light on the intersection of subjective beliefs, asset demand, and asset prices.

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Appendix

Aditya Chaudhry

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A Reverse Causality Supplements

A.1 Identification from Ownership Shares Illustrative Example

This example follows directly from the argument in Goldsmith-Pinkham, Sorkin and Swift (2020).

Assume there are only two mutual funds, one analyst (so drop subscript a), and one time period (so drop subscript t).

We have a simultaneous system of equations

$$\Delta p_n = C\Delta G_n + M\text{FIT}_n + \epsilon_n$$
$$\Delta G_n = \alpha \Delta p_n + \nu_n,$$

where

$$\text{FIT}_n = S_{1,n} f_1 + S_{2,n} f_2.$$

$S_{i,n}$ is the ex-ante ownership share (i.e. from quarter $t-2$) of fund i in stock n and f_i is the inflow into fund i (in quarter t) expressed as a percentage of fund i's ex-ante total net assets. For simplicity, assume

$$S_{1,n} + S_{2,n} = 1, \forall n,$$

although this assumption is not necessary.

The exclusion restriction is

$$\mathbb{E}\left[\text{FIT}_n \nu_n\right] = 0.$$

I claim the following assumption proves sufficient for this exclusion restriction to hold:

$$\mathbb{E}\left[S_{i,n}\nu_n\right] = 0.$$

The point is using the actual FIT instrument (composed of the ownership shares and flows) is equivalent to using the ownership shares as instruments. To see why, consider the following five steps:

1. Reexpress the simultaneous system of equations in reduced-form:

$$\Delta p_n = \underbrace{\frac{M}{1-\alpha C}}_{\equiv\gamma}\text{FIT}_n + \underbrace{\frac{1}{1-\alpha C}\epsilon_n}_{\equiv\tilde{\epsilon}_n^p} + \underbrace{\frac{C}{1-\alpha C}\nu_n}_{\equiv\tilde{\nu}_n^p}$$
$$\Delta G_n = \underbrace{\frac{\alpha M}{1-\alpha C}}_{\equiv\alpha\gamma}\text{FIT}_n + \underbrace{\frac{\alpha}{1-\alpha C}\epsilon_n}_{\equiv\tilde{\epsilon}_n^g} + \underbrace{\frac{1}{1-\alpha C}\nu_n}_{\equiv\tilde{\nu}_n^g}$$

2. Reexpress the reduced-form equations in terms of the ownership shares

$$\begin{aligned}\Delta p_n &= \gamma\left(S_{1,n}f_1 + S_{2,n}f_2\right) + \tilde{\epsilon}_n^p + \tilde{\nu}_n^p \\ &= \underbrace{(\gamma f_1)}_{\equiv\gamma_1}S_{1,n} + \underbrace{(\gamma f_2)}_{\equiv\gamma_2}S_{2,n} + \tilde{\epsilon}_n^p + \tilde{\nu}_n^p \\ &= \gamma_2 + (\gamma_1-\gamma_2)S_{1,n} + \tilde{\epsilon}_n^p + \tilde{\nu}_n^p \qquad (44)\\ \Delta G_n &= \alpha\gamma\left(S_{1,n}f_1 + S_{2,n}f_2\right) + \tilde{\epsilon}_n^g + \tilde{\nu}_n^g \\ &= \underbrace{(\alpha\gamma f_1)}_{\equiv\alpha\gamma_1}S_{1,n} + \underbrace{(\alpha\gamma f_2)}_{\equiv\alpha\gamma_2}S_{2,n} + \tilde{\epsilon}_n^g + \tilde{\nu}_n^g \\ &= \alpha\gamma_2 + \alpha(\gamma_1-\gamma_2)S_{1,n} + \tilde{\epsilon}_n^g + \tilde{\nu}_n^g. \qquad (45)\end{aligned}$$

3. The first-stage cross-sectional regression of price changes (Δp_n) on fund 1's ownership shares ($S_{1,n}$) (44) identifies $\gamma_1 - \gamma_2$.

4. The reduced-form cross-sectional regression of growth expectation changes (ΔG_n) on fund 1's ownership shares ($S_{1,n}$) (45) identifies $\alpha(\gamma_1-\gamma_2)$.[43]

5. Thus, I have identified α (given $\gamma_1-\gamma_2$ and $\alpha(\gamma_1-\gamma_2)$) with no assumptions about the exogeneity of flows f_1 and f_2.

[43] Note that $\mathbb{E}\left[S_{i,n}\epsilon_n\right] \neq 0$ is not a problem. In this case, the first-stage regression (44) obtains

$$b_1 = \gamma_1 - \gamma_2 + \frac{Cov\left(S_{1,n}, \tilde{\epsilon}_n^g\right)}{Var\left[S_{1,n}\right]} = \gamma_1 - \gamma_2 + \frac{1}{1-\alpha C}\frac{Cov\left(S_{1,n}, \epsilon_n\right)}{Var\left[S_{1,n}\right]}$$

The reduced-form regression (45) obtains

$$b_2 = \alpha(\gamma_1-\gamma_2) + \frac{Cov\left(S_{1,n}, \tilde{\epsilon}_n^g\right)}{Var\left[S_{1,n}\right]} = \alpha(\gamma_1-\gamma_2) + \frac{\alpha}{1-\alpha C}\frac{Cov\left(S_{1,n}, \epsilon_n\right)}{Var\left[S_{1,n}\right]} = \alpha b_1.$$

Thus, I still identify α from the ratio of reduced-form and first-stage coefficients

$$\alpha = \frac{b_2}{b_1}.$$

To summarize, the identifying variation is cross-sectional variation in ownership shares. Hence, the ownership shares provide the variation that must satisfy the exclusion restriction (i.e. the ownership shares must be uncorrelated with non-price determinants of growth expectations ν_n).

Nothing changes with multiple mutual funds, time periods, or analysts.

With $I > 2$ funds, the system of equations (44) and (45) will be overidentified: there will be $I-1$ instruments but only one structural parameter to identify (α). Per Proposition 1 in Goldsmith-Pinkham, Sorkin and Swift (2020), using the actual FIT instrument is equivalent to using the ownership shares as instruments in GMM with a particular weighting matrix.

With $T > 1$ time periods, reduced-form coefficients γ_1 and γ_2 become $\gamma_{1,t}$ and $\gamma_{2,t}$, which can be identified by interacting the ownership shares $S_{1,n,t-2}$ with time dummies. Thus, α can be identified from the following first-stage and reduced-form regressions:

$$\Delta p_{n,t} = \gamma_{2,s} + \sum_s (\gamma_{1,s} - \gamma_{2,s}) 1_{t=s} S_{1,n,t-2} + \tilde{\epsilon}^p_{n,t} + \tilde{\nu}^p_{n,t} \qquad \text{(First Stage)}$$

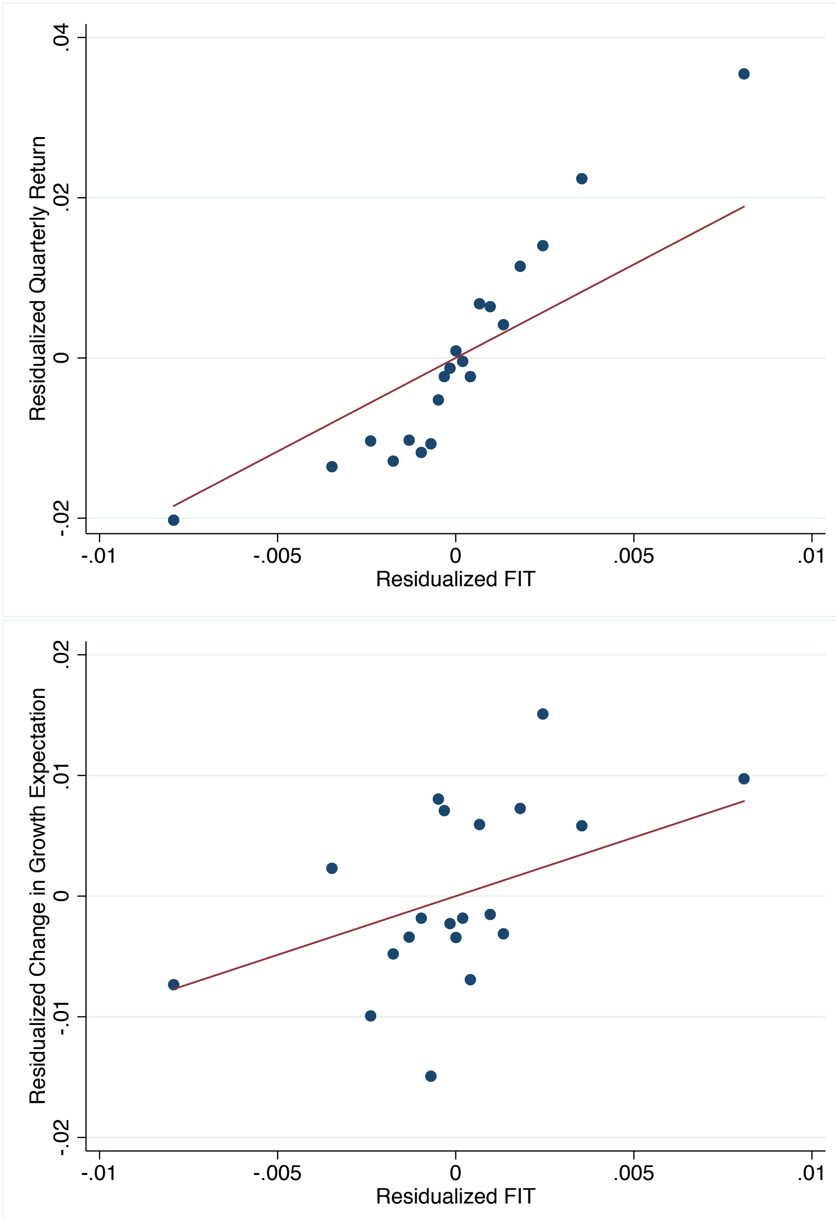
$$\Delta G_{n,t} = \alpha\gamma_{2,s} + \alpha \sum_s (\gamma_{1,s} - \gamma_{2,s}) 1_{t=s} S_{1,n,t-2} + \tilde{\epsilon}^g_{n,t} + \tilde{\nu}^g_{n,t}. \qquad \text{(Reduced Form)}$$

Per Appendix D in Goldsmith-Pinkham, Sorkin and Swift (2020), using the actual FIT instrument in this setting is equivalent to using the ownership shares interacted with time dummies as instruments in an overidentified GMM system with a particular weighting matrix.

Extending to multiple analysts just involves replacing ΔG_n with $\Delta G_{a,n}$. As long as the corresponding identifying assumption ($\mathbb{E}\left[S_{i,n}\nu_{a,n}\right] = 0$) holds, all of the same arguments still apply.

A.2 Supplements to Baseline Specification

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

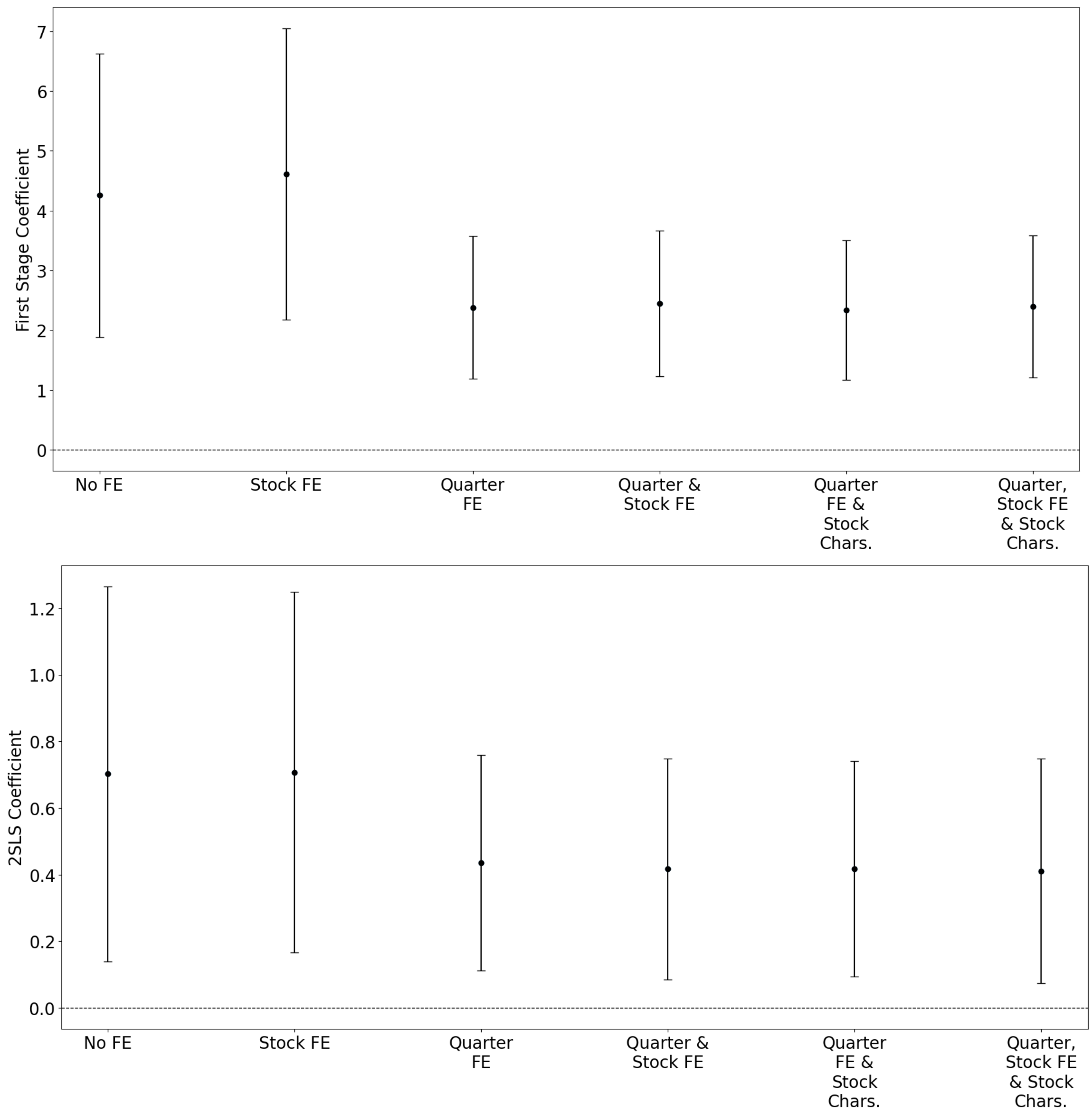


This figure displays binscatter plots for the following first-stage and reduced-form regressions:

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

The first stage regresses quarterly percent price changes ($\Delta p_{a,n,t}$) on the flow-induced trading instrument ($\text{FIT}_{n,t}$). The reduced form regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) on the flow-induced trading instrument ($\text{FIT}_{n,t}$). $X_{n,t}$ 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.

Figure A2: Alternative Specifications Using Standard FIT Measure



This figure displays results for different specifications of the following two-stage least squares regression:

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

The first stage regresses quarterly percent price changes ($\Delta p_{a,n,t}$) on the flow-induced trading instrument ($\mathrm{FIT}_{n,t}$). The second stage regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) 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.

Table A1: Causal Effect of Prices on Growth Expectations — Lagged Price Changes

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
$\Delta p_{a,n,t}$	0.673***	0.659***	0.674**	0.666**	0.722**	0.716**	0.809**	0.800**
	(0.238)	(0.237)	(0.282)	(0.281)	(0.348)	(0.346)	(0.378)	(0.375)
$\Delta p_{a,n,t-1}$	-0.304	-0.304	-0.216	-0.228	-0.241	-0.249	-0.285	-0.298
	(0.185)	(0.188)	(0.272)	(0.271)	(0.340)	(0.339)	(0.406)	(0.404)
$\Delta p_{a,n,t-2}$			-0.150	-0.142	-0.222	-0.223	-0.167	-0.155
			(0.289)	(0.292)	(0.454)	(0.451)	(0.531)	(0.524)
$\Delta p_{a,n,t-3}$					0.221	0.238	0.158	0.146
					(0.391)	(0.394)	(0.583)	(0.577)
$\Delta p_{a,n,t-4}$							0.148	0.191
							(0.376)	(0.375)
Stock Characteristics		Y		Y		Y		Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
N	893672	893672	646570	646570	507873	507873	406493	406493

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:

$$\Delta G_{a,n,t} = b_0 + \sum_{s=0}^{h} \alpha_s \Delta \hat{p}_{a,n,t-s} + X_{n,t} + e_{2,n,t},$$

where each $\Delta \hat{p}_{a,n,t-s}$ is instrumented with $\text{FIT}_{n,t}, \ldots, \text{FIT}_{n,t-h}$. The time period is 1984-01:2021-12.

Table A2: Causal Effect of Prices on Growth Expectations — Controlling for Lagged Characteristics

	(1) OLS	(2) First Stage	(3) Reduced Form	(4) 2SLS
$\Delta p_{a,n,t}$	0.310***			0.424**
	(0.0249)			(0.177)
$\text{FIT}_{n,t}$		2.434***	1.032**	
		(0.598)	(0.475)	
Investment_{t-1}	-0.0833***	-0.0286***	-0.0921***	-0.0800***
	(0.0229)	(0.0104)	(0.0235)	(0.0237)
D/BE_{t-1}	0.221*	-0.181*	0.165	0.241*
	(0.114)	(0.104)	(0.125)	(0.123)
Market Beta_{t-1}	0.0409	0.00179	0.0416	0.0408
	(0.0340)	(0.0308)	(0.0416)	(0.0316)
Log BE_{t-1}	-0.0277***	-0.0178***	-0.0333***	-0.0257***
	(0.00888)	(0.00443)	(0.00950)	(0.00957)
$\text{Profitability}_{t-1}$	-0.150***	0.00203	-0.150***	-0.150***
	(0.0229)	(0.00911)	(0.0236)	(0.0228)
Investment_{t-2}	0.0524***	-0.00737	0.0501***	0.0532***
	(0.0175)	(0.00739)	(0.0175)	(0.0178)
D/BE_{t-2}	-0.125	-0.00847	-0.128	-0.124
	(0.0899)	(0.0984)	(0.101)	(0.0881)
Market Beta_{t-2}	-0.0343	-0.00646	-0.0363	-0.0335
	(0.0310)	(0.0292)	(0.0384)	(0.0288)
Log BE_{t-2}	0.0257***	-0.00343	0.0247***	0.0261***
	(0.00848)	(0.00416)	(0.00888)	(0.00824)
$\text{Profitability}_{t-2}$	0.121***	0.00737	0.123***	0.120***
	(0.0197)	(0.00870)	(0.0206)	(0.0193)
Stock Characteristics	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y	Y
N	1240412	1240412	1240412	1240412
F	20.15	11.60	6.875	7.393
R-Squared	0.0938	0.232	0.0806	

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:

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

The first stage regresses 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 annual growth expectations ($\Delta G_{a,n,t}$) on the instrumented price changes ($\Delta \hat{p}_{a,n,t}$). Stock characteristics are log book equity, profitability, investment, market beta, and the dividend to book equity ratio from quarters $t-1$ and $t-2$. The time period is 1984-01:2021-12.

