Beliefs and Stock Market Fluctuations: New Evidence from the Past Seven Decades*

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Abstract

We construct a new long-run series of subjective expected equity returns from an independent equity analysis firm, spanning 1956–2024. These expected returns are strongly positively correlated with the earnings-price ratio, respond negatively to past returns, and predict future returns. These patterns contrast with subjective expectations of individual investors and professional forecasters, which are weakly or negatively correlated with our new measure. Disagreement between sophisticated and individual investors is associated with higher trading volume. Our findings are consistent with a model of heterogeneous beliefs, where naive investors extrapolate past returns, rather than past dividends, while sophisticated investors are close to rational.

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1 Introduction

What role do investor expectations play in understanding stock market fluctuations? A longstanding literature argues that rational, time-varying expected returns linked to movements in risk premia account for most of the variation in stock prices (Campbell and Shiller, 1988b; Campbell and Cochrane, 1999; Cochrane, 2011). According to this view, investor expectations of returns should be high when valuations are low. However, recent research finds that subjective return expectations are inconsistent with this prediction (Greenwood and Shleifer, 2014; Adam et al., 2017; Nagel and Xu, 2023). A growing literature instead attributes stock market fluctuations to non-rational shifts in investor beliefs about future returns or cash flows (De La O and Myers, 2021; Bordalo et al., 2024).

The existing evidence on subjective return expectations raises two related questions. First, most survey evidence captures the beliefs of individual investors, but what about the beliefs of more sophisticated market participants? Second, a long theoretical tradition in finance emphasizes the importance of heterogeneous beliefs, with agents holding rational and biased beliefs interacting to shape asset prices and trading volume (e.g., Harrison and Kreps, 1978; De Long et al., 1990; Scheinkman and Xiong, 2003; Barberis et al., 2015). Yet most empirical studies of subjective expected returns place limited emphasis on belief heterogeneity and typically focus on non-rational investors' beliefs. Is there a role for heterogeneous beliefs in understanding the relationship between subjective expectations of returns and stock market fluctuations?

This paper provides new long-run evidence on the expectations of sophisticated investors and the relevance of heterogeneous beliefs. We build a novel dataset on expectations of stock returns and corporate earnings from Value Line (VL), an independent equity analysis firm. The data cover 1956–2024, providing a uniquely long sample to understand the relation between beliefs and stock market fluctuations. We provide four main findings. First, VL's expectations of returns are very different from the expectations of other investors. The beliefs of VL and individual investors are weakly or even negatively correlated, depending on the survey. Second, VL expected returns are contrarian and account for most of the fluctuations in the earnings-price ratio, in a manner consistent with rational econometric benchmarks. This contrasts with the expectations of individual investors, whom we find extrapolate past returns, though not past cash flows. Third, VL expected returns predict future realized returns. Finally, greater disagreement about expected returns between VL and individual investors is associated with increased trading volume and volatility. Our findings highlight the importance of sophisticated investors and heterogeneous beliefs for understanding stock market fluctuations.

We use a model à la Barberis et al. (2015) to organize our empirical analysis. We assume that naive investors predict future returns by extrapolating past returns, while sophisticated investors have rational expectations but face limits to arbitrage. In this class of models, the market-clearing condition generically imposes that the beliefs of sophisticated and naive investors are negatively correlated. Further, sophisticated investors' expected returns correlate negatively with valuation ratios, as these investors recognize that naive investor sentiment will mean-revert. Thus, the share of valuation movements accounted for by variation in sophisticated investors' return expectations is nontrivial. The contrarian beliefs of sophisticated investors also correlate negatively with past returns, but not with past dividend growth. Since sophisticated investors are rational, their time-varying beliefs predict future returns. Finally, disagreement about expected returns between naive and sophisticated investors should lead to higher trading volume (Campbell et al., 1993; Scheinkman and Xiong, 2003; Hong and Stein, 2007).

We examine the predictions of this framework using a new dataset of subjective cash flow and return expectations from Value Line (VL) spanning nearly the full post-WWII sample, 1956-2024. We build this dataset by digitizing the physical volumes of the *Value Line Investment Survey* from 1956 to 1989. We combine these newly digitized data with digitally available data from VL for 1987-2024. The underlying data provide expectations for approximately 1,500 firms per year in most years. We compute the expected return for each firm by combining long-term (three to five years) earnings expectations and price targets. We then aggregate these earnings and return expectations to an annual time series. We complement these new data with eight existing survey measures of return expectations for other finance professionals, forecasters, and individuals drawn from the literature.

The VL expectations data offer two main contributions relative to the existing literature. First, VL expectations cover a sample that is two to three times longer than existing data on investors' expectations of returns (see the literature review in Table B.1). This allows for higher statistical power, a benefit recently stressed by Brunnermeier et al. (2021), given that fluctuations in valuation ratios are slow-moving. Second, the VL data provide expected cash flow and return expectations from the *same* analyst. As we show, subjective expectations differ considerably across investors. Thus, combining cash flow and return forecasts from different financial market participants can yield misleading results.

We present four main findings, all consistent with our framework. First, we document substantial heterogeneity in expected returns. VL expected returns are weakly correlated with those of professional forecasters and weakly, or even negatively, correlated with individual investors' expectations. VL expected returns are also more volatile than most

other survey-based measures. Overall, subjective expectations data reject the assumption of common beliefs.

Second, VL expected returns are highly correlated with the earnings-price ratio. A time series regression of the cyclically adjusted earnings-price ratio on the expected return from VL yields a t-statistic of 5.2 and an R^2 of 65%. Thus, VL analysts expect returns to be high when valuation ratios are low, consistent with *countercyclical* expected returns implied by rational benchmark models. In contrast, no other expected return series among the nine we examine is significantly positively correlated with the earnings-price ratio. In fact, in our sample, expected returns from most surveys of individuals are acyclical or, if anything, procyclical, as documented by Greenwood and Shleifer (2014) and Adam et al. (2017).

Through the lens of VL's expectations, variation in expected returns accounts for most of the fluctuations in equity valuation ratios. Following Campbell and Shiller (1988a), we decompose the current price-earnings ratio into (i) expected returns over the next four years, (ii) expected earnings growth over the same horizon, and (iii) the expected long-term price-earnings multiple four years ahead. The strength of the VL data is that we observe each of these three objects for each firm from the same forecaster, so an exact accounting identity holds between these variables. Future expected returns explain roughly 60% of the variation in the price-earnings ratio, while the expected long-term multiple explains the remaining 40%. In contrast, expected cash flows explain essentially none of the variation in the price-earnings ratio. Consistent with this evidence, we also show that time variation in VL's expected returns depends mostly on expectations of mean-reversion in the price-earnings multiple to a long-term target but little on changes in expected dividend growth.

We further show that VL expected returns are *negatively* correlated with past returns, consistent with countercyclical expectations of returns. In contrast, expected returns from other professional forecasters are essentially *uncorrelated* with past realized returns, and expected returns of individuals tend to be *positively* correlated with past realized returns, as documented in the literature on extrapolative beliefs (e.g., Greenwood and Shleifer, 2014). Interestingly, past realized cash flow growth is not predictive of expected returns across all surveys we consider. This tilts the evidence towards a heterogeneous investor model where naive traders extrapolate past prices, as in Barberis et al. (2015), rather than past fundamentals.

Third, expected returns from VL predict future aggregate stock returns. Return predictability is especially strong for future realized *nominal* total returns. Across the nine annual measures of subjective expected returns we explore, VL's expected return is

the only series that significantly and robustly predicts returns. Moreover, VL expected returns predict future returns approximately as well as the cyclically adjusted earnings-price ratio (CAPE). There is also evidence of return predictability using realized *excess* returns, especially in recent decades, but it is weaker than for nominal returns and only statistically significant at longer horizons. In our sample period, however, excess returns are also less predictable using conventional predictors such as CAPE, and VL expected return does not perform worse than CAPE. Moreover, while our main sample is annual over 1956-2024, we find stronger predictability with quarterly data from VL covering 1987Q3-2024Q3.

Finally, we show that belief disagreement between VL and individual investors is associated with higher trading volume. Belief disagreement is also associated with higher return volatility. This evidence suggests that heterogeneity in beliefs matters for market dynamics and pricing.

Overall, our findings paint a picture of an equity market where sophisticated investors with near-rational beliefs interact with naive investors who extrapolate past returns. An increase in the expected return of naive investors raises their demand, driving up prices. Sophisticated investors understand that high prices are associated with lower expected returns. This story aligns with our evidence on the beliefs of sophisticated and individual investors, as well as trading volume. An alternative view is that only the beliefs of sophisticated investors matter, as in rational models with time-varying risk premia. This view, however, requires taking seriously only the survey evidence from VL and arguing that individual investors are merely bystanders whose beliefs do not affect prices. Moreover, some of the evidence described above challenges this view. First, the negative correlation between VL expectations and individual investors' expectations suggests that forecasts by VL somehow respond to shifting sentiment—a prediction of the market-clearing condition. Second, the correlation between trading volume and the difference in beliefs implies that the different types of agents trade with one another.

Related literature. Our work contributes to three strands of literature.

First, we contribute to the growing literature on subjective expectations in equity markets. Appendix Table B.1 provides a summary of the findings in the empirical literature on return expectations. Several studies document that stock market return expectations of individual investors and some institutions are acyclical or even procyclical and extrapolative, in contrast to model-based expected returns (Bacchetta et al., 2009; Greenwood and Shleifer, 2014; Adam et al., 2017; Andonov and Rauh, 2021; Nagel and Xu, 2023). A smaller set of recent papers, focusing on analyst or institutional investors, find

expected returns that are countercyclical and contrarian, closer to model-based expected returns (Wang, 2020; Dahlquist and Ibert, 2024; Bastianello, 2025; Büsing and Mohrschladt, 2024), although these papers rely on short samples.

We provide several contributions relative to these studies. We provide evidence on contrarian and countercyclical return expectations from a sophisticated agent for a much longer sample spanning nearly seven decades. In contrast, these studies typically have data starting in the 2000s. As a result, they generally do not provide evidence of return predictability or only do so on short samples. Besides the gain in statistical power, our study also informs debates about out-of-sample return predictability (Welch and Goyal, 2008). Aggregate return expectations implied in VL's forecasts are strongly correlated with past valuations, even before it was statistically established that valuation ratios predict aggregate returns (Campbell and Shiller, 1988b). In addition, we document belief disagreement across different investor classes and show that the findings are consistent with the predictions from a model of heterogeneous beliefs.

Second, a related literature uses subjective expectations to explain variation in stock market valuations. Traditional econometric-based decompositions of the price-dividend ratio find that most of the variation in valuation ratios comes from variation in expected returns, not expected cash flows (Campbell and Shiller, 1988a; Campbell and Ammer, 1993; Cochrane, 2011). This is mostly because long-term future returns are predictable using valuation ratios, while dividend growth rates are less predictable. This view has, however, been challenged in a number of papers showing that subjective cash flow expectations can account for stock price fluctuations. Bordalo et al. (2024) show that long-term expected earnings growth (LTG) from sell-side analysts is volatile enough to explain stock price movements, assuming constant expected returns. Consistent with this, De La O and Myers (2021) show that changes in expected returns from Livingston are too small to explain valuations, while changes in short-term expected earnings growth are much more volatile and account for most (between 60 and 90%) of the variation in the price-dividend ratio.

Relative to these studies, we highlight that such decompositions of valuations between expectations of cash flows and returns crucially depend on *whose* expectations one considers. From the perspective of a sophisticated analyst, we find that it is changes in expected returns, rather than expected dividend growth, that account for most of the variation in equity valuation. Naturally, this result does not have to hold for all investors. Indeed, given that the Campbell-Shiller decomposition can hold for various sets of beliefs, our findings suggest caution in using such decompositions to causally ascribe fluctuations in the stock market to a given set of beliefs. Moreover, a key strength of our analysis is to

jointly exploit data on expected returns and expected cash flows. As noted by Giglio et al. (2021), it is crucial to use both series to perform the decomposition, since they tend to be positively correlated.

Third, our paper highlights the role of heterogeneous beliefs in asset price formation. We find two pieces of evidence consistent with generic predictions of asset pricing models with heterogeneous investors. First, market clearing generally constrains returns expectations of different agents to be negatively correlated. Consistent with this, VL's beliefs are negatively correlated with most surveys of individuals' expectations. Second, trading volume should rise when disagreement increases (Barberis, 2018). In line with this, we find that when beliefs of VL and individuals diverge, trading volume is higher. This result suggests that both types of return expectations "matter" for asset price formation.

Consistent with our findings, McCarthy and Hillenbrand (2025) find that expected returns of individuals and equity analysts' long-term earnings growth forecasts (LTG) are negatively correlated.[1] Our paper brings novel data on cash-flow and return expectations for a sophisticated investment adviser over a considerably longer time sample. While McCarthy and Hillenbrand (2025) argue that analysts extrapolate past cash flows, we find the opposite in our data, consistent with VL being representative of "rational traders" in heterogeneous models.

Roadmap. The remainder of the paper is structured as follows. Section 2 presents a simple model to organize our empirical analysis. Section 3 presents our new dataset. Sections 4, 5, and 6 summarize the properties of our subjective expected return series and document that it is strongly correlated with the earnings-price ratio, past returns, and volatility. Section 7 shows our new expected return series predicts future returns. Section 8 shows belief disagreement about returns is associated with higher trading volume, and Section 9 concludes.

2 Heterogeneous Investors: Model Predictions

2.1 Model Layout

The model is a discrete-time variant of De Long et al. (1990) and Barberis et al. (2015). Time is indexed by t. There are two assets: a safe asset in infinite supply that pays return r, and a risky asset in unit supply that pays a dividend D_t and trades at a price

[1] Mian and Sufi (2022) focus on the housing market during the 2000s housing boom. They provide evidence of heterogeneous beliefs across optimistic buyers and the more pessimistic broader population.

P_t. Dividend growth, $G_t = D_t - D_{t-1}$, follows an AR(1) process with mean zero and persistence ρ. The two assets are traded by two types of investors indexed by $i \in \{N, S\}$ (naive and sophisticated). The share of naive traders is α. As in Campbell et al. (1993), we assume that, every period, agents maximize the expected utility of next period wealth. Their utility is CARA and proportional to $-\exp\{-\gamma x_{it} R_{t+1}\}$, where

$$R_{t+1} = P_{t+1} + D_{t+1} - (1+r)P_t$$

is the excess stock return, x_{it} their holding of risky asset, and γ their risk aversion.

Given this set-up, asset demands x_{it} depend on return expectations. We assume that sophisticated traders have rational expectations $F_t^S R_{t+1} \equiv E_t R_{t+1}$, consistent with our empirical results on VL expectations from Section 6.3. The expectation of naive traders is assumed to be extrapolative: $F_t^N R_{t+1} \equiv E_t R_{t+1} + \mu R_t$. This assumption is in line with the recent literature (Greenwood and Shleifer, 2014; Nagel and Xu, 2022), as well as our own results in Section 6.1. Finally, we denote σ^2 the conditional variance of R_{t+1}. In equilibrium, this variance can be computed and is constant.

2.2 Model Predictions

We obtain the following expressions for prices and expected returns (detailed derivations are in Appendix A):

$$P_t = -\frac{\gamma\sigma^2}{r} . \frac{1+r}{1+r+\alpha\mu} + \frac{1}{r} D_t + \frac{1+r}{r} \frac{\rho}{1+r-\rho} G_t + \frac{\alpha\mu}{1+r+\alpha\mu} R_t \tag{1}$$

$$F_t^N R_{t+1} = \gamma\sigma^2 + (1-\alpha)\mu R_t \tag{2}$$

$$F_t^S R_{t+1} = \gamma\sigma^2 - \alpha\mu R_t \tag{3}$$

When naive investors extrapolate past returns ($\mu > 0$), valuations are increasing in past returns, which boosts the demand of naive traders (equations (1), (2)). Recognizing this, sophisticated traders rationally expect lower future returns (equation (3)). While dividend growth raises current valuations, it does not affect future returns, as both investor types are assumed here to be rational about future dividends.

Predictions are intuitive and formally derived in Appendix A. The first set of predictions is not related to our specific assumptions about expectations formation but only rely on market clearing:

Prediction 1. ***Market equilibrium with heterogeneous traders:***

- *Expected returns of sophisticated investors are negatively correlated with expected returns of naive investors.*

- *Trading volume covaries positively with the absolute change in disagreement about expected returns.*

$$vol = \frac{1}{2\gamma\sigma^2}|\Delta\left(\alpha F_t^N R_{t+1} - (1-\alpha)F_t^S R_{t+1}\right)|$$

The first bullet point follows from the market-clearing condition. When naive investors are bullish, their demand is high. Prices have to increase to compress the demand of rational investors, so their expected returns decline. This prediction does not require any specific assumption about expectation formation. The second bullet point comes from defining volume as the absolute change in naive (or sophisticated) trader demand (Campbell et al., 1993). In our tests, we will focus on both the level and the change in disagreement. The two are positively correlated, and the link between volume and the level disagreement is a more generic prediction of this class of models (Hong and Stein, 2007; Barberis, 2018).

The second set of predictions characterizes expectations formation. These arise from specific assumptions made about how expectations are formed:

Prediction 2. ***Characterizing expectations of returns***

- *Expected returns of sophisticated investors are* negatively *correlated with past realized returns.*

- *Controlling for past returns, expected returns of sophisticated and naive investors should not depend on past dividend growth (Equations (3) and (2)).*

Since expected returns are negatively correlated and naive traders extrapolate on past returns, sophisticated traders are mechanically contrarian. By assumption, both investor types do not extrapolate past dividends, which gives the second prediction.

The last set of predictions arise from the equilibrium relationships between valuations, returns, and expectations.

Prediction 3. ***Expectations and valuation***

- *Return expectations of sophisticated investors predict future realized returns.*

- *When the persistence of cash flow growth is low, return expectations of sophisticated investors are negatively correlated with valuations.*

- *When the persistence of cash flow growth is low, valuations are mostly driven by sophisticated expectations.*
- *When the share of naive investors is low, valuations are more strongly affected by sophisticated expectations than by naive ones.*

The first bullet point comes from our assumption that sophisticated investors are rational. The second one holds controlling for cash flow growth, or if the persistence of growth is low (in the data, $\rho \approx 0$, see Appendix Table B.10). In this case, valuations are mostly affected by shifts in naive investor expectations, which are themselves negatively correlated with sophisticated investors' forecasts of returns. The third and fourth bullet points interpret equation (1) as a kind of Campbell-Shiller decomposition. When cash flow growth is not persistent, all valuation shifts come from movements in expectations (third bullet point). The fourth bullet point is intuitive: a given shift in naive expectations has a smaller effect on valuations when there are fewer naive investors. As a result, valuation movements are explained predominantly by sophisticated rather than naive beliefs when the share of naive traders α is low.

3 Data

We build a new annual time series dataset containing subjective expectations of returns and earnings from Value Line. The data are annual and cover the period 1956-2024. We complement these data with subjective expectations of equity returns from various surveys of (i) other finance professionals, (ii) professional forecasters, and (iii) individuals. We further match these data with standard data on realized returns and firm fundamentals.

3.1 New Expectations Data from Value Line, 1956-2024

Data source and collection. Our main data contribution is a new database of analyst forecasts of firm fundamentals and stock prices spanning 1956 to 2024. This sample is significantly longer than existing datasets on analyst expectations, such as IBES, which has limited coverage starting in 1976 and only provides price targets starting in 2002. The forecasts are from Value Line (VL), a publicly traded independent investment research firm widely used by retail and institutional investors.[2] Since 1956, VL has provided

[2]For example, Value Line is supposedly the only investment research subscription used by Warren Buffett, while Charlie Munger has called the Value Line charts (figures and data tables) a "human triumph." Other examples of investors who have relied on Value Line's analysis include Peter Lynch and David Dreman. The latter worked at Value Line early in his career. At the time of writing, Value Line had a

forecasts of firm-level fundamentals such as sales, earnings per share (EPS), and dividends per share (DPS). The forecasts are usually provided for the remainder of the current year and for a 3-5 year horizon. For each firm, Value Line also provides a stock price target at the 3-5 year horizon. VL covers 500 to 1600 publicly listed firms per year, with coverage stabilizing around 1600 in the middle of the 1970s (see Figure B1). Firms in VL account for over 80% of the total market cap in the CRSP universe in most years (see Figure B2). We obtain forecasts for 92,117 firm-year observations.

We build our VL database in two steps. First, for the period 1987-2024, we use VL's estimates and projections database, which is available digitally from VL. Second, for the 1956-1989 period, we digitized the physical volumes and microfilm scans of the *Value Line Investment Survey*. We first scanned physical volumes and microfilm records from various libraries. Appendix Figures B3 and B4 provide examples of the underlying source for General Motors in 1956 and 1975. We then applied state-of-the-art optical character recognition (OCR) and layout detection tools to extract the actual realization of fundamentals, the forecasts of fundamentals, and stock price targets (Correia and Luck, 2023). We also extracted other relevant information, including firm name, ticker, and the recent actual stock price. Through this procedure, we digitized 38,696 investment analysis reports, or an average of 1,138 per year. For each firm-year in VL, we match the firm to its PERMNO using a fuzzy match algorithm based on firm name and stock ticker.

To minimize errors in the digitization, we manually verified the digitization and tested whether identities between variables hold (e.g., verifying that sales, sales per share, and number of common shares outstanding are consistent). We also used the overlapping years covered in both the VL digital database and our digitized data to verify the quality of the digitization. We further verified that the actual realizations are strongly correlated with Compustat data.[3] We note that collecting data from print versions of published documents ensures that the data are not subject to backfilling concerns.

We collect the forecasts from VL made between January and March of each year. Firms in VL are surveyed four times per year, so this implies we take the first survey in a calendar year. The motivation for this choice was twofold. First, projections for the remainder of the calendar year made in Q1 of the year can be thought of as forecasts for the next year. Second, focusing on one quarter made the digitization more manageable than if we had collected data for all quarters. Using data from one forecast per year is suitable for our purposes, as we are interested in variation in valuation ratios and return predictability, which tend to be strongest at longer horizons. We also construct quarterly

market cap of about $320 million.

[3]Appendix D provides further details on the data collection and quality checks.

expected returns for the 1987-2024 subsample.

We are far from the first to use the VL expectations data. Value Line ratings and expectations were the subject of a large literature in the 1970s and 1980s that debated whether their stock rankings contained information for future returns. Several studies, always relying on a few years or a small sample of the data, find that Value Line timeliness rankings had predictive power for subsequent returns (see Black and Kaplan, 1973; Holloway, 1981; Copeland and Mayers, 1982). Stickel (1985) found that VL rank changes are associated with an increase in stock prices, suggesting that the information published by VL was incorporated into stock prices.[4] Szakmary et al. (2008) find limited evidence that VL expected returns predict returns in the cross-section, though they focus on only 65 firms during a limited set of years.[5] We are the first to construct a long firm-level panel dataset of subjective expectations spanning almost 70 years. This long sample is invaluable for testing time series properties, such as return predictability and correlation with valuation ratios.

Value Line expected return. We denote VL expected annualized aggregate return over the next three to five years as $\mathrm{F}^{\mathrm{VL}} r_{t \to t+4}$. These expected returns are based on projected future earnings and price targets made in Q1 of calendar year t. Specifically, for each firm f in Q1 of year t, we compute the expected return implied by VL's reported recent price $(P_{f,t})$, EPS forecasts for the end of year t ($\mathrm{F}^{\mathrm{VL}} EPS_{f,t}$), EPS forecasts for year $t+4$ ($\mathrm{F}^{\mathrm{VL}} EPS_{f,t+4}$), and price target in 4 years ($\mathrm{F}^{\mathrm{VL}} P_{f,t+4}$).[6] The VL expected firm-level return $\mathrm{F}^{\mathrm{VL}} r_{f,t \to t+4}$ as of the beginning of year t (Q1) is the solution x to this equation:

$$\frac{P_{f,t}}{\mathrm{F}^{\mathrm{VL}} EPS_{f,t}} = b \left[\sum_{i=0}^{4} \frac{(1 + \mathrm{F}^{\mathrm{VL}} g_{f,t \to t+4})^i}{(1+x)^{i+1}} \right] + \frac{1}{(1+x)^5} \times \frac{\mathrm{F}^{\mathrm{VL}} P_{f,t+4}}{\mathrm{F}^{\mathrm{VL}} EPS_{f,t}} \tag{4}$$

where we assume constant dividend growth $\mathrm{F}^{\mathrm{VL}} g_{f,t \to t+4} = (\frac{\mathrm{F}^{\mathrm{VL}} EPS_{f,t+4}}{\mathrm{F}^{\mathrm{VL}} EPS_{f,t}})^{\frac{1}{4}} - 1$ from t to $t+4$, and a constant payout rate $b = 0.41$ obtained as the average from the data.[7]

[4] Note that we do not employ the Value Line "rankings" in this paper.

[5] Brav et al. (2005) use VL to study the factors that explain subjective expected returns. They find that VL expected returns are correlated with market beta and size (see also Jensen, 2022).

[6] To be more precise, long-term EPS and price forecasts range from year $t+3$ to $t+5$. We take the convention that the horizon is $t+4$.

[7] In some years, VL also forecasts $t+1$ earnings per share. In this case, we incorporate growth from t to $t+1$ and from $t+1$ to $t+4$. We also note that the results are highly robust to deriving the expected return in levels, which allows for the inclusion of firms with negative expected earnings in year t (see Figure B.1). We also constructed the VL expected return using projected dividends per share (instead of earnings per share). The time series of the expected return based on dividends per share is very similar (Figure B.1). We

To compute the aggregate expectation of return from year t to $t+4$, we then compute a market cap-weighted average of the firm-level expected return:

$$\mathrm{F}^{\mathrm{VL}} r_{t \to t+4} = \sum_f w_{f,t} \mathrm{F}^{\mathrm{VL}} r_{f,t \to t+4},$$

where $w_{f,t}$ is firm f's share of total market cap in the VL universe in December of year $t-1$.[8] $\mathrm{F}^{\mathrm{VL}} r_{t \to t+4}$ is the expected return implied by VL's EPS and price targets based on expectations formed and published in Q1 of year t. Similarly, we compute market-cap weighted expectations of earnings growth, $\mathrm{F}_t^{\mathrm{VL}} g_{t \to t+4}$, current forward price-earnings multiple $\frac{P_t}{\mathrm{F}_t^{\mathrm{VL}} E_t}$, and expected future price-earnings multiple $\frac{\mathrm{F}^{\mathrm{VL}} P_{t+4}}{\mathrm{F}_t^{\mathrm{VL}} E_{t+4}}$.

3.2 Additional Data

We collect data on subjective expected equity returns from various sources used in the literature. We focus on expectations data, rather than balances of opinion, as the latter is less directly comparable to return realizations (see Greenwood and Shleifer (2014) for a review of balance of opinion data).

Expectations of other finance professionals. First, we collect two additional measures of expected returns from analysts or institutional investors ("finance professionals"). We use data on price targets and dividends per share forecasts from the Institutional Brokers' Estimate System (IBES). IBES generally reports price targets for next year. This variable is well populated starting in 2003. Similar to Bastianello (2025), we compute the IBES expected return using the most recent price ($P_{f,t}$), the consensus forecast of dividends per share for year $t+1$ ($\mathrm{F}^{\mathrm{IBES}} DPS_{f,t}$), and the consensus price target ($\mathrm{F}_t^{\mathrm{IBES}} P_{f,t+1}$)

$$\mathrm{F}^{\mathrm{IBES}} r_{f,t \to t+1} = \frac{\mathrm{F}^{\mathrm{IBES}} DPS_{f,t} + \mathrm{F}^{\mathrm{IBES}} P_{f,t+1} - P_{f,t}}{P_{f,t}}.$$

We then compute the aggregate expected return as the market-cap weighted average of the firm-level expected returns: $\mathrm{F}_t^{\mathrm{IBES}} r_{t \to t+1} = \sum_f w_{f,t} \mathrm{F}_t^{\mathrm{IBES}} r_{f,t \to t+1}$, where $w_{f,t}$ is firm f's share of the total market cap in the IBES universe at time t. To make the series comparable with VL, we take expectations in IBES as of March of each year.[9] Note that this measure

choose to rely on EPS due to the well-known decline in the dividend payout ratio over the sample.

[8] The main results are also robust to aggregating expected earnings and market capitalization and then computing the expected return directly from the aggregate series (see Figure B.1).

[9] The exception is March 2020, which results in a very high expected return that meaningfully distorts the results, especially given the short sample. For 2020, we thus use expectations in IBES from February.

of expected return relies on the price target, not the long-term earnings growth (LTG) measure in IBES. As an additional source on expectations of finance professionals, we use data on the expectations of institutional investors from the Robert Shiller Investor Confidence survey (Shiller, 2000). These data provide the expected return on the Dow Jones index at various horizons and are available with gaps since 1999 and continuously since 2001.

Expectations of professional forecasters. Second, we obtain subjective expectations about expected stock returns from professional forecasters. The first source is the Livingston Survey, which provides forecasts by economists from industry, government, banking, and academia (used, for instance, by De La O and Myers (2021)). It is published in June and December. To obtain forecasts made as close as possible to VL's forecasts in Q1 of year t, we use forecasts from December of year $t-1$. The Livingston survey expectations on stock returns are available since 1952. It is thus the only data on subjective expected returns with a longer availability than Value Line. We compute the Livingston expected return as

$$\mathrm{F}_t^{\mathrm{Liv}} r_{t\to t+1} = \left(\frac{SPIF_12M_t}{SPIF_BP_t}\right)^{\frac{12}{k}} - 1, \tag{5}$$

where $SPIF_12M_t$ is the predicted index level of the S&P 500 12 months ahead of t and $SPIF_BP_t$ is the current base value. We use the $(12/k)$ adjustment based on the month of the reported base value. Second, we collect expected returns from the Survey of Professional Forecasters. We use the median 10-year expected stock return ($STOCK10$), which is available starting in 1992. This variable captures forecasts for the annual-average rate of return on equities (S&P 500) over the next 10 years. This variable is surveyed only in Q1 of each year, so the timing of this variable is consistent with our VL data.

Expectations of individuals. Third, we collect data on expected returns from various surveys of individuals. We use data on the expectations of individuals from the Robert Shiller Investor Confidence survey (Shiller, 2000) (used, for instance, by Greenwood and Shleifer (2014)). In addition, we collect Graham and Harvey CFO Survey's forecasts for the return on the S&P 500 index over the next 12 months and average annual returns over the next 10 years (Graham and Harvey, 2005; Duke University's Fuqua School of Business and Federal Reserve Banks of Richmond and Atlanta, 2025). The Graham-Harvey data are available from 2002 onwards. Further, we use the subjective expected return series constructed by Nagel and Xu (2022). This series combines expected returns at the one-year

horizon from various surveys: UBS/Gallup survey, Vanguard Research Initiative, surveys of from several studies in the 1970s, the Michigan Survey of Consumers, Conference Board Survey, and Roper Center Surveys.[10]

Data on realizations and fundamentals. We use data on stock returns and trading volume from CRSP and firm fundamentals from Compustat, both via the Wharton Research Data Services. We match the Value Line database with CRSP stock returns and Compustat fundamentals using PERMNO. Finally, we also use the cyclically adjusted price-earnings ratio (CAPE) from Robert Shiller's website.

4 Heterogeneous Subjective Expected Returns

4.1 Summary Statistics

Table 1 reports summary statistics of the expected returns from our novel VL data (Panel A), eight additional survey-based expected return measures (Panel B), and realizations (Panel C). In panel B, we also report the properties of a simple model-based expected return, $\widehat{r}^{EP}_{t\to t+1}$. Specifically, we calculate the expected return implied by the risk-free rate (one-year Treasury yield) plus the predicted value from a regression of the realized excess return over the next year on the earnings-price ratio. We take this as a "rational benchmark," similar to Dahlquist and Ibert (2024).

The average VL annualized expected nominal return, $F^{VL}r_{t\to t+4}$, is 13% for the 1956-2024 sample. This is 2 percentage points too optimistic compared to the average realized return of 11%. The VL expected return also fluctuates considerably, with a standard deviation of 8%. Indeed, Figure 1 shows that the VL's expected nominal return varies substantially over time, with large fluctuations at business cycle frequencies. Expected returns are especially high in the 1970s and after major market downturns, such as the 2008 Global Financial Crisis. The variation in the VL expected return is higher than the standard deviation of model-based expected return, $\widehat{r}^{EP}_{t\to t+1}$, which has a standard deviation of 4%.

VL expected returns also exhibit higher volatility compared to the expected returns of individuals and professional forecasters. For example, individual expected returns have a standard deviation of 1-2% per year. In contrast, in overlapping samples, $F^{VL}r_{t\to t+4}$ has a standard deviation of roughly 3%. These patterns are visually apparent in Figure 1, which plots all nine expected return measures. Long-horizon forecasts (GH 10 years, SPF 10

[10] See Nagel and Xu (2022) for details. We obtain the data from Xu's webpage.

Table 1: *Summary Statistics*

	Mean	SD	N	RMSE	Start	End
Panel A: Value Line Subjective Expectations						
Expected return, Value Line, $F^{VL}r_{t\to t+4}$	0.13	0.08	69	0.161	1956	2024
Expected EPS growth, Value Line, $F^{VL}g_{t\to t+4}$	0.12	0.03	69		1956	2024
Forward PE Ratio, Value Line, $\frac{P_t}{F^{VL}EPS_t}$	16.14	4.79	69		1956	2024
Long-term PE Ratio, Value Line, $\frac{F^{VL}P_{t+4}}{F^{VL}EPS_{t+4}}$	16.00	3.44	69		1956	2024
Panel B: Other Subjective Expectations						
Expected return, IBES, $F^{IBES}r_{t\to t+1}$	0.16	0.06	22	0.195	2003	2024
Expected return, Shiller-institutional, $F^{Sh\text{-}inst}r_{t\to t+1}$	0.04	0.04	35	0.184	1990	2025
Expected return, Livingston, $F^{Liv}r_{t\to t+1}$	0.06	0.05	73	0.174	1953	2025
Expected return, Shiller-individual, $F^{Sh\text{-}indiv}r_{t\to t+1}$	0.04	0.03	26	0.186	1999	2025
Expected return, SPF, $F^{SPF}r_{t\to t+10}$	0.07	0.01	33	0.173	1992	2025
Expected return, Graham-Harvey (10-year), $F^{GH}r_{t\to t+10}$	0.07	0.01	23	0.177	2002	2024
Expected return, Nagel-Xu (2022), $F^{NX}r_{t\to t+1}$	0.09	0.02	36	0.169	1988	2023
Expected return, Graham-Harvey (1-year), $F^{GH}r_{t\to t+1}$	0.05	0.02	23	0.184	2002	2024
Expected return, EP regression, $\widehat{r}^{EP}_{t\to t+1}$	0.11	0.04	69	0.159	1956	2024
Panel C: Realizations						
Realized return, Value Line sample, 1 year, $r_{t\to t+1}$	0.11	0.16	69		1956	2024
Realized return, Value Line sample, 4 year, $r_{t\to t+4}$	0.10	0.06	66		1956	2021
Realized return, CRSP sample, 1 year, $r_{t\to t+1}$	0.11	0.16	69		1956	2024
Realized return, CRSP sample, 4 year, $r_{t\to t+4}$	0.10	0.07	66		1956	2021
Realized EPS growth, Value Line sample, 4 year, $g_{t\to t+4}$	0.07	0.04	65		1956	2020
Trailing EP Ratio, CRSP sample, E/P_t	0.06	0.03	69		1956	2024
Inverse of Shiller CAPE ratio, $\frac{1}{CAPE_t}$	0.06	0.03	69		1956	2024
Risk-free rate, r^f_t	0.05	0.03	69		1956	2024

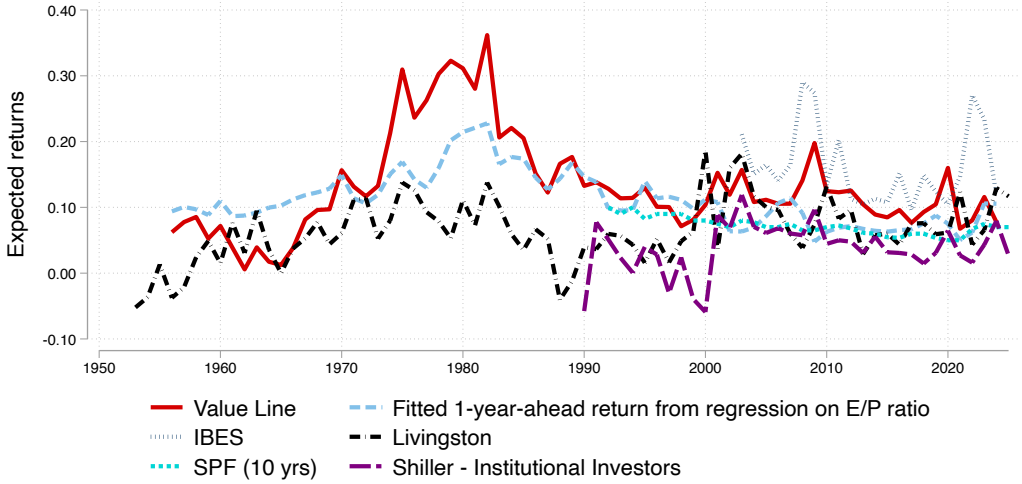
Notes: This table reports summary statistics for our annual time series dataset. All returns and growth rates are nominal and annualized. The Forward PE ratio is based on the most recent price divided by the forecast of earnings per share for year t made at the beginning of year t. The risk-free rate is the 90-day T-bill return.

years) have markedly lower volatility, as expected given lower long-run return variability. Moreover, VL expected returns are slightly more optimistic than expectations from individuals and professional forecasters. However, one should be careful in making this comparison with the Livingston and Shiller series, as these do not include dividends.[11]

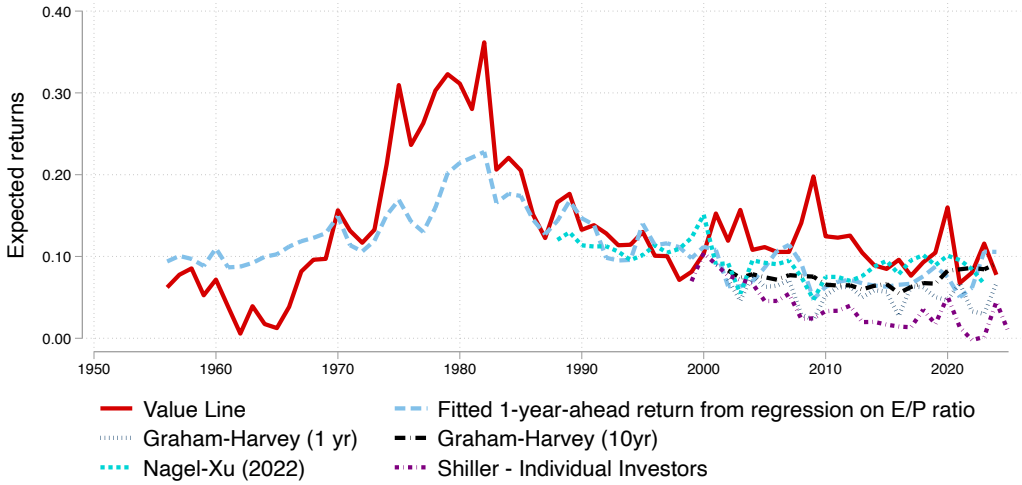
[11]Nagel and Xu (2023) find that Livingston survey expectations are still pessimistic when adjusting these expectations with the dividend yield.

Figure 1: *Subjective Expected Equity Returns: Value Line and Other Surveys*

(a) *Finance Professionals and Professional Forecasters*



(b) *Individuals*



Notes: This figure plots various subjective expected return time series. Panel (a) plots expected returns from Value Line, other finance professionals, and professional forecasters. Panel (b) plots expected returns from Value Line and surveys of individuals. We also plot the expected return constructed as the one-year Treasury yield plus the fitted value from a predictive regression of next year's realized excess return on the earnings-price ratio.

Overall, these simple summary statistics indicate substantial heterogeneity in both the mean and variance of nominal expected returns.

4.2 Correlation of Subjective Expected Returns

Table 2 reports the pairwise correlations of VL expected returns and the eight other expected return series. VL expected returns are positively and significantly correlated with expected returns from other finance professionals (IBES and Shiller's survey of institutional investors). VL expectations are more weakly positively correlated with expectations of professional forecasters in the Livingston survey and the SPF. At the same time, VL expected returns are weakly or even negatively correlated with expected returns from individuals in the Graham-Harvey CFO survey and the Nagel-Xu series. The negative correlation between the VL and GH series is statistically significant.

Table 2 thus highlights the heterogeneity in subjective return expectations. In periods when VL analysts expect *high* returns, such as at the start of 2009, individuals usually do not share these beliefs and often expect *low* returns. As shown in Section 2, this prediction emerges naturally in an equilibrium model with two classes of traders that hold different return expectations. Due to market clearing, if extrapolative agents are bullish about future returns, more sophisticated traders' demand has to shrink, which can only happen if they become bearish about future returns.

5 Subjective Expected Returns and Valuation Ratios

This section documents that VL expected returns are strongly correlated with measures of the earnings-price ratio. This pattern contrasts with expected returns from professional forecasters and individuals (e.g., De La O and Myers, 2021). At the same time, VL expected earnings growth is not correlated with the earnings-price ratio. As a result, from the lens of VL's expectations, fluctuations in stock market valuations are accounted for by variation in expected returns.

5.1 Earnings-Price Ratio and Expected Returns

As has been well known since Campbell and Shiller (1988b), movements in the earnings-price ratio must be driven by either changes in expected returns or expected earnings growth. To fix intuition, suppose earnings grow at rate g, the payout ratio is b, and r is expected returns. In this case, the earnings yield is $\frac{E}{P} = \frac{1}{b}(r - g)$. Thus, the earnings-price ratio should be related to higher required returns or lower earnings growth. We provide a formal derivation of this in our model (Appendix A). In recent work, De La O and Myers (2021) show that expected returns from the Graham-Harvey and Livingston Survey contribute little to valuation movements.

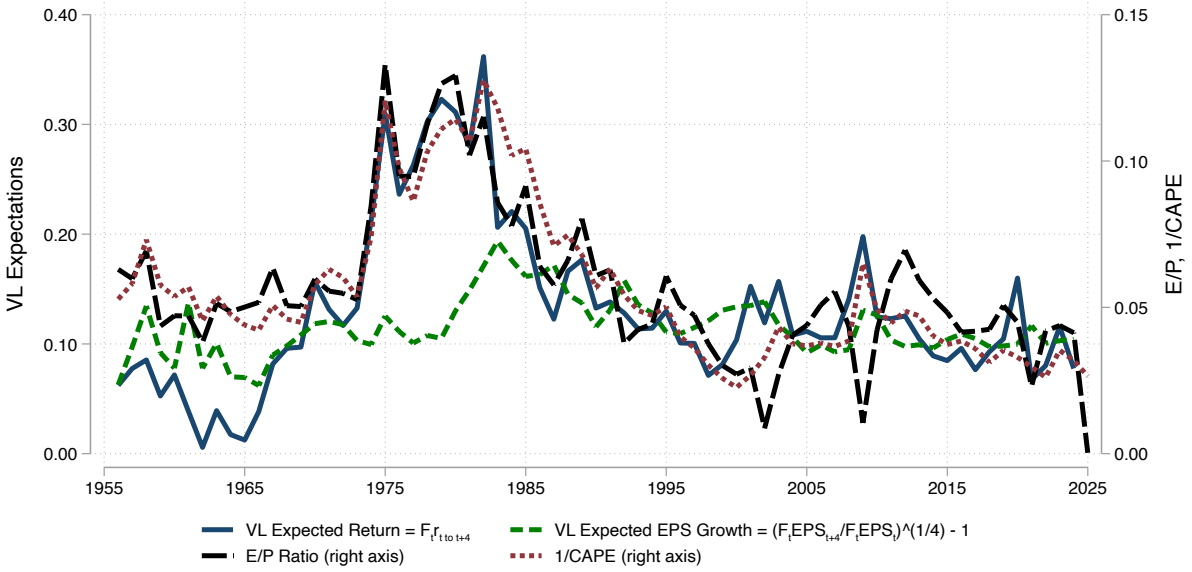
Table 2: *Correlation between Expected Equity Returns across Surveys*

	$F^{VL}r_{t\to t+4}$	$F^{IBES}r_{t\to t+1}$	$F^{Sh\text{-}inst}r_{t\to t+1}$	$F^{Liv}r_{t\to t+1}$	$F^{Sh\text{-}indiv}r_{t\to t+1}$	$F^{SPF}r_{t\to t+10}$	$F^{GH}r_{t\to t+10}$	$F^{NX}r_{t\to t+1}$	$F^{GH}r_{t\to t+1}$
$F^{VL}r_{t\to t+4}$	1.000								
$F^{IBES}r_{t\to t+1}$	0.447	1.000							
$F^{Sh\text{-}inst}r_{t\to t+1}$	0.446	0.248	1.000						
$F^{Liv}r_{t\to t+1}$	0.292	-0.089	0.187	1.000					
$F^{Sh\text{-}indiv}r_{t\to t+1}$	0.271	-0.168	0.025	0.489	1.000				
$F^{SPF}r_{t\to t+10}$	0.075	0.392	-0.209	-0.089	0.587	1.000			
$F^{GH}r_{t\to t+10}$	0.049	0.374	0.317	0.333	0.220	0.265	1.000		
$F^{NX}r_{t\to t+1}$	-0.176	-0.565	-0.653	-0.204	0.476	0.347	0.091	1.000	
$F^{GH}r_{t\to t+1}$	-0.445	-0.636	0.005	0.457	0.537	0.169	0.060	0.622	1.000

Notes: This table reports pairwise correlation among the subjective expected equity returns series across surveys. Subjective expected returns are nominal and annual.

In contrast, we find here that VL expected returns account for a large share of movements in valuation. Figure 2 plots the time series of the VL expected return and the VL expected aggregate EPS growth. We also plot the earnings-price ratio and inverse of the CAPE. In the time series, the VL expected return is strongly positively correlated with the earnings-price ratio. The correlation is even stronger for the inverse CAPE. VL expected returns are high during times when valuations are low. Examples include the 1958 recession, the stagflation of the 1970s, the early 1980s recession, and the 2008 financial crisis.

Figure 2: *Valuation Ratios, Expected Returns, and Expected Earnings Growth*



Notes: This figure shows expectations of returns and EPS growth from Value Line on the left vertical axis and the earnings-price ratio and inverse CAPE on the right vertical axis. Expected returns and EPS growth plotted for year t are based on expectations formed in Q1 of year t. The expected returns and EPS growth are annualized. The earnings-price ratio plotted for t is earnings over year $t-1$ relative to the market cap at the end of year $t-1$, so this earnings price ratio is known as of Q1 of year t when we measure expectations. Similarly, the inverse CAPE plotted for t is the December $t-1$ value.

Table 3 examines the relation between the cyclically adjusted earnings-price ratio (inverse-CAPE) and subjective expected returns from VL and the eight other surveys. Specifically, we estimate regressions of the form:

$$1/CAPE_t = \alpha + \beta \mathrm{F}^k r_{t \to t+j_k} + u_t,$$

where $1/CAPE_t$ is the inverse-CAPE ratio as of December of $t-1$, and $\mathrm{F}^k r_{t \to t+j_k}$ is the expected return formed in Q1 of year t. The results are not sensitive to the exact timing.