Table A3: Causal Effect of Prices on Growth Expectations — Further Lagged Ownership Shares

	(1) $t-2$ Shares	(2) $t-3$ Shares	(3) $t-4$ Shares
$\text{FIT}_{n,t}$	2.449***	2.117***	1.545***
	(0.620)	(0.640)	(0.584)
Quarter FE	Y	Y	Y
Stock FE	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y
N	1311394	1311394	1311394
F	15.60	10.94	7.000
R-Squared	0.226	0.225	0.224

Standard errors in parentheses

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

	(1) $t-2$ Shares	(2) $t-3$ Shares	(3) $t-4$ Shares
$\Delta p_{a,n,t}$	0.417**	0.436**	0.414*
	(0.169)	(0.187)	(0.247)
Quarter FE	Y	Y	Y
Stock FE	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y
N	1311394	1311394	1311394
F	6.066	5.438	2.812
R-Squared	0.0124	0.0117	0.0125

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:

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

where $\text{FIT}_{n,t}$ is constructed from different lags s of the ownership shares:

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

The first stage (top panel) regresses percent price changes between analyst reports ($\Delta p_{a,n,t}$) on the flow-induced trading instrument ($\text{FIT}_{n,t}$). The second stage (bottom panel) regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) on the instrumented price change ($\Delta \hat{p}_{a,n,t}$). 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, 2022) 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 4.1, I run the following two-stage least squares regression:

$$\begin{aligned} \Delta p_{a,n,t} &= a_0 + a_1 \mathrm{FIT}_{n,t} + X_{n,t} + e_{1,n,t} \\ \Delta \mathrm{LTG}_{a,n,t} &= b_0 + \alpha \Delta \hat{p}_{a,n,t} + X_{n,t} + e_{2,n,t}, \end{aligned} \tag{46}$$

where $\Delta\mathrm{LTG}_{a,n,t}$ 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 ($\mathrm{FIT}_{n,t}$). The second stage regresses the change in LTG expectations ($\Delta\mathrm{LTG}_{a,n,t}$) 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).[44]

Table A4 displays the results of this regression. The OLS regressions of LTG expectations on prices in columns 1 and 2 display a strong correlation between these objects, as documented in previous work (Bordalo et al. (2019, 2022); 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 17 and 12, 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 α 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 16 basis points. Thus, the reverse causality issue raised in Section 4 exists in the LTG expectations data as well.

[44]Appendix Figure A3 displays residualized binscatter plots for the first-stage and reduced-form regressions in (46).

Table A4: Causal Effect of Prices on LTG Expectations

	(1) OLS	(2) OLS	(3) First Stage	(4) First Stage	(5) Reduced Form	(6) Reduced Form	(7) 2SLS	(8) 2SLS
$\Delta p_{a,n,t}$	0.0628***	0.0434***					0.164***	0.163***
	(0.00845)	(0.00326)					(0.0452)	(0.0463)
$\text{FIT}_{n,t}$			3.158***	3.116***	0.517**	0.509**		
			(0.760)	(0.757)	(0.221)	(0.222)		
Stock Characteristics		Y		Y		Y		Y
Quarter FE		Y	Y	Y	Y	Y	Y	Y
Stock FE		Y	Y	Y	Y	Y	Y	Y
Quarter-Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
N	227598	227598	227598	227598	227598	227598	227598	227598
F	55.11	41.14	17.28	11.89	5.480	12.03	13.13	11.94
R-Squared	0.0182	0.117	0.227	0.230	0.108	0.111		

Standard errors in parentheses

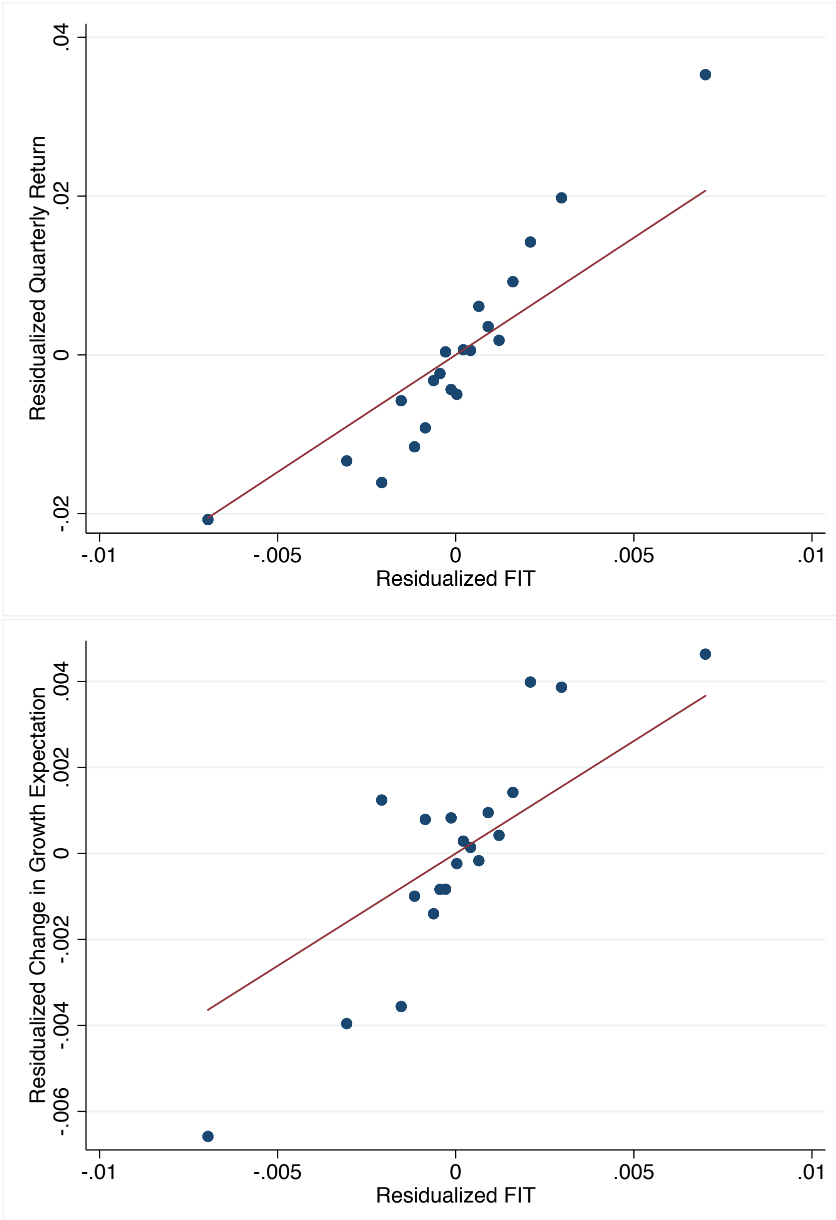
* p<0.10, ** p<0.05, *** p<0.01

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

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

The first stage regresses percent price changes between analyst reports ($\Delta p_{a,n,t}$) on the flow-induced trading instrument ($\text{FIT}_{n,t}$). The second stage regresses quarterly changes in LTG expectations ($\Delta \text{LTG}_{a,n,t}$) on the instrumented price change ($\Delta \hat{p}_{a,n,t}$). The time period is 1982-04:2021-12.

Figure A3: 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:

$$\Delta p_{a,n,t} = a_0 + a_1 \text{FIT}_{n,t} + X_{n,t} + e_{1,n,t}$$
$$\Delta \text{LTG}_{a,n,t} = b_0 + b_1 \text{FIT}_{n,t} + X_{n,t} + e_{2,n,t},$$

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

Figure A4: Within Stock-Quarter Timeline

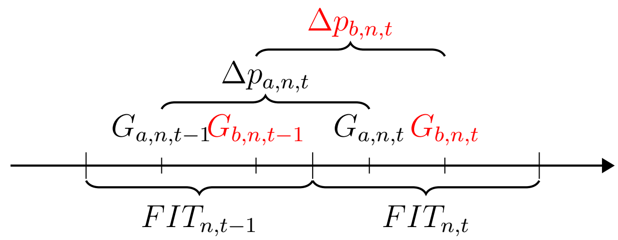


Illustration of staggered timing of analyst expectation releases for two analysts a and b for the same stock n and quarter t.

A.4 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 4.1. Multiple analyst institutions issue growth expectations for each stock in each quarter and generally not on the same day. Thus, the timing of analyst report releases creates variation across analysts in exposure to the stock-quarter 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 $\text{FIT}_{n,t}$ and less exposed to $\text{FIT}_{n,t-1}$ than that of analyst institution a. This variation in analyst report timing allows us to construct an analyst-stock-quarter specific FIT measure[45]:

$$\text{FIT}_{a,n,t} = \underbrace{\frac{\#\text{ days elapsed in } t-1 \text{ since } G_{a,n,t-1}}{92}}_{\equiv w^1_{a,n,t}} \cdot \text{FIT}_{n,t-1} + \underbrace{\frac{\#\text{ days elapsed in } t \text{ until } G_{a,n,t}}{92}}_{\equiv w^2_{a,n,t}} \cdot \text{FIT}_{n,t}.$$

[45]In this section I use a different construction for $\text{FIT}_{n,t}$ than in Section 4.1:

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

Here I use the ownership share weights from quarter $t-1$

$$S_{i,n,t-1} = \frac{\text{SharesHeld}_{\ n,i,t-1}}{\text{SharesOutstanding}_{n,t-1}}.$$

instead of those from quarter $t-2$ in 4.1. Doing so improves power (although using $S_{i,n,t-2}$ also yields similar results to those in Table A5). Using $S_{i,n,t-1}$ in Section 4.1 would potentially violate the exclusion restriction there because $S_{i,n,t-1}$ (measured at the end of quarter $t-1$) occurs in the middle of the growth expectation update from quarter $t-1$ to quarter t. In this section, however, the endogeneity of $S_{i,n,t-1}$ is not a problem: the identifying assumption is now $\mathbb{E}_{n,t}\left[w_{a,n,t-1}\nu_{a,n,t}\right] = \mathbb{E}_{n,t}\left[w_{a,n,t}\nu_{a,n,t}\right] = 0$, not $\mathbb{E}_{n,t}\left[S_{i,n,t-1}\nu_{a,n,t}\right] = 0$.

This measure allows exploitation of within stock-quarter variation. For example, assume for a fixed stock n and quarter t $\text{FIT}_{n,t} > \text{FIT}_{n,t-1}$, 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 α.

Returning to the system of simultaneous equations (4) and (5), the exclusion restriction is $\mathbb{E}_{n,t}\left[\text{FIT}_{a,n,t}\nu_{a,n,t}\right] = 0$, where $\mathbb{E}_{n,t}$ denotes the expectation taken across analysts a within stock-quarter pair (n,t). Following the logic of shift-share instruments, the identifying variation is within stock-quarter variation in the timing weights $w^1_{a,n,t}$ and $w^2_{a,n,t}$. Thus, the identifying assumptions is:

$$\mathbb{E}_{n,t}\left[w^1_{a,n,t}\nu_{a,n,t}\right] = \mathbb{E}_{n,t}\left[w^2_{a,n,t}\nu_{a,n,t}\right] = 0.$$

That is, the timing of analyst report releases is not correlated with non-price determinants of growth expectations. In other words, analyst institutions who report later than average for stock n in quarter t are not more (or less) bullish than average on stock n. To give a concrete example, Goldman Sachs reporting expectations for Apple before J.P. Morgan does must not correlate with the non-price determinants of Goldman Sachs's growth expectation update for Apple relative to J.P. Morgan. If analyst institutions pick announcement dates ex ante (i.e. in the previous quarter) and do not deviate from that preset schedule based on new information that affects growth expectations, then this assumption is satisfied.

To assuage any concerns about the potential endogeneity of analyst announcement timing, Appendix A.4.1 conducts a version of this within stock-quarter identification strategy that exploits only predictable variation in analyst announcement timing based on ex-ante information. In this case, the identifying assumption is that the historical tendency of Goldman Sachs to report expectations for Apple before J.P. Morgan does not predict Goldman Sachs's growth expectation shock (ν) for Apple relative to J.P. Morgan in quarter t. This alternative strategy also finds significant α estimates.

Table A5 displays the results of the following two-stage least-squares regression:

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

where $X_{a,n,t}$ represents controls, including stock-quarter and analyst institution-quarter fixed effects. The first stage regressions of price changes on the FIT instrument in columns 3 and 4 are strong with F-statistics of over 24 (partial F-statistic of 24 for both). The reduced form regression of growth expectations on the FIT instrument in columns 5 and 6 are also strong. The second-stage estimates of α in columns 7 and 8 are quantitatively similar to that in Table 1: a 1% increase in price raises annual growth expectations by $30-31$ basis points instead of 41 basis points in Table 1. Note that this within stock-quarter specification has more power than the within quarter specification (the second-stage coefficient standard errors are 0.06 and 0.14, respectively) since the stock-quarter and analyst institution-quarter 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 α estimates from the within-quarter specification in Table 1 and the within-stock quarter specification in Table A5 assuage concerns about the potential threats to identification laid out in Section 4.3.

Table A5: Causal Effect of Prices on Growth Expectations — Within Stock-Quarter Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	First Stage	First Stage	Reduced Form	Reduced Form	2SLS	2SLS
$\Delta p_{a,n,t}$	0.365***	0.157***					0.313***	0.299***
	(0.0475)	(0.0105)					(0.0631)	(0.0617)
$\text{FIT}_{a,n,t}$			5.121***	4.999***	1.603***	1.496***		
			(1.026)	(1.002)	(0.385)	(0.383)		
Stock x Quarter FE		Y	Y	Y	Y	Y	Y	Y
Analyst Instit. x Quarter FE		Y		Y		Y		Y
Quarter-Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
N	1311394	1281546	1311394	1311394	1311394	1311394	1311394	1311394
F	58.97	224.1	24.90	24.90	17.38	15.29	24.59	23.49
R-Squared	0.0245	0.841	0.848	0.854	0.821	0.827		

Standard errors in parentheses

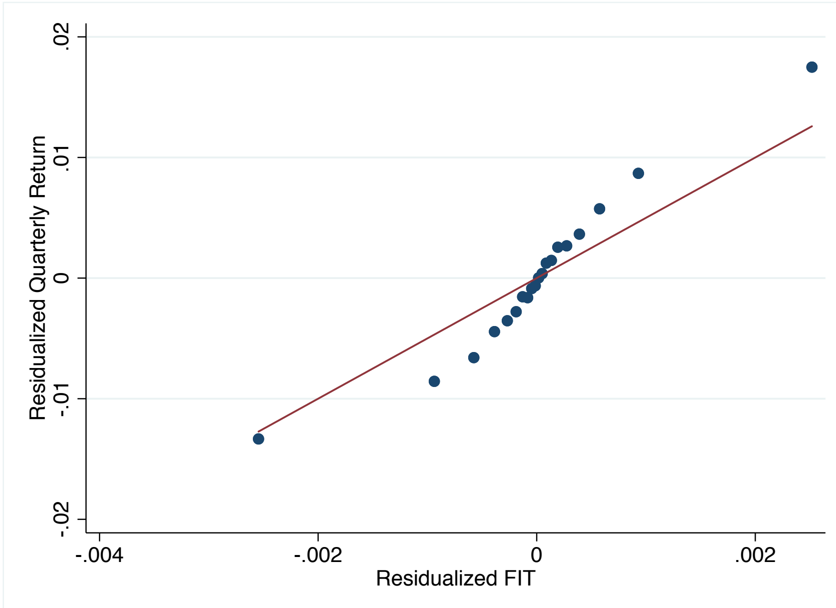
* p<0.10, ** p<0.05, *** p<0.01

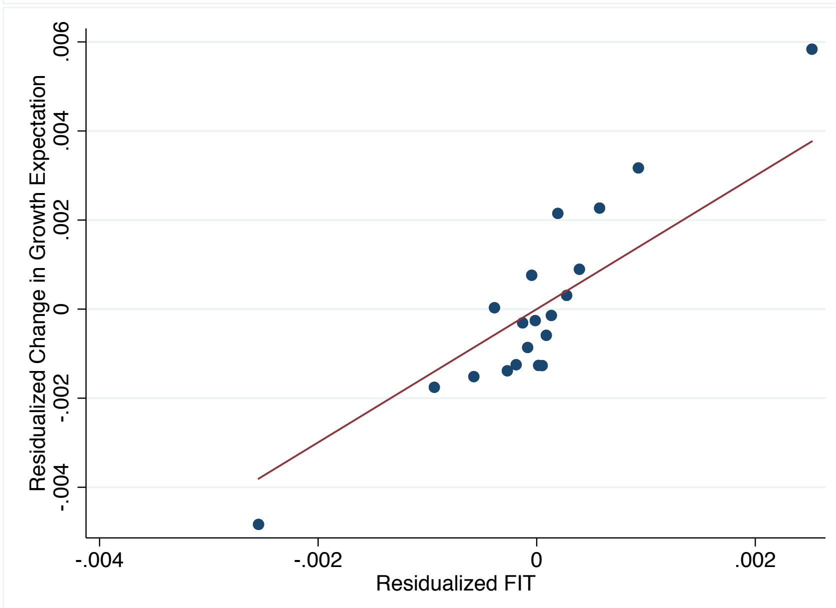
This table displays results for the following two-stage least squares regression:

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

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 second stage regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) on the instrumented price change ($\Delta \hat{p}_{a,n,t}$). 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:

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

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 annual growth expectations ($\Delta G_{a,n,t}$) on the analyst-specific flow-induced trading instrument ($\text{FIT}_{a,n,t}$). $X_{n,t}$ includes stock-quarter and analyst-quarter fixed effects. The time period is 1984-01:2021-12.

A.4.1 Exploiting Only Ex-Ante Predictable Variation in Analyst Timing

To assuage any concerns about a violation of the sufficient condition for exclusion

$$\mathbb{E}_{n,t}\left[w^1_{a,n,t}\nu_{a,n,t}\right] = \mathbb{E}_{n,t}\left[w^2_{a,n,t}\nu_{a,n,t}\right] = 0$$

due to the endogeneity of analyst announcement timing, I consider a robustness check using only predictable variation in the timing weights $w^1_{a,n,t}$ and $w^2_{a,n,t}$ based on ex-ante information. This strategy also yields significant α estimates.

The predicted timing weights based on ex-ante information do not correlate with quarter-t expectations updates. When using the realized timing in the previous section, one may be concerned both analyst timing and belief shocks (ν) both respond to stock-specific news in quarter t. For example, J.P. Morgan may receive positive private information about Apple that both raises its growth expectations and induces it to report later (than other analyst institutions) in this quarter. This concern does not arise when using the predicted timing. To undermine the identification strategy with predicted timing, one must believe that the historical (prior to quarter $t-1$) order in which analyst institutions report growth expectations for stock n (i.e. the within stock-quarter variation in the timing weights) correlates with the growth expectations shocks in the current quarter (t). This concern proves implausible. For example, J.P. Morgan historically reporting growth expectations for Apple after Goldman Sachs reports implies nothing about these institutions update their expectations about Apple in the current quarter. If good news raised J.P. Morgan's growth expectations in quarter $t-2$ and induced it to report later than Goldman Sachs, the predicted timing weights for quarter t will depend on news from quarter $t-2$. However, by definition news is uncorrelated over time (i.e. the nature of shocks is that they are unpredictable). Thus, the predicted weights are uncorrelated with news in quarter t that impacts growth expectations ($\nu_{a,n,t}$) in quarter t.

Due to the difficulty of predicting within stock-quarter variation in the timing weights $w^1_{a,n,t}$ and $w^2_{a,n,t}$, I use the following three sets of predictors:

1. The lagged weights between quarter $t-2$ and quarter $t-s$ for $s \in [2, 16]$:

$$w^{1,s,lag}_{a,n,t} = w^1_{a,n,t-1-s}$$
$$\bar{w}^{2,s,lag}_{a,n,t} = w^2_{a,n,t-1-s}$$

2. Weights constructed based on the previous quarter's announcement date and the lagged gap between quarterly announcement dates between quarter $t-2$ and quarter $t-s$ for $s \in [2, 16]$. Let $d_{a,n,t}$ be the analyst report date for analyst institution a and stock n in quarter t. Let $g_{a,n,t} = d_{a,n,t} - d_{a,n,t-1}$ be the gap in days between analyst report date for analyst institution

a and stock n in consecutive quarters. The predicted announcement days in quarters $t-1$ and t are then

$$\hat{d}^s_{a,n,t-1} = d_{a,n,t-2} + g_{a,n,t-1-s}$$
$$\hat{d}^s_{a,n,t} = d_{a,n,t-1} + g_{a,n,t-1-s}.$$

The corresponding predicted weights are then

$$w^{1,s,gap}_{a,n,t} = \frac{\#\text{ days elapsed in } t-1 \text{ since } \hat{d}^s_{a,n,t-1}}{92}$$
$$w^{2,s,gap}_{a,n,t} = \frac{\#\text{ days elapsed in } t \text{ until } \hat{d}^s_{a,n,t}}{92}.$$

3. Weights constructed based on the current quarter's EPS announcement date and the average number of days between EPS announcements and analyst report releases between quarter $t-2$ and quarter $t-s$ for $s \in [2,16]$. Let $e_{n,t}$ be the EPS announcement date for stock n in quarter t. Let $\tilde{g}_{a,n,t} = d_{a,n,t} - e_{n,t}$ be the gap in days between analyst report date for analyst institution a and stock n and the EPS announcement for stock n in quarter t. The predicted announcement days in quarters $t-1$ and t are then

$$\tilde{d}^s_{a,n,t-1} = e_{n,t-1} + \frac{1}{s}\sum_{k=1}^{s} \tilde{g}_{a,n,t-1-s}$$
$$\tilde{d}^s_{a,n,t} = e_{n,t} + \frac{1}{s}\sum_{k=1}^{s} \tilde{g}_{a,n,t-1-s}.$$

Note that $\hat{d}^s_{a,n,t-1}$ and $\hat{d}^s_{a,n,t}$ are constructed using only ex-ante information since the EPS announcement dates in quarters $t-1$ and t are prescheduled. The corresponding predicted weights are then

$$w^{1,s,EPS}_{a,n,t} = \frac{\#\text{ days elapsed in } t-1 \text{ since } \tilde{d}^s_{a,n,t-1}}{92}$$
$$w^{2,s,EPS}_{a,n,t} = \frac{\#\text{ days elapsed in } t \text{ until } \tilde{d}^s_{a,n,t}}{92}.$$

I run predictive regressions of the true weights on these ex-ante predictors

$$w^i_{a,n,t} = \sum_{j\in\{avg,gap,EPS\}} \sum_{s=2}^{16} b^i_{j,s} w^{i,s,j}_{a,n,t} + FE_{n,t} + \epsilon^i_{a,n,t}$$

and use the fitted values $\hat{w}^1_{a,n,t}$ and $\hat{w}^2_{a,n,t}$ to construct $\text{FIT}^{pred}_{a,n,t}$:

$$\text{FIT}^{pred}_{a,n,t} = \hat{w}^1_{a,n,t} \cdot \text{FIT}_{n,t-1} + \hat{w}^2_{a,n,t} \cdot \text{FIT}_{n,t}.$$

Crucially this regression includes stock-quarter fixed effects because I need a good prediction of the within stock-quarter variation in analyst timing. Tables A6 and A7 present the results of these predictive regressions.

Table A8 displays the results of the following two-stage least-squares regression:

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

where $X_{a,n,t}$ represents controls, including stock-quarter and analyst institution-quarter fixed effects. The first stage regressions of price changes on the FIT instrument in columns 3 and 4 are strong with F-statistics (and partial F-statistics) of 16 and 14, respectively. The reduced form regressions of growth expectations on the FIT instrument in columns 5 and 6 are also strong. The second-stage estimates of α in columns 7 and 8 are significantly positive: a 1% increase in price raises annual growth expectations by $98 - 110$ basis points. While these point estimates prove larger than the baseline estimate of 41 basis points in Table 1, note that this specification has less power than that in Table A5 due to noise in the constructed instrument stemming from the predicted weights not perfectly correlating with the true weights. Statistically, the larger point estimates in Table A8 cannot be distinguished from the baseline point estimate of 41 basis points at the 95% confidence level. Moreover, taking the point estimates at face value, the α estimates from this predicted-timing strategy are larger than those from Table A5 above. These larger point estimates provide evidence against the concern that the significant α estimates from the realized-timing version of this strategy arise from a positive correlation of announcement timing and non-price determinants of growth expectations ($\mathbb{E}_{n,t}\left[w^i_{a,n,t}\nu_{a,n,t}\right] > 0$). If there is a correlation of announcement timing and non-price determinants of expectations, it appears to be negative, which means the α estimates from the realized-timing version of this strategy are actually biased downwards.

Figure A6 displays residualized binscatter plots for the first-stage and reduced-form regressions.

Table A6: Timing Predictive Regression $w^1_{a,n,t} = \sum_{j \in \{avg,gap,EPS\}} \sum_{s=2}^{16} b^1_{j,s} w^{1,s,j}_{a,n,t} + FE_{n,t} + \epsilon^1_{a,n,t}$

	$w^1_{a,n,t}$	
$w^1\_a, n, t^{1,1,gap}$	0.262***	(0.00919)
$w^1\_a, n, t^{1,2,gap}$	0.0416***	(0.00153)
$w^1\_a, n, t^{1,3,gap}$	-0.0230***	(0.00119)
$w^1\_a, n, t^{1,4,gap}$	-0.0149***	(0.00145)
$w^1\_a, n, t^{1,5,gap}$	-0.0178***	(0.00144)
$w^1\_a, n, t^{1,6,gap}$	-0.00599***	(0.00149)
$w^1\_a, n, t^{1,7,gap}$	-0.00350**	(0.00165)
$w^1\_a, n, t^{1,8,gap}$	-0.00360*	(0.00183)
$w^1\_a, n, t^{1,9,gap}$	-0.00609***	(0.00231)
$w^1\_a, n, t^{1,10,gap}$	-0.00257	(0.00203)
$w^1\_a, n, t^{1,11,gap}$	-0.00282	(0.00202)
$w^1\_a, n, t^{1,12,gap}$	0.000133	(0.00215)
$w^1\_a, n, t^{1,13,gap}$	-0.00291	(0.00201)
$w^1\_a, n, t^{1,14,gap}$	-0.00218	(0.00275)
$w^1\_a, n, t^{1,15,gap}$	-0.00176	(0.00276)
$w^1\_a, n, t^{1,16,gap}$	-0.00117	(0.00343)
$w^1\_a, n, t^{1,1,lag}$	0.0813***	(0.0139)
$w^1\_a, n, t^{1,2,lag}$	0.0561***	(0.0169)
$w^1\_a, n, t^{1,3,lag}$	0.0607***	(0.0220)
$w^1\_a, n, t^{1,4,lag}$	0.0836***	(0.0232)
$w^1\_a, n, t^{1,5,lag}$	-0.0271	(0.0279)
$w^1\_a, n, t^{1,6,lag}$	-0.0179	(0.0399)
$w^1\_a, n, t^{1,7,lag}$	0.0403	(0.0276)
$w^1\_a, n, t^{1,8,lag}$	0.101**	(0.0472)
$w^1\_a, n, t^{1,9,lag}$	0.0154	(0.0486)
$w^1\_a, n, t^{1,10,lag}$	0.0724	(0.0569)
$w^1\_a, n, t^{1,11,lag}$	0.0369	(0.0406)
$w^1\_a, n, t^{1,12,lag}$	-0.0242	(0.0630)
$w^1\_a, n, t^{1,13,lag}$	-0.0733	(0.0775)
$w^1\_a, n, t^{1,14,lag}$	0.0120	(0.0587)
$w^1\_a, n, t^{1,15,lag}$	0.0347	(0.0810)
$w^1\_a, n, t^{1,16,lag}$	0.211**	(0.0916)
$w^1\_a, n, t^{1,1,EPS}$	-0.000627	(0.0141)
$w^1\_a, n, t^{1,2,EPS}$	0.0412**	(0.0169)
$w^1\_a, n, t^{1,3,EPS}$	-0.0338	(0.0219)
$w^1\_a, n, t^{1,4,EPS}$	-0.0336	(0.0237)
$w^1\_a, n, t^{1,5,EPS}$	0.0511*	(0.0274)
$w^1\_a, n, t^{1,6,EPS}$	0.0460	(0.0398)
$w^1\_a, n, t^{1,7,EPS}$	-0.00868	(0.0279)
$w^1\_a, n, t^{1,8,EPS}$	-0.0577	(0.0471)
$w^1\_a, n, t^{1,9,EPS}$	0.0118	(0.0491)
$w^1\_a, n, t^{1,10,EPS}$	-0.0548	(0.0571)
$w^1\_a, n, t^{1,11,EPS}$	-0.0192	(0.0412)
$w^1\_a, n, t^{1,12,EPS}$	0.0609	(0.0622)
$w^1\_a, n, t^{1,13,EPS}$	0.0927	(0.0764)
$w^1\_a, n, t^{1,14,EPS}$	0.00675	(0.0591)
$w^1\_a, n, t^{1,15,EPS}$	-0.0194	(0.0811)
$w^1\_a, n, t^{1,16,EPS}$	-0.183**	(0.0912)
Stock x Quarter FE	Y	
N	1945611	
Within R-Squared	0.0676	

Standard errors in parentheses

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

This table displays results for the timing predictive regression of $w^1_{a,n,t}$ on the three sets of predictors discussed in Appendix A.4.1. The time period is 1984-01:2021-12.

Table A7: Timing Predictive Regression $w^2_{a,n,t} = \sum_{j\in\{avg,gap,EPS\}} \sum_{s=2}^{16} b^2_{j,s} w^{2,s,j}_{a,n,t} + FE_{n,t} + \epsilon^2_{a,n,t}$

	$w^2_{a,n,t}$	
$w^{2,2,lag}_{a,n,t}$	0.0412**	(0.0167)
$w^{2,3,lag}_{a,n,t}$	0.0200	(0.0225)
$w^{2,4,lag}_{a,n,t}$	0.0501*	(0.0255)
$w^{2,5,lag}_{a,n,t}$	0.0153	(0.0232)
$w^{2,6,lag}_{a,n,t}$	-0.0242	(0.0280)
$w^{2,7,lag}_{a,n,t}$	-0.0234	(0.0302)
$w^{2,8,lag}_{a,n,t}$	-0.00387	(0.0366)
$w^{2,9,lag}_{a,n,t}$	-0.0497	(0.0397)
$w^{2,10,lag}_{a,n,t}$	0.101**	(0.0476)
$w^{2,11,lag}_{a,n,t}$	-0.0234	(0.0448)
$w^{2,12,lag}_{a,n,t}$	-0.0460	(0.0610)
$w^{2,13,lag}_{a,n,t}$	-0.0247	(0.0591)
$w^{2,14,lag}_{a,n,t}$	0.0710	(0.0727)
$w^{2,15,lag}_{a,n,t}$	-0.0730	(0.0791)
$w^{2,16,lag}_{a,n,t}$	-0.0246	(0.0739)
$w^{2,2,gap}_{a,n,t}$	0.0120***	(0.00172)
$w^{2,3,gap}_{a,n,t}$	0.00594***	(0.00182)
$w^{2,4,gap}_{a,n,t}$	0.00757***	(0.00240)
$w^{2,5,gap}_{a,n,t}$	0.00102	(0.00228)
$w^{2,6,gap}_{a,n,t}$	0.00227	(0.00249)
$w^{2,7,gap}_{a,n,t}$	0.00369	(0.00262)
$w^{2,8,gap}_{a,n,t}$	0.000149	(0.00307)
$w^{2,9,gap}_{a,n,t}$	-0.00792**	(0.00317)
$w^{2,10,gap}_{a,n,t}$	0.000209	(0.00344)
$w^{2,11,gap}_{a,n,t}$	0.00211	(0.00384)
$w^{2,12,gap}_{a,n,t}$	-0.000419	(0.00482)
$w^{2,13,gap}_{a,n,t}$	0.00777	(0.00481)
$w^{2,14,gap}_{a,n,t}$	-0.00456	(0.00544)
$w^{2,15,gap}_{a,n,t}$	0.00278	(0.00556)
$w^{2,16,gap}_{a,n,t}$	-0.00661	(0.00538)
$w^{2,2,EPS}_{a,n,t}$	0.0108	(0.0168)
$w^{2,3,EPS}_{a,n,t}$	0.0313	(0.0219)
$w^{2,4,EPS}_{a,n,t}$	0.0222	(0.0260)
$w^{2,5,EPS}_{a,n,t}$	0.0287	(0.0244)
$w^{2,6,EPS}_{a,n,t}$	0.0573**	(0.0280)
$w^{2,7,EPS}_{a,n,t}$	0.0602**	(0.0304)
$w^{2,8,EPS}_{a,n,t}$	0.0574	(0.0359)
$w^{2,9,EPS}_{a,n,t}$	0.0880**	(0.0387)
$w^{2,10,EPS}_{a,n,t}$	-0.0719	(0.0469)
$w^{2,11,EPS}_{a,n,t}$	0.0464	(0.0453)
$w^{2,12,EPS}_{a,n,t}$	0.0791	(0.0621)
$w^{2,13,EPS}_{a,n,t}$	0.0400	(0.0596)
$w^{2,14,EPS}_{a,n,t}$	-0.0488	(0.0728)
$w^{2,15,EPS}_{a,n,t}$	0.0955	(0.0788)
$w^{2,16,EPS}_{a,n,t}$	0.0692	(0.0753)
Stock x Quarter FE	Y	
N	1945611	
Within R-Squared	0.0121	

Standard errors in parentheses

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

This table displays results for the timing predictive regression of $w^2_{a,n,t}$ on the three sets of predictors discussed in Appendix A.4.1. The time period is 1984-01:2021-12.

Table A8: Causal Effect of Prices on Earnings Growth Expectations — Within Stock-Quarter Specification, Using Predicted Timing

	(1) OLS	(2) OLS	(3) First Stage	(4) First Stage	(5) Reduced Form	(6) Reduced Form	(7) 2SLS	(8) 2SLS
$\Delta p_{a,n,t}$	0.365***	0.149***					0.985***	1.103**
	(0.0475)	(0.0104)					(0.368)	(0.442)
$\text{FIT}^{pred}_{a,n,t}$			4.025***	3.589***	3.967***	3.957***		
			(1.006)	(0.933)	(1.447)	(1.499)		
Stock x Quarter FE		Y	Y	Y	Y	Y	Y	Y
Analyst Instit. x Quarter FE		Y		Y		Y		Y
Quarter-Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
N	1311394	1311394	1311394	1311394	1311394	1311394	1311394	1311394
F	58.97	203.77	16.01	14.79	7.518	6.964	7.177	6.235
R-Squared	0.0245	0.828	0.847	0.853	0.821	0.827		

Standard errors in parentheses

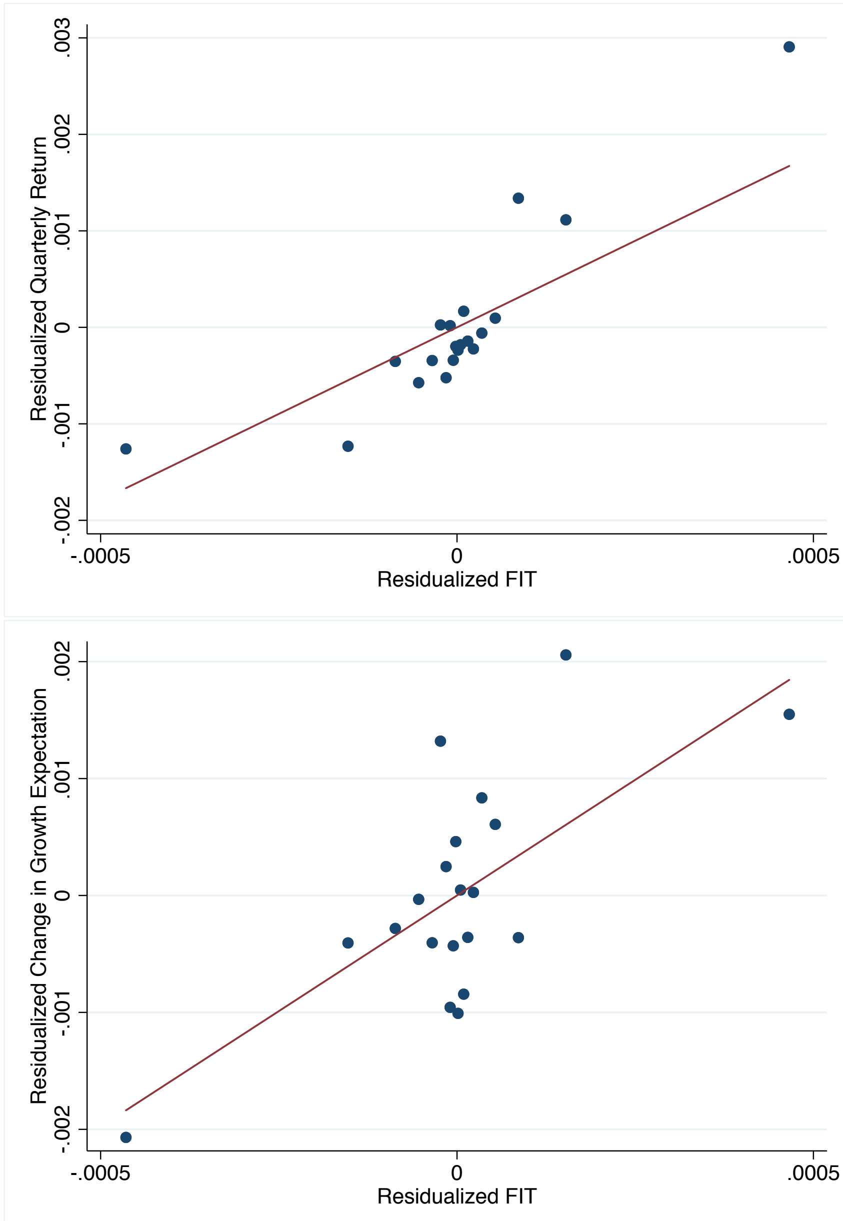
* p<0.10, ** p<0.05, *** p<0.01

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

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

The first stage regresses percent price changes between analyst reports ($\Delta p_{a,n,t}$) on the analyst-specific flow-induced trading instrument using the predicted timing of analyst reports ($\text{FIT}^{pred}_{a,n,t}$). The second stage regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) on the instrumented price change ($\Delta \hat{p}_{a,n,t}$). The time period is 1984-01:2021-12.

Figure A6: Binscatter Plots for First Stage and Reduced Form of Within Stock-Quarter Specification Using Predicted Timing



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

$$\Delta p_{a,n,t} = a_0 + a_1 \mathrm{FIT}^{pred}_{a,n,t} + X_{a,n,t} + e_{1,n,t}$$
$$\Delta G_{a,n,t} = b_0 + b_1 \mathrm{FIT}^{pred}_{a,n,t} + X_{a,n,t} + e_{2,n,t},$$

The first stage regresses percent price changes between analyst reports ($\Delta p_{a,n,t}$) on the analyst-specific flow-induced trading instrument using the predicted timing of analyst reports ($\mathrm{FIT}^{pred}_{a,n,t}$). The reduced form regresses quarterly changes in annual growth expectations ($\Delta G_{a,n,t}$) on the analyst-specific flow-induced trading instrument using the predicted timing of analyst reports ($\mathrm{FIT}^{pred}_{a,n,t}$). $X_{n,t}$ includes stock-quarter and analyst-quarter fixed effects. The time period is 1984-01:2021-12.

B Supplemental Material for Section 5

B.1 Measuring Persistence in I/B/E/S Expectations

Let $G^h_{n,t}$ represent one-year dividend growth starting $h-1$ 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 ρ by running the following regression using the I/B/E/S analyst EPS forecasts:

$$G^{h,A}_{a,n,t+1} = \rho^{annual} G^{h-1,A}_{a,n,t+1} + X_{n,t} + \epsilon^h_{a,n,t+1}.$$

$G^{h,A}_{a,n,t+1}$ is analyst a's expectation of $G^h_{n,t+1}$. That is, within the term structure of growth expectations made by analyst a for stock n in quarter t, I regress consecutive annual growth expectations. For example, for $h=2$ I would regress analyst a's annual growth expectation starting one year from now (i.e. from quarter $t+5$ to quarter $t+8$) on the annual growth expectation 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 B9 displays the results of this regression. I am use the ρ estimate without stock fixed effects: $\rho^{annual} \approx 0.24$. I then convert ρ^{annual} into a quarterly persistence ρ:

$$\rho^{annual} = \rho^4,$$

which yields $\rho = 0.7$.

Table B9: ρ^{annual} Estimates

	(1)	(2)	(3)	(4)
ρ^{annual}	0.238***	0.244***	0.141***	0.143***
	(0.00625)	(0.00561)	(0.00565)	(0.00502)
Quarter FE		Y		Y
Stock FE			Y	Y
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.2 Derivation of Expressions and Propositions in Section 5.3

This Appendix derives (14)

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

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

The proof uses the following three lemmas, which I prove in Appendix B.3.