Table 3: *Subjective Expected Returns and Inverse of CAPE*

	$\frac{1}{\text{CAPE}_t}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{F}^{\text{VL}}\text{r}_{t\to t+4}$	0.278								
	(5.28)								
$\text{F}^{\text{IBES}}\text{r}_{t\to t+1}$		0.023							
		(0.68)							
$\text{F}^{\text{Sh-inst}}\text{r}_{t\to t+1}$			0.061						
			(1.45)						
$\text{F}^{\text{Liv}}\text{r}_{t\to t+1}$				-0.002					
				(-0.01)					
$\text{F}^{\text{Sh-indiv}}\text{r}_{t\to t+1}$					-0.078				
					(-0.92)				
$\text{F}^{\text{SPF}}\text{r}_{t\to t+10}$						0.145			
						(1.02)			
$\text{F}^{\text{GH}}\text{r}_{t\to t+10}$							-0.363		
							(-2.57)		
$\text{F}^{\text{NX}}\text{r}_{t\to t+1}$								-0.012	
								(-0.05)	
$\text{F}^{\text{GH}}\text{r}_{t\to t+1}$									-0.154
									(-1.26)
R^2	0.649	0.027	0.054	0.000	0.057	0.044	0.177	0.000	0.089
N	69	22	36	73	27	34	23	36	23

Notes: This table reports results from annual time series regressions of the inverse CAPE ratio on expected returns. The inverse CAPE ratio is as of December of year $t-1$. Subjective expectations are as of Q1 of year t. Table B.2 shows robustness to using the unadjusted earnings-price ratio as the dependent variable, and Tables B.3 and B.4 present the same regressions using expected *excess* returns as the regressor. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

We report Newey-West standard errors with a bandwidth of $S = 1.3\sqrt{T}$, following the recommendation in Lazarus et al. (2018). Appendix Table B.2 presents the same regression with the simple earnings-price ratio as the dependent variable.

Column (1) in Table 3 confirms the strong positive relation between VL's expected return and the cyclically adjusted earnings-price ratio. The t-statistic exceeds 5.2, and the R^2 is 65%. The remaining columns in Table B.2 reveal that none of the other eight expected return series is significantly positively correlated with the inverse-CAPE ratio. Measures of expected returns from other finance professionals and professional forecasters are weakly correlated with the inverse-CAPE, with some exhibiting a positive sign and others a negative sign. The weak correlation for Livingston is consistent with De La O and Myers (2021) and Nagel and Xu (2023).

Table 3 further shows that measures of expected returns of individuals tend to be negatively correlated with the inverse-CAPE, in line with evidence from Greenwood and Shleifer (2014) and Adam et al. (2017). The correlation is usually insignificant, except in the case of GH. This evidence lines up with the model of Section 2. When extrapolators are bullish, valuations are high, but market clearing imposes that sophisticated traders are bearish. Treating VL as sophisticated and individuals as extrapolative, this generates a positive correlation between valuation and individual expectations, and a negative one with VL expectations.

Appendix Table B.2 shows that these results are robust to using the simple earnings-price ratio as the dependent variable, where the earnings-price ratio measures earnings over year $t-1$ relative to the market cap at the end of year $t-1$. See Appendix Figure B.2 for a scatterplot of these correlations. Moreover, Appendix Tables B.3 and B.4 show that the patterns are robust to using the expected excess return, calculated as the nominal expected return net of the one-year Treasury yield. In both exercises, only VL expected excess returns are significantly positively correlated with the earnings-price ratio. The fit when using the inverse-CAPE is slightly better than when using the basic E/P_t ratio.

In contrast to VL expected returns, VL expected earnings growth is weakly correlated with valuation ratios. Figure 2 illustrates the weak correlation in the time series. Table 4 regresses the inverse-CAPE ratio ($1/CAPE_t$) on VL expected return and VL expected earnings growth. In a simple regression, expected cash flow growth is positively correlated with the cyclically adjusted earnings-price ratio (column (2)). When including both variables in the regression (column (3)), the expected return is positively associated with the earnings-price ratio, while expected earnings growth is essentially uncorrelated with the earnings-price ratio. Thus, the correlation with valuation is much stronger for VL expected returns than VL expected earnings growth.[12] In columns (4)-(6), we confirm that the relation between $1/CAPE_t$ and VL expected returns is robust to controlling for inflation and the 10-year bond yield. Inflation is here to test robustness to the high inflation period of the 1970s. The 10-year yield allows us to check that the relationship between earnings yield and expected returns is primarily driven by movements in the risk premium component of VL's expectations.

[12]Table B.5 shows the results are similar when using the unadjusted earnings-price ratio as the outcome variable.

Table 4: *Inverse of CAPE and Value Line Expected Returns and Earnings Growth*

	$\frac{1}{\text{CAPE}_t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{F}^{\text{VL}}\text{r}_{t\to t+4}$	0.278		0.254	0.208	0.181	0.178
	(5.28)		(5.25)	(3.44)	(3.27)	(3.29)
$\text{F}^{\text{VL}}\text{g}_{t\to t+4}$		0.494	0.142	0.166	-0.018	-0.015
		(2.97)	(0.99)	(1.18)	(-0.17)	(-0.15)
Inflation				0.146		0.011
				(1.44)		(0.13)
10-year bond yield					0.391	0.388
					(4.50)	(3.86)
R^2	0.649	0.252	0.665	0.674	0.735	0.735
N	69	69	69	69	69	69

Notes: This table reports results from regressions of the inverse of the current CAPE ratio on VL expected returns and expected EPS growth. The inverse-CAPE ratio is as of December of year $t-1$. Expectation variables are as of Q1 of year t. Inflation and the 10-year bond yield are as of December of year $t-1$. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

5.2 Campbell-Shiller Decomposition

Next, we show that, through the lens of VL's expectations, movements in expected returns account for most of the time variation in valuation ratios. To do this, we assume a constant payout ratio and perform the standard Campbell-Shiller decomposition up to $t+4$:

$$p_t - \log \text{F}^{\text{VL}} E_t \approx \tilde{k} + \underbrace{\sum_{j=1}^{4} \alpha^{j-1} \ln(1 + \text{F}^{\text{VL}} g_{t\to t+4})}_{\text{CF}_t} \underbrace{- \sum_{j=1}^{4} \alpha^{j-1} \ln(1 + \text{F}^{\text{VL}} r_{t\to t+4})}_{\text{ER}_t} + \underbrace{\alpha^4 \ln\left(\frac{\text{F}^{\text{VL}} P_{t+4}}{\text{F}^{\text{VL}} E_{t+4}}\right)}_{\text{LT}_t}. \tag{6}$$

where $\tilde{k}$ and α are constants, and p_t is the log price. We ignore Jensen terms and equate forecasts of logs with logs of forecasts. As it will turn out, our decomposition will be nearly exact. Equation (6) captures the well-known intuition that the price-earnings ratio can be high either because expected future cash flows are high (CF_t), expected future returns are low (ER_t), or expected future valuation ratios are high (LT_t).

From VL, we observe all objects in the valuation decomposition in (6): Expected

earnings growth, expected returns, the expected future price-earnings ratio, and the current price-earnings ratio. Panel A in Table 5 presents the results from a decomposition of the form:

$$1 = \underbrace{\frac{\text{cov}\left(\ln(P_t/E_t), \text{CF}_t\right))}{\text{var}\left(\ln(P_t/E_t)\right)}}_{\text{CF}} + \underbrace{\frac{\text{cov}\left(\ln(P_t/E_t), \text{ER}_t\right))}{\text{var}\left(\ln(P_t/E_t)\right)}}_{\text{ER}} + \underbrace{\frac{\text{cov}\left(\ln(P_t/E_t), \text{LT}_t\right))}{\text{var}\left(\ln(P_t/E_t)\right)}}_{\text{LT}}$$

Through the lens of VL's expectations, return expectations over the next four years account for 59% of the variation in realized price-to-earnings ratio. Cash flow expectations over the next four years only explain 3%. The remaining 38% is explained by the expected future price-earnings multiple.[13] The important role of the long-term multiple indicates that beliefs about returns or cash flow growth after the three-to-five year horizon forecasted by VL are important for understanding equity fluctuations. Thus, for expected cash flow growth to play an important role in VL's understanding of price-earnings fluctuations, this must be driven by expected cash flow growth further in the future than the four-year horizon. The log-linear approximation holds well, as the three items sum to almost exactly 100%.

Overall, VL beliefs are more consistent with traditional econometric-based price-earnings decompositions (e.g., Cochrane, 2011) than cash flow expectations from IBES, which have been shown to explain a large share of price fluctuations (De La O and Myers, 2021; Bordalo et al., 2024).

Before proceeding, we note that this decomposition should not be interpreted causally. The fact that VL expected returns account for most of the variation in the stock market does not necessarily imply that fluctuations in expected returns or discount rates *cause* fluctuations in the stock market. The Campbell-Shiller decomposition holds for both rational and non-rational beliefs, as long as these beliefs satisfy return identities. Our findings could, for instance, be consistent with a model where naive investors perceive high valuations to be mostly driven by high future cash flow growth, while sophisticated investors view valuations as being mostly driven by low future returns (as prices will eventually revert to realized dividend growth).

[13]The results from the Campbell-Shiller decomposition are robust to various approaches to aggregation. In the baseline, we compute market-cap weighted expected returns, expected EPS growth, current forward PE multiple, and expected long-term PE multiple from firm-level VL expectations. As an alternative approach, we can directly aggregate each variable and compute expected returns based on the aggregate series. Appendix Table B.13 shows that the results are similar using this alternative aggregation.

Table 5: *Campbell-Shiller Decomposition Based on Value Line's Expectations*

Panel A: Price-Earnings Decomposition

	CF	ER	LT
	(1)	(2)	(3)
$\ln(P/E_t)$	0.031	0.593	0.383
	(0.48)	(4.50)	(4.30)

Panel B: Expected Return Decomposition

	Cash Flow Expectations	Repricing
	(1)	(2)
Return Expectations	0.128	0.873
	(2.11)	(12.59)

Notes: This table reports variance decompositions of the price-earnings ratio and the subjective expected return based on Value Line's expectations. Panel A reports results from regressions of each term on the right-hand side of the Campbell-Shiller decomposition in (6) on the current log price-earnings ratio from the left-hand side of (6). Panel B reports results from regressing each of the two terms on the right-hand side of the return decomposition in (7) on the log expected return from the left-hand side of (7). t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

5.3 Decomposing the Subjective Expected Return and the Role of Repricing

Given the important role of expected future returns in accounting for the log price-earnings ratio when using expectations from VL, a related question is what explains the variation in expected returns. Rearranging (6) allows us to decompose the variation in expected returns into expected cash flow growth and expected "repricing" (Dahlquist and Ibert, 2024):

$$\underbrace{\ln(1+\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4})}_{\text{Expected return}} \approx \underbrace{\frac{1-\alpha}{1-\alpha^4}\sum_{j=1}^{4}\alpha^{j-1}\ln(1+\mathrm{F}^{\mathrm{VL}}\mathrm{g}_{t\to t+4})}_{\text{Expected CF growth}} + \underbrace{\frac{1-\alpha}{1-\alpha^4}\left(\alpha^4\ln\left(\frac{\mathrm{F}^{\mathrm{VL}}P_{t+4}}{\mathrm{F}^{\mathrm{VL}}E_{t+4}}\right)-\ln\left(\frac{P_t}{\mathrm{F}^{\mathrm{VL}}E_t}\right)\right)}_{\text{Expected repricing}}. \tag{7}$$

This equation summarizes the intuition that expected subjective returns can be high for two reasons. First, expected returns are high when expected cash-flow growth over the next 4 years is high. Second, expected returns are high when there is an expected

repricing between t and $t+4$, whereby the expected future multiple is higher than the current multiple.

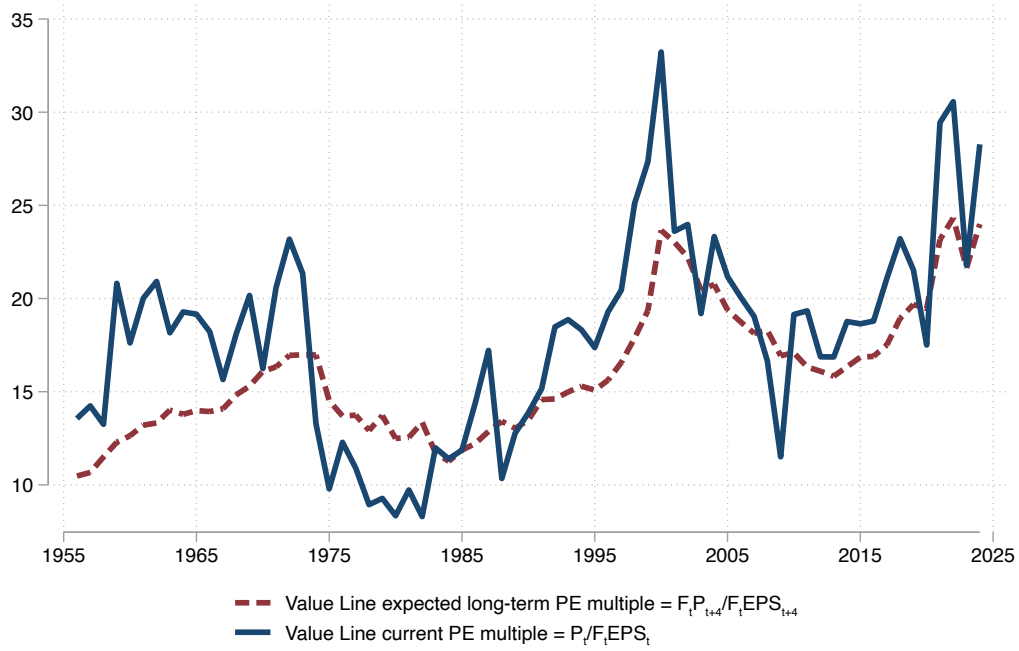
Panel B in Table 5 reports the results from a variance decomposition of VL's expected return using equation (7). The expected repricing term explains 87% of the variation in the expected return. Thus, most of the fluctuations in VL's expected return come from the repricing term. Higher expected cash flow growth is also associated with higher expected returns, as expected, but it accounts for only 13% of the variation in the expected return.

To better understand the repricing term, Figure 3 plots the current price-earnings multiple, $P_t/F^{VL}E_t$, and the expected future PE multiple, $F^{VL}P_{t+4}/F^{VL}E_{t+4}$. The expected long-term PE multiple is less volatile than the current forward PE multiple. This implies that, when current valuations are high relative to earnings, VL expects future valuation ratios to fall. In the tradition of value investing, VL analysis effectively incorporates mean-reversion in valuation ratios. The importance of the repricing term contrasts with evidence from Ben-David and Chinco (2024) for sell-side equity analysts, who often set price targets based on trailing price-earnings multiples. At the same time, Figure 3 shows there is considerable time-series variation and a secular upward trend in the expected long-term multiple. This explains why this component accounts for a significant share of the variation in the current price-earnings ratio in the Campbell-Shiller decomposition.

The relative stability of the expected long-term PE multiple relative to the current forward PE multiple is intimately tied to the valuation methodology employed by VL going back to the 1950s. Indeed, it is in the name. "Value Line" was a valuation ratio line that Value Line analysts would superimpose onto price charts. This line captured some moving average of a stock's valuation ratio. Thus, when valuation ratios were high, the multiple applied to future price targets tended to be lower than current valuation ratios.[14] As a concrete example, in their 1956 valuation analysis of General Motors displayed in Figure B3, VL write "In the hypothesized 1959-61 economic environment, characterized by automobile output averaging 7.8 million units annually... earnings then could average \$4.25 a share and dividends \$2.75. Such dividends, capitalized at 6% *as suggested by past norms adjusted to trend*, would command an average price of 46" (emphasis added). This average price was only slightly above the current price of 44, as the "value line" indicated that the current price was high relative to "past norms" for the valuation ratio. Consistent with this, Table B.15 shows that the expected long-term PE multiple is well-predicted by a distributed lag of past price-earnings multiples. For example, predicting the expected long-term PE multiple with six annual lags of the PE multiple yields an R^2 of over 80%.

[14]Interestingly, Bastianello et al. (2025) find that valuations based on multiples tend to better predict future stock returns.

Figure 3: *VL Current and Expected Long-Term Price-Earnings Multiples*



Notes: This figure plots VL's current price-earnings multiple, $P_t/F^{VL}E_t$, and VL's expected long-term price-earnings multiple, $F^{VL}P_{t+4}/F^{VL}E_{t+4}$.

6 Determinants of Expected Returns

6.1 Past Returns and Past Cash Flow Growth

Our baseline model in Section 2 assumes that naive investors extrapolate past returns. This is consistent with a long-standing tradition in behavioral finance (see Barberis (2018) for a review), but recent literature tends to highlight the overreacting behavior of cash-flow expectations (De La O and Myers, 2021; Bordalo et al., 2024). These two options have different predictions. Cash-flow extrapolation by naive investors would make VL expected returns negatively correlated with past dividend growth, even controlling for past returns. The opposite would hold if naive investors extrapolate from past returns. In that case, VL expected returns should not depend on past dividend growth.

To analyze these predictions, we estimate regressions of the following form

$$F^k r_{t \to t+k} = \alpha + \beta x_{t-1} + u_t$$

where $F^k r_{t \to t+k}$ are measures of expectations of returns from VL and the other surveys,

and x_{t-1} are potential drivers of expected returns. Given our discussion on the sources of extrapolation, we pay particular attention to past dividend growth and past returns. We also look at measures of risk. Estimates are reported in Table 6.

Table 6: *Determinants of Expected Returns: Past Returns, Earnings Growth, and Volatility*

Panel A: Expected Returns on Past Returns

	$F^{VL} r_{t\to t+4}$ (1)	$F^{IBES} r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst} r_{t\to t+1}$ (3)	$F^{Liv} r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv} r_{t\to t+1}$ (5)	$F^{SPF} r_{t\to t+10}$ (6)	$F^{GH} r_{t\to t+10}$ (7)	$F^{NX} r_{t\to t+1}$ (8)	$F^{GH} r_{t\to t+1}$ (9)
$r_{t-2\to t-1}$	-0.087	-0.148	-0.103	-0.023	0.000	0.012	0.000	0.064	0.042
	(-3.27)	(-4.77)	(-2.70)	(-1.12)	(0.02)	(1.05)	(0.04)	(6.08)	(3.77)
R^2	0.039	0.215	0.215	0.007	0.000	0.025	0.000	0.296	0.243
N	69	22	36	73	27	34	23	36	23

Panel B: Expected Returns on Past EPS Growth

	$F^{VL} r_{t\to t+4}$ (1)	$F^{IBES} r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst} r_{t\to t+1}$ (3)	$F^{Liv} r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv} r_{t\to t+1}$ (5)	$F^{SPF} r_{t\to t+10}$ (6)	$F^{GH} r_{t\to t+10}$ (7)	$F^{NX} r_{t\to t+1}$ (8)	$F^{GH} r_{t\to t+1}$ (9)
$g_{t-2\to t-1}$	-0.007	0.014	-0.003	-0.017	-0.004	-0.003	-0.003	0.002	-0.003
	(-0.33)	(0.28)	(-0.20)	(-0.93)	(-0.24)	(-0.58)	(-0.80)	(0.28)	(-0.23)
$r_{t-2\to t-1}$	-0.086	-0.155	-0.102	-0.022	0.002	0.013	0.002	0.063	0.044
	(-3.12)	(-4.73)	(-2.44)	(-1.01)	(0.10)	(1.05)	(0.25)	(5.60)	(4.45)
R^2	0.039	0.219	0.215	0.012	0.001	0.030	0.009	0.297	0.247
N	69	22	36	73	27	34	23	36	23

Panel C: Expected Returns on Standard Deviation of Past Daily Returns

	$F^{VL} r_{t\to t+4}$ (1)	$F^{IBES} r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst} r_{t\to t+1}$ (3)	$F^{Liv} r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv} r_{t\to t+1}$ (5)	$F^{SPF} r_{t\to t+10}$ (6)	$F^{GH} r_{t\to t+10}$ (7)	$F^{NX} r_{t\to t+1}$ (8)	$F^{GH} r_{t\to t+1}$ (9)
SD_{t-1}	3.002	3.722	1.879	0.844	0.028	-0.228	0.090	-0.944	-1.110
	(2.36)	(7.68)	(4.63)	(0.71)	(0.05)	(-0.75)	(0.82)	(-1.87)	(-5.86)
R^2	0.056	0.253	0.101	0.011	0.000	0.014	0.005	0.120	0.299
N	69	22	36	73	27	34	23	36	23

Panel D: Expected Returns on Past VIX

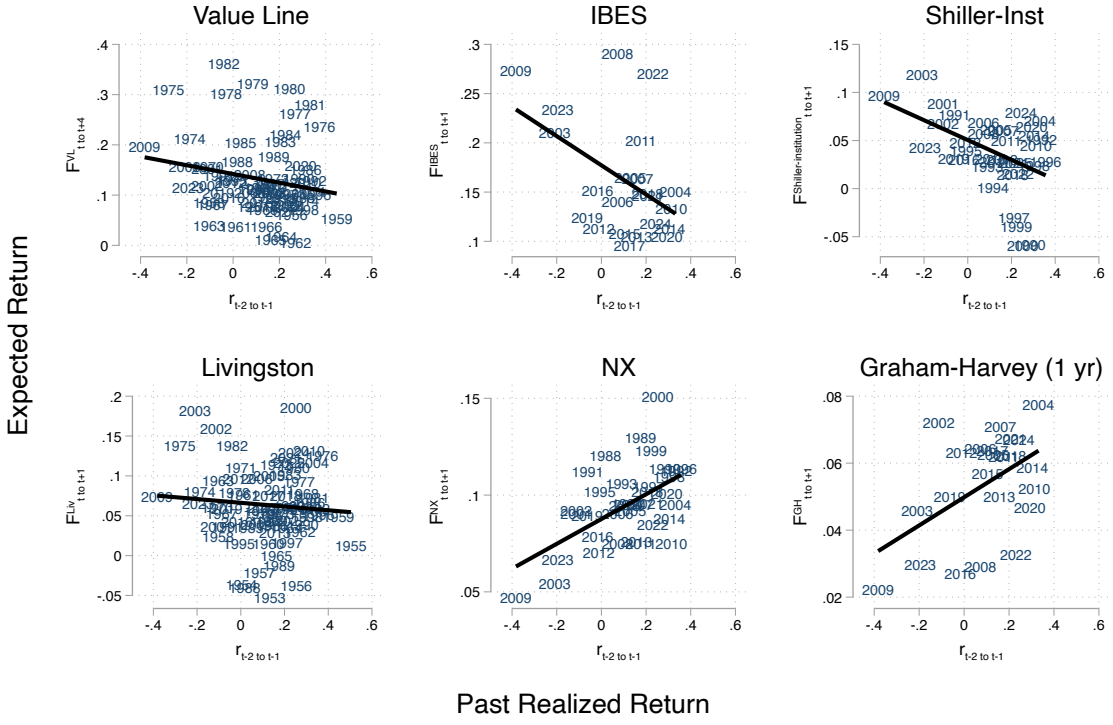
	$F^{VL} r_{t\to t+4}$ (1)	$F^{IBES} r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst} r_{t\to t+1}$ (3)	$F^{Liv} r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv} r_{t\to t+1}$ (5)	$F^{SPF} r_{t\to t+10}$ (6)	$F^{GH} r_{t\to t+10}$ (7)	$F^{NX} r_{t\to t+1}$ (8)	$F^{GH} r_{t\to t+1}$ (9)
VIX_{t-1}	0.181	0.356	0.100	0.066	0.026	-0.012	0.009	-0.099	-0.097
	(2.93)	(8.04)	(2.34)	(1.10)	(0.36)	(-0.48)	(0.82)	(-3.51)	(-7.31)
R^2	0.258	0.291	0.047	0.014	0.006	0.005	0.008	0.157	0.289
N	34	22	35	35	27	34	23	33	23

Notes: This table reports results from regressions of expected returns as of Q1 of year t on: past realized returns from December of year $t-2$ to December of $t-1$ (Panel A), past realized EPS growth from $t-2$ to $t-1$ (Panel B), the standard deviation of daily returns in Q4 of year $t-1$ (Panel C), and the VIX index as of December of year $t-1$. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Motivated by our model, we first look at whether return forecasts correlate with past returns. Specifically, we use the market return from December $t-2$ to December $t-1$, denoted $r_{t-2\to t-1}$, to predict the subjective expected returns reported in Q1 of year t. The

key result is that VL expectations of returns are strongly negatively correlated with past returns (Panel A, column (1)). The top-left panel in Figure 4 visualizes this clear negative correlation in the data. This is consistent with our baseline model. Since naive traders extrapolate, sophisticated traders are mechanically contrarian. Otherwise, the market cannot clear.

Figure 4: *Subjective Expected Returns and Past Realized Returns*



Notes: This figure shows subjective expected returns from various surveys against past realized returns. Subjective expected returns are as of Q1 in year t. Past realized returns are returns on the market from December of year $t-2$ to December of year $t-1$. See Figure B.6 for the same figure with all nine expected return series.

Other financial professionals also have contrarian expectations of returns. In particular, the middle and top-right panels of Figure 4 show the negative relation for expected returns from IBES and Shiller's survey of institutional investors. Columns 2 and 3 in Table 6 Panel A show that the R^2 for IBES and Shiller's institutional investors are above 20%, suggesting that reactions to past returns explain an important share of subjective expected returns for these groups.[15] This pattern of contrarian beliefs does not, however, hold for beliefs of professional forecasters. Expected returns from Livingston and SPF are

[15]When we restrict to the same shorter sample, R^2 for VL expected returns is also above 20%.

essentially uncorrelated with past returns. The bottom-left panel in Figure 4 visualizes this result for Livingston survey expected returns.

Like the naive traders in our model, Table 6 shows that individuals display extrapolation from past returns. For example, expected returns from Nagel-Xu and Graham-Harvey are significantly positively related to past returns, as shown in the bottom middle and right panels of Figure 4. Moreover, R^2 is over 20% for both regressions.

In Panel B, we test whether expectations of returns are driven by past returns or whether they extrapolate past cash flows. We calculate earnings per share growth from year $t-2$ to year $t-1$. We find that past earnings growth has no additional predictive power for expected returns across the nine expected return measures. When we use lower frequency variation in earnings in Table B.6, we again find that extrapolation is stronger on past returns, though there is some extrapolation on past earnings for the Nagel-Xu series.

Overall, the evidence in Table 6, Panels A and B supports two key predictions of the model. First, finance professionals such as VL analysts, who are arguably relatively sophisticated, are contrarian, expecting mean reversion in returns. On the other hand, individuals are extrapolative. Second, expected returns appear to be more strongly related to past returns than to past cash-flow news, consistent with learning from prices (Bastianello and Fontanier, 2025), at least for a subset of investors.

6.2 Expectations of Returns and Risk

In Table 6 Panels C and D, we further test whether return expectations are correlated with measures of risk. Traditional finance theory argues that this relationship should be positive. While this is outside of our model, if VL expectations are close to rational, they should correlate positively with risk. We thus regress return expectations in Q1 of year t on: (1) the standard deviation of daily returns in the last quarter of year $t-1$ (panel C), and (2) the implied volatility based on the VIX (Panel D). Implied volatility can be seen as a proxy of the expected risk premium (Martin, 2017); it contains both the price and the quantity of risk.

We again see a clear separation between finance professionals, professional forecasters, and individuals. Higher volatility is positively associated with higher subjective expected returns from VL, as in rational models. IBES and Shiller institutional investors display a similar pattern. Expected returns from professional forecasters do not significantly react to past realized or implied volatility. At the other end, individual investor expectations are negatively related to past volatility. Across the Graham-Harvey and Nagel-Xu series,

higher recent volatility is associated with lower expected returns. This evidence is consistent with Giglio et al. (2021), who document, in a panel of individual investors, a negative relationship between expected returns and the subjective probability of stock market crash, inconsistent with disaster risk theories of the equity premium. The evidence points to the near rationality of VL expectations of returns.

6.3 Value Line Expectation Errors

As a further exploration of the rationality of VL expectations, we study whether VL forecast errors are predictable based on variables in the information set of VL that have been shown to predict forecast errors.

We start with expectations of returns. Table B.7 studies the predictive power of CAPE. The inverse-CAPE predicts both higher VL expected returns (column 1) and higher realized returns (column 2). However, VL expected returns are too sensitive to valuation ratios, as suggested by Figure 1. That is, VL expected returns fluctuate too much in response to valuation ratios. This is in sharp contrast to other survey-based measures of expected returns (Nagel and Xu, 2023). As a result, the inverse-CAPE negatively forecasts VL return expectation errors. This result, however, is driven entirely by the first half of the sample, as illustrated by the large fluctuations in the VL expected return in the 1960s and 1970s period (Figure 1). Return forecast errors are not as predictable with the CAPE in the second half of the sample. In an additional exercise, we also find that past returns do not systematically predict return forecast errors (Table B.8).

We now move to the expected long-term multiple. Table B.9 tests the predictability of forecast errors for expectations of the long-term multiple. When the current price-earnings multiple is higher, VL expects the price-earnings multiple to remain high in the future (column 1), indicating they believe in slow mean-reversion in the price-earnings multiple. These beliefs are consistent with the actual behavior of the PE multiple (column 2). Thus, the current multiple does not predict forecast errors about the future multiple (column 3).

Finally, we analyze EPS growth forecasts. Table B.10 examines the predictability of VL earnings growth forecast errors. Past earnings growth from $t-2$ to $t-1$ predicts slightly lower expected earnings growth, as seen in Panel A, column 1. Using realized earnings growth over the same period as the dependent variable, we obtain a similar negative estimate (column 2). Thus, earnings growth over the past year does not predict VL forecast errors for earnings growth (column 3). Panel B Table B.10 repeats the same exercise using lower frequency shocks to earnings. We use the log of earnings relative to cyclically adjusted earnings in $t-5$ as in Bordalo et al. (2024). This measure captures

times when current earnings are high compared to a long-term moving average. For this measure, Panel B shows that there is some evidence of overreaction. Low-frequency earnings shocks negatively predict future growth, but are not taken into account by VL, leading to significantly negative forecast errors.

Overall, this evidence suggests that VL expectations are close to, albeit not fully, rational.

7 Subjective Expected Returns and Realized Returns

If VL expectations of returns are close to rational, we would expect them to predict future realized returns, to the extent returns are predictable. The long time series of our data makes such a test possible. We next regress future realized equity returns on expected returns from various surveys:

$$r_{t\to t+h} = \alpha_h + \beta_h \mathrm{F}^S \mathrm{r}_{t\to k} + u_{t\to t+h}, \quad h = 1, ..., H. \tag{8}$$

The predictor, $\mathrm{F}^S \mathrm{r}_{t\to k}$, is an annualized expected return from survey S. This expected return is as of Q1 of year t. The left-hand-side variable, $r_{t\to t+h}$, is the cumulative value-weighted realized CRSP market return. The return is computed from April of year t to April of year $t+h$. We consider April-to-April returns, as expectations are formed in the first quarter of year t. In our baseline analysis, we use annual data to maximize the sample length. Below, we also report results using quarterly data over a shorter time sample.

7.1 Nominal Returns

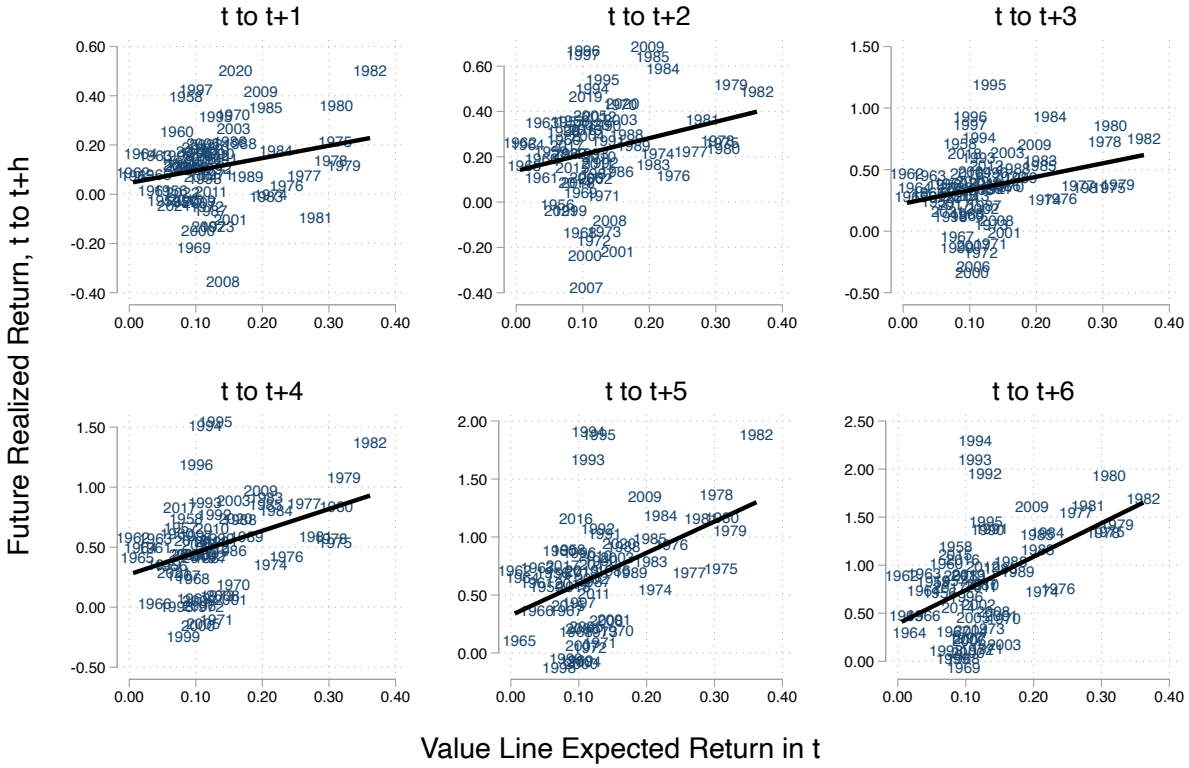
We begin by considering nominal market returns as the dependent variable. The advantage of focusing on nominal returns is that this is the variable directly forecasted in the surveys. This approach also sidesteps the need to make assumptions about how to compute excess returns across different horizons.

Figure 5 plots the nominal cumulative realized market returns from year t to $t+h$ against VL's expected return reported in Q1 of year t. Panel A in Table 7 reports the corresponding regression estimates. To address potential Stambaugh bias (Stambaugh, 1999), in addition to the basic OLS estimates, we also report bias-adjusted estimates using two approaches. The first is a bootstrap approach following Nagel and Xu (2023). The second employs the analytical correction suggested by Boudoukh et al. (2022). We also

report bootstrapped p-values using a stationary block bootstrap. Details are provided in Appendix C.

Based on data covering nearly the full post-WWII sample, Figure 5 shows that there is an unmistakably strong positive relation between VL's expected return and future realized nominal stock returns. The fit is especially good at longer horizons. The R^2 is 14% at the four-year horizon, 19% at the five-year horizon, and 24% at the six-year horizon. In years that were followed by high returns, such as the early 1980s or 2009, VL analysts correctly anticipated high future returns. While the bias-adjusted coefficients in panel A of Table 7 are usually slightly lower than the baseline OLS estimates, the predictive relation for nominal returns is quantitatively similar and statistically significant at all horizons based on bootstrapped p-values.

Figure 5: *Value Line Expected Equity Returns and Future Realized Nominal Returns*



Notes: This figure plots Value Line's expected return against future realized nominal market returns. Value Line expected returns are annualized nominal returns as of Q1 of year t. The realized return is the CRSP value-weighted total return from April of year t to April of year $t+h$. All returns are in decimal form (%/100). The marker labels refer to year t. The sample period covers 1956 to 2024.

Table 8 presents estimates of specification (8) for the eight other survey-based expected return series. The surveys capture the expectations of other financial professionals, professional forecasters, and individuals. Figure 6 presents visualizations of these regressions

Table 7: *Predicting Future Returns with Value Line Expected Returns*

Panel A: Nominal Returns

	$r_{t\to t+1}$ (1)	$r_{t\to t+2}$ (2)	$r_{t\to t+3}$ (3)	$r_{t\to t+4}$ (4)	$r_{t\to t+5}$ (5)	$r_{t\to t+6}$ (6)
$F^{VL}r_{t\to t+4}$	0.505	0.722	1.092	1.813	2.695	3.483
{Bias-adj Coef$_1$}	{0.242}	{0.510}	{1.007}	{1.695}	{2.572}	{3.695}
{Bias-adj Coef$_2$}	{0.346}	{0.416}	{0.648}	{1.240}	{1.998}	{2.669}
(p-value)	(0.047)	(0.032)	(0.023)	(0.013)	(0.006)	(0.002)
R^2	0.057	0.063	0.083	0.139	0.194	0.243
N	69	68	67	66	65	64

Panel B: Excess Returns

	$xr_{t\to t+1}$ (1)	$xr_{t\to t+2}$ (2)	$xr_{t\to t+3}$ (3)	$xr_{t\to t+4}$ (4)	$xr_{t\to t+5}$ (5)	$xr_{t\to t+6}$ (6)
$F^{VL}xr_{t\to t+4}$	0.462	0.489	0.672	1.263	1.946	2.366
{Bias-adj Coef$_1$}	{0.156}	{0.221}	{0.476}	{0.929}	{1.516}	{2.291}
{Bias-adj Coef$_2$}	{0.287}	{0.160}	{0.200}	{0.670}	{1.242}	{1.552}
(p-value)	(0.223)	(0.414)	(0.330)	(0.154)	(0.091)	(0.043)
R^2	0.031	0.018	0.020	0.045	0.072	0.082
N	69	68	67	66	65	64

Notes: This table reports results from estimating equation (8). Panel A uses future cumulative realized nominal returns on the left-hand side and expected annualized nominal returns from Value Line as of Q1 of year t on the right-hand side. The realized nominal return is the total return on the market from April of year t to April of year $t+h$. Panel B uses future cumulative realized excess returns on the left-hand side and expected excess returns from VL on the right-hand side. The realized excess return is the return on the market from April of year t to April of year $t+h$ minus the h-year yield to maturity from December of year $t-1$. We address Stambaugh (1999) bias using two complementary corrections: a bootstrap approach following Nagel and Xu (2023) (method 1) and an alternative correction following Boudoukh et al. (2022) (method 2). We also compute bootstrapped p-values from a stationary block bootstrap. Details on these corrections are provided in Appendix C. In each panel, OLS coefficients are reported on the first row, bootstrap bias-adjusted coefficients are reported in braces, and bootstrapped p-values are reported in parentheses.

at the five-year horizon ($h = 5$).

None of the eight other expected return series positively and significantly predicts realized returns. For instance, despite also representing expected returns from finance professionals, expected returns from IBES and Shiller institutional investors do not reliably predict realized returns.[16] The estimated coefficients are small and not statistically significant. Expectations from professional forecasters and households also fail to predict realized future returns. In some cases (Shiller individual and Graham-Harvey), these

[16]When using monthly data for IBES, we do find that these sell-side analyst expectations significantly predict both nominal and excess returns, in line with the findings of Bastianello (2025). However, once we time-aggregate to annual data, this result becomes much weaker and is usually insignificant.

Table 8: *Predicting Future Returns with Subjective Expected Returns from Other Surveys: Nominal Returns*

	$r_{t\to t+1}$ (1)	$r_{t\to t+2}$ (2)	$r_{t\to t+3}$ (3)	$r_{t\to t+4}$ (4)	$r_{t\to t+5}$ (5)	$r_{t\to t+6}$ (6)
$F^{IBES}r_{t\to t+1}$	-0.611	0.061	0.472	-0.074	0.262	0.166
{Bias-adj Coef}	{-0.611}	{0.067}	{0.226}	{-0.409}	{-0.395}	{0.589}
(p-value)	(0.147)	(0.816)	(0.239)	(0.875)	(0.837)	(0.931)
R^2	0.044	0.000	0.013	0.000	0.002	0.001
N	22	21	20	19	18	17
$F^{Sh\text{-}inst}r_{t\to t+1}$	0.272	0.269	0.523	1.227	1.365	-0.134
{Bias-adj Coef}	{0.338}	{0.300}	{0.712}	{1.307}	{1.330}	{-0.100}
(p-value)	(0.698)	(0.807)	(0.793)	(0.594)	(0.616)	(0.970)
R^2	0.004	0.002	0.004	0.013	0.011	0.000
N	35	34	33	32	31	30
$F^{Liv}r_{t\to t+1}$	-0.386	-1.389	-1.752	-1.378	-1.498	-2.239
{Bias-adj Coef}	{-0.532}	{-1.401}	{-1.650}	{-1.411}	{-1.854}	{-2.515}
(p-value)	(0.382)	(0.026)	(0.061)	(0.196)	(0.331)	(0.239)
R^2	0.013	0.084	0.077	0.031	0.023	0.038
N	72	71	70	69	68	67
$F^{Sh\text{-}indiv}r_{t\to t+1}$	-0.988	-3.672	-4.182	-5.276	-8.054	-10.222
{Bias-adj Coef}	{-1.770}	{-3.635}	{-4.477}	{-5.615}	{-8.303}	{-10.428}
(p-value)	(0.457)	(0.017)	(0.034)	(0.023)	(0.002)	(0.002)
R^2	0.023	0.176	0.167	0.171	0.290	0.481
N	26	25	24	23	22	21
$F^{SPF}r_{t\to t+10}$	1.164	2.803	5.360	8.225	6.180	9.316
{Bias-adj Coef}	{1.182}	{3.515}	{6.747}	{8.948}	{7.236}	{7.144}
(p-value)	(0.435)	(0.498)	(0.379)	(0.455)	(0.687)	(0.648)
R^2	0.008	0.022	0.047	0.067	0.024	0.041
N	33	32	31	30	29	28
$F^{GH}r_{t\to t+10}$	-1.334	-3.294	-4.481	-6.316	-14.529	-22.296
{Bias-adj Coef}	{0.294}	{-1.614}	{-4.134}	{-6.848}	{-15.240}	{-28.042}
(p-value)	(0.662)	(0.175)	(0.050)	(0.235)	(0.185)	(0.090)
R^2	0.005	0.018	0.026	0.032	0.096	0.193
N	23	22	21	20	19	18
$F^{NX}r_{t\to t+1}$	-1.184	-2.689	-3.159	-3.461	-4.739	-1.417
{Bias-adj Coef}	{-1.024}	{-2.066}	{-2.201}	{-2.417}	{-1.816}	{1.240}
(p-value)	(0.293)	(0.217)	(0.438)	(0.515)	(0.486)	(0.863)
R^2	0.022	0.052	0.039	0.028	0.036	0.003
N	36	36	35	34	33	32
$F^{GH}r_{t\to t+1}$	-2.397	-5.779	-5.266	-6.282	-15.890	-12.629
{Bias-adj Coef}	{-1.734}	{-5.392}	{-5.165}	{-6.418}	{-17.013}	{-13.325}
(p-value)	(0.208)	(0.028)	(0.005)	(0.114)	(0.004)	(0.025)
R^2	0.047	0.176	0.117	0.106	0.447	0.280
N	23	22	21	20	19	18

Notes: This table reports results from estimating (8) with future cumulative realized nominal returns on the left-hand-side and expected nominal returns from various surveys on the right-hand-side. The realized nominal return is the total return on the market from April of year t to April of year $t+h$. Expectations are based on surveys from Q1 of year t. We address Stambaugh (1999) bias following the bootstrap approach in Nagel and Xu (2023). For each independent variable, OLS coefficients are reported; bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p-values are reported in parentheses.

expected returns are even negatively correlated with future returns. In sum, among all nine expected return series, the VL expected return is the only series that robustly and positively predicts future returns.

Table 9: *Predicting Returns with Value Line Expected Returns: Controls and Subsamples*

Panel A: Nominal Returns

	$r_{t\to t+5}$				
	1956-2020			1956-1987	1988-2020
	(1)	(2)	(3)	(4)	(5)
$F^{VL}r_{t\to t+4}$	2.695		0.993	2.535	6.386
{Bias-adj Coef}	{2.572}		{0.645}	{2.005}	{6.020}
(p-value)	(0.006)		(0.260)	(0.115)	(0.033)
$\frac{1}{CAPE_t}$		8.614	6.260		
{Bias-adj Coef}		{6.887}	{5.742}		
(p-value)		(0.006)	(0.103)		
R^2	0.194	0.228	0.237	0.390	0.130
N	65	65	65	32	33

Panel B: Excess Returns

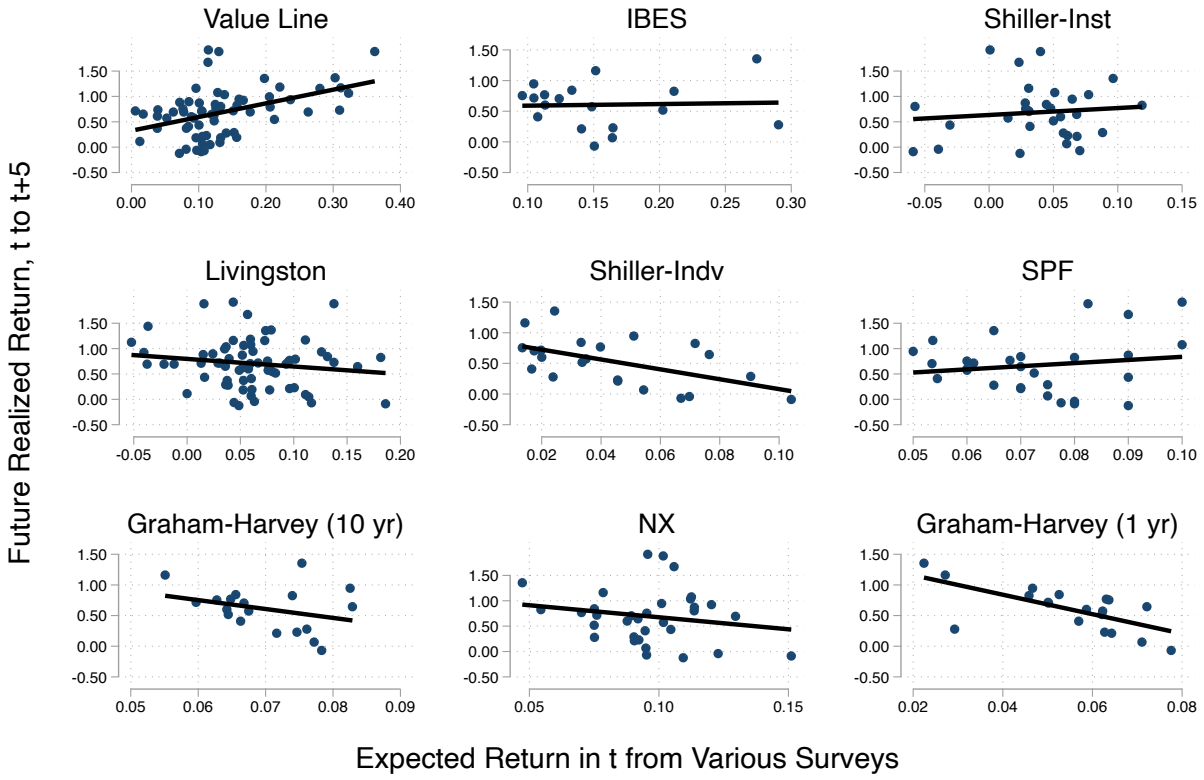
	$xr_{t\to t+5}$				
	1956-2020			1956-1987	1988-2020
	(1)	(2)	(3)	(4)	(5)
$F^{VL}xr_{t\to t+4}$	1.946		1.959	1.375	5.731
{Bias-adj Coef}	{1.516}		{1.946}	{0.747}	{5.377}
(p-value)	(0.091)		(0.194)	(0.388)	(0.097)
$\frac{1}{CAPE_t}$		2.914	-0.048		
{Bias-adj Coef}		0.316	-0.024		
(p-value)		(0.440)	(0.991)		
R^2	0.072	0.029	0.072	0.107	0.135
N	65	65	65	32	33

Notes: This table reports results from regressions of cumulative realized returns over the next five years on expected returns. The dependent variables are the five-year cumulative nominal return (Panel A) and the five-year cumulative excess return (Panel B). The realized return is calculated as the value-weighted average of the CRSP universe of firms. Returns are calculated from April of t to April of $t+5$. VL expected returns are as of Q1 of year t. The CAPE control variable is as of December of $t-1$. We adjust for Stambaugh (1999) bias using the bootstrap approach in Nagel and Xu (2023). Each column reports OLS coefficients, bootstrap bias-adjusted coefficients in braces, and bootstrapped p-values in parentheses.