Lemma 1 (Linearization of Portfolio Weight Demanded (10))**.** *Starting in the ex-ante equilibrium at $t-$, 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:*

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

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 $t+$):

$$\Delta q_{n,t} \approx (\theta_{n,t-} - 1)\Delta p_{n,t} + \kappa \Delta\mu_{n,t} + \Delta\epsilon_{n,t}. \tag{47}$$

See Appendix B.3.1 for a proof of this linearization.

Lemma 2 (Linearization of Expected Return (11))**.** *Starting in the ex-ante equilibrium at $t-$, consider small percentage deviations in: 1) current price $\Delta p_{n,t}$ (from $P_{n,t-}$ to $P_{n,t+}$), 2) expected next period price $\Delta p^e_{n,t,1}$ (from $\tilde{\mathbb{E}}_{t-}[P_{n,t+1}]$ to $\tilde{\mathbb{E}}_{t+}[P_{n,t+1}]$), and 3) expected next period dividend $\Delta d^e_{n,t,1}$ (from $\tilde{\mathbb{E}}_{t-}[D_{n,t+1}]$ to $\tilde{\mathbb{E}}_{t+}[D_{n,t+1}]$). Linearizing around $(\Delta p_{n,t}, \Delta p^e_{n,t,1}, \Delta d^e_{n,t,1}) = (0,0,0)$ yields change in expected return:*

$$\Delta\mu_{n,t} \approx (-1-\delta)(1+\bar{g})\Delta p_{n,t} + \delta(1+\bar{g})\Delta d^e_{n,t,1} + (1+\bar{g})\Delta p^e_{n,t,1}. \tag{48}$$

where δ is the average dividend-price ratio and $\bar{g}$ is average dividend growth rate.

See Appendix B.3.2 for a proof of this approximation.

Lemma 3 (Quarterly Expected Dividend Growth Shock Impact on Price Expectation)**.** *A shock to annual growth expectation of $\Delta G^e_{n,t}$ induces the following change in the expectation of next period's price:*

$$\Delta p^e_{n,t,1} = \Delta p_{n,t} + M_\mu \delta \frac{\rho}{1 - M_\mu \rho} \frac{1}{1+\rho+\rho^2+\rho^3} \Delta G^e_{n,t},$$

where

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

See Appendix B.3.3 for a proof of this lemma.

In deriving (14), I also prove the following proposition, which provides the general expressions for ζ and κ^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 in Section 5.4.

Proposition 2 (κ^g, ζ, and M_g in General)**.** *In general, we have:*

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

Proof of Proposition 2 and derivation of (14). Plugging the expected return linearization (48) into the linearized demand function (47) yields the following demand function:

$$\Delta q_{n,t} = \left(\theta_{n,t-} - 1 - \kappa(1+\delta)(1+\bar{g})\right)\Delta p_{n,t} + \kappa(1+\bar{g})\left[\delta \Delta d^e_{n,t,1} + \Delta p^e_{n,t,1}\right] + \Delta\epsilon_{n,t}. \tag{49}$$

We need to substitute for $\Delta d^e_{n,t,1}$ and $\Delta p^e_{n,t,1}$. 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

$$\Delta d^e_{n,t,1} = \frac{\Delta G^e_{n,t}}{1+\bar{g}}.$$

See the Proof of Lemma 3 in Appendix B.3.3 for a proof of this expression. The shock to dividend growth also changes the expectation of next period price. By Lemma 3, the change in expectation of next period's price driven by $\Delta G^e_{n,t}$ is

$$\Delta p_{n,t} + M_\mu \delta \frac{\rho}{1-M_\mu \rho}\frac{1}{1+\rho+\rho^2+\rho^3}\Delta G^e_{n,t}. \tag{50}$$

Plugging this last expression into the demand function (49) yields

$$\Delta q_{n,t} = \underbrace{\left(\theta_{n,t-} - 1 - \kappa(1+\bar{g})\delta\right)}_{\equiv -\zeta}\Delta p_{n,t} + \underbrace{\kappa(1+\bar{g})\delta\left[\frac{1}{1+\bar{g}} + \frac{M_\mu \rho}{1-\rho M_\mu}\right]\frac{1}{1+\rho+\rho^2+\rho^3}}_{\equiv \kappa^g}\Delta G^e_{n,t} + \Delta\epsilon_{n,t}, \tag{51}$$

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. $\square$

B.3 Supporting Proofs For Appendix B.2

B.3.1 Proof of Lemma 1

Proof. This proof follows from Gabaix and Koijen (2020*b*).

The true percentage change in quantity of shares demanded is

$$\begin{aligned}\Delta q^D_{n,t} &= \frac{Q^D_{n,t+}}{Q^D_{n,t-}} - 1 \\ &= \frac{W_{i,t+}}{W_{i,t-}} \frac{P_{n,t-}}{P_{n,t+}} \frac{\theta_{n,t+}}{\theta_{n,t-}} - 1 \\ &= \frac{W_{i,t+}}{W_{i,t-}} \frac{P_{n,t-}}{P_{n,t+}} \exp[\kappa \Delta \mu_{n,t} + \Delta \epsilon_{n,t}] - 1 \\ &= \frac{1 + \Delta w_t}{1 + \Delta p_{n,t}} \exp[\kappa \Delta \mu_{n,t} + \Delta \epsilon^D_{n,t}] - 1.\end{aligned}$$

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

$$\Delta q^D_{n,t} \approx \Delta w_t - \Delta p_{n,t} + \kappa \Delta \mu_{n,t} + \Delta \epsilon^D_{n,t}. \tag{52}$$

Note that the dollar change in wealth is

$$W_{t+} - W_{t-} = (P_{n,t+} - P_{n,t-}) Q^D_{n,t-},$$

so

$$\Delta w_t = \frac{W_{i,t+} - W_{t-}}{W_{t-}} = \frac{(P_{n,t+} - P_{n,t-}) Q^D_{n,t-}}{W_{t-}} = \frac{(P_{n,t+} - P_{n,t-})}{W_{t-}} \frac{\theta_{n,t-} W_{t-}}{P_{n,t-}} = \theta_{n,t-} \Delta p_{n,t}. \tag{53}$$

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

$$Q^D_{n,t-} = \frac{\theta_{n,t-} W_{t-}}{P_{n,t-}}.$$

Plugging this expression for Δw_t into (52) yields[46]:

$$\begin{aligned}\Delta q^D_{n,t} &\approx \theta_{n,t-}\Delta p_{n,t} - \Delta p_{n,t} + \kappa\Delta\mu_{n,t} + \Delta\epsilon_{n,t}\\ &= (\theta_{n,t-} - 1)\Delta p_{n,t} + \kappa\Delta\mu_{n,t} + \Delta\epsilon_{n,t}.\end{aligned}$$

□

B.3.2 Proof of Lemma 2

Proof. This proof follows from Gabaix and Koijen (2020*b*).

The definition of the expected return is

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

So at time $t-$ we have

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

and at time $t+$ we have

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

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

$$R^f_t + \mu_{n,t-} + \Delta\mu_{n,t} = \frac{\tilde{\mathbb{E}}_{t-}[P_{n,t+1}](1 + \Delta p^e_{n,t,1}) + \tilde{\mathbb{E}}_{t-}[D_{n,t+1}](1 + \Delta d^e_{n,t,1})}{P_{n,t-,}(1 + \Delta p_{n,t})}, \tag{54}$$

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

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

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

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

[46] Strictly speaking, $\Delta\xi_t$ in $\Delta\epsilon_{n,t} = \Delta\epsilon^D_{n,t} + \Delta\xi_t$ depends on $\Delta\mu_{n,t}$ through $\hat{\theta}_{n,t}$.

$$\begin{aligned}\left.\frac{\partial\xi_t}{\partial\mu_{n,t}}\right|_{\hat{\theta}_{m,t}=\hat{\theta}_{m,t-},\forall m} &= -\frac{\sum_{m=1}^N \left.\frac{\partial\hat{\theta}_{m,t}}{\partial\mu_{n,t}}\right|_{\hat{\theta}_{m,t}=\hat{\theta}_{m,t-}}}{1 + \sum_{m=1}^N \hat{\theta}_{m,t-}}\\ &= -\theta_{n,t-}\kappa.\end{aligned}$$

Taking this dependence into account yields the following demand function

$$\Delta q_{n,t} \approx (\theta_{n,t-} - 1)\Delta p_{n,t} + \kappa(1 - \theta_{n,t-})\Delta\mu_{n,t} + \Delta\epsilon^D_{n,t} + \Delta\xi_{n,t},$$

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 (47).

Now linearize the right-hand side of (54) around $(\Delta p_{n,t}, \Delta p^e_{n,t,1}, \Delta d^e_{n,t,1}) = (0,0,0)$:

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

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

Now rearrange to obtain:

$$R^f_t + \mu_{n,t-} + \Delta\mu_{n,t} \approx (1+\bar{g})(1+\delta) + (1+\bar{g})\left[\Delta p^e_{n,t,1} - \Delta p_{n,t} + \delta(\Delta d^e_{n,t,1} - \Delta p_{n,t})\right]. \tag{55}$$

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

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

Thus, from (55) we obtain:

$$\Delta\mu_{n,t} \approx (-1-\delta)(1+\bar{g})\Delta p_{n,t} + \delta(1+\bar{g})\Delta d^e_{n,t,1} + (1+\bar{g})\Delta p^e_{n,t,1},$$

as desired. □

B.3.3 Proof of Lemma 3

The proof uses the following present value relation, which I prove in Appendix B.3.4.

Lemma 4 (Present Value Relation)**.** *Let $\Delta d^e_{n,t,s} = \frac{\mathbb{E}_{t+}[D_{n,t+s}]}{\mathbb{E}_{t-}[D_{n,t+s}]} - 1$ represent the percentage change between $t-$ and $t+$ in the expectation of the dividend in period $t+s$ and $\Delta\epsilon^e_{n,t,s} = \mathbb{E}_{t+}[\epsilon^D_{n,t+s} + \xi_{t+s}] - \mathbb{E}_{t-}[\epsilon^D_{n,t+s} + \xi_{t+s}]$ 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:*

$$\Delta p_{n,t} = M_\mu \delta \sum_{s=0}^{\infty} M^s_\mu \Delta d^e_{n,t,s+1} + \sum_{s=0}^{\infty} M^s_\mu \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta\epsilon^e_{n,t,s}, \tag{56}$$

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.3.5.

Lemma 5 (Quarterly Expected Dividend Growth Shock Price Impact)**.** *A shock of $\Delta G^e_{n,t}$ to annual expected dividend growth requires a shock of $\Delta x_{n,t}$ to quarterly expected dividend growth, where:*

$$\Delta x_{n,t} \equiv \frac{\Delta G^e_{n,t}}{1+\rho+\rho^2+\rho^3}.$$

Proof of Lemma 3. First I derive the price impact of a quarterly growth expectation shock:

$$\tilde{\mathbb{E}}_{t+}\left[g_{n,t+1}\right] - \tilde{\mathbb{E}}_{t-}\left[g_{n,t+1}\right] = \Delta x_{n,t}.$$

At the end I plug in the quarterly growth expectation shock implied by an annual growth expectation shock from Lemma 5:

$$\Delta x_{n,t} = \frac{\Delta G^e_{n,t}}{1+\rho+\rho^2+\rho^3}.$$

Let $g^{e-}_{n,t+s} = \tilde{\mathbb{E}}_{t-}\left[g_{t+s}\right]$. The percentage increase in the expected level of next period's dividend is:

$$\Delta d^e_{n,t,1} = \frac{1+g^{-}_{n,t+1}+\Delta x_{n,t}}{1+g^{-}_{n,t+1}} - 1.$$

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

$$\Delta d^e_{n,t,2} = \frac{(1+g^{e-}_{n,t+1}+\Delta x_{n,t})(1+g^{e-}_{n,t+2}+\rho\Delta x_{n,t})}{(1+g^{e-}_{n,t+1})(1+g^{e-}_{n,t+2})} - 1.$$

For $s+1$ periods from now we have

$$\begin{aligned}
1+\Delta d^e_{n,t,s+1} &= \frac{\prod_{j=0}^{s}\left(1+g^{e-}_{n,t+j+1}+\rho^j\Delta x_{n,t}\right)}{\prod_{j=0}^{s}\left(1+g^{e-}_{n,t+j+1}\right)} \\
\to \Delta\tilde{d}_{n,t,s+1} \approx \log\left(1+\Delta\tilde{d}_{n,t,s+1}\right) &= \sum_{j=0}^{s}\log\left(1+g^{e-}_{n,t+j+1}+\rho^j\Delta x_{n,t}\right) - \sum_{j=0}^{s}\log\left(1+g^{e-}_{n,t+j+1}\right) \\
&\approx \sum_{j=0}^{s}\rho^j\Delta x_{n,t} \\
&= \frac{1-\rho^{s+1}}{1-\rho}\Delta x_{n,t}. \qquad (57)
\end{aligned}$$

Plugging this last result (57) into the present-value identity from Lemma 4 (and setting all other demand shock expectations $\Delta\epsilon^e_{n,t,s} = 0$ for brevity) yields the following market-clearing price change[47]:

$$\begin{aligned}\Delta p_{n,t} &= M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \Delta d_{n,t,s+1}^e \\ &= M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \left[\frac{1-\rho^{s+1}}{1-\rho}\right] \Delta x_{n,t} \\ &= M_\mu \frac{\delta}{1-\rho} \left[\frac{1}{1-M_\mu} - \frac{\rho}{1-\rho M_\mu}\right] \Delta x_{n,t}. \end{aligned} \tag{58}$$

Now plug in the quarterly dividend growth shock implied by an annual dividend growth shock from Lemma 5

$$\Delta x_{n,t} = \frac{\Delta G_{n,t}^e}{1+\rho+\rho^2+\rho^3},$$

to obtain

$$\Delta p_{n,t} = M_\mu \frac{\delta}{1-\rho} \left[\frac{1}{1-M_\mu} - \frac{\rho}{1-\rho M_\mu}\right] \frac{1}{1+\rho+\rho^2+\rho^3} \Delta G_{n,t}^e.$$

Projecting the present-value identity (56) from Lemma 4 forward one period in time, we have

[47] This framework can handle non-zero demand shocks $\Delta\epsilon_{n,t,s}^e$ as well. If the residual demand shock in period t ($\Delta\epsilon_{n,t} \equiv \Delta\epsilon_{n,t}^D + \xi_t$) is permanent (i.e. $\Delta\epsilon_{n,t,s}^e = \Delta\epsilon_{n,t}, \forall s > 0$), then the result of this lemma (60) holds exactly.

If the residual demand shock today has some persistence or reversion, then (60) 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):

$$\Delta q_{n,t} = -\zeta \Delta p_{n,t} + \kappa^g \Delta \nu_{n,t} + \underbrace{\Delta\epsilon_{n,t} + \kappa(1+\bar{g})\omega_{n,t}}_{\text{New Residual Demand Shock}}.$$

In this case, redefine $\Delta\epsilon_{n,t}$ to be the sum of the original residual demand shock $\Delta\epsilon_{n,t}$ and $\kappa(1+\bar{g})\omega_{n,t}$.

the change in expected next period price is:

$$\begin{aligned}
\Delta\tilde{p}_{n,t,1} &= \delta\sum_{s=1}^{\infty} M_\mu^s \Delta d^e_{n,t,s+1} \\
&= \delta\sum_{s=1}^{\infty} M_\mu^s \frac{1-\rho^{s+1}}{1-\rho}\Delta x_{n,t} \\
&= \delta M_\mu \sum_{s=0}^{\infty} M_\mu^s \frac{1-\rho^{s+2}}{1-\rho}\Delta x_{n,t} \\
&= M_\mu \frac{\delta}{1-\rho}\left[\frac{1}{1-M_\mu} - \frac{\rho^2}{1-\rho M_\mu}\right]\Delta x_{n,t} \\
&= \Delta p_{n,t} + \left[M_\mu \frac{\delta}{1-\rho}\frac{\rho}{1-\rho M_\mu} - M_\mu \frac{\delta}{1-\rho}\frac{\rho^2}{1-\rho M_\mu}\right]\Delta x_{n,t} \qquad (59)\\
&= \Delta p_{n,t} + M_\mu \frac{\delta}{1-\rho}\frac{\rho}{1-\rho M_\mu}\left[1-\rho\right]\Delta x_{n,t} \\
&= \Delta p_{n,t} + M_\mu \delta \frac{\rho}{1-\rho M_\mu}\Delta x_{n,t} \\
&= \Delta p_{n,t} + M_\mu \delta \frac{\rho}{1-\rho M_\mu}\frac{1}{1+\rho+\rho^2+\rho^3}\Delta G^e_{n,t}, \qquad (60)
\end{aligned}$$

where (59) follows from (58). The last line follows from plugging in the quarterly dividend growth shock implied by an annual dividend growth shock: $\Delta x_{n,t} = \frac{\Delta G^e_{n,t}}{1+\rho+\rho^2+\rho^3}$ from Lemma 5. □

B.3.4 Proof of Lemma 4

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

Plugging the expected return linearization (48) into the linearized demand function (47) yields the following demand function:

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

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

$$\Delta p_{n,t} = \underbrace{\frac{\kappa(1+\bar{g})}{1-\theta_{n,t-}+\kappa(1+\delta)(1+\bar{g})}}_{\equiv M_\mu}\left(\delta\Delta d^e_{n,t,1} + \Delta p^e_{n,t,1}\right) + \frac{1}{1-\theta_{n,t-}+\kappa(1+\delta)(1+\bar{g})}\Delta\epsilon_{n,t}. \qquad (61)$$

Note that
$$\frac{1}{1-\theta_{n,t-}+\kappa(1+\delta)(1+\bar{g})} = \frac{1}{\zeta+\kappa(1+\bar{g})},$$
for ζ as defined in Proposition 2.

Rolling (61) one period forward, we see next period's actual price change $\Delta p_{n,t+1}$ can be written as:

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

where $d^e_{n,t+1,1}$ and $\Delta p^e_{n,t+1,1}$ are the changes in expected dividend and price for 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:

$$\Delta p^e_{n,t,1} = M_\mu \left(\delta \Delta d^e_{n,t,2} + \Delta p^e_{n,t,2}\right) + \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,1},$$

by the law of iterated expectations.