Table 9 further explores the predictability of returns using VL expectations, focusing on the five-year horizon ($h = 5$) and controlling for the inverse-CAPE. Columns (1) and (2) in Panel A compare the predictive performance of $F^{VL}r_{t\to t+4}$ and the inverse-CAPE. Both variables predict nominal returns, but the R^2 is slightly higher with the inverse-CAPE.

When controlling for CAPE (column 3), the predictive power of VL forecasts becomes insignificant. Table 9 columns (4) and (5) examine the predictability of VL expectations across subsamples. Although the coefficient in the first half of the sample is not significant using the bootstrapped p-values ($p = 11.5\%$), the positive coefficient and high R^2 of 39% suggest VL expected returns contain some information about future returns before it was widely accepted that there was some degree of aggregate return predictability (column 4). However, the magnitude and significance of the predictability are substantially higher in the second half of the sample (column 5).

Figure 6: *Subjective Expected Returns across Surveys and Future Realized Returns*



Notes: This figure plots realized cumulative nominal returns from April of year t to April of year $t+5$ against expectations of nominal expected returns from nine surveys. Expected returns are measured as of Q1 of year t. Returns are in decimal form (%/100). Note that the number of observations differs across panels due to differences in sample lengths of the various expected return measures.

7.2 Excess Returns

Panel B in Table 7 reports regressions of future realized excess returns against expected excess returns based on Value Line's expectations. The realized excess return from year t

to $t+h$ is computed as the nominal return from April of year t to April of $t+h$ minus the yield to maturity from the US treasury yield curve over the same horizon from Fama and Bliss (1987) and Liu and Wu (2021). The yield is measured as of December $t-1$, $xr_{t\to t+h} = r_{t\to t+h} - y^h_{Dec,t-1}$. Similarly, when forecasting returns over the next h years, we subtract the yield to maturity of the same horizon from the nominal expected return measures: $\mathrm{F^k}xr_{t\to t+j_k} = \mathrm{F^k}r_{t\to t+j_k} - y^h_{Dec,t-1}$. We use the December $t-1$ yield to ensure that it is known to forecasters at the start of Q1 when they form expectations.

When using excess returns, we again find some evidence that VL expected returns predict future returns (Table 7 Panel B). However, the predictive relation is not as strong as for nominal realized returns. The estimates are statistically significant at the 10% level at the 5-year horizon and at the 5% level at the 6-year horizon based on the bias-adjusted coefficients and bootstrapped p-values. Comparing Panel A and B, the R^2 values are also uniformly lower for excess returns compared to nominal returns. While the estimates always have the correct sign, it is also worth noting that the magnitude of the predictive relation is below one. For example, the estimate in column (1) is 0.46, below the full-information-rational-expectations benchmark of 1.

Panel B in Table 9 examines excess return predictability from Value Line expectations more closely at the five-year horizon. Comparing columns 1 and 2 shows that, in this particular time-series sample (1956-2024), excess returns are not strongly predictable based on the CAPE, and the fit is slightly *better* using VL expected excess returns. In unreported results, we find similar evidence when using the dividend-price ratio, following Cochrane (2011). Thus, it is important to note that the modest predictability of excess returns using VL returns should be understood in the context of a sample where return predictability based on conventional predictors is also weak. Column (5) shows that the excess return predictability based on VL expected returns is stronger and borderline statistically significant in the second half of the sample.

Table B.11 reports the results for excess return predictability based on subjective expected returns from the eight other surveys. As with nominal returns, these expected return series do not reliably predict excess returns.

7.3 Return Predictability with Quarterly Data

Our annual dataset has the advantage of covering a long time series of nearly seven decades. However, because it is annual, it does not capture within-year variation. Table 10 examines whether VL expected returns predict future realized returns in a quarterly time

series from 1987Q3 to 2024Q3. We again estimate regressions of the form

$$r_{t\to t+h} = \alpha + \beta \mathrm{F}_t^{\mathrm{VL}} r + u_{t+h}, \quad h = 4, 8, ..., 24$$

where the left-hand-side variable is the realized return (or excess return) from the end of quarter t until the end of quarter $t+h$. The VL expected return, $\mathrm{F}_t^{\mathrm{VL}} r$, on the right-hand side is the annualized expected return over the next four years as of quarter t.

Table 10: *Predicting Returns with Value Line Expected Returns: Quarterly Data, 1987Q3-2024Q3*

Panel A: Nominal Returns

	$\mathrm{r}_{t\to t+4}$ (1)	$\mathrm{r}_{t\to t+8}$ (2)	$\mathrm{r}_{t\to t+12}$ (3)	$\mathrm{r}_{t\to t+16}$ (4)	$\mathrm{r}_{t\to t+20}$ (5)	$\mathrm{r}_{t\to t+24}$ (6)
$\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+16}$	1.083	2.071	2.826	3.702	6.329	6.576
{Bias-adj Coef$_1$}	{0.857}	{1.754}	{2.560}	{3.570}	{5.785}	{6.196}
{Bias-adj Coef$_2$}	{0.993}	{1.901}	{2.582}	{3.390}	{5.952}	{6.138}
(p-value)	(0.079)	(0.066)	(0.001)	(0.026)	(0.033)	(0.042)
R^2	0.036	0.062	0.069	0.074	0.130	0.112
N	149	145	141	137	133	129

Panel B: Excess Returns

	$\mathrm{xr}_{t\to t+4}$ (1)	$\mathrm{xr}_{t\to t+8}$ (2)	$\mathrm{xr}_{t\to t+12}$ (3)	$\mathrm{xr}_{t\to t+16}$ (4)	$\mathrm{xr}_{t\to t+20}$ (5)	$\mathrm{xr}_{t\to t+24}$ (6)
$\mathrm{F}^{\mathrm{VL}}\mathrm{xr}_{t\to t+16}$	1.208	2.502	3.520	4.574	6.778	6.443
{Bias-adj Coef$_1$}	{1.066}	{2.336}	{3.384}	{4.564}	{6.493}	{6.529}
{Bias-adj Coef$_2$}	{1.107}	{2.311}	{3.251}	{4.233}	{6.372}	{5.972}
(p-value)	(0.122)	(0.169)	(0.147)	(0.102)	(0.067)	(0.151)
R^2	0.055	0.101	0.113	0.118	0.161	0.115
N	149	145	141	137	133	129

Notes: This table reports results from regressions of future realized returns on VL expected returns. The sample is quarterly from 1987Q3-2024Q3. We address Stambaugh (1999) bias using two complementary corrections: a bootstrap approach following Nagel and Xu (2023) (method 1) and an alternative correction following Boudoukh et al. (2022) (method 2). For each independent variable, OLS coefficients are reported; bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p-values are reported in parentheses.

Panel A in Table 10 shows that VL expected returns predict future realized nominal returns in this quarterly dataset. The bias-corrected estimates are statistically significant at the 10% level for the 4- and 8-quarter horizons, and at the 5% level or better from the 12- to 24-quarter horizon. The estimates are larger in magnitude than for the 1956-2024 annual dataset, consistent with higher predictability in the second half of the sample. For example, the estimate is close to one at the four-quarter horizon, growing to over 6 at

the 20-quarter horizon. Panel B considers excess returns. The estimates are similar as for nominal returns. However, the statistical significance is weaker, and only the 20-quarter estimate is statistically significant at conventional levels.

8 Belief Disagreement and Trading Volume

Like most models with heterogeneous beliefs, the model in Section 2 implies that trading volume is increasing with disagreement between naive and sophisticated traders about future returns. To be more accurate, our model directly links volume with the *change* in disagreement. However, level and change in disagreement are positively correlated. Also, many other models with heterogeneous beliefs predict that volume increases with the *level* of disagreement rather than its change (for reviews, see Hong and Stein (2007) and Barberis (2018)). Thus, we test here whether trading volume is correlated with the level and change in disagreement between investors.

We measure disagreement as the difference between VL beliefs and individual beliefs about future returns. We use the following specification:

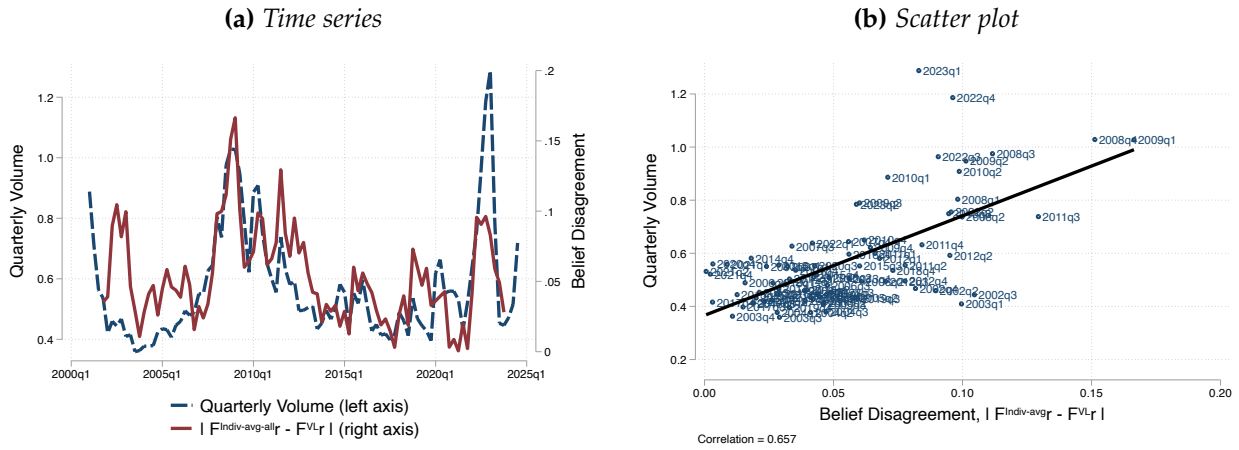
$$Volume_t = \beta_0 + \beta_1 |\mathrm{F}^{\mathrm{Indiv}} r_t - \mathrm{F}^{\mathrm{VL}} r_t| + u_t.$$

Given that this exercise requires expectations from VL and from individual surveys, which tend to be shorter, we use quarterly data to maximize the sample size. $Volume_t$ is aggregate trading volume scaled by aggregate market cap, defined as $Volume_t = \frac{\sum_i \mathrm{vol}_{i,t} \times \mathrm{P}_{i,t-4}}{\sum_i \mathrm{MCAP}_{i,t-4}}$, where $\mathrm{vol}_{i,t}$ is the number of shares traded of firm i in quarter t, $\mathrm{P}_{i,t-4}$ is the price per share four quarters ago, and $\mathrm{MCAP}_{i,t-4}$ is the market cap of firm i four quarters ago. We lag the price by four quarters to mitigate a mechanical correlation coming directly from an increase in prices.

The right-hand-side variable, $|\mathrm{F}^{\mathrm{Indiv}} r_t - \mathrm{F}^{\mathrm{VL}} r_t|$, measures the absolute difference between expected returns from VL and expected returns from individual investors. Below, we also consider the revision in beliefs. In the baseline, we compute the expected return of individual investors as the average of expected returns in the Shiller survey, Graham-Harvey survey, and Nagel-Xu data. This series starts in 2001Q4, as this is the first quarter that the Graham-Harvey measure is available. Further, we consider the unbalanced average of any available series and each of the individual surveys separately. This allows us to extend the right-hand-side variable as far back as 1987Q3 using the Nagel-Xu expected return measure.

Figure 7 examines the correlation between trading volume and belief disagreement

Figure 7: *Disagreement about Expected Returns and Trading Volume*



Notes: This figure plots trading volume scaled by market capitalization against belief disagreement, $|\mathrm{F}^{\mathrm{Indiv}} r_t - \mathrm{F}^{\mathrm{VL}} r_t|$. The data are quarterly. The expected return of individual investors is the average of expected returns in the Shiller survey, Graham-Harvey survey, and Nagel-Xu data. Appendix Figure B.4 reports the same figure computing the expected return of individuals as the unbalanced average of any available series, extending the sample back to 1987Q3.

between VL and individual investors. The figure shows a clear positive correlation between disagreement and volume. Times of high disagreement, such as during the 2008 Global Financial Crisis and the aftermath of the COVID-19 recession, are times when volume is high.

Table 11, Panel A confirms this visual relationship. Columns (1)-(3) use each one of the three measures of disagreement separately. The correlation is always strongly significant. Column (4) uses the average of all three measures. The estimated relation is even more strongly significant, with a t-statistic of over 5, and an R^2 of 43%. Column (5) uses the longest possible sample by constructing the belief disagreement measure with the unbalanced quarterly average of any available individual expected return series. Again, the relation is strongly positive ($t = 4.2$, $R^2 = 31\%$).

As further exploration, Panel B in Table 11 examines whether belief disagreement is associated with high price volatility. This is not predicted by the model (where conditional volatility is constant) but more generally we expect volatility to be higher when disagreement is the most pronounced. This turns out to be very significantly the case. In Appendix Table B.14, we use the change in beliefs, $|\Delta \mathrm{F}^{\mathrm{Indiv}} r_t - \Delta \mathrm{F}^{\mathrm{VL}} r_t|$, which is closer to our model's predictions but further from the rest of the literature. This yields qualitatively similar findings to using the level of disagreement.

Table 11: *Belief Disagreement, Trading Volume, and Volatility*

Panel A: Belief Disagreement and Trading Volume

	Volume				
	(1)	(2)	(3)	(4)	(5)
$\lvert F^{NX}r - F^{VL}r\rvert$	3.185				
	(2.79)				
$\lvert F^{\text{Sh-indiv}}r - F^{VL}r\rvert$		2.835			
		(2.78)			
$\lvert F^{GH}r - F^{VL}r\rvert$			3.256		
			(5.05)		
$\lvert F^{\text{Indiv-avg-all}}r - F^{VL}r\rvert$				3.747	
				(5.04)	
$\lvert F^{\text{Indiv-avg-unbal}}r - F^{VL}r\rvert$					3.843
					(4.23)
R^2	0.179	0.266	0.384	0.431	0.312
N	146	104	89	86	149

Panel B: Belief Disagreement and Return Volatility

	Volatility				
	(1)	(2)	(3)	(4)	(5)
$\lvert F^{NX}r - F^{VL}r\rvert$	0.128				
	(7.09)				
$\lvert F^{\text{Sh-indiv}}r - F^{VL}r\rvert$		0.077			
		(2.48)			
$\lvert F^{GH}r - F^{VL}r\rvert$			0.120		
			(5.35)		
$\lvert F^{\text{Indiv-avg-all}}r - F^{VL}r\rvert$				0.129	
				(5.29)	
$\lvert F^{\text{Indiv-avg-unbal}}r - F^{VL}r\rvert$					0.108
					(4.86)
R^2	0.423	0.195	0.608	0.600	0.364
N	146	104	89	86	149

Notes: This table reports results from regressions of trading volume (Panel A) and the standard deviation of daily market returns (Panel B) on the absolute difference between expected returns of individuals (from Shiller survey, Nagel-Xu, Graham-Harvey survey) and Value Line in the same quarter t. $|F^{\text{Indiv-avg-avail}}r - F^{VL}r|$ uses the average of the individual expected return series available in a given quarter to maximize the sample length (if only one series is available, the average is just the value from that one series). $|F^{\text{Indiv-avg-all}}r - F^{VL}r|$ uses the average of all three individual expected return series, so it requires that all three are available in a given quarter. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

9 Conclusion

This paper studies the relation between subjective expected returns and stock market fluctuations. We organize our analysis around a simple model of heterogeneous beliefs with limits to arbitrage. In the model, naive investors who extrapolate past returns drive prices away from fundamental values. Sophisticated investors understand that expected returns are high when valuation ratios are low, trade against naive investors, and can predict future returns. Beliefs of sophisticated and naive investors are negatively correlated. Disagreement in beliefs is thus associated with portfolio changes, which can be interpreted as generating higher trading volume.

To test these predictions, we build a novel time series of subjective expected returns from an independent equity analysis firm. This series covers a sample spanning seven decades, allowing us to credibly study the relation between expected returns, valuations, and realized returns. First, we document significant heterogeneity in expected returns across our novel data and existing series based on finance professionals, professional forecasters, and individuals, consistent with the empirical relevance of heterogeneous beliefs. Second, our novel expected return series accounts for most of the variation in valuation ratios and is contrarian in response to past returns. These findings contrast with the expectations of professional forecasters and individuals, whose return expectations exhibit extrapolation based on past returns and are weakly or even negatively correlated with the earnings-price ratio. Third, our novel expected return series significantly predicts future returns, indicating that our data represent the beliefs of relatively sophisticated investors. Finally, we document that belief disagreement across sophisticated agents and individuals predicts aggregate trading volume, suggesting that heterogeneous beliefs matter for market dynamics. Overall, our findings suggest that the interactions between sophisticated and naive investors are important for shaping trading volume and asset price fluctuations.

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Beliefs and Stock Market Fluctuations: New Evidence from the Past Seven Decades

Online Appendix

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May 26, 2026

- Appendix A: Derivation of the model described in Section 2.
- Appendix B: Additional figures and tables.
- Appendix C: Details on Stambaugh bias correction.
- Appendix D: Data appendix.

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A Model Derivation

The market-clearing condition is given by:

$$1 = \alpha \frac{F_t^N R_{t+1}}{\gamma \sigma^2} + (1-\alpha) \frac{F_t^S R_{t+1}}{\gamma \sigma^2}$$

Return expectations are assumed to follow:

$$\begin{aligned} F_t^S R_{t+1} &= E_t R_{t+1} \\ F_t^N R_{t+1} &= E_t R_{t+1} + \mu R_t. \end{aligned}$$

which leads to the equilibrium condition:

$$\gamma \sigma^2 = E_t R_{t+1} + \alpha \mu R_t \tag{A.1}$$

We are looking for a linear Rational Expectations Equilibrium so that

$$P_t = a + bD_t + cG_t + dR_t.$$

In equilibrium, rational expectations are given by:

$$\begin{aligned} E_t R_{t+1} &= a + (1+b) E_t D_{t+1} + c E_t G_{t+1} + d E_t R_{t+1} \\ &\quad - (1+r)\left(a + bD_t + cG_t + dR_t\right) \\ &= \frac{1}{1-d}\left(-ra + (1-rb)D_t + (\rho(1+b) - c(1+r-\rho))G_t - (1+r)dR_t\right) \end{aligned}$$

Substituting this expression into the equilibrium equation (A.1) yields the equilibrium price:

$$P_t = -\frac{\gamma \sigma^2}{r} . \frac{1+r}{1+r+\alpha\mu} + \frac{1}{r} D_t + \frac{1+r}{r} \frac{\rho}{1+r-\rho} G_t + \frac{\alpha\mu}{1+r+\alpha\mu} R_t$$

Prediction 1 The first bullet point follows from:

$$\begin{aligned} F_t^S R_{t+1} &= E_t R_{t+1} = \gamma \sigma^2 - \alpha \mu R_t \\ F_t^N R_{t+1} &= E_t R_{t+1} + \mu R_t = \gamma \sigma^2 + (1-\alpha)\mu R_t \end{aligned}$$

where the first equation comes from the market clearing condition (A.1) and the second one follows by combining with the definition of naive trader forecasts. Since these two are affine functions of R_t with opposite signs, the two forecasts are negatively correlated.

The second bullet point is related to volume. Volume is the change in position of each agent from one period to the next, i.e.:

$$\text{Volume}_t = \frac{|\Delta F_t^S R_{t+1}|}{\gamma\sigma^2} = \frac{|\Delta F_t^N R_{t+1}|}{\gamma\sigma^2}.$$

From the market clearing condition (A.1), we know that $\Delta F_t^S R_{t+1} = -\Delta F_t^N R_{t+1}$ so that:

$$\frac{|\Delta F_t^S R_{t+1} - \Delta F_t^N R_{t+1}|}{\gamma\sigma^2} = \frac{2|\Delta F_t^S R_{t+1}|}{\gamma\sigma^2} = 2\text{Volume}_t$$

Prediction 2 This follows directly from the expressions of forecasts above.

Prediction 3 We rewrite the price equation as:

$$\underbrace{P_t - \frac{1}{r}D_t}_{\text{valuation}} = \text{constant} + \underbrace{\frac{1+r}{r}\frac{\rho}{1+r-\rho}G_t}_{\text{cash flow shocks}} - \underbrace{\frac{1}{1+r+\alpha\mu}F_t^S R_{t+1}}_{\text{sophisticated expected returns}}$$

which can alternatively be written as a function of naive expected returns:

$$\underbrace{P_t - \frac{1}{r}D_t}_{\text{valuation}} = \text{constant} + \underbrace{\frac{1+r}{r}\frac{\rho}{1+r-\rho}G_t}_{\text{cash flow shocks}} + \underbrace{\frac{\alpha}{1-\alpha}\frac{1}{1+r+\alpha\mu}F_t^N R_{t+1}}_{\text{naive expected returns}}.$$

A comparison between these two expressions shows that valuations are (1) more sensitive to sophisticated expectations when G_t has low persistence and (2) more sensitive to sophisticated expectations than naive ones when α is low.

B Additional Figures and Tables

Table B.1: *Correlates of Stock Returns Expectations: Literature Review*

	Data	Returns forecasters	Period	Corr. with valuation	Corr. with past returns	Predicts fut. returns	Analyzes flow cash forecasts
Bacchetta et al. (2009)	UBS-Gallup	Retail/Institutions	1998-2003	> 0			No
Greenwood and Shleifer (2014)	AAII/II/Gallup	Retail/Institutions	1996-2012	> 0	> 0		No
Adam et al. (2017)	UBS-Gallup	Retail/Institutions	1998-2008	> 0			No
Wang (2020)	Bloomberg	Institutions	2002-2019		< 0		No
De La O and Myers (2021)	IBES/CFO survey	Analysts/CFOs	2003-2015	> 0			Yes, mix
Andonov and Rauh (2021)	Disclosure	Pension funds	2014-2017		> 0		No
Nagel and Xu (2022)	Various+imputation	Individuals	1987/2000-2021	$= 0$	> 0		No
Nagel and Xu (2023)	CFO survey	CFOs	2000-2021	$= 0$	$= 0$		No
	Livingston	Forecasters	1952-2021	$= 0$	< 0		No
Couts et al. (2024)	Institutions' websites	Institutions	1987-2022				No
Dahlquist and Ibert (2024)	Institutions' websites	Institutions	2000-2024	< 0			No
Büsing and Mohrschladt (2024)	IBES	Analysts, PTG+Rec	2002-2024	< 0	< 0	> 0	No
Bastianello (2025)	IBES	Analysts PTG	2002-2024	$= 0$	< 0	> 0	No
This paper	Value Line	Value Line	1956-2024	< 0	< 0	> 0	Yes

Notes: This table summarizes papers that explicitly study expectations about returns. Nagel and Xu (2023) data has six observations from 1972 to 1977, but consistent coverage without gaps starts in 1987.