Iterating this process forward, we see

$$\begin{aligned}\Delta p^e_{n,t,1} &= \delta M_\mu \Delta d^e_{n,t,2} + \delta M_\mu^2 \Delta d^e_{n,t,3} + \delta M_\mu^3 \Delta d^e_{n,t,4} + \dots \\ &\quad + \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,1} + M_\mu \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,2} + M_\mu^2 \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,3} + \dots, \qquad (62) \\ &= \delta \sum_{s=1}^{\infty} M_\mu^s \Delta d^e_{n,t,s+1} + \sum_{s=0}^{\infty} M_\mu^s \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,s+1}. \qquad (63)\end{aligned}$$

Thus, we have

$$\delta \Delta d^e_{n,t,1} + \Delta p^e_{n,t,1} = \delta \sum_{s=0}^{\infty} M_\mu^s \Delta d^e_{n,t,s+1} + \sum_{s=0}^{\infty} M_\mu^s \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,s+1}. \qquad (64)$$

So the change in price today from (61) becomes:

$$\Delta p_{n,t} = M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \Delta d^e_{n,t,s+1} + \sum_{s=0}^{\infty} M_\mu^s \frac{1}{\zeta + \kappa(1+\bar{g})}\Delta \epsilon^e_{n,t,s}, \qquad (65)$$

as desired. □

B.3.5 Proof of Lemma 5

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

$$\begin{aligned}1 + G_{n,t+1} &= \prod_{s=1}^{4} (1 + g_{n,t+s}) \\ \leftrightarrow G_{n,t+1} &\approx \sum_{s=1}^{4} g_{n,t+s},\end{aligned}$$

using $\log(1+x) \approx x$ for small x. $G_{n,t+1}$ is annual realized growth from quarter $t+1$ to $t+4$. Now plug in the dynamics for quarterly dividend growth $g_{n,t}$ from (12) into the second expression:

$$\begin{aligned} G_{n,t+1} &\approx \sum_{s=1}^{4} g_{n,t+s} \\ &= \sum_{s=1}^{4} x_{n,t+s-1} + \sum_{s=1}^{4} \epsilon^g_{n,t+s}. \end{aligned}$$

Thus,

$$\begin{aligned} \tilde{\mathbb{E}}_t\left[G_{n,t+1}\right] &= \sum_{s=1}^{4} \tilde{\mathbb{E}}_t\left[x_{n,t+s-1}\right] + \sum_{s=1}^{4} \tilde{\mathbb{E}}_t\left[\epsilon^g_{n,t+s}\right] \\ &= \sum_{s=1}^{4} \tilde{\mathbb{E}}_t\left[x_{n,t+s-1}\right]. \end{aligned}$$

Note that

$$\begin{aligned} x_{n,t+s-1} &= \bar{x} + \rho(x_{n,t+s-2} - \bar{x}) + \epsilon^x_{n,t+s-1} \\ &\vdots \\ &= \bar{x}(1-\rho)\sum_{j=1}^{s-2} \rho^j + \rho^{s-1} x_{n,t} + \sum_{j=1}^{s-1} \rho^{s-1-j} \epsilon^x_{n,t+s-1}. \end{aligned}$$

Therefore,

$$\begin{aligned} \tilde{\mathbb{E}}_t\left[G_{n,t+1}\right] &= x_{n,t}(1+\rho+\rho^2+\rho^3) + \bar{x}(1-\rho)\Big[1 + (1+\rho) + (1+\rho+\rho^2)\Big] \\ \rightarrow \Delta G^e_{n,t} \equiv \tilde{\mathbb{E}}_{t+}\left[G_{n,t+1}\right] - \tilde{\mathbb{E}}_{t-}\left[G_{n,t+1}\right] &= \left(x_{n,t+} - x_{n,t-}\right)(1+\rho+\rho^2+\rho^3) \\ &= \Delta x_{n,t}(1+\rho+\rho^2+\rho^3) \\ \leftrightarrow \Delta x_{n,t} &= \frac{\Delta G^e_{n,t}}{1+\rho+\rho^2+\rho^3}, \end{aligned}$$

as desired. □

B.4 M_g in a Standard Model

The representative investor has CRRA utility over consumption:

$$U(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}.$$

Log consumption growth is i.i.d.

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

From Section 5.2, realized (quarterly) log dividend growth for stock n has the following dynamics:

$$\begin{aligned} \Delta g_{n,t+1} &= x_{n,t} + \epsilon^g_{n,t+1} \\ x_{n,t+1} &= \bar{x} + \rho(x_{n,t} - \bar{x}) + \epsilon^x_{n,t+1}, \end{aligned}$$

ϵ^c_{t+1} and $\epsilon^g_{n,t+1}$ are arbitrarily correlated but $\epsilon^x_{n,t+1}$ is uncorrelated with both.

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

$$\begin{aligned} M_{t+1} &= \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \\ \leftrightarrow m_{t+1} \equiv \log M_{t+1} &= \log \beta - \gamma \Delta c_{t+1}, \end{aligned} \tag{66}$$

for subjective discount factor β.

Gross returns $R_{n,t+1}$ must satisfy

$$\mathbb{E}_t \left[\beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} R_{n,t+1} \right] = 1. \tag{67}$$

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

$$r_{n,t+1} = \kappa_0 + \kappa_1 z_{n,t+1} - z_{n,t} + \Delta d_{n,t+1}, \tag{68}$$

where $r_{n,t+1} = \log R_{n,t+1}$, $z_{n,t} = \log(P_{n,t}/D_{n,t})$, and $\kappa_1 = \frac{1}{1+\exp[\mathbb{E}[-z_{n,t}]]}$ 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 $z_{n,t}$.

I solve the model by guess and verify. I conjecture the following form for $z_{n,t}$:

$$z_{n,t} = A_0 + A_1 x_{n,t}.$$

Plugging this expression into

$$\mathbb{E}_t \left[\exp[m_{t+1} + r_{n,t+1}] \right] = 1 \tag{69}$$

yields

$$
\begin{aligned}
A_1 &= \frac{1}{1-\kappa_1\rho} \\
A_0 &= \frac{1}{1-\kappa_1}\left[\log\beta - \gamma\mu_c + \kappa_0 + A_1\kappa_1\bar{x}(1-\rho) + \mathbb{V}\left[\kappa_1 A_1 \epsilon^x_{n,t+1} + \epsilon^g_{n,t+1} - \gamma\epsilon^c_{n,t+1}\right]\right].
\end{aligned}
$$

From (13), an annual growth expectation shock of $\Delta G^e_{n,t}$ corresponds to a quarterly shock of

$$
\Delta x_{n,t} = \frac{1}{1+\rho+\rho^2+\rho^3}\Delta G^e_{n,t}.
$$

Thus, the percentage price change from $t-$ to $t+$ due to shock $\Delta x_{n,t}$ is

$$
\begin{aligned}
\Delta p_{n,t} &\approx \log\left(P_{t+}/D_t\right) - \log\left(P_{t-}/D_t\right) \\
&= z_{n,t+} - z_{n,t-} \\
&= A_1 \Delta x_{n,t} \\
&= \underbrace{\frac{A_1}{1+\rho+\rho^2+\rho^3}}_{\equiv M_g}\Delta G^e_{n,t},
\end{aligned}
$$

so

$$
M_g = \frac{1}{1-\kappa_1\rho}\frac{1}{1+\rho+\rho^2+\rho^3}.
$$

For $\rho = 0$, this equation collapses to $M_g = 1$. For the estimated $\rho = 0.7$ in the I/B/E/S data (see Appendix B.1), $M_g \approx 1.3$ (calibrating $\kappa_1 = 1/1.01$, since the historical average quarterly dividend-price ratio for the aggregate market is about 0.01).

B.5 Learning from Prices

Learning from prices changes the investor's price elasticity of demand. Investor i's demand curve is still as in (20), but the price elasticity has a different functional form.

Let the equilibrium change in growth expectation be

$$
\Delta\tilde{G}^e_{i,n,t} = \alpha_i \Delta p_{n,t} + \Delta G^e_{i,n,t},
$$

so $\Delta G^e_{i,n,t}$ is still the shock to growth expectation and $\alpha_i\Delta p_{n,t}$ captures the endogenous expectation update due to learning from prices. Investor i's demand curve is then:

$$
\Delta q_{i,n,t} = -\underbrace{(\zeta_i - \kappa^g_i\alpha_i)}_{\equiv\tilde{\zeta}_i}\Delta p_{n,t} + \kappa^g_i\Delta G^e_{i,n,t} + \Delta\epsilon_{i,n,t},
$$

where ζ_i and κ_i^g are as described in Propositions 1 and 2. Holding all else (i.e. demand sensitivity to expected return κ_i) constant, learning from prices makes demand more inelastic.[48] In this case, the causal effect of subjective growth expectations on prices is $M_g = \kappa_S^g / \tilde{\zeta}_S$ and incorporates price impact amplification due to learning from prices (as in Bastianello and Fontanier (2021*b*)).

My empirical strategy does not take a stance on if investors learn from prices. In Section 6, I identify M_g in reduced-form from prices and analyst beliefs. In Section 7, I identify κ_i^g and price elasticity in reduced form at the investor level from prices, analyst beliefs, and investor holdings. The elasticity I identify is in general $\tilde{\zeta}_i$, which will be ζ_i if investors do not learn from prices.

[48]Davis, Kargar and Li (2022) discuss this mechanism.

C Alternative Learning Specifications

C.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, the definition of analyst influence from (23) becomes

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

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

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

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 $A_n = |\mathcal{A}_n|$ 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

$$B_{i,a,n} \approx \underbrace{\beta_i}_{\equiv \frac{x_i}{1+Ax_i}} - \beta_i^2 \tilde{A}_n + \underbrace{y_{i,a}}_{\equiv \frac{x_{i,a}-x_i}{1+Ax_i}} - \beta_i \sum_{a' \in \mathcal{A}_n} y_{i,a'} \tag{70}$$

Note that analyst influence depends on:

1. β_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 β_i for the average stock.
3. $\mathcal{A}_n$: The set of analysts that rate stock n. $\mathcal{A}_n$ enters (70) in two places:
   (a) $\beta_i^2 \tilde{A}_n$: Each additional analyst added to the rating set reduces the influence of analyst a. $\tilde{A}_n$ is the demeaned number of analysts in $\mathcal{A}_n$.
   (b) $-\beta_i \sum_{a' \in \mathcal{A}_n} y_{i,a'}$: Analyst a's influence falls by more when higher-influence analysts (higher $y_{i,a'}$) enter $\mathcal{A}_n$.

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 (24):

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

(70) can be taken to the data. In general, β_i and all $y_{i,a}$ can be identified using beliefs, price, and holdings data. If we suppress investor-level heterogeneity, β and all y_a can be identified from beliefs and price data. The baseline specification (28) uses only idiosyncratic growth expectations shocks and their interaction with the demeaned number of analysts. To allow for heterogeneous influence across analysts, you would also need to include interactions with analyst-specific indicators.

C.2 Identifying Analyst Influence Using Order of Analyst Reports

An alternative identification strategy is to exploit the order in which analysts report their expectations. Let $\bar{\tau}$ be investor i's prior precision before the first analyst reports. After learning from the first analyst, investor i's posterior precision is $\bar{\tau}^{-1} + \sigma^{-2}$. After learning from k analysts, investor i's posterior precision is $\bar{\tau}^{-1} + k\sigma^{-2}$. Thus for the k-th analyst to report this quarter for stock n, investor i's belief update is

$$\Delta G^I_{i,a,n} = \underbrace{\frac{\sigma^{-2}}{\bar{\tau}^{-1} + k\sigma^{-2}}}_{\equiv B_{n,k}} \left(G^A_{a,n} - \bar{G}^I_{i,a,n} \right).$$

So the influence of the k-th analyst to report is

$$\begin{aligned} B_{n,k} &= \frac{\sigma^{-2}}{\bar{\tau}^{-1} + k\sigma^{-2}} \\ &\approx \frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}_n\sigma^{-2}} - \left(\frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}_n\sigma^{-2}} \right)^2 (k - \bar{k}_n) \\ &\approx \frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}\sigma^{-2}} - \left(\frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}\sigma^{-2}} \right)^2 (k - \bar{k}) \\ &\approx \frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}\sigma^{-2}} - \left(\frac{\sigma^{-2}}{\bar{\tau}^{-1} + \bar{k}\sigma^{-2}} \right)^2 (\bar{k}_n - \bar{k}) \end{aligned} \tag{71}$$

The second line follows from a first-order approximation around $k = \bar{k}_n \equiv \frac{(A_n+1)}{2}$, the average analyst order rank for stock n (i.e. $\bar{k}_n \equiv \frac{1}{A_n}(1 + 2 + \ldots + A_n)$). The third line follows from a first-order approximation around $\bar{k}_n = \bar{k} \equiv \mathbb{E}[\bar{k}_n]$. Either of these specifications can be taken directly to the data.

The fourth line follows from a first-order approximation around $k = \bar{k}_n$ again. This final approximation implies

$$B_{n,k} = B_n = \underbrace{\beta}_{=\frac{\sigma^{-2}}{(\bar{\tau})^{-1}+\bar{k}\sigma^{-2}}} - \underbrace{\beta^2}_{=\left(\frac{\sigma^{-2}}{(\bar{\tau})^{-1}+\bar{k}\sigma^{-2}}\right)^2} \underbrace{\frac{\tilde{A}_n}{2}}_{=\bar{k}_n-\bar{k}}.$$

Thus (71) implies that my baseline specification underestimates β by a factor of 2 and so overestimates M_g by a factor of 2.

C.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 6.2, Benjamin (2019) use the following specification of the posterior distribution for the unknown growth rate G_n that investor i is learning about:

$$\mathbb{P}\left(G_n^e \mid \{G_{a,n}\}_{a\in\mathcal{A}_n}\right) = \frac{\mathbb{P}\left(\{G_{a,n}^A\}_{a\in\mathcal{A}_n} \mid G_n^e\right)^c \mathbb{P}\left(G_n^e \mid \bar{G}_{i,a,n}^I\right)^d}{\int_{G_n^{e'}} \mathbb{P}\left(\{G_{a,n}^A\}_{a\in\mathcal{A}_n} \mid G_n^{e'}\right)^c \mathbb{P}\left(G_n^{e'} \mid \bar{G}_{i,a,n}^I\right)^d}.$$

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 6.2, one can easily show that the posterior mean growth expectation after learning from A_n analysts is

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

and so the update to mean growth expectation is

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

Thus we have analyst influence

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

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 (24) in Section (6.2). The underlying structure of average influence β 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.

D 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

$$\mathbf{G}_t = \mathbf{\Lambda}_t \mathbf{H}_t + \boldsymbol{u}_t,$$

where $\mathbf{G}_t$ is the $A \times N$ matrix of reported expected returns for number of analyst institutions A and number of stocks N, $\mathbf{\Lambda}_t \in \mathbb{R}^{A \times F}$ is the stacked matrix of institution-specific loading vectors $\tilde{\boldsymbol{\lambda}}_{a,t} \in \mathbb{R}^F$, $\mathbf{H}_t \in \mathbb{R}^{F \times N}$ is the stacked matrix of stock-specific characteristic vectors $\tilde{\boldsymbol{\eta}}_{n,t} \in \mathbb{R}^F$, and $\boldsymbol{u}_t$ is the $A \times N$ matrix of idiosyncratic residual expected return shocks.

One can estimate matrices $\mathbf{\Lambda}_t$ and $\mathbf{H}_t$ as the minimizers of the following loss function

$$\begin{aligned} &\min_{\mathbf{\Lambda}_t, \mathbf{H}_t} \sum_{a,n} \left(\Delta G^A_{a,n,t} - \Delta \hat{G}_{a,n,t} \right)^2 \\ \text{s.t. } \Delta \hat{G}^A_{a,n,t} &= \tilde{\boldsymbol{\lambda}}^\top_{a,t} \tilde{\boldsymbol{\eta}}_{n,t} \\ &= b_{a,t} + c_{n,t} + \boldsymbol{\lambda}^\top_{a,t} \boldsymbol{\eta}_{n,t} \end{aligned}$$

where $\boldsymbol{\lambda}_{a,t}$ and $\boldsymbol{\eta}_{n,t}$ are the unconstrained components of $\tilde{\boldsymbol{\lambda}}_{a,t}$ and $\tilde{\boldsymbol{\eta}}_{n,t}$, while $b_{a,t}$ is the element of $\tilde{\lambda}_{a,t}$ constrained to load on a constant $\tilde{\eta}_{n,t,f} = 1$ (i.e. an analyst institution-quarter fixed effect) and $c_{n,t}$ is the element of $\tilde{\eta}_{n,t}$ constrained to be loaded on by $\tilde{\lambda}_{a,t,f} = 1$ (i.e. a stock-quarter fixed effect).

Empirically, each institution only covers a small subset of stocks in each quarter (in the average quarter roughly 2% of the entries in $\mathbf{G}_t$ are filled). For this reason, I can attain more efficient estimates of $\mathbf{\Lambda}_t$ and $\mathbf{H}_t$ by adding L2 penalties to the least-squares loss function (Funk (2006); Bai and Ng (2019)):

$$\begin{aligned} &\min_{\Lambda_*, \mathbf{H}_*} \sum_{a,n} \left(\Delta G^A_{a,n,t} - \Delta \hat{G}^A_{a,n,t} \right)^2 + \gamma_{1,t} b^2_{a,t} + \gamma_{2,t} c^2_{n,t} + \gamma_{3,t} \left\| \boldsymbol{\lambda}_{a,t} \right\|^2 + \gamma_{4,t} \left\| \boldsymbol{\eta}_{n,t} \right\|^2 \\ &\text{s.t. } \Delta \hat{G}^A_{a,n,t} = b_{a,t} + c_{n,t} + \boldsymbol{\lambda}^\top_{a,t} \boldsymbol{\eta}_{n,t}, \end{aligned}$$

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 $\hat{u}_{a,n,t}$.[49]

[49]Nevertheless, since the fixed effects $b_{a,t}$ and $c_{n,t}$ are jointly estimated with the factors $\boldsymbol{\eta}_{n,t}$ and loadings $\boldsymbol{\lambda}_{a,t}$, regularizing $\boldsymbol{\eta}_{n,t}$ and $\boldsymbol{\lambda}_{a,t}$ will somewhat affect the estimates of $b_{a,t}$ and $c_{n,t}$. To avoid this issue, one could remove

D.1 Factor Structure with Staggered Analyst Releases

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: $\Delta G^A_{a,n} = (\phi_a + \phi_n)\Delta p^-_{a,n} + \boldsymbol{\lambda}^{'}_a \boldsymbol{\eta}_n + u_{a,n}$. Let $\mathcal{D}_{a,n}$ be the set of days that elapse between the two 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 $\tilde{\boldsymbol{\eta}}_n$ can capture. Let all such days belong to set $\mathcal{D}_n$. Then we can decompose $\Delta p^-_{a,n} = \boldsymbol{\lambda}^{'}_{a,Timing}\Delta \boldsymbol{p}^-_n + \Delta\tilde{p}^-_{a,n}$, where $\Delta \boldsymbol{p}^-_n$ 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 $\mathcal{D}_{a,n} \setminus \mathcal{D}_n$. Thus, $(\phi_a+\phi_n)\Delta p^-_{a,n} = \phi_a \lambda^{'}_{a,Timing}\Delta \boldsymbol{p}^-_n + \lambda^{'}_{a,Timing}\left(\phi_n \Delta \boldsymbol{p}^-_n\right) + \phi_a \Delta\tilde{p}^-_{a,n} + \phi_n \Delta\tilde{p}^-_{a,n}$. $\tilde{\boldsymbol{\lambda}}^{\top}_a \tilde{\boldsymbol{\eta}}_n$ can absorb the first two terms $(\phi_a \lambda^{'}_{a,Timing}\Delta \boldsymbol{p}^-_n + \lambda^{'}_{a,Timing}\left(\phi_n \Delta \boldsymbol{p}^-_n\right))$, but not the second two terms $(\phi_a \Delta\tilde{p}^-_{a,n} + \phi_n \Delta\tilde{p}^-_{a,n})$. The second two terms would appear in the estimated residual $\hat{u}_{a,n}$. These price changes prove unlikely to cause problems 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 (28) 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 and the last analyst to report in this quarter for each stock n when estimating (28).

analyst-quarter and stock-quarter fixed effects from $\Delta G^A_{a,n,t}$ before estimating the factor model.

E Decomposition of Structural Error Terms

E.1 Market Clearing with Homogeneity (28) Error Term Decomposition

The full version of market clearing expression (28) is:

$$
\begin{aligned}
\Delta p^{+}_{a,n} &= M_g \beta u_{a,n} - M_g \beta^2 u_{a,n} \tilde{A}_n \\
&\quad + M_g B_n \left(\underbrace{(\alpha_a + \alpha_n)\Delta p^{-}_n + \boldsymbol{\lambda}^{'}_a \boldsymbol{\eta}_n}_{\text{Other Determinants of Analyst Expectations}} \right) \\
&\quad - M_g B_n (\underbrace{\bar{G}^I_{S,a,n}}_{\text{Investors' Prior Expectations}} - \underbrace{G^{Lag}_{a,n}}_{\text{Lagged Analyst Expectation}}) \\
&\quad + M_g \underbrace{\nu^I_{S,a,n}}_{\text{Other Contemporaneous Signals}} + \frac{1}{\zeta} \underbrace{\Delta \epsilon_{S,a,n}}_{\text{Other Demand Shocks}} \\
&= M_g \beta u_{a,n} - M_g \beta^2 u_{a,n} \tilde{A}_n + e_{a,n}.
\end{aligned}
$$

E.2 Low-Frequency Growth Expectation Update (36) Error Term Decomposition

The full version of low-frequency (quarterly) growth expectation update (36) is:

$$
\begin{aligned}
\Delta G^I_{i,n} &= \sum_{a \in \mathcal{A}_n} \Delta G^I_{i,a,n} + \nu^I_{i,n} \\
&= \beta_i \sum_{a \in \mathcal{A}_n} u_{a,n} - \beta_i^2 \sum_{a \in \mathcal{A}_n} u_{a,n} \tilde{A}_n \\
&\quad + \left(\beta_i - \beta_i^2 \tilde{A}_n \right) \sum_{a \in \mathcal{A}_n} \left(\underbrace{(\alpha_a + \alpha_n)\Delta p^{-}_n + \boldsymbol{\lambda}^{'}_a \boldsymbol{\eta}_n}_{\text{Other Determinants of Analyst Expectations}} \right) \\
&\quad - \left(\beta_i - \beta_i^2 \tilde{A}_n \right) \sum_{a \in \mathcal{A}_n} \left(\underbrace{\bar{G}^I_{i,a,n}}_{\text{Investor Prior Expectations}} - \underbrace{G^{Lag}_{a,n}}_{\text{Lagged Analyst Expectation}} \right) \\
&\quad + \sum_{a \in \mathcal{A}_n} \underbrace{\nu^I_{i,a,n}}_{\text{Other High-Frequency Signals}} + \underbrace{\nu^I_{i,n}}_{\text{Other Low-Frequency Signals}} \\
&= \beta_i \sum_{a \in \mathcal{A}_n} u_{a,n} - \beta_i^2 \sum_{a \in \mathcal{A}_n} u_{a,n} \tilde{A}_n + e^G_{i,n}.
\end{aligned}
$$

F 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 F10 provides details of estimates from previous work.

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

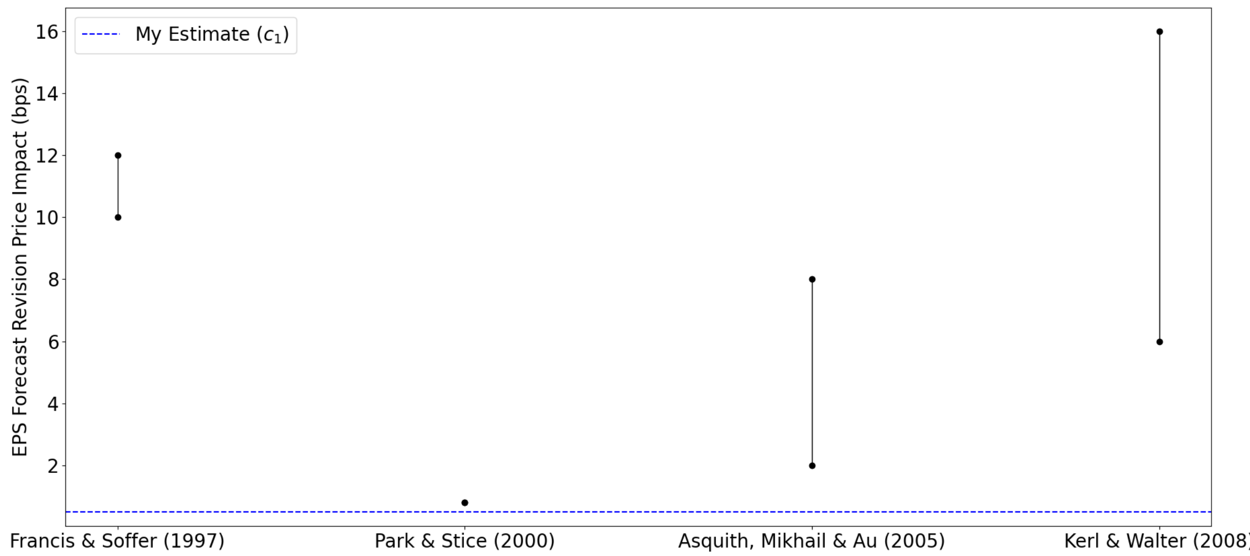
1. Previous estimates may suffer from omitted variable bias. Analyst EPS growth expectations announcements tend to cluster around actual EPS announcements by firms. If positive EPS surprises cause positive high-frequency price changes (potentially at a lag due to post-earnings announcement drift) and positive analyst growth expectations updates, then regressions of price changes on analyst growth expectations updates will suffer from positive omitted variable bias. My identification strategy strips out all variation in analyst growth expectation updates due to stock-quarter characteristics (including public signals like EPS surprises) and so does not suffer from this omitted variable bias.

2. The previous literature uses a different specification than this paper. This paper focuses on how 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 β), 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 β I estimate is the analyst influence of a particular piece of information in analyst reports. Other pieces of information having different β values (e.g. due to different perceived signal precisions) does not invalidate the β 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 5.

3. Analyst influence β 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 β 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.

4. 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).

Figure F7: Comparison of Average Analyst Price Impact c_1 to Previous Literature



Graphical comparison of my analyst price impact estimate ($c_1 \approx 0.5$ basis points from Table 3) to values found in previous work. See Table F10 for details of previous estimates.

As discussed in Section 5.4, 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.

5. Statistically, my estimate proves consistent with the smaller estimates from the previous literature. My $c_1 = 0.5$ basis points estimate is within the 95% confidence interval for the analyst price impact estimate from Park and Stice (2000). The lower estimate of 2 basis points from Asquith, Mikhail and Au (2005) is not statistically significant.

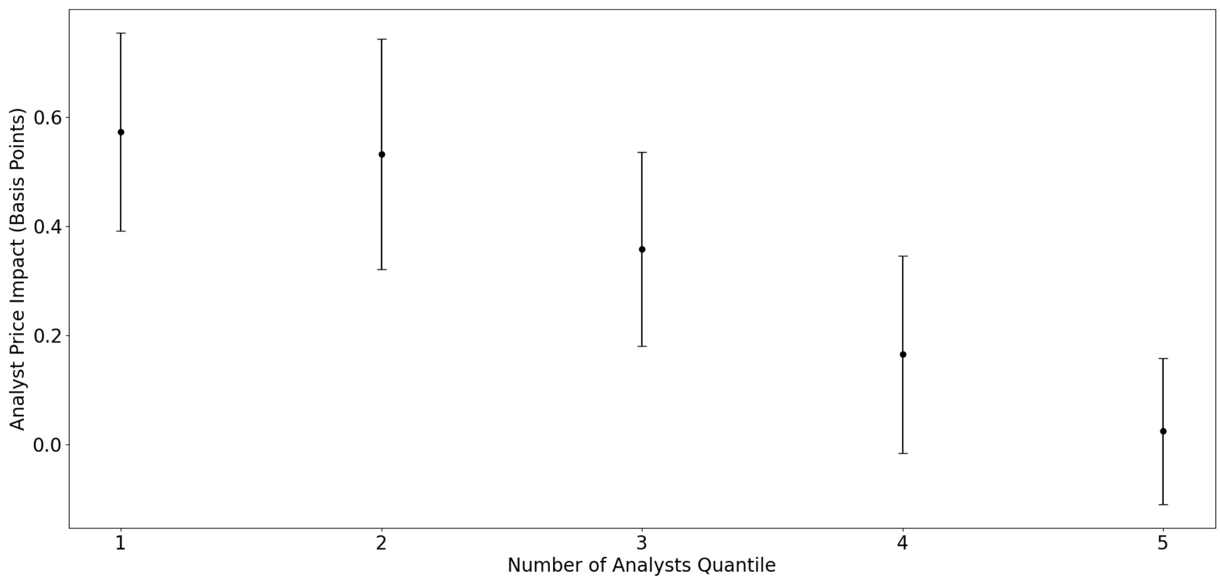
Table F10: Details of Recovering κ Estimates from Previous Work

Paper	Raw Estimates	My Assumptions	Converted Estimates	Empirical Measure
Francis & Soffer (1997)	Table 3: Regression of 3-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.10-0.12	None	10-12 bps	Percentage change in current fiscal year EPS forecast.
Park & Stice (2000)	Table 2: Regression of 3-day return (centered window) on change in EPS forecast implied earnings yield has coefficient 0.13.	Divide coefficient by average P/E for S&P 500 from Robert Shiller's data library (16) to convert to the effect of a 1% increase in EPS forecast.	0.8 bps	Change in EPS forecast implied earnings yield.
Asquith, Mikhail & Au (2005)	Table 3: Regression of 5-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.08 Table 8: After adding controls, coefficient drops to 0.02	None	2-8 bps	Percentage change in current fiscal year EPS forecast.
Kerl & Walter (2008)	Table 3: Regression of 5-day return (centered window) on percentage change in current fiscal year EPS forecast has coefficient 0.06-0.16	None	6-16 bps	Percentage change in current fiscal year EPS forecast.

G Supplements to Empirical Results in Section 6.5

G.1 Non-Parametric Evidence of Signal Averaging

Figure G8: Analyst Price Impact by Quintile of Number of Analysts



Plot of regression coefficients and 95% confidence intervals for

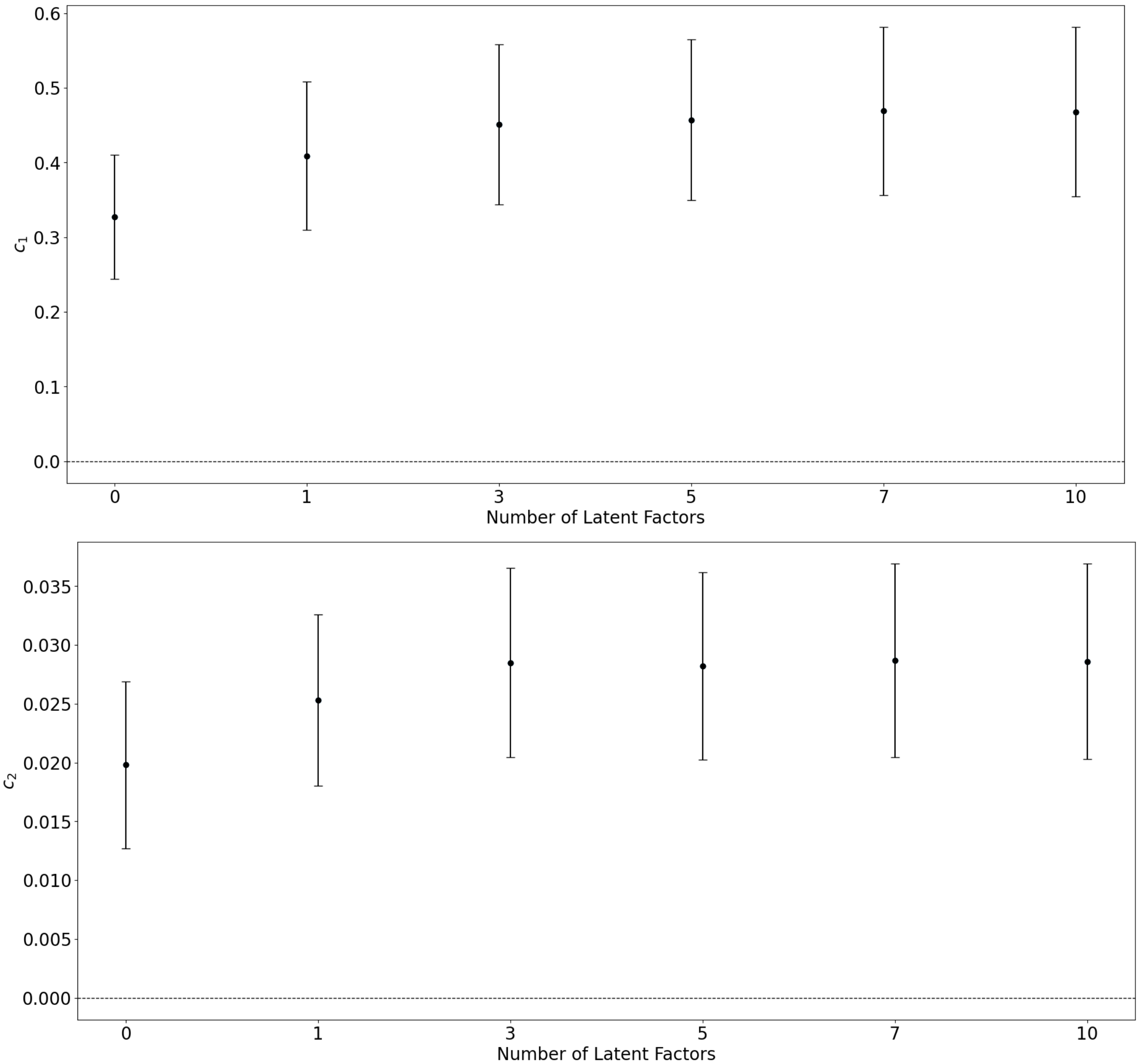
$$\Delta p^{+}_{a,n,t} = \sum_{k=1}^{5} b_k 1 \left(\tilde{A}_{n,t-1} \in \text{Quintile } k \right) u_{a,n,t} + e_{a,n,t}.$$

G.2 Alternative Numbers of Latent Factors

The baseline specification in Section 6.5 uses 5 latent factors. Figures G9 and G10 display estimates for reduced-form coefficients c_1 and c_2 as well as structural parameters β and M_g for alternative numbers of latent factors. All results prove robust to using alternative numbers of latent factors.

Figure G11 displays the cumulative percentage variation in $\Delta G^A_{a,n,t}$ 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 $\Delta G^A_{a,n,t}$. Adding more factors explains only marginally more variation: 5 more factors (for a total of 10) explain less than 1% additional variation in $\Delta G^A_{a,n,t}$.

Figure G9: c_1 and c_2 Results for Numbers of Latent Factors

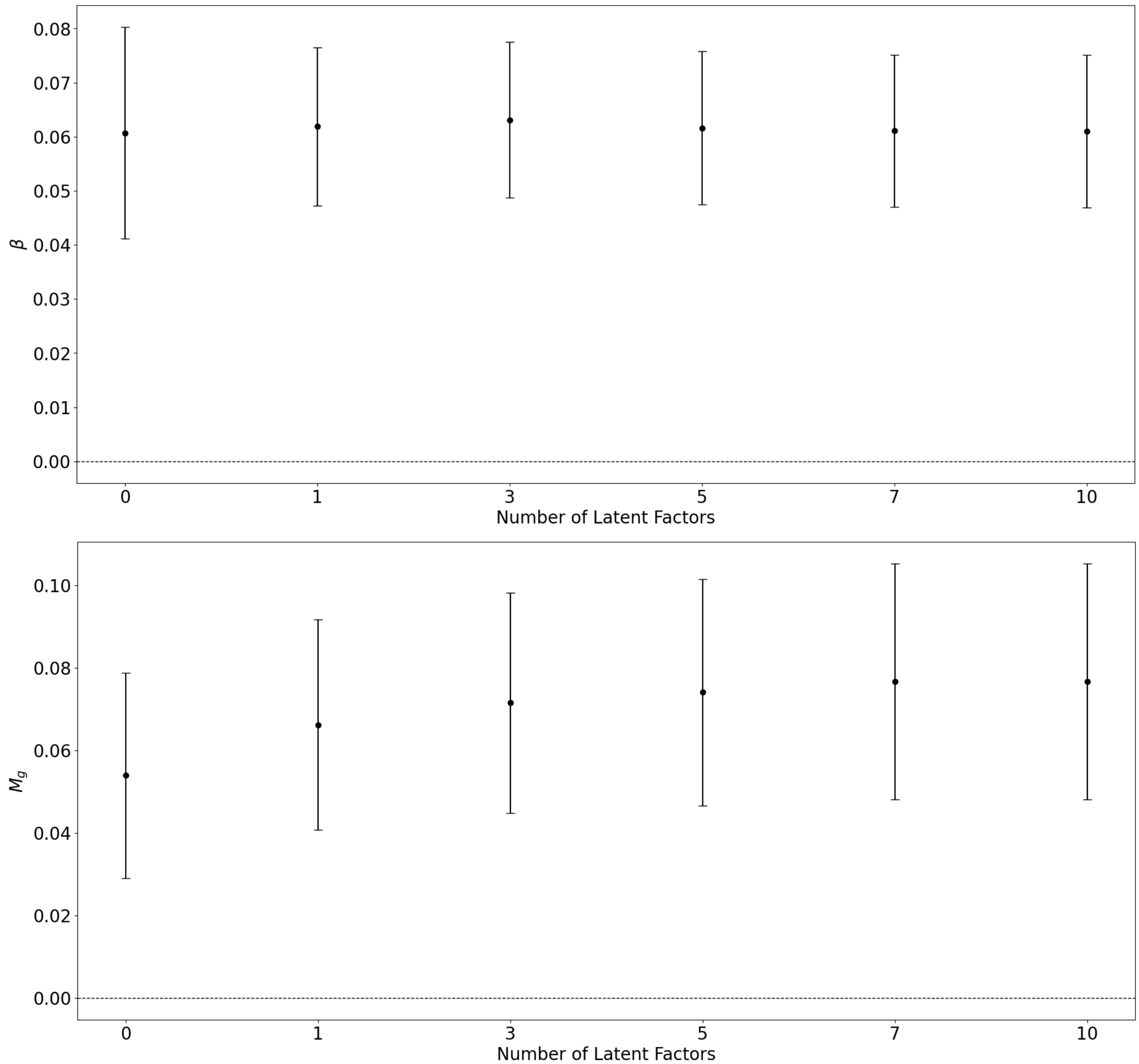


Estimates of reduced-form parameters c_1 and c_2 from the following regression:

$$\Delta p^{+}_{a,n,t} = \underbrace{c_1}_{\equiv M_g \beta} u_{a,n,t} - \underbrace{c_2}_{\equiv M_g \beta^2} u_{a,n,t} \tilde{A}_{n,t-1} + FE_{n,t} + e_{a,n,t},$$

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 $\Delta G^{A}_{a,n,t}$.

Figure G10: β and M_g Results for Numbers of Latent Factors

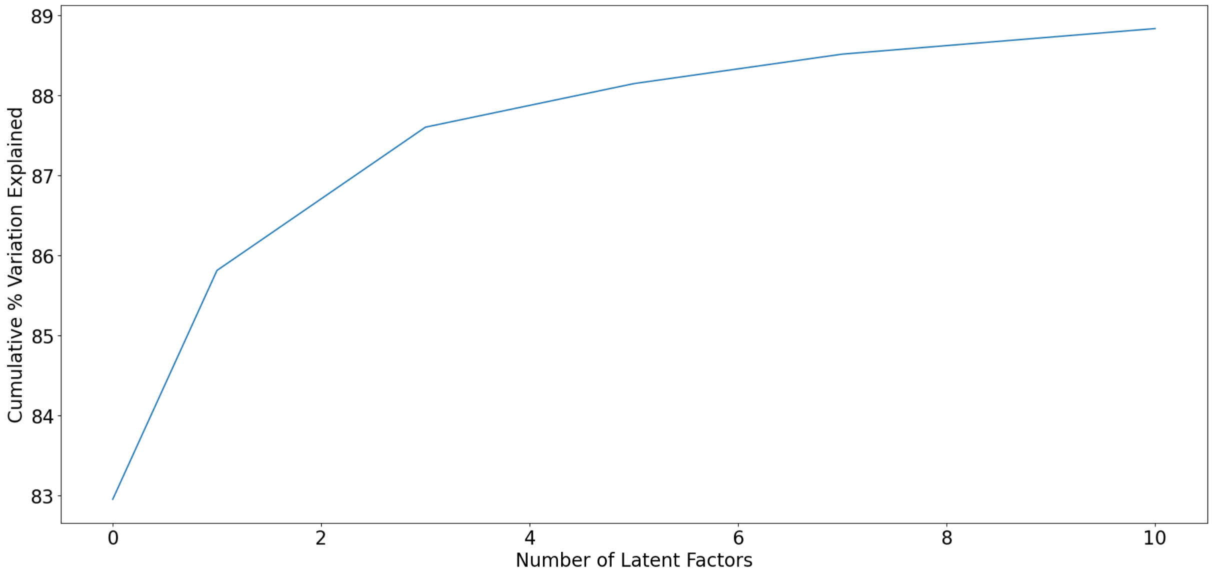


Estimates of implied structural parameters β and M_g from the following regression:

$$\Delta p^{+}_{a,n,t} = \underbrace{c_1}_{\equiv M_g \beta} u_{a,n,t} - \underbrace{c_2}_{\equiv M_g \beta^2} u_{a,n,t} \tilde{A}_{n,t-1} + FE_{n,t} + X_{n,t} + e_{a,n,t},$$

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 $\Delta G^{A}_{a,n,t}$.