Table B.2: *Subjective Expected Returns and the Earnings-Price Ratio*

	E/P_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$F^{VL}r_{t\to t+4}$	0.260								
	(4.75)								
$F^{IBES}r_{t\to t+1}$		-0.091							
		(-2.21)							
$F^{Sh\text{-}inst}r_{t\to t+1}$			-0.038						
			(-0.81)						
$F^{Liv}r_{t\to t+1}$				-0.040					
				(-0.34)					
$F^{Sh\text{-}indiv}r_{t\to t+1}$					-0.114				
					(-0.87)				
$F^{SPF}r_{t\to t+10}$						-0.001			
						(-0.01)			
$F^{GH}r_{t\to t+10}$							-0.673		
							(-2.24)		
$F^{NX}r_{t\to t+1}$								0.156	
								(0.84)	
$F^{GH}r_{t\to t+1}$									0.149
									(0.57)
R^2	0.593	0.184	0.009	0.005	0.038	0.000	0.199	0.045	0.027
N	69	22	36	73	27	34	23	36	23

Notes: This table reports results from annual time series regressions of the current earnings-price ratio on expected returns from various surveys. The earnings-price ratio measures earnings over year $t-1$ relative to the market cap at the end of year $t-1$. Expected returns are as of Q1 of year t. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.3: *Inverse-CAPE and Subjective Expected Excess Returns*

	$\frac{1}{\text{CAPE}_t}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$F^{VL}xr_{t\to t+4}$	0.275								
	(3.16)								
$F^{IBES}xr_{t\to t+1}$		0.036							
		(0.93)							
$F^{Sh\text{-}inst}xr_{t\to t+1}$			0.029						
			(0.54)						
$F^{Liv}xr_{t\to t+1}$				-0.163					
				(-2.83)					
$F^{Sh\text{-}indiv}xr_{t\to t+1}$					0.035				
					(0.53)				
$F^{SPF}xr_{t\to t+10}$						0.246			
						(2.81)			
$F^{GH}xr_{t\to t+10}$							0.055		
							(0.34)		
$F^{NX}xr_{t\to t+1}$								-0.268	
								(-2.52)	
$F^{GH}xr_{t\to t+1}$									0.013
									(0.27)
R^2	0.401	0.067	0.022	0.128	0.008	0.209	0.010	0.196	0.001
N	69	22	35	72	26	33	23	36	23

Notes: This table reports results from annual time series regressions of the current inverse CAPE ratio on expected excess returns from various surveys. Expected returns are as of Q1 in year t. Expected excess return is calculated by subtracting the 1-year bond yield as of December of year $t-1$. The inverse-CAPE is as of December of year $t-1$. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.4: *Earnings-Price Ratio and Subjective Expected Excess Returns*

	E/P_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$F^{VL}xr_{t\to t+4}$	0.256								
	(2.37)								
$F^{IBES}xr_{t\to t+1}$		-0.096							
		(-2.36)							
$F^{Sh\text{-}inst}xr_{t\to t+1}$			-0.047						
			(-1.02)						
$F^{Liv}xr_{t\to t+1}$				-0.176					
				(-3.97)					
$F^{Sh\text{-}indiv}xr_{t\to t+1}$					-0.179				
					(-1.26)				
$F^{SPF}xr_{t\to t+10}$						-0.026			
						(-0.15)			
$F^{GH}xr_{t\to t+10}$							-0.334		
							(-2.73)		
$F^{NX}xr_{t\to t+1}$								-0.192	
								(-1.17)	
$F^{GH}xr_{t\to t+1}$									0.047
									(0.26)
R^2	0.364	0.208	0.033	0.159	0.087	0.001	0.123	0.066	0.005
N	69	22	35	72	26	33	23	36	23

Notes: This table reports results from annual time series regressions of the current earnings-price ratio on expected excess returns from various surveys. Expected returns are as of Q1 in year t. Expected excess return is calculated by subtracting the 1-year bond yield as of December of year $t-1$. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.5: *Earnings-Price Ratio and Value Line Expected Returns and Earnings Growth*

	E/P_t					
	(1)	(2)	(3)	(4)	(5)	(6)
$F^{VL}r_{t\to t+4}$	0.260		0.295	0.183	0.216	0.156
	(4.75)		(6.86)	(2.45)	(4.51)	(2.61)
$F^{VL}g_{t\to t+4}$		0.204	-0.204	-0.146	-0.377	-0.306
		(1.48)	(-1.88)	(-1.35)	(-3.17)	(-3.07)
Inflation				0.359		0.239
				(2.00)		(1.89)
10-year bond yield					0.422	0.343
					(3.04)	(2.94)
R^2	0.593	0.045	0.627	0.685	0.712	0.735
N	69	69	69	69	69	69

Notes: This table reports results from regressions of current earnings-price ratio on VL expected returns and expected EPS growth. The earnings-price ratio measures earnings over $t-1$ to the market cap at the end of $t-1$. Expectation variables are as of Q1 of year t. Inflation and the 10-year bond yield are as of December of year $t-1$. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.6: *Subjective Expected Returns and Cyclically Adjusted Earnings Growth*

Panel A: Expected returns and cyclically adjusted earnings growth

	$F^{VL}r_{t\to t+4}$ (1)	$F^{IBES}r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst}r_{t\to t+1}$ (3)	$F^{Liv}r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv}r_{t\to t+1}$ (5)	$F^{SPF}r_{t\to t+10}$ (6)	$F^{GH}r_{t\to t+10}$ (7)	$F^{NX}r_{t\to t+1}$ (8)	$F^{GH}r_{t\to t+1}$ (9)
$e_{t-1} - cae_{t-6}$	0.043	-0.047	-0.041	-0.035	0.003	-0.000	0.000	0.026	0.010
	(0.60)	(-1.69)	(-2.81)	(-1.40)	(0.24)	(-0.09)	(0.11)	(2.75)	(0.96)
R^2	0.023	0.091	0.128	0.038	0.001	0.000	0.000	0.175	0.065
N	69	22	36	73	27	34	23	36	23

Panel B: Controlling for past returns

	$F^{VL}r_{t\to t+4}$ (1)	$F^{IBES}r_{t\to t+1}$ (2)	$F^{Sh\text{-}inst}r_{t\to t+1}$ (3)	$F^{Liv}r_{t\to t+1}$ (4)	$F^{Sh\text{-}indiv}r_{t\to t+1}$ (5)	$F^{SPF}r_{t\to t+10}$ (6)	$F^{GH}r_{t\to t+10}$ (7)	$F^{NX}r_{t\to t+1}$ (8)	$F^{GH}r_{t\to t+1}$ (9)
$e_{t-1} - cae_{t-6}$	0.063	-0.011	-0.021	-0.033	0.003	-0.004	0.000	0.013	-0.002
	(0.95)	(-0.38)	(-2.11)	(-1.32)	(0.21)	(-0.53)	(0.10)	(1.79)	(-0.14)
$r_{t-2\to t-1}$	-0.115	-0.136	-0.084	-0.009	-0.003	0.016	-0.000	0.053	0.044
	(-3.63)	(-3.84)	(-2.28)	(-0.42)	(-0.11)	(0.92)	(-0.02)	(4.60)	(3.49)
R^2	0.085	0.218	0.241	0.039	0.002	0.035	0.000	0.333	0.245
N	69	22	36	73	27	34	23	36	23

Notes: This table reports results from annual time series regressions of subjective expected equity returns as of Q1 of year t on log earnings in December $t-1$ relative to the cyclically adjusted log earnings in December $t-6$ (panel A). Panel B adds past returns from December $t-2$ to December $t-1$ as a second explanatory variable. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.7: *VL Expectation Errors: Returns and the Inverse CAPE*

Panel A: 1956-2024

	$\underline{\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}-\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$
	(1)	(2)	(3)
$\frac{1}{\mathrm{CAPE}_t}$	2.369	1.164	-1.205
	(6.21)	(3.92)	(-2.09)
R^2	0.648	0.192	0.144
N	66	66	66

Panel B: 1956-1987

	$\underline{\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}-\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$
	(1)	(2)	(3)
$\frac{1}{\mathrm{CAPE}_t}$	3.517	1.511	-2.005
	(9.14)	(4.27)	(-2.89)
R^2	0.836	0.466	0.368
N	32	32	32

Panel B: 1988-2020

	$\underline{\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}}$	$\underline{\mathrm{r}_{t\to t+4}-\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}}$
	(1)	(2)	(3)
$\frac{1}{\mathrm{CAPE}_t}$	1.609	3.438	1.829
	(5.48)	(2.38)	(1.18)
R^2	0.428	0.293	0.092
N	34	34	34

Notes: This table reports results from regressions of realized return, Value Line's expected returns, and Value Line's return forecast errors on inverse of the Shiller CAPE ratio. t-statistics in parentheses based on Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.8: *VL Expectation Errors: Returns and Past Returns*

	$\mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}$	$\mathrm{r}_{t\to t+4}$	$\mathrm{r}_{t\to t+4} - \mathrm{F}^{\mathrm{VL}}\mathrm{r}_{t\to t+4}$
	(1)	(2)	(3)
$\mathrm{r}_{t-2\to t-1}$	-0.089	-0.039	0.050
	(-3.27)	(-1.23)	(1.18)
R^2	0.038	0.009	0.010
N	66	66	66

Notes: This table reports results from regressions of VL expected returns, realized returns, and VL return forecast errors on past 1-year market returns. Expectations are as of Q1 of year t. t-statistics in parentheses based on Newey-West standard errors.

Table B.9: *VL Expectation Errors: Price-Earnings Multiple*

	$\frac{\mathrm{F}_t^{\mathrm{VL}}\mathrm{P}_{t+4}}{\mathrm{F}_t^{\mathrm{VL}}\mathrm{EPS}_{t+4}}$	$\frac{\mathrm{P}_{t+4}}{\mathrm{F}_{t+4}^{\mathrm{VL}}\mathrm{EPS}_{t+4}}$	$\frac{\mathrm{P}_{t+4}}{\mathrm{F}_{t+4}^{\mathrm{VL}}\mathrm{EPS}_{t+4}} - \frac{\mathrm{F}_t^{\mathrm{VL}}\mathrm{P}_{t+4}}{\mathrm{F}_t^{\mathrm{VL}}\mathrm{EPS}_{t+4}}$
	(1)	(2)	(3)
$\frac{\mathrm{P}_t}{\mathrm{F}_t^{\mathrm{VL}}\mathrm{EPS}_t}$	0.504	0.623	0.119
	(5.28)	(3.67)	(0.48)
R^2	0.509	0.292	0.011
N	65	65	65

Notes: This table reports results from regressions of the VL expected long-term price-earnings multiple, the realized long-term price-earnings multiple, and VL long-term price-earnings multiple forecast error on the current price-earnings multiple. Expectations are as of Q1 of year t. t-statistics in parentheses based on Newey-West standard errors.

Table B.10: *VL Expectation Errors: EPS Growth*

Panel A: Past EPS Growth from $t-2$ to $t-1$

	$\underline{F^{VL}g_{t\to t+4}}$	$\underline{g_{t\to t+4}}$	$\underline{g_{t\to t+4} - F^{VL}g_{t\to t+4}}$
	(1)	(2)	(3)
$g_{t-2\to t-1}$	-0.052	-0.038	0.015
	(-3.46)	(-1.63)	(0.50)
R^2	0.124	0.029	0.003
N	65	65	65

Panel B: Earnings Relative to Cyclically Adjusted EPS Growth

	$\underline{F^{VL}g_{t\to t+4}}$	$\underline{g_{t\to t+4}}$	$\underline{g_{t\to t+4} - F^{VL}g_{t\to t+4}}$
	(1)	(2)	(3)
$e_{t-1} - cae_{t-6}$	-0.012	-0.065	-0.054
	(-1.04)	(-3.99)	(-2.40)
R^2	0.013	0.189	0.102
N	65	65	65

Notes: This table reports results from regressions of expected EPS growth, realized EPS growth, and forecast errors on past EPS growth. Expectations are as of Q1 of year t. Expectations of EPS growth are from Value Line. In Panel A, past EPS growth is from year $t-2$ to $t-1$. In Panel B, past EPS growth is the log of earnings for the S&P 500 in year t relative to cyclically adjusted earnings in year $t-5$ as in Bordalo et al. (2024). t-statistics in parentheses based on Newey-West standard errors.

Table B.11: *Predicting Future Returns with Subjective Expected Returns from Other Surveys: Excess Returns*

	$xr_{t\to t+1}$ (1)	$xr_{t\to t+2}$ (2)	$xr_{t\to t+3}$ (3)	$xr_{t\to t+4}$ (4)	$xr_{t\to t+5}$ (5)	$xr_{t\to t+6}$ (6)
$F^{IBES}xr_{t\to t+1}$	-0.427	0.394	1.023	0.672	1.126	1.086
{Bias-adj Coef}	{-0.402}	{0.065}	{0.683}	{0.380}	{0.572}	{1.618}
(p-value)	(0.209)	(0.691)	(0.298)	(0.665)	(0.519)	(0.612)
R^2	0.021	0.010	0.051	0.012	0.021	0.018
N	22	21	20	19	18	17
$F^{Sh\text{-}inst}xr_{t\to t+1}$	0.457	0.840	1.184	1.835	2.037	1.143
{Bias-adj Coef}	{0.470}	{0.935}	{1.330}	{1.751}	{1.816}	{0.954}
(p-value)	(0.447)	(0.419)	(0.501)	(0.374)	(0.449)	(0.729)
R^2	0.020	0.031	0.035	0.050	0.041	0.010
N	35	34	33	32	31	30
$F^{Liv}xr_{t\to t+1}$	0.057	-0.210	-0.260	0.008	-0.203	-0.630
{Bias-adj Coef}	{0.006}	{-0.251}	{-0.227}	{-0.142}	{-0.353}	{-1.019}
(p-value)	(0.883)	(0.733)	(0.782)	(0.992)	(0.880)	(0.685)
R^2	0.000	0.003	0.003	0.000	0.001	0.004
N	69	68	67	66	65	64
$F^{Sh\text{-}indiv}xr_{t\to t+1}$	0.795	-0.608	0.711	-0.078	-6.086	-13.408
{Bias-adj Coef}	{-0.075}	{-1.236}	{-1.950}	{-3.838}	{-10.479}	{-16.160}
(p-value)	(0.747)	(0.865)	(0.920)	(0.987)	(0.451)	(0.086)
R^2	0.010	0.002	0.001	0.000	0.050	0.215
N	26	25	24	23	22	21
$F^{SPF}xr_{t\to t+10}$	2.022	5.651	7.518	11.104	9.866	15.456
{Bias-adj Coef}	{2.037}	{5.721}	{7.390}	{10.199}	{9.786}	{16.035}
(p-value)	(0.366)	(0.270)	(0.528)	(0.416)	(0.479)	(0.139)
R^2	0.039	0.110	0.097	0.107	0.047	0.084
N	33	32	31	30	29	28
$F^{GH}xr_{t\to t+10}$	2.551	6.011	10.350	14.003	24.858	40.877
{Bias-adj Coef}	{2.683}	{5.928}	{9.529}	{13.256}	{25.651}	{43.897}
(p-value)	(0.425)	(0.477)	(0.430)	(0.353)	(0.104)	(0.010)
R^2	0.046	0.131	0.277	0.293	0.335	0.524
N	23	22	21	20	19	18
$F^{NX}xr_{t\to t+1}$	-0.588	-1.348	-2.780	-3.770	-7.492	-5.861
{Bias-adj Coef}	{-0.346}	{-1.226}	{-2.474}	{-3.094}	{-5.641}	{-5.457}
(p-value)	(0.672)	(0.546)	(0.597)	(0.600)	(0.434)	(0.523)
R^2	0.005	0.011	0.024	0.026	0.062	0.029
N	36	36	35	34	33	32
$F^{GH}xr_{t\to t+1}$	0.298	0.034	2.900	3.929	-2.882	2.103
{Bias-adj Coef}	{0.643}	{0.743}	{3.490}	{4.984}	{-0.679}	{3.564}
(p-value)	(0.879)	(0.993)	(0.485)	(0.290)	(0.574)	(0.603)
R^2	0.001	0.000	0.036	0.042	0.012	0.006
N	23	22	21	20	19	18

Notes: This table reports results from estimating equation (8) with future cumulative realized excess returns on the left-hand-side and expected excess returns from various surveys on the right-hand-side. The realized excess return is the return on the market from April of year t to April of year $t+h$ minus the h-year yield to maturity from December of year $t-1$. Expectations are based on surveys from Q1 of year t. We address Stambaugh (1999) bias using the bootstrap approach in Nagel and Xu (2023). For each independent variable, OLS coefficients are reported; bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p-values are reported in parentheses.

Table B.12: *Predicting Returns with Value Line Expected Returns: Robustness using VL Universe of Firms*

Panel A: Nominal Returns

	$r_{t\to t+1}$ (1)	$r_{t\to t+2}$ (2)	$r_{t\to t+3}$ (3)	$r_{t\to t+4}$ (4)	$r_{t\to t+5}$ (5)	$r_{t\to t+6}$ (6)
$F^{VL} r_{t\to t+4}$	0.499	0.763	1.167	1.875	2.711	3.603
{Bias-adj Coef$_1$}	{0.231}	{0.560}	{1.053}	{1.787}	{2.570}	{3.743}
{Bias-adj Coef$_2$}	{0.343}	{0.463}	{0.732}	{1.313}	{2.028}	{2.806}
(p-value)	(0.045)	(0.022)	(0.013)	(0.010)	(0.007)	(0.001)
R^2	0.058	0.080	0.115	0.174	0.237	0.299
N	69	68	67	66	65	64

Panel B: Excess Returns

	$xr_{t\to t+1}$ (1)	$xr_{t\to t+2}$ (2)	$xr_{t\to t+3}$ (3)	$xr_{t\to t+4}$ (4)	$xr_{t\to t+5}$ (5)	$xr_{t\to t+6}$ (6)
$F^{VL} xr_{t\to t+4}$	0.486	0.553	0.757	1.294	1.944	2.455
{Bias-adj Coef$_1$}	{0.187}	{0.299}	{0.587}	{1.051}	{1.609}	{2.338}
{Bias-adj Coef$_2$}	{0.320}	{0.238}	{0.304}	{0.724}	{1.267}	{1.670}
(p-value)	(0.246)	(0.372)	(0.277)	(0.157)	(0.103)	(0.035)
R^2	0.035	0.027	0.031	0.057	0.089	0.108
N	69	68	67	66	65	64

Notes: This table reports results from regressions of future realized returns on expected returns (panel A) and of future realized excess returns on expected excess returns (panel B). Realized returns are calculated for the universe of firms in VL at time t. Expected excess returns are calculated by subtracting the horizon-matched Fama-Bliss/Liu-Wu bond yield from cumulative nominal returns. The realized excess return from t to $t+h$ is computed as the cumulative nominal return over that horizon minus the time t yield to maturity on a Treasury bond with maturity of h years. We address Stambaugh (1999) bias using two complementary corrections: a bootstrap approach following Nagel and Xu (2023) (method 1) and an alternative correction following Boudoukh et al. (2022) (method 2). For each independent variable, OLS coefficients are reported; bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p-values are reported in parentheses.

Table B.13: *Price-Earnings Variance Decomposition: Robustness to Aggregation Methdology*

	CF	ER	LT
	(1)	(2)	(3)
$\ln(\mathrm{P}/\mathrm{E}_t)$	0.110	0.597	0.287
	(1.57)	(6.01)	(4.04)

Notes: This table reports results from regressions of each term in the Campbell-Shiller decomposition on the current log price-earnings ratio. Relative to Table 5, we calculate each term in the Campbell-Shiller decomposition by first aggregating all variables in the VL expectations data and then calculating the expected return based directly on the aggregated series, instead of calculating the expected return as the market-cap-weighted firm-level expected return. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.14: *Implications of Belief Disagreement: Change in Beliefs*

Panel A: Belief Disagreement and Trading Volume

	Volume				
	(1)	(2)	(3)	(4)	(5)
$\lvert\Delta F^{\text{NX}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$	3.261				
	(2.73)				
$\lvert\Delta F^{\text{Sh-indiv}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$		1.144			
		(1.98)			
$\lvert\Delta F^{\text{GH}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$			2.185		
			(1.84)		
$\lvert\Delta F^{\text{Indiv-avg-all}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$				2.314	
				(1.68)	
$\lvert\Delta F^{\text{Indiv-avg-unbal}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$					1.602
					(1.31)
R^2	0.055	0.015	0.037	0.030	0.015
N	145	100	86	83	148

Panel B: Belief Disagreement and Return Volatility

	Volatility				
	(1)	(2)	(3)	(4)	(5)
$\lvert\Delta F^{\text{NX}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$	0.237				
	(7.75)				
$\lvert\Delta F^{\text{Sh-indiv}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$		0.083			
		(3.05)			
$\lvert\Delta F^{\text{GH}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$			0.143		
			(6.77)		
$\lvert\Delta F^{\text{Indiv-avg-all}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$				0.160	
				(5.11)	
$\lvert\Delta F^{\text{Indiv-avg-unbal}}\text{r} - \Delta F^{\text{VL}}\text{r}\rvert$					0.169
					(5.42)
R^2	0.422	0.076	0.185	0.169	0.243
N	145	100	86	83	148

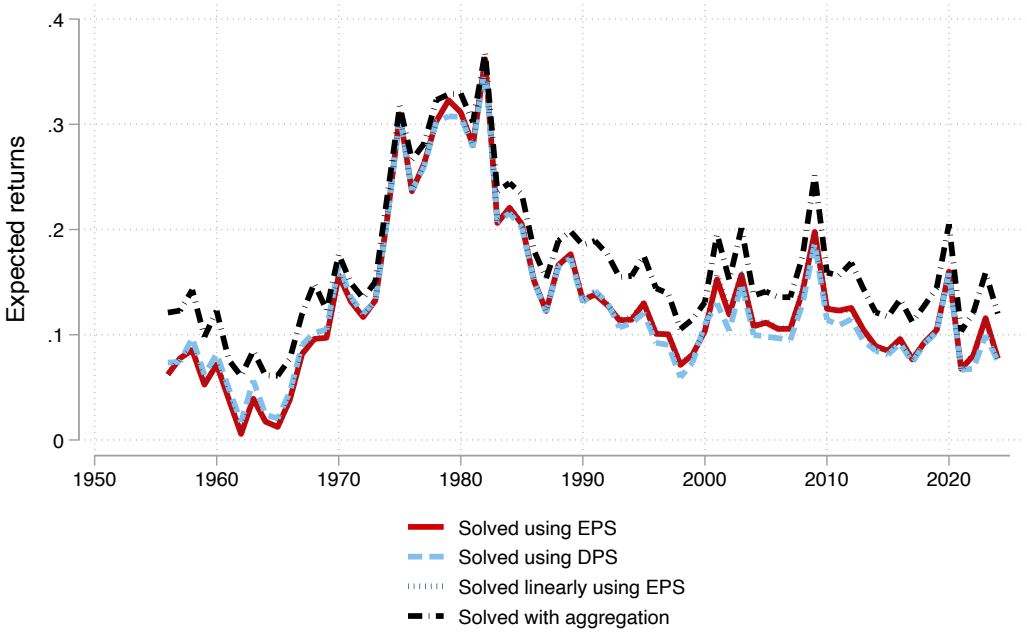
Notes: This table reports results from regressions of trading volume and standard deviation of daily market returns in quarter t on the absolute difference between the change in expected returns of individuals (from the Shiller survey, Nagel-Xu, Graham-Harvey survey) and the change in expected returns of Value Line in the same quarter t. $|\Delta F^{\text{Indiv-avg-avail}}\text{r} - \Delta F^{\text{VL}}\text{r}|$ uses the average of the individual expected return series available in a given quarter to maximize the sample length (if only one series is available, the average is just the value from that one series). $|\Delta F^{\text{Indiv-avg-all}}\text{r} - \Delta F^{\text{VL}}\text{r}|$ uses the average of all three individual expected return series, so it requires that all three are available in a given quarter. t-statistics in parentheses. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

Table B.15: *Long-term and Short-term Multiples*

	$\frac{F^{VL}P_{t+4}}{F^{VL}EPS_{t+4}}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\frac{P_t}{F^{VL}EPS_t}$	0.564	0.297	0.226	0.217	0.242	0.255	0.273	0.272	0.285	0.311
	(7.03)	(2.76)	(1.91)	(2.40)	(2.83)	(2.79)	(2.98)	(3.18)	(3.28)	(3.72)
$\frac{P_{t-1}}{F^{VL}EPS_{t-1}}$		0.337	0.191	0.154	0.142	0.144	0.143	0.173	0.168	0.157
		(4.77)	(3.76)	(3.14)	(2.46)	(2.57)	(2.37)	(4.40)	(4.18)	(3.66)
$\frac{P_{t-2}}{F^{VL}EPS_{t-2}}$			0.247	0.139	0.094	0.102	0.105	0.086	0.102	0.097
			(3.17)	(2.03)	(1.56)	(1.51)	(1.46)	(1.20)	(1.61)	(1.49)
$\frac{P_{t-3}}{F^{VL}EPS_{t-3}}$				0.179	0.105	0.049	0.050	0.064	0.056	0.075
				(4.20)	(2.80)	(1.16)	(0.98)	(1.75)	(1.17)	(3.09)
$\frac{P_{t-4}}{F^{VL}EPS_{t-4}}$					0.131	0.023	-0.028	-0.015	-0.001	-0.025
					(2.27)	(0.32)	(-0.39)	(-0.18)	(-0.01)	(-0.31)
$\frac{P_{t-5}}{F^{VL}EPS_{t-5}}$						0.159	0.066	-0.000	0.015	0.051
						(2.06)	(1.12)	(-0.01)	(0.31)	(1.22)
$\frac{P_{t-6}}{F^{VL}EPS_{t-6}}$							0.140	0.066	-0.007	-0.006
							(2.30)	(1.18)	(-0.15)	(-0.12)
$\frac{P_{t-7}}{F^{VL}EPS_{t-7}}$								0.119	0.020	-0.051
								(1.99)	(0.42)	(-1.13)
$\frac{P_{t-8}}{F^{VL}EPS_{t-8}}$									0.154	0.089
									(2.91)	(2.35)
$\frac{P_{t-9}}{F^{VL}EPS_{t-9}}$										0.116
										(1.61)
Constant	6.901	5.890	5.500	5.184	4.867	4.625	4.416	4.216	3.856	3.573
	(4.99)	(3.71)	(3.55)	(3.29)	(2.96)	(3.01)	(3.19)	(3.31)	(3.23)	(3.11)
R^2	0.618	0.696	0.737	0.758	0.772	0.787	0.808	0.830	0.853	0.877
N	69	68	67	66	65	64	63	62	61	60

Notes: This table reports results from regressions of Value Line's forecast for long-term multiples on current forward multiples and its lags. Newey-West standard errors with bandwidth $S = 1.3\sqrt{T}$.