Figure G11: Percentage Variation in $\Delta G^{A}_{a,n,t}$ Explained



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.3 Alternative Price Reaction Windows

The baseline specification in Section 6.5 uses the 5-day return following an analyst report to measure the high-frequency price change $\Delta p^{+}_{a,n,t}$. Figures G12 and G13 display estimates for reduced-form coefficients c_1 and c_2 as well as structural parameters β 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.

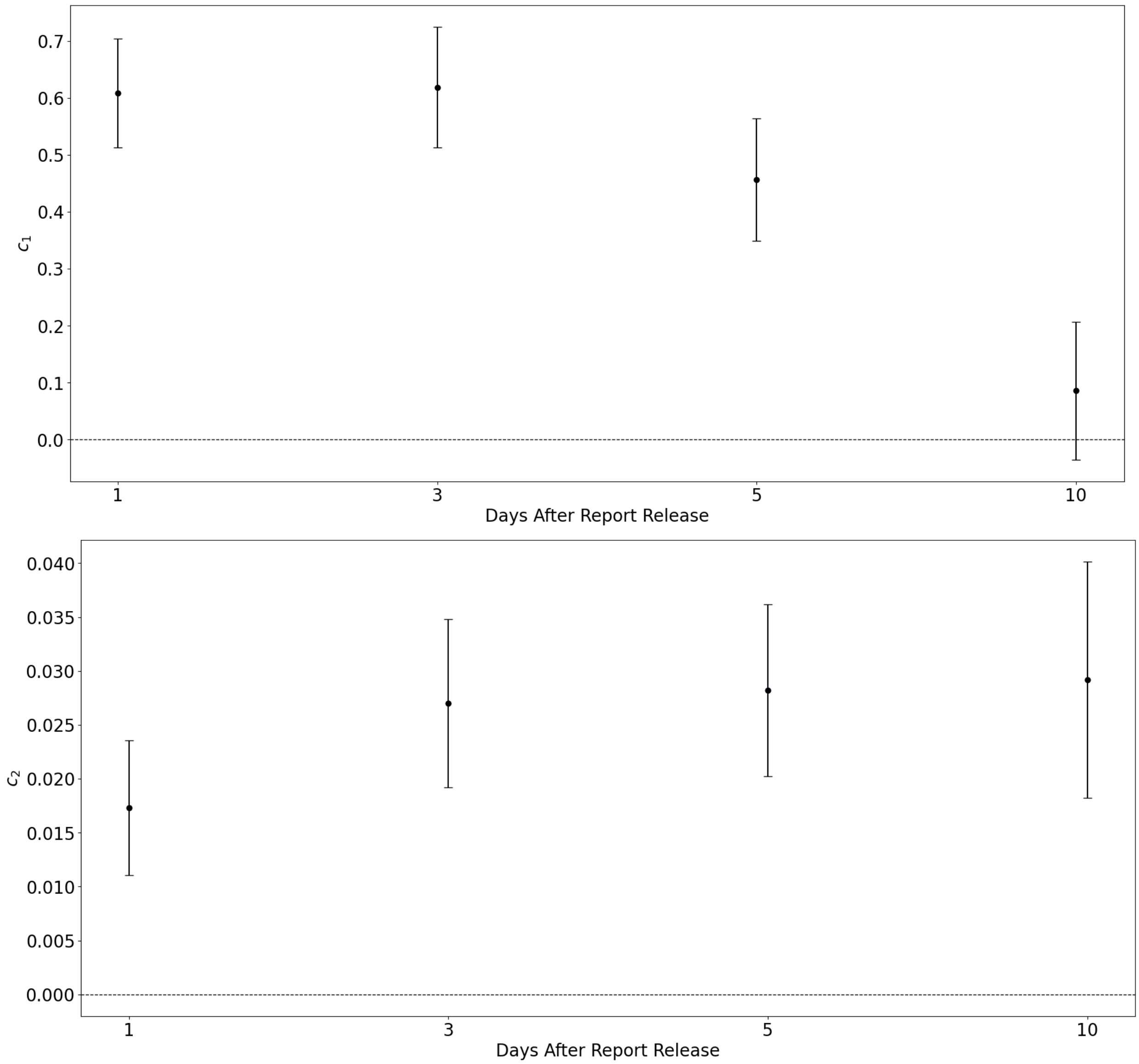
I use 5-days for the baseline specification to account for the possibility of a delayed investor reaction to analyst reports. Ideally, I would like to go out further than 5 days but, as Figures G12 and G13 exhibit, past 5 days regression (29) lacks power. In particular, the estimate of analyst price 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 expectations 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 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 G12 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.

Figure G12: c_1 and c_2 Results for Different Price Reaction Windows

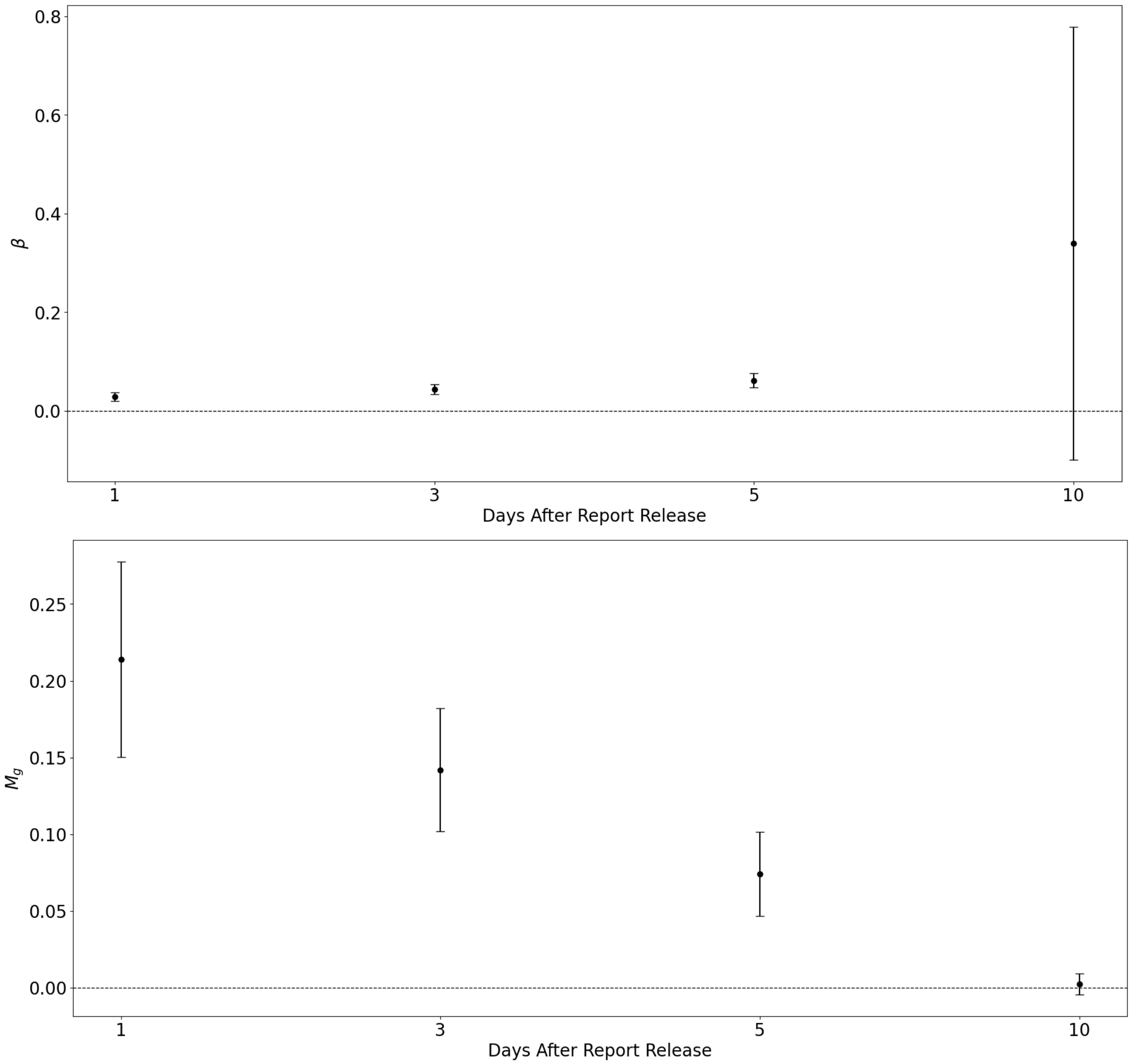


Estimates of reduced-form parameters c_1 and c_2 from the following regression:

$$\Delta p^{+}_{a,n,t} = \underbrace{c_1}_{\equiv M_g \beta} u_{a,n,t} - \underbrace{c_2}_{\equiv M_g \beta^2} u_{a,n,t} \tilde{A}_{n,t-1} + FE_{n,t} + e_{a,n,t},$$

where $\Delta p^{+}_{a,n,t}$ is measured over different post-announcement windows from 1 to 10 days.

Figure G13: β and M_g Results for Different Price Reaction Windows



Estimates of implied structural parameters β and M_g from the following regression:

$$\Delta p^+_{a,n,t} = \underbrace{c_1}_{\equiv M_g \beta} u_{a,n,t} - \underbrace{c_2}_{\equiv M_g \beta^2} u_{a,n,t} \tilde{A}_{n,t-1} + FE_{n,t} + e_{a,n,t},$$

where $\Delta p^+_{a,n,t}$ is measured over post-announcement 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:

$$\Delta p^+_{a,n,t} = c_1 \Delta G_{a,n,t} + c_2 \Delta G_{a,n,t} \tilde{A}_{n,t} + FE_n + FE_t + e_{a,n,t}. \tag{72}$$

Figures G14 and G15 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 (72) can still estimate c_1. For this reason, the c_1 estimates in Figure G14 are all significant stable across window lengths.[50]

Of course, $\hat{c}_1$ and $\hat{c}_2$ from (72) are not consistent estimates of the parameters c_1 and c_2 because $\Delta G_{a,n,t}$ likely does not satisfy moment conditions (31) and (32):

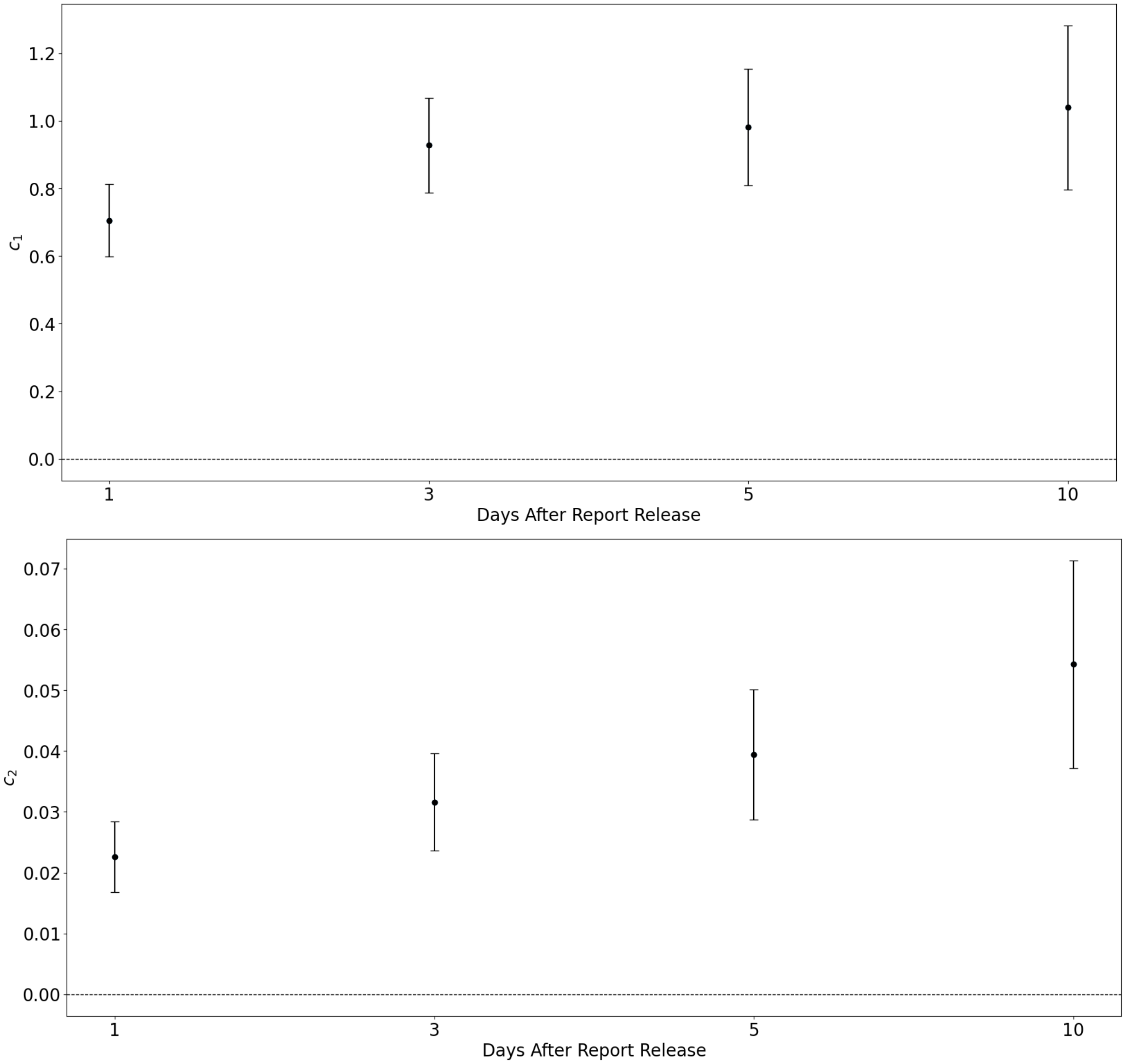
$$\mathbb{E}\left[\Delta G_{a,n,t} e_{a,n}\right] \neq 0 \tag{73}$$

$$\mathbb{E}\left[\Delta G_{a,n,t} \tilde{A}_n e_{a,n}\right] \neq 0. \tag{74}$$

Nevertheless, the M_g estimates implied by $\hat{c}_1$ and $\hat{c}_2$ from (72) actually prove broadly consistent (if slightly larger) with those from the baseline regression (29). The M_g estimates in Figure G15 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. The larger M_g estimates from (29) also yield the same economic conclusion: the causal effect of subjective growth expectations on asset prices is far smaller than in standard models (i.e. far smaller than the benchmark value $M_g = 1$).

[50]If ex-post reversal explained the insignificance of the c_1 estimates from the baseline regression (29), we would not see stable c_1 estimates across window lengths from regression (72).

Figure G14: c_1 and c_2 Results for Different Price Reaction Windows and Full $\Delta G^A_{a,n,t}$

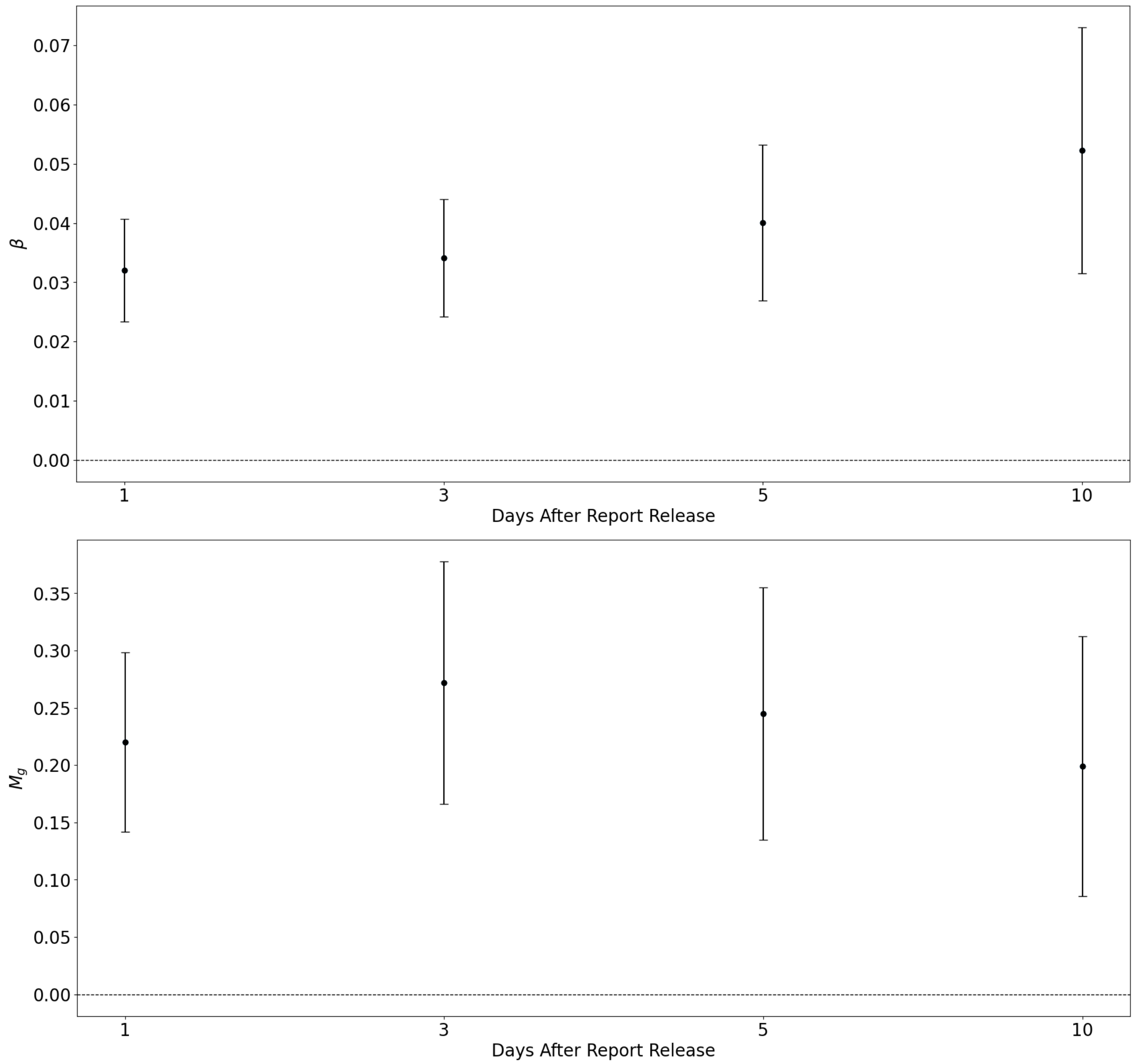


Estimates of reduced-form parameters c_1 and c_2:

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

where $\Delta p^+_{a,n,t}$ is measured over different post-announcement windows from 1 to 10 days.

Figure G15: β and M_g Results for Different Price Reaction Windows and Full $\Delta G^A_{a,n,t}$



Estimates of reduced-form parameters implied structural parameters β and M_g from the following regression:

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

where $\Delta p^+_{a,n,t}$ is measured over different post-announcement windows from 1 to 10 days.

G.4 Allowing for Analyst Heterogeneity

This appendix extends the baseline analysis in Section 6 to allow for heterogeneous influence across analyst institutions.

As discussed in Appendix C.1, allowing for heterogeneous signal precisions across analysts (but maintaining homogeneity across investors) yields the following form for analyst a's influence for stock n:

$$B_{a,n} \approx \beta - \beta^2 \tilde{A}_n + y_a - \beta_i \sum_{a' \in \mathcal{A}_n} y_{a'},$$

β is the average analyst's influence for the average stock. y_a is the deviation of a's influence for the average stock from β, so the sum of y_a across all analysts is zero.