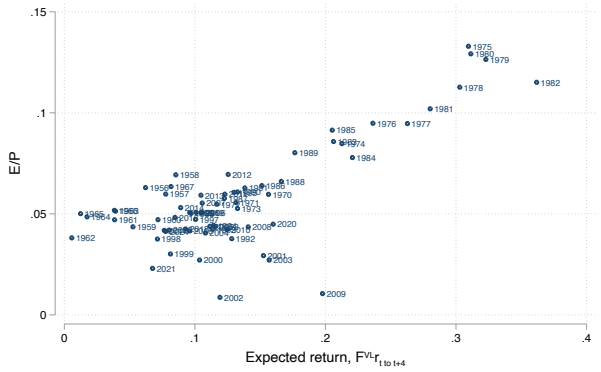
Figure B.1: *Value Line Expected Returns: Alternative Calculation Approaches*



Notes: This figure plots the VL expected return using various calculation approaches. "Solved using EPS" is the baseline measure in the paper. "Solved using DPS" directly uses VL's forecast of dividends per share. "Solved using linearly interpolated level of EPS" uses the level of EPS and linearly interpolates EPS forecasts from year t to $t+4$, allowing for negative values of year t EPS. "Solved with aggregation" first aggregates all variables (current market cap, expected earnings in t, expected earnings in $t+4$, and expected market cap in $t+4$) in VL and then computes the expected return from the aggregate series.

Figure B.2: *Valuation Rations and Measures of Expected Return from Value Line*

(a) *Current EP Ratio and VL Expected Return*



Corr(E/P, Expected Return) = 0.770, regression coefficient on expected return = 0.260, R-squared = 0.593

(b) *Current EP Ratio and VL Expected Excess Return*



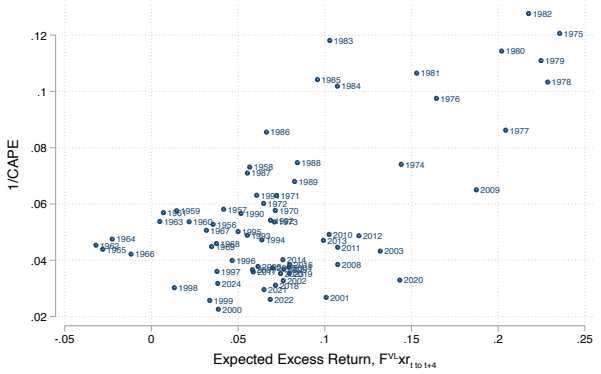
Corr(E/P, expected xr) = 0.636, regression coefficient on expected xr = 0.271, R-squared = 0.405

(c) *1/CAPE and VL Expected Return*



Corr(1/CAPE, expected r) = 0.806, regression coefficient on expected r = 0.278, R-squared = 0.649

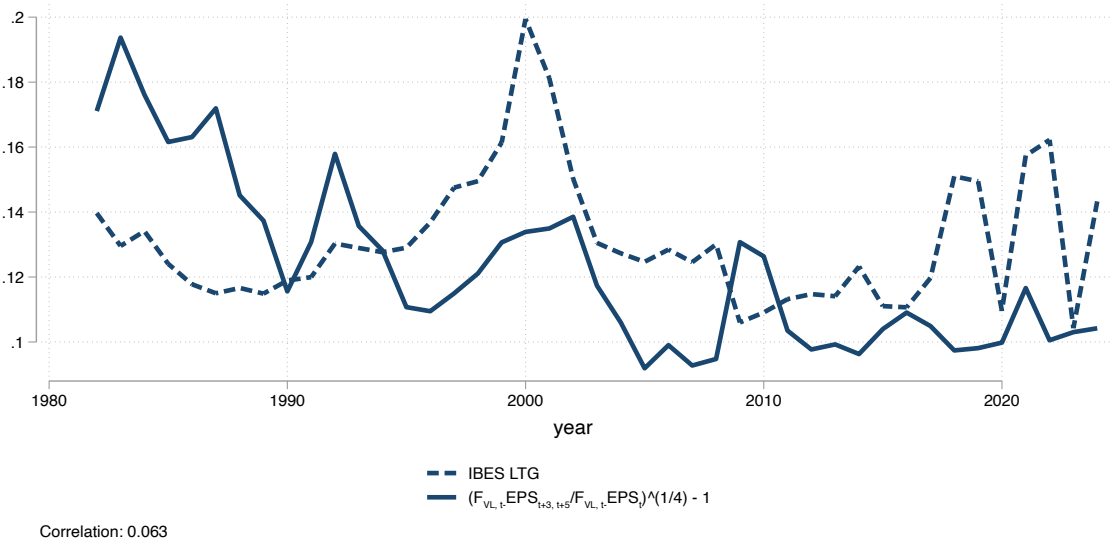
(d) *1/CAPE and VL Expected Excess Return*



Corr(1/CAPE, expected xr) = 0.639, regression coefficient on expected xr = 0.279, R-squared = 0.408

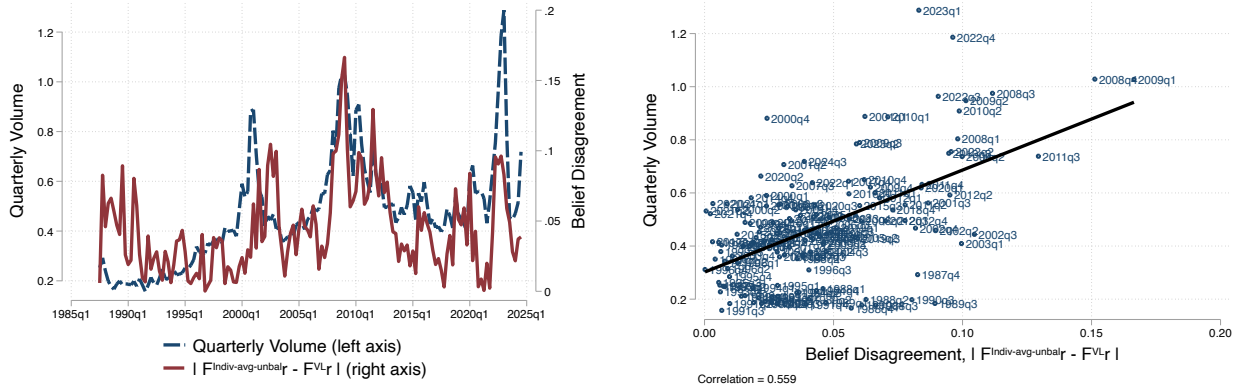
Notes: This figure plots measures of the earnings-price ratio against measures of expected returns. VL expected returns are as of Q1 of year t. The VL expected excess return is calculated by subtracting the horizon-matched bond yield (four years) as of December of year $t-1$.

Figure B.3: *Subjective Expected Long-Term EPS Growth: Value Line and IBES LTG*



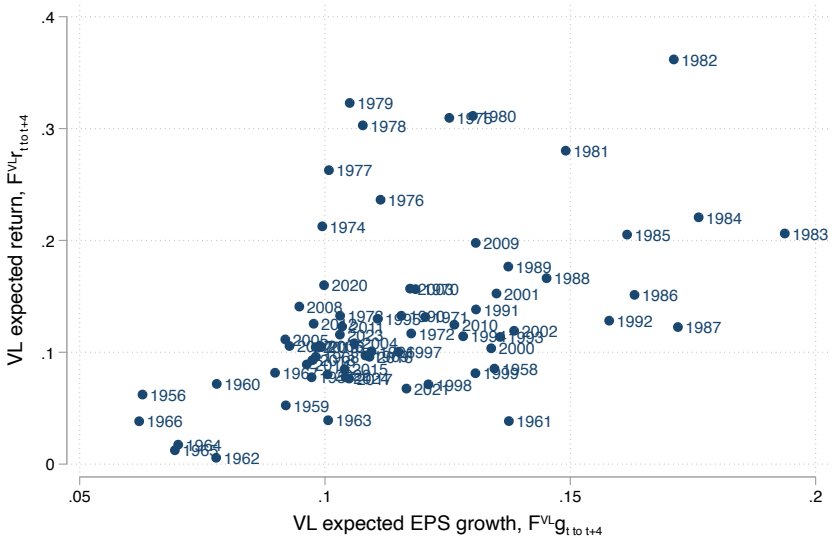
Notes: This figure shows subjective expected EPS growth from IBES and Value Line. Subjective expected EPS Growth from IBES is LTG forecast as of Q1 in year t, defined as the expected annual increase in operating earnings over the company's next full business cycle, a period ranging from three to five years. Expected EPS growth from VL is as of Q1 of year t and meausures the annualized expected growth in EPS from t to $t+4$.

Figure B.4: *Disagreement about Expected Returns and Trading Volume: Robustness using Unbalanced Average*



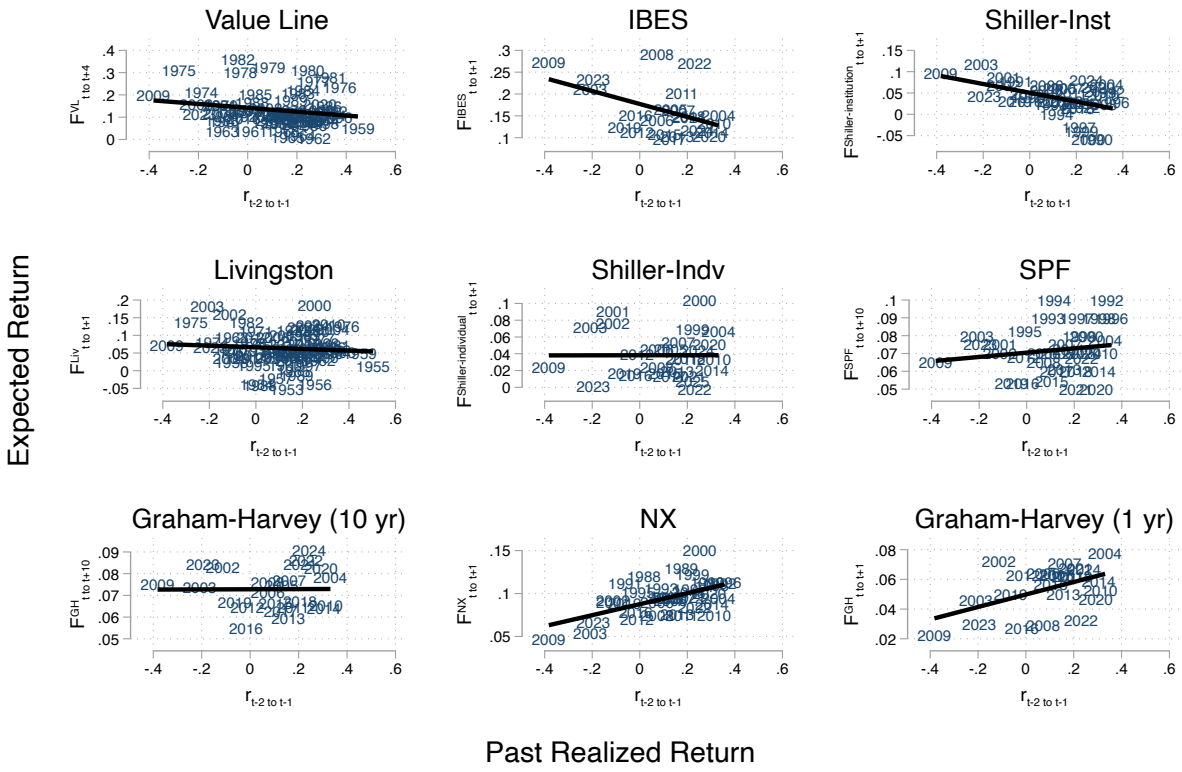
Notes: This figure is similar to Figure 7, but computes the individual expected return in the belief disagreement measure by taking the average of any available series (an unbalanced average). For example, in early years when Nagel-Xu is the only available series, we just use this series. When additional series become available, we take the within-quarter average across available series.

Figure B.5: *VL Expected Cash Flow and Expected Return*



Notes: The figure plots VL's expected return from t to $t+4$ against their expected EPS growth from t to $t+4$. Both measures are annualized. VL expectations for year t are formed in Q1.

Figure B.6: *Survey Expected Return and Past Realized Return*



Notes: This figure shows subjective expected returns from various surveys against past realized returns. Subjective expected returns are as of Q1 in year t. Past realized returns are returns on the market from December of year $t-2$ to December of year $t-1$.

C Details on Stambaugh Bias Correction

This appendix provides details on the two approaches we use to correct for Stambaugh (1999) bias.

C.1 Method 1: Nagel and Xu (2023) Approach

We consider the following two predictive regressions for horizon H:

$$z_{t+H} = \alpha_H + \beta_H x_t + \eta_{t+H}, \tag{B.1}$$
$$x_{t+1} = \kappa + \Phi x_t + \iota_{t+1}. \tag{B.2}$$

1. We estimate an AR(1) model for the predictor, x_t. To correct for the bias in the AR estimates, we use the approach in Amihud et al. (2008) that relies on the analytical expressions from Nicholls and Pope (1988). This allows us to obtain the bias-adjusted coefficients and shocks: $\tilde{\kappa}$, $\tilde{\Phi}$, and $\{\tilde{\iota}_t\}$, given by

$$\begin{aligned}
\tilde{\Phi} &= \hat{\Phi} + \frac{1+3\hat{\Phi}}{T} + \frac{3(1+3\hat{\Phi})}{T^2}, \\
\tilde{\kappa} &= (1-\tilde{\Phi})\bar{x}, \\
\tilde{\iota}_t &= x_t - \tilde{\kappa} - \tilde{\Phi} x_{t-1},
\end{aligned}$$

   where $\bar{x} = T^{-1}\sum_t x_t$ is the sample mean of the predictor.

2. We next estimate the predictive regression in (B.1) with OLS, obtain $\hat{\alpha}_H$, $\hat{\beta}_H$, residuals $\hat{\eta}_{t+H}$, and the corresponding t-statistic $\hat{t}_H$ for $\hat{\beta}_H$ computed using Newey–West standard errors with bandwidth $S = 1.3\sqrt{T}$.

3. We then construct pseudo-samples by bootstrapping the time-series of residual vectors $(\tilde{\iota}_t, \hat{\eta}_t)$. We use a stationary block bootstrap, where the optimal block length is determined as in Politis and White (2004).

4. To compute the bootstrap p-value: For each bootstrap sample i and horizon H, with bootstrapped residuals, we impose the null of no predictability by generating data from

$$z^{null,i}_{t+H} = \bar{z} + \hat{\eta}^i_{t+H}, \tag{B.3}$$
$$x^i_{t+1} = \tilde{\kappa} + \tilde{\Phi} x^i_t + \tilde{\iota}^i_{t+1}. \tag{B.4}$$

   - We then re-run the predictive regression in the sample i and record the t-statistic t^i_H.

- The $\{t_H^i\}$ are used to obtain the small-sample p-value by comparing with the sample t-statistic $\hat{t}_H$. The bootstrap p-value is computed as

$$\hat{p}_H = \frac{1}{B}\sum_{i=1}^{B} \mathbf{1}\Big(|t_H^i| \geq |\hat{t}_H|\Big).$$

5. To compute the bias-adjusted bootstrap coefficient: For each bootstrap sample j and horizon H, with bootstrapped residuals, we generate data under the alternative that $\beta_H = \hat{\beta}_H$ as

$$z_{t+H}^{alter,j} = \hat{\alpha}_H + \hat{\beta}_H x_t^j + \hat{\eta}_{t+H}^j, \tag{B.5}$$

$$x_{t+1}^j = \tilde{\kappa} + \tilde{\Phi} x_t^j + \tilde{\imath}_{t+1}^j. \tag{B.6}$$

   - We then re-run the predictive regression in the sample j and record the coefficients $\hat{\beta}_H^j$.
   - From the distribution of bootstrapped coefficients, we estimate the finite-sample bias as the difference between the mean of bootstrapped coefficients and the sample OLS estimate:

$$\widehat{\text{Bias}}_H = \frac{1}{B}\sum_{j=1}^{B} \hat{\beta}_H^j - \hat{\beta}_H.$$

   - The bias-adjusted coefficient is

$$\tilde{\beta}_H = \hat{\beta}_H - \widehat{\text{Bias}}_H = 2\hat{\beta}_H - \frac{1}{B}\sum_{j=1}^{B} \hat{\beta}_H^j.$$

     where B is the number of bootstrap simulations, set to 5000.

C.2 Method 2: Boudoukh-Israel-Richardson Correction

1. Steps 1–3 are identical to Method 1.

2. To compute the bias-adjusted coefficient: For each horizon H,

   - Estimate the AR(1) process for the predictor (eq. (B.2)), obtain the OLS coefficient $\hat{\Phi}$, residuals $\hat{\imath}_{t+1}$, and compute the variance,

$$(\sigma_\imath^2) = \text{Var}(\hat{\imath}_{t+1}).$$

   - Next, estimate the one-period predictive regression (eq. (B.1) with H=1), obtain the OLS residuals $\hat{\eta}_{t+1}$, and compute the contemporaneous innovation covariance

$$(\sigma_{\eta\imath}) = \text{Cov}(\hat{\eta}_{t+1}, \hat{\imath}_{t+1}).$$

- Estimate the biased coefficients $\hat{\beta}_H^{\text{ols}}$ from the H-horizon regression:

$$z_{t\to t+H} = \alpha_H + \beta_H x_t + \eta_{t+H}.$$

- Compute the bias following the formula in Boudoukh et al. (2022):

$$\widehat{\text{Bias}}_H^{BIR} = -\frac{1}{T}\left[H(1+\hat{\Phi}) + 2\hat{\Phi}\left(\frac{1-(\hat{\Phi})^H}{1-\hat{\Phi}}\right)\right]\frac{(\sigma_{\eta\iota})}{(\sigma_\iota^2)}.$$

- Compute the bias-adjusted coefficient: $\bar{\beta}_H^{BIR} = (\hat{\beta}_H^{\text{ols}}) - \widehat{\text{Bias}}_H^{BIR}$.

3. To compute the bootstrap p-value: For each bootstrap sample j and horizon H, with bootstrapped residuals, impose the null of no predictability by generating data as

$$z_{t+H}^{null,j} = \bar{z} + \hat{\eta}_{t+H}^j, \tag{B.7}$$

$$x_{t+1}^j = \tilde{\kappa} + \tilde{\Phi} x_t^j + \tilde{\iota}_{t+1}^j. \tag{B.8}$$

- We then re-run the predictive regression on the resulting pseudo-sample and record the t-statistic t_H^j.
- The small-sample p-value under the null is obtained by comparing the bootstrap distribution of $\{t_H^j\}$ with the sample t-statistic $\hat{t}_H$. Formally, the bootstrap p-value is computed as

$$\hat{p}_H = \frac{1}{B}\sum_{j=1}^{B} \mathbf{1}\left(|t_H^j| \geq |\hat{t}_H|\right).$$

where B denotes the number of bootstrap replications.

D Data Appendix

D.1 New Value Line Database, 1956-1989

Data source. We digitize *Value Line Investment Survey* from 1956 through 1989. We digitize the first quarter reports of each year. This dataset covers 38,696 firm-year observations, with an average of 1,138 firms each year for 34 years. The VL reports contain actual realizations of major accounting variables for approximately past 10 years. Moreover, the reports contain forecast data of the past year, current year, the next year, and a 3-5 horizon.[1]

Data construction. With a team of research assistants and the assistance of the MIT Library, we scanned physical volumes and microfilm images of the VL reports published between January and March each year from 1956 to 1989. We then separated pages with industry reports from pages containing the analysis of individual firms. Figures B3 and B4 contain examples of the raw data we digitize. We then apply a few preprocessing techniques to enhance the quality of the scanned photo (enhancing the scans, rotating, and cropping the images). We then OCR the images using the Amazon Web Services Textract OCR engine to obtain the JSON file with block objects containing all the strings and coordinates that Amazon Textract was able to read. From the JSON file, we locate the firm name, ticker, and pages. We then locate the coordinates of the table we needed from the block objects and use them to calculate the slope and the skewed angle, then rotate page and all coordinates by that angle to straighten it up. We cropped the table of interest from the straightened page and uploaded to Amazon Textract again to get a precise translation of all the cells and their deskewed coordinates. The returned block objects are then reconstructed into tables. We also use Textract's query feature to extract additional information from the page, such as the recent price, dividend yield, P/E ratio, and Value Line rankings. In early years (1956-1963), the 3-5 year forecasts are reported in the text, so we extract these using AWS's query function. We then combine all the above information we obtained in one excel sheet containing: forecast and actual tables, names and dates, and query answers.

To ensure that the digitization was high quality, we applied a range of checks. We manually checked all tables for misread strings, unaligned columns, and jammed rows or cells. We pay special attention to suspicious cells and cells with a low confidence score. Further, we applied a range of accounting and financial identities. For example, we checked consistency between sales, sales per share, and common shares outstanding. We also checked for outliers in the current P/E ratio, earnings per share, and recent price.

Data cleaning and panel construction. We appended the data tables for each firm and year. We then use the CRSP database to construct a firm-year panel of firms with actuals and forecasts. To match firms across years, we cleaned the tickers and firm names. In particular, we standardize firm names by constructing a ground truth list of names and

[1] For a few years, the long-term forecasts are at the 2-4 year horizon.

tickers. We then applied a fuzzy match to the CRSP database to find PERMNO code corresponding to each firm-year, applying a confidence threshold of 95 percent.

D.2 Modern Value Line Database, 1987-2024

The Value Line data we use from 1988 onwards was purchased from Value Line. Data purchased includes two products: Fundamental Datafile and Historical Estimates File.

The Value Line Fundamental Datafile only contains realizations data and includes detailed annual income statements, balance sheets, and cash flow statements for around 7,000 major public companies across 10 economic sectors and 97 industry categories.