With this general form of analyst influence, the analogous market-clearing expression to (29) is

$$\Delta p^+_{a,n,t} = M_g \sum_{a'} (\beta + y_{a'})\, 1_{a'=a} u_{a,n,t} - M_g \beta \sum_{a'} (\beta + y_{a'})\, 1_{a' \in \mathcal{A}_{n,t-1}} u_{a,n,t} + M_g \beta A_{t-1} u_{a,n,t} + e_{a,n,t}, \quad (75)$$

where A_{t-1} is the average number of analyst institutions per stock in quarter $t-1$. Note that if all $y_{a'} = 0$ so there is no analyst heterogeneity, (75) collapses to (29).

In the baseline analysis, cross-sectional variation in the number of analysts that cover each stock identifies the the shrinkage rate of analyst price impact as the number of analysts grows and influence declines ($c_2 = M_g \beta^2$). Combined with average analyst price impact ($c_1 = M_g \beta$), I identify both M_g and β.

In this general case, cross-sectional variation in the *set* — not the number — of analysts covering each stock identifies how much a's price impact for the average stock shrinks when adding analyst a' ($M_g \beta (\beta + y_{a'})$). Note that adding more influential (higher $y_{a'}$) analysts will reduce a's price impact to a greater extent. Combined with analyst a''s price impact for the average stock ($M_g (\beta + y_{a'})$), I identify β. Since all y_a sum to zero, the sum of analyst-specific price impacts for the average stock ($\sum_a M_g (\beta + y_a)$) identifies the average analyst's price impact on the average stock ($M_g \beta$). Given β and $M_g \beta$, I identify M_g.

I fit (75) as a nonlinear regression of post-announcement price changes ($\Delta p^+_{a,n,t}$) on the idiosyncratic growth expectations shocks interacted with analyst-specific dummies ($1_{a'=a} u_{a,n,t}$) and on the idiosyncratic growth expectations shocks interacted with dummies capturing the set of analysts who cover stock n in the previous quarter ($1_{a' \in \mathcal{A}_{n,t-1}} u_{a,n,t}$).[51] If there are A total analysts, then there are $A+1$ total structural parameters to identify: M_g, β, and $A-1$ of y_a (since the y_a sum to zero). There are $2A$ instruments: A of $1_{a'=a} u_{a,n,t}$ and A of $1_{a' \in \mathcal{A}_{n,t-1}} u_{a,n,t}$. Thus, the system is

[51] As in the baseline analysts, I use the lagged coverage set to avoid any potential endogeneity issues with analysts initiating (or ending) coverage due to particularly bullish (or bearish) information. Irvine (2003) discusses some of these concerns.

Table G11: Estimation Results Allowing for Investor Heterogeneity

	β_S	M_g
Point Estimate	0.044***	0.046***
95% Confidence Interval	(0.031, 0.12)	(0.0095, 0.098)

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

This table displays the estimated β and M_g from (75). Point estimates are the medians of the block-bootstrapped sampling distributions (I sample quarters). Confidence intervals report the 2.5th and 97.5th quantiles of the are block-bootstrapped sampling distributions. All estimates represent the marginal effect in percentage points of a 1 percentage point increase in growth expectations (analyst expectations for β and investor expectations for M_g). The time period is 1984-01:2021-12.

overidentified with the following set of moment conditions

$$\mathbb{E}\left[1_{a'=a} u_{a,n,t} e_{a,n,t}\right] = 0, \forall a'$$
$$\mathbb{E}\left[1_{a' \in \mathcal{A}_{n,t-1}} u_{a,n,t} e_{a,n,t}\right] = 0, \forall a'.$$

Due to computational limitations, I run regression (75) using only analyst institutions that report at least 100 expectations in the full sample. This filter leaves $1,513,888$ analyst institution-stock-quarter observations (out of $1,530,391$ in the baseline analysis) from 413 analyst institutions (out of $1,150$ in the baseline analysis).

Table G11 displays the estimated M_g and β from regression (75). Both the $\beta = 0.04$ and $M_g = 0.05$ estimates are quantitatively similar to the baseline results from Table 4 ($\beta = 0.06$ and $M_g = 0.07$).

G.5 Evidence from LTG Expectations

This appendix extends the baseline analysis in Section 6 to measure the causal effect of long-term (as opposed to one-year) 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 6.5. Appendix G.5.1 provides a simple benchmark range for the causal effect of long-term growth expectations on prices (Appendix G.5.3 considers alternative benchmark ranges). Appendix G.5.2 presents the empirical results.

G.5.1 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 growth expectations depends (somewhat) on the timing of the quarterly growth expectations shocks over that time period. The simplest assumption is that the entire increase in average forecasted growth is driven by a higher growth expectation 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's growth expectation 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 5.5.

Other timing assumptions do not significantly alter this benchmark range, as discussed in Appendix G.5.3 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 forecasted growth over the next H years being driven by a shock to quarterly growth expectation in the last quarter of that time period (i.e. quarter $t + 4H$).

G.5.2 Empirical Results

The key empirical challenge raised by the LTG expectations is the lack of coverage. Specifically, the baseline analysis in Section 6 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 $\boldsymbol{\eta}_n$ in the latent factor model (25) when extracting the idiosyncratic analyst growth expectation shocks $u_{a,n}$.

2. To pin down the shrinkage rate of analyst price impact as the number of analysts rises (c_2 in regression (29)) 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 2, the average stock in the average quarter has one-year growth expectations reported by 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 β (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 6:

$$\Delta p^{+}_{a,n,t} = \underbrace{c_1}_{\equiv M_{LTG}\beta} \Delta \mathrm{LTG}_{a,n,t} - \underbrace{c_2}_{\equiv M_{LTG}\beta^2} \Delta \mathrm{LTG}_{a,n,t}\tilde{A}_{n,t-1} + X_{n,t} + e_{a,n,t},$$

where $\Delta\mathrm{LTG}_{a,n,t}$ the full LTG expectation update, not an idiosyncratic shock. 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 4 to back out M_{LTG} from c_1.

Table G12 displays the regression results. The specification in column 4 proves most likely to satisfy moment conditions (31) and (32) 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 4 (and dividing again by 100 to convert from basis points to percentages) yields

$$M_{LTG} = 0.23.$$

A 1% rise in investor long-term 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 4, which is consistent with investors interpreting analyst LTG expectations as $3-4$ year growth expectations, as discussed in Appendix G.5.1.

Since $\Delta\mathrm{LTG}_{a,n,t}$ likely does not satisfy moment conditions (31) and (32):

$$\mathbb{E}\left[\Delta\mathrm{LTG}_{a,n,t} e_{a,n}\right] \neq 0$$
$$\mathbb{E}\left[\Delta\mathrm{LTG}_{a,n,t}\tilde{A}_n e_{a,n}\right] \neq 0,$$

I run the same regression using the idiosyncratic LTG shock $u_{a,n,t}$ extracted from factor model (25) using 5 latent factors. Table G13 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 G12, 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 G12: c_1 and c_2 Estimates Using Full LTG Updates

	(1)	(2)	(3)	(4)
c_1	3.00**	3.10***	2.78***	1.41**
	(1.18)	(0.960)	(0.922)	(0.686)
c_2	-0.783	-0.615	-0.672	-0.516
	(0.494)	(0.479)	(0.453)	(0.498)
Quarter FE		Y	Y	
Stock FE			Y	
Stock x Quarter FE				Y
Quarter-Clustered SE	Y	Y	Y	Y
N	65428	65428	65428	65428
R-Squared	0.000953	0.0230	0.102	0.615

Standard errors in parentheses

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

This table displays regression results for

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

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, $\Delta \mathrm{LTG}_{a,n,t}$ 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 estimates represent the marginal effect in basis points of a 1 percentage point increase in analyst growth expectations. The time period is 1982-01:2021-12.

Table G13: c_1 and c_2 Estimates Using Idiosyncratic LTG Shocks

	(1)	(2)	(3)	(4)
c_1	1.81*	1.81*	1.81*	1.68*
	(0.986)	(0.985)	(1.00)	(0.971)
c_2	-0.926	-0.923	-0.921	-0.876
	(0.601)	(0.601)	(0.614)	(0.608)
Quarter FE		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-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.5.3 Other Benchmark Ranges for M_{LTG}

From the present-value identity in Lemma 4 in Appendix B.3.3, the general price impact of a change in expected future dividends is:

$$\Delta p_{n,t} = M_\mu \delta \sum_{s=0}^{\infty} M_\mu^s \Delta \tilde{d}_{n,t,s+1}, \tag{76}$$

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_μ is[52]

$$M_\mu = \frac{1}{1+\delta},$$

[52]From Lemma 4, we have

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

As discussed in Section 5.5, the benchmark case corresponds to $\kappa = \infty$, in which case

$$M_\mu = \frac{1}{1+\delta}.$$

for average dividend-price ratio δ.

Since $M_\mu < 1$, the smallest price impact occurs when the long-term growth expectations shock is driven by quarterly growth expectations shocks as far into the future as possible. Generating a 1% increase in average expected growth over the next H years requires a growth expectations 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 $t+4H$[53]:

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

The price impact of this shock is

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

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

$$M_{LTG} = \begin{cases} 2.7, & H = 3 \text{ years} \\ 4.1, & H = 5 \text{ years} \end{cases}$$

[53]For simplicity assume average quarterly dividend growth is small ($\bar{g} \approx 0$). In general (assuming no persistence in expected dividend growth, $\rho = 0$) the full change in expected future dividend levels is

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

as discussed in Appendix B.3.3.

H 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 t 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 (10) and model the portfolio weight demanded in stock n as a function of stock characteristics, including the market equity (i.e. price, denoted me_n) of the stock:

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

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

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

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 j. 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:

$$\mathbb{E}\left[\epsilon_{i,n}^D \mid \widehat{\mathrm{me}}_{i,n}, \boldsymbol{x}_n\right] = 0.$$

The price elasticities of demand for investor i (ζ_i) can then be computed as the diagonal elements of

$$\frac{\partial \boldsymbol{q}_i}{\partial \boldsymbol{p}'} = -\mathbf{I} + \alpha_{0,i} \left(\text{diag}\boldsymbol{\theta}_i\right)^{-1} \left(\text{diag}\boldsymbol{\theta}_i - \boldsymbol{\theta}_i\boldsymbol{\theta}_i'\right), \tag{77}$$

where $\boldsymbol{q}_i$ is the vector of log shares held, $\boldsymbol{p}$ is the vector of log prices, and $\boldsymbol{\theta}_i$ is the vector of log portfolio weights.[54]

[54]Strictly speaking, the price elasticities from (77) 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 (40).

I.1 Optimization Problem

I solve the following optimization problem:

$$\min_{\{b_{1,i},b_{2,i}\}_i} \sum_{i,n} \left[\Delta\tilde{q}_{i,n,t} - \left(b_{1,i}S_{n,t} - b_{2,i}S_{n,t} \cdot \tilde{A}_{n,t-1}\right)\right]^2 + \lambda \sum_i \left(\left(\frac{b_{1,i} - b_{1,S}}{b_{1,S}}\right)^2 + \left(\frac{b_{2,i} - b_{2,S}}{b_{2,S}}\right)^2 \right) \quad (78)$$

$$\begin{aligned} \text{s.t. } \tilde{q}_{i,n,t} &= \Delta q_{i,n} + \zeta_{i,n,t}\Delta p_{n,t} \\ b_{2,i} &\leq b_{1,i} \text{ (enforces } \beta_i \leq 1) \\ b_{1,S} &= c_1\zeta_S \text{ (definition of } c_1) \\ b_{2,S} &= c_2\zeta_S \text{ (definition of } c_2) \end{aligned}$$

The first term in (78) 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 $b_{2,i} = \beta_i b_{1i}$ and $\beta_i < 1$) and I want to take ratios of these coefficients. Thus, I express the penalty in terms of percentage deviations from $b_{1,S1}$ 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 λ 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)).

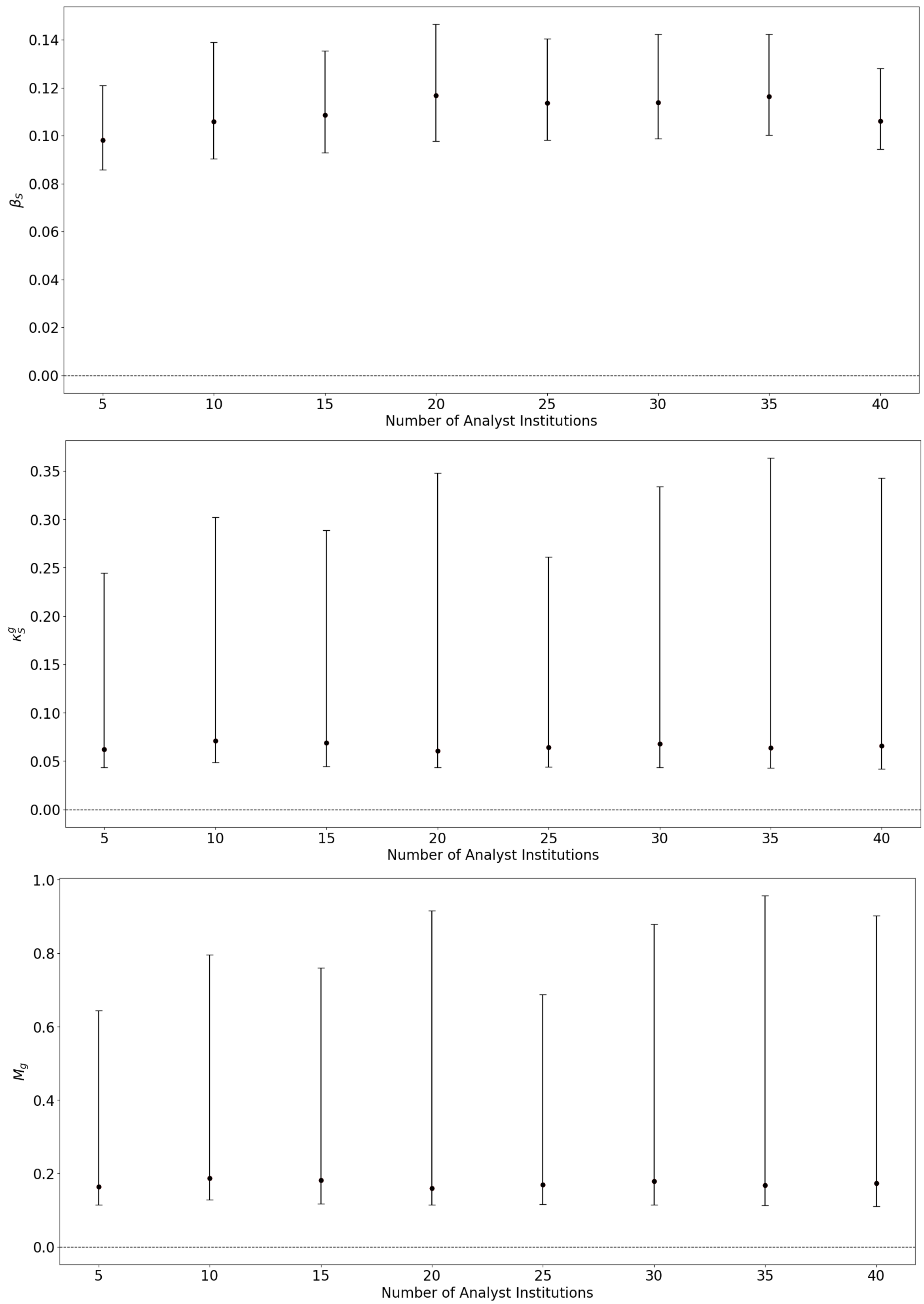
I use $\zeta_S = 0.38$, the average stock-level, ownership-share weighted price elasticity of demand in my sample using the estimated investor price elasticities from the approach of Koijen and Yogo (2019).

I.2 Subset of Analyst Institutions

While I use all institutions in each quarter to estimate factor model (25) and to estimate the analyst price impact panel regression (29), to estimate the investor-level regression (40) I retain only the idiosyncratic expected growth shocks associated with the 5 largest analyst institutions in each quarter (by number of expectations issued). Since, as discussed in Appendix D, 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 κ_i^g and β_i. Using 5 analyst institutions maximizes power. As displayed in Figure I16, 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 instrumental variable estimator of Gabaix and Koijen (2020*a*).

Figure I16: Investor-Level Results for Varying Number of Analyst Institutions



This figure displays the estimated κ_S^g, β_S, and M_g from (40) 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 κ_S^g, β_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 all investors i that holds stock n in quarter t, collect holdings changes $\Delta q_{i,n,t}$.
3. Repeat steps 1 and 2 a total of N_t times.

I compute regression (40) on this bootstrapped dataset and calculate κ_S^g, β_S, and M_g from the estimated κ_i^g and β_i. I repeat this process 500 times and report 2.5th, 50th, and 97.5th percentile estimates of each parameter κ_S^g, β_S, and M_g.

J κ Estimates from Previous Work

Table J14: Details of Recovering κ Estimates from Previous Work

Paper	Raw Estimates	My Assumptions	Converted Estimates	Empirical Setting
Vissing-Jorgensen (2003)	Table 2: Regression of portfolio weight on dummies for if expected return is in 0%-5%, 10%-15%, 15%-20%, 20+% (omitted category is expected return <= 0%). Dummy coefficents: 2.7, 4.6, 10.2, 10.2, 5	1. Expected return of <= 0 corresponds to 0 portfolio weight 2. Average portfolio share of about 50% (constant in regression) 3. Calculate kappa = (Dummy Coefficient - 0)/(Expected Return Bin Midpoint -0) * 1 / 0.5	0.5-2.5	Households, Aggregate Equity Market
Amronin & Sharpe (2014)	Table 8: Regression of log portfolio weight on log 10-year expected return has coefficient of 0.05. Regression of portfolio weight on 10-year expected return has coefficient 0.3.	1. Table 3: 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 = .05 / .1 * 1 / .37 3. For level-level specification calculate kappa = .3 / .37.	0.5 (from log-log specification) - 0.8 (from level-level specification)	Households, Aggregate Equity Market
Ameriks, Kezdi, Lee & Shapiro (2020)	Table 5: Regression of portfolio weight on 1-year expected return has coefficient 0.05	1. Table 1: Average portfolio share is 50%. 2. Calculate kappa = coefficient / 0.5	0.1	Households, Aggregate Equity Market
Giglio, Maggiori, Stroebel & Utkus (2021)	Table 3: Cross-sectional regression of portfolio weight on 1-year expected return has coefficient of 0.7-1.2 depending on specification. Table 4: Accounting for heterogeneity, above coefficient can rise to 3.5 Table 5: Regression of change in portfolio weight on change in 1-year expected return has coefficient 0.2.	1. Table 1: Average portfolio share is 70%. 2. For all specifications, calculate kappa = coefficient / 0.7	.3-5	Households, Aggregate Equity Market

Paper	Raw Estimates	My Assumptions	Converted Estimates	Empirical Setting
Beutel & Weber (2022)	Table 4: 1% Regression of portfolio weight on expected return has coefficient of 1.3% (OLS) - 2.8% (2SLS)	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	4-8.5	Households, Aggregate Equity Market, Germany
Bacchetta, Tieche & Van Wincoop (2020)	Table 3: Regression of portfolio weight on long-run expected return (see paper for more details) has coefficient of 8-10	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. 2. Median portfolio weight is 6%. 3. Calculate kappa = coefficient / 12 * 1 /0.06	11-14	US Mutual Funds, International Allocation. Note this paper does not use subjective beliefs data, but instead uses forecasting regressions to measure expected returns.
Dahlquist & Ibert (2022)	Tables 4, 5, 6: Regressions of log portfolio weights on 1-year expected return have coefficients of 9-14, 9-16, and 9-14, respectively	None	9-16	Mutual Funds (managed by "Large Asset Managers"), Allocation Between US vs. Developped and Emerging Market Equities. This paper focuses on active mutual funds (e.g. target-date funds are dropped), which rationalizes the larger estimated sensitivities.
Anodov & Rauh (2021)	Table 9: Regression of portfolio weight on annual risk premium has coefficient of 1 (for all risky assets), 3.1 (for equity), 0.6 (for real assets), and 0.2 (for private equity)	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.	1-6	Pension Funds, Asset Class