The Value Line Historical Estimates File contains both realizations and forecast data, including estimated income statement and balance sheet data for about 1,600 major public companies across 10 economic sectors and 97 industry groups, along with identifiers for over 7,000 companies. Generally, for each stock, the data provides forecasts for the current year, next year, and 3 to 5 years ahead. We use E&P data to construct forecast and realizations data for the modern period. In Historical Estimates files, Value Line uses a stock's historical eight-digit CUSIP and exchange ticker as the identifier. We merge firms to CRSP stocknames table from WRDS by CUSIP-year to assign PERMNO to each CUSIP. PERMNO is assigned by historical CUSIP and year. As Value Line sometimes backfills CUSIPs, if this merge fails, we use header CUSIP, the next historical CUSIP, or refer to Value Line's historical CUSIP changes file to assign PERMNO.

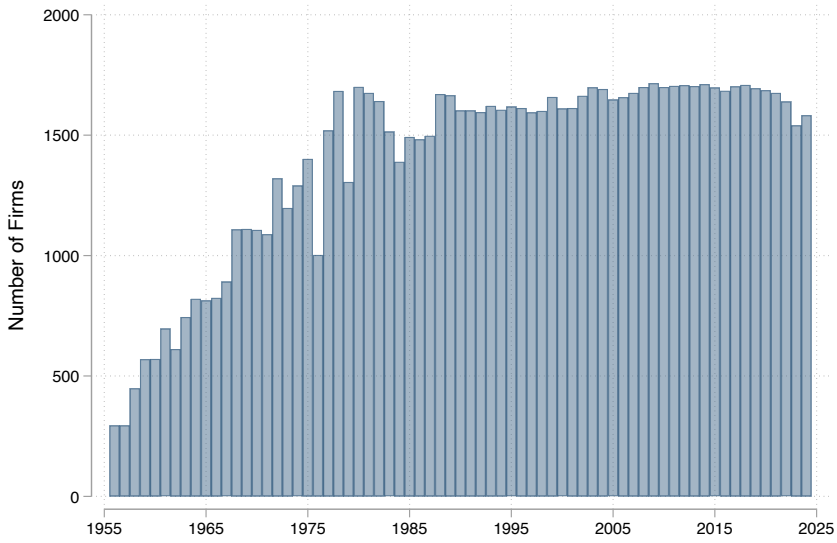
To extract actual realizations data, we take estimates which have been identified as actual data by Value Line (with actual indicator filled with an "A"). If the actual data is missing for a certain PERMNO-year, impute the data using actual values from Compustat. To be consistent with digitized historical digitized data, only keep forecasts with pricing date in quarter 1 of each year. If a CUSIP shows up multiple times in pricing quarter 1, we use the forecasts from the latest pricing date.

To combine the digitized and modern data, we simply append the datasets for non-overlapping years. For overlapping years (1988-1989), if a firm shows up in both digitized and modern data, we first use the forecast from modern data. In rare instances where a firm is not in the modern data but is in the historical data, we use the information from the historical data.

D.3 Value Line Data Coverage

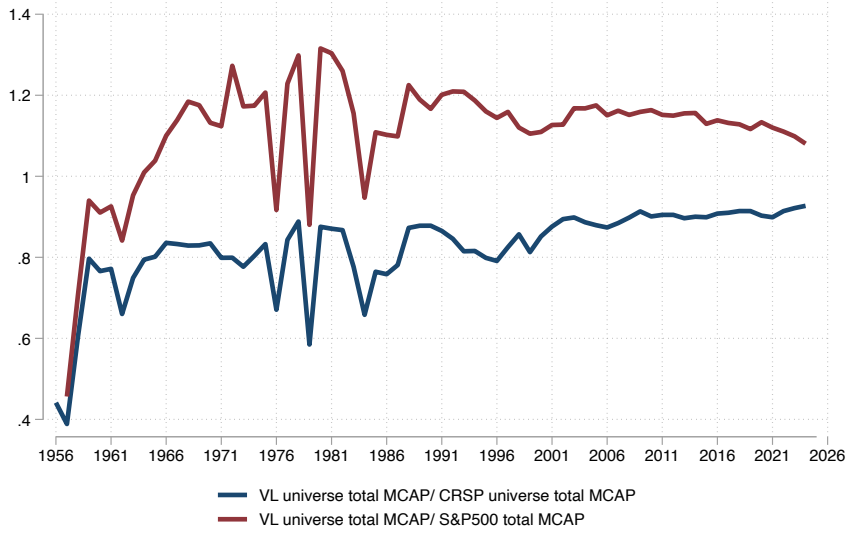
Firm coverage. Figure B1 plots the number of firms in our Value Line dataset in each year. In the early part of the sample (1950s), Value Line covers about 300-500 firms. Coverage rises to about 1000 firms in the mid-1960s and 1500-1600 by the mid-1970s. Figure B2 shows that VL firms account for 80% or more of the total CRSP market cap in most years after 1960.

Figure B1: *Value Line Forecasts: Number of Firms by Year*



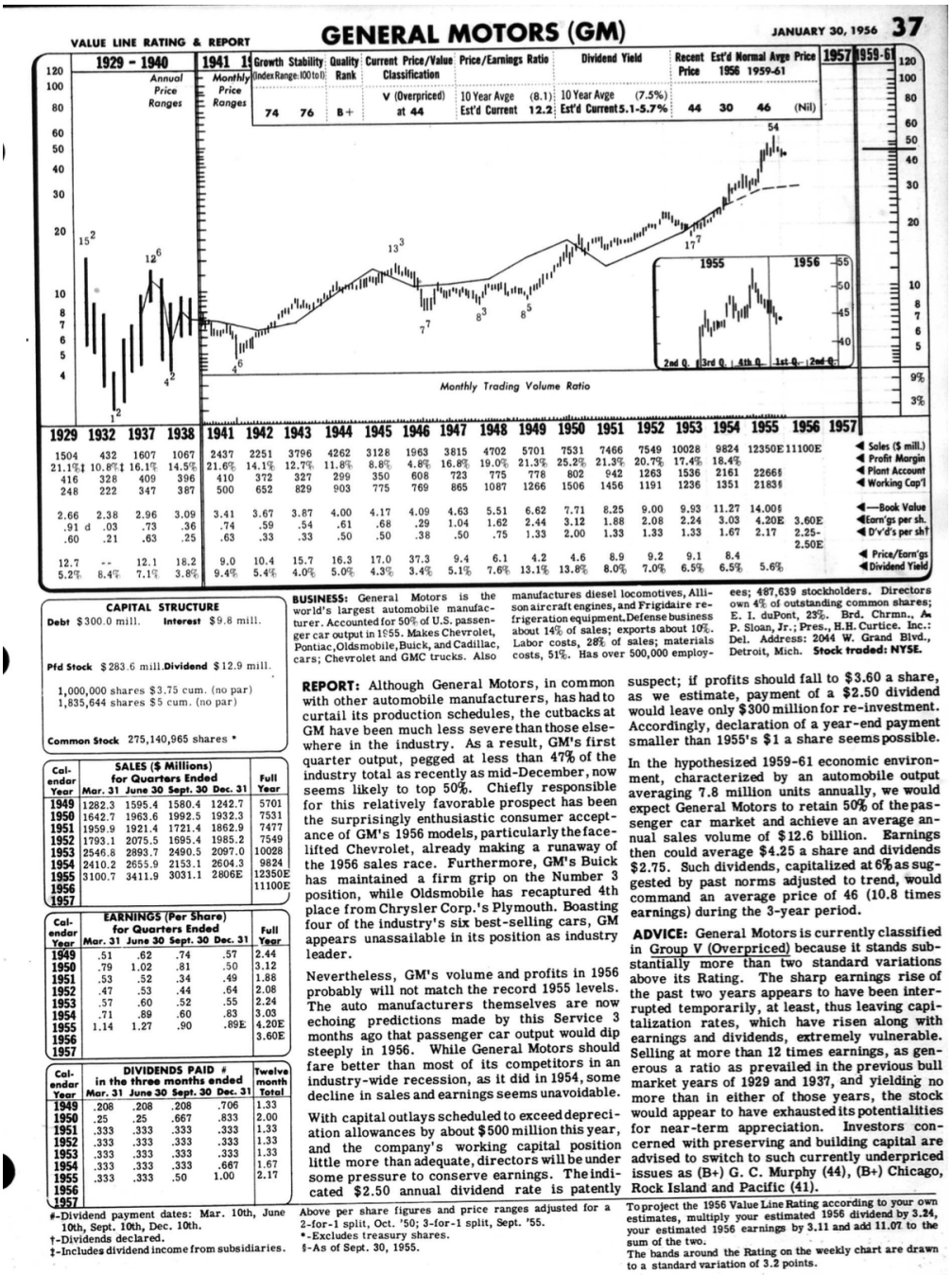
Notes: This figure shows the number of unique firms covered in Value Line in the first quarter of each year.

Figure B2: *Value Line Forecasts: Total Market Capitalization Relative to CRSP and S&P500 Universe by Year*



Notes: This figure shows the total market capitalization of firms covered in Value Line in the first quarter of each year, relative to the total market capitalization of (i) firms in the CRSP universe and (ii) constituents of the S&P 500. The S&P 500 was started in 1957, so this ratio is missing for 1956.

Figure B3: *Example of Value Line Original Data: General Motors, 1956*



VALUE LINE RATING & REPORT

GENERAL MOTORS (GM)

JANUARY 30, 1956 **37**

1929 – 1940 Annual Price Ranges | 1941 1[illegible] Monthly Price Ranges

Growth	Stability	Quality Rank	Current Price/Value Classification	Price/Earnings Ratio	Dividend Yield	Recent Price	Est'd Normal Avge Price 1956	1959-61
(Index Range: 100 to 0)								
74	76	B+	V (Overpriced) at 44	10 Year Avge (8.1) Est'd Current 12.2	10 Year Avge (7.5%) Est'd Current 5.1-5.7%	44	30	46 (Nil)

1957 1959-61

Monthly Trading Volume Ratio

1955 1956

	1929	1932	1937	1938	1941	1942	1943	1944	1945	1946	1947	1948	1949	1950	1951	1952	1953	1954	1955	1956	1957	
	1504	432	1607	1067	2437	2251	3796	4262	3128	1963	3815	4702	5701	7531	7466	7549	10028	9824	12350E	11100E		Sales ($ mill.)
	21.1%‡	10.8%‡	16.1%	14.5%	21.6%	14.1%	12.7%	11.8%	8.8%	4.8%	16.8%	19.0%	21.3%	25.2%	21.3%	20.7%	17.4%	18.4%				Profit Margin
	416	328	409	396	410	372	327	299	350	608	723	775	778	802	942	1263	1536	2161	2266§			Plant Account
	248	222	347	387	500	652	829	903	775	769	865	1087	1266	1506	1456	1191	1236	1351	2183§			Working Cap'l
	2.66	2.38	2.96	3.09	3.41	3.67	3.87	4.00	4.17	4.09	4.63	5.51	6.62	7.71	8.25	9.00	9.93	11.27	14.00§			—Book Value
	.91 d	.03	.73	.36	.74	.59	.54	.61	.68	.29	1.04	1.62	2.44	3.12	1.88	2.08	2.24	3.03	4.20E	3.60E		Earn'gs per sh.
	.60	.21	.63	.25	.63	.33	.33	.50	.50	.38	.50	.75	1.33	2.00	1.33	1.33	1.33	1.67	2.17	2.25-2.50E		D'v'd's per sh†
	12.7	--	12.1	18.2	9.0	10.4	15.7	16.3	17.0	37.3	9.4	6.1	4.2	4.6	8.9	9.2	9.1	8.4				Price/Earn'gs
	5.2%	8.4%	7.1%	3.8%	9.4%	5.4%	4.0%	5.0%	4.3%	3.4%	5.1%	7.6%	13.1%	13.8%	8.0%	7.0%	6.5%	6.5%	5.6%			Dividend Yield

CAPITAL STRUCTURE

Debt $300.0 mill. **Interest** $9.8 mill.

Pfd Stock $283.6 mill. **Dividend** $12.9 mill.

1,000,000 shares $3.75 cum. (no par)
1,835,644 shares $5 cum. (no par)

Common Stock 275,140,965 shares *

BUSINESS: General Motors is the world's largest automobile manufacturer. Accounted for 50% of U.S. passenger car output in 1955. Makes Chevrolet, Pontiac, Oldsmobile, Buick, and Cadillac, cars; Chevrolet and GMC trucks. Also manufactures diesel locomotives, Allison aircraft engines, and Frigidaire refrigeration equipment. Defense business about 14% of sales; exports about 10%. Labor costs, 28% of sales; materials costs, 51%. Has over 500,000 employees; 487,639 stockholders. Directors own 4% of outstanding common shares; E. I. duPont, 23%. Brd. Chrmn., A. P. Sloan, Jr.; Pres., H.H. Curtice. Inc.: Del. Address: 2044 W. Grand Blvd., Detroit, Mich. **Stock traded: NYSE.**

Calendar Year	SALES ($ Millions) for Quarters Ended Mar. 31	June 30	Sept. 30	Dec. 31	Full Year
1949	1282.3	1595.4	1580.4	1242.7	5701
1950	1642.7	1963.6	1992.5	1932.3	7531
1951	1959.9	1921.4	1721.4	1862.9	7477
1952	1793.1	2075.5	1695.4	1985.2	7549
1953	2546.8	2893.7	2490.5	2097.0	10028
1954	2410.2	2655.9	2153.1	2604.3	9824
1955	3100.7	3411.9	3031.1	2806E	12350E
1956					11100E
1957					

Calendar Year	EARNINGS (Per Share) for Quarters Ended Mar. 31	June 30	Sept. 30	Dec. 31	Full Year
1949	.51	.62	.74	.57	2.44
1950	.79	1.02	.81	.50	3.12
1951	.53	.52	.34	.49	1.88
1952	.47	.53	.44	.64	2.08
1953	.57	.60	.52	.55	2.24
1954	.71	.89	.60	.83	3.03
1955	1.14	1.27	.90	.89E	4.20E
1956					3.60E
1957					

Calendar Year	DIVIDENDS PAID # in the three months ended Mar. 31	June 30	Sept. 30	Dec. 31	Twelve month Total
1949	.208	.208	.208	.706	1.33
1950	.25	.25	.667	.833	2.00
1951	.333	.333	.333	.333	1.33
1952	.333	.333	.333	.333	1.33
1953	.333	.333	.333	.333	1.33
1954	.333	.333	.333	.667	1.67
1955	.333	.333	.50	1.00	2.17
1956					
1957					

REPORT: Although General Motors, in common with other automobile manufacturers, has had to curtail its production schedules, the cutbacks at GM have been much less severe than those elsewhere in the industry. As a result, GM's first quarter output, pegged at less than 47% of the industry total as recently as mid-December, now seems likely to top 50%. Chiefly responsible for this relatively favorable prospect has been the surprisingly enthusiastic consumer acceptance of GM's 1956 models, particularly the facelifted Chevrolet, already making a runaway of the 1956 sales race. Furthermore, GM's Buick has maintained a firm grip on the Number 3 position, while Oldsmobile has recaptured 4th place from Chrysler Corp.'s Plymouth. Boasting four of the industry's six best-selling cars, GM appears unassailable in its position as industry leader.

Nevertheless, GM's volume and profits in 1956 probably will not match the record 1955 levels. The auto manufacturers themselves are now echoing predictions made by this Service 3 months ago that passenger car output would dip steeply in 1956. While General Motors should fare better than most of its competitors in an industry-wide recession, as it did in 1954, some decline in sales and earnings seems unavoidable.

With capital outlays scheduled to exceed depreciation allowances by about $500 million this year, and the company's working capital position little more than adequate, directors will be under some pressure to conserve earnings. The indicated $2.50 annual dividend rate is patently suspect; if profits should fall to $3.60 a share, as we estimate, payment of a $2.50 dividend would leave only $300 million for re-investment. Accordingly, declaration of a year-end payment smaller than 1955's $1 a share seems possible.

In the hypothesized 1959-61 economic environment, characterized by an automobile output averaging 7.8 million units annually, we would expect General Motors to retain 50% of the passenger car market and achieve an average annual sales volume of $12.6 billion. Earnings then could average $4.25 a share and dividends $2.75. Such dividends, capitalized at 6% as suggested by past norms adjusted to trend, would command an average price of 46 (10.8 times earnings) during the 3-year period.

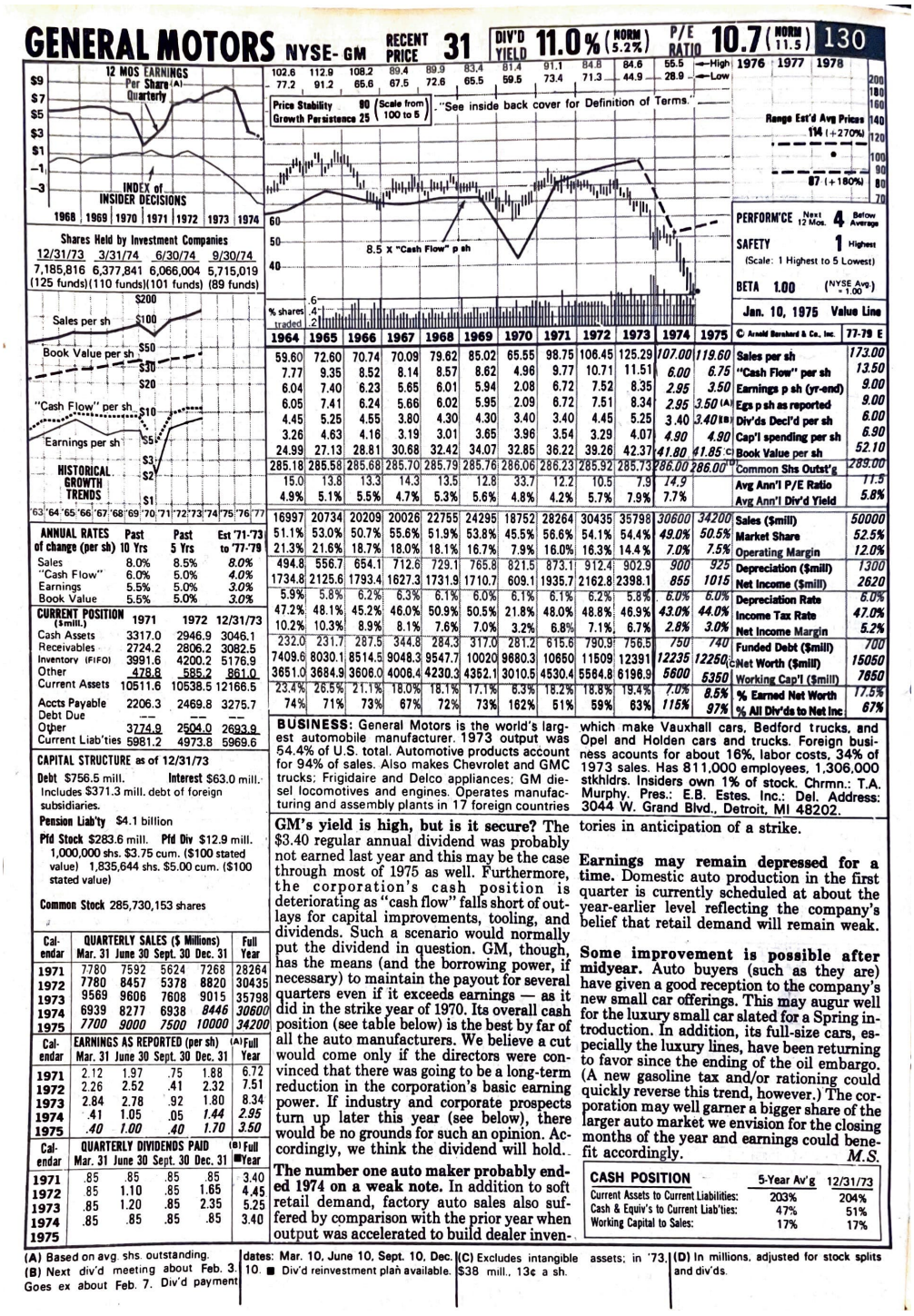
ADVICE: General Motors is currently classified in Group V (Overpriced) because it stands substantially more than two standard variations above its Rating. The sharp earnings rise of the past two years appears to have been interrupted temporarily, at least, thus leaving capitalization rates, which have risen along with earnings and dividends, extremely vulnerable. Selling at more than 12 times earnings, as generous a ratio as prevailed in the previous bull market years of 1929 and 1937, and yielding no more than in either of those years, the stock would appear to have exhausted its potentialities for near-term appreciation. Investors concerned with preserving and building capital are advised to switch to such currently underpriced issues as (B+) G. C. Murphy (44), (B+) Chicago, Rock Island and Pacific (41).

#-Dividend payment dates: Mar. 10th, June 10th, Sept. 10th, Dec. 10th.
†-Dividends declared.
‡-Includes dividend income from subsidiaries.

Above per share figures and price ranges adjusted for a 2-for-1 split, Oct. '50; 3-for-1 split, Sept. '55.
*-Excludes treasury shares.
§-As of Sept. 30, 1955.

To project the 1956 Value Line Rating according to your own estimates, multiply your estimated 1956 dividend by 3.24, your estimated 1956 earnings by 3.11 and add 11.07 to the sum of the two.
The bands around the Rating on the weekly chart are drawn to a standard variation of 3.2 points.

Figure B4: *Example of Value Line Original Data: General Motors, 1975*



GENERAL MOTORS NYSE-GM

RECENT PRICE 31 — DIV'D YIELD 11.0% (NORM 5.2%) — P/E RATIO 10.7 (NORM 11.5) — 130

12 MOS EARNINGS Per Share (A) Quarterly

INDEX of INSIDER DECISIONS

Price Stability 80 (Scale from 100 to 5) — Growth Persistence 25 — "See inside back cover for Definition of Terms."

8.5 X "Cash Flow" p sh

Range Est'd Avg Prices 114 (+270%) — 87 (+180%)

PERFORM'CE Next 12 Mos. 4 Below Average

SAFETY 1 Highest (Scale: 1 Highest to 5 Lowest)

BETA 1.00 (NYSE Avg = 1.00)

Jan. 10, 1975 Value Line

Shares Held by Investment Companies

12/31/73	3/31/74	6/30/74	9/30/74
7,185,816 (125 funds)	6,377,841 (110 funds)	6,066,004 (101 funds)	5,715,019 (89 funds)

	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973	1974	1975	© Arnold Bernhard & Co., Inc.	77-79 E
	59.60	72.60	70.74	70.09	79.62	85.02	65.55	98.75	106.45	125.29	107.00	119.60	Sales per sh	173.00
	7.77	9.35	8.52	8.14	8.57	8.62	4.98	9.77	10.71	11.51	6.00	6.75	"Cash Flow" per sh	13.50
	6.04	7.40	6.23	5.65	6.01	5.94	2.08	6.72	7.52	8.35	2.95	3.50	Earnings p sh (yr-end)	9.00
	6.05	7.41	6.24	5.66	6.02	5.95	2.09	6.72	7.51	8.34	2.95	3.50 (A)	Egs p sh as reported	9.00
	4.45	5.25	4.55	3.80	4.30	4.30	3.40	3.40	4.45	5.25	3.40	3.40 (B)	Div'ds Decl'd per sh	6.00
	3.26	4.63	4.16	3.19	3.01	3.65	3.96	3.54	3.29	4.07	4.90	4.90	Cap'l spending per sh	6.90
	24.99	27.13	28.81	30.68	32.42	34.07	32.85	36.22	39.26	42.37	41.80	41.85 (C)	Book Value per sh	52.10
	285.18	285.58	285.68	285.70	285.79	285.76	286.06	286.23	285.92	285.73	286.00	286.00 (D)	Common Shs Outst'g	289.00
	15.0	13.8	13.3	14.3	13.5	12.8	33.7	12.2	10.5	7.9	14.9		Avg Ann'l P/E Ratio	11.5
	4.9%	5.1%	5.5%	4.7%	5.3%	5.6%	4.8%	4.2%	5.7%	7.9%	7.7%		Avg Ann'l Div'd Yield	5.8%
	16997	20734	20209	20026	22755	24295	18752	28264	30435	35798	30600	34200	Sales ($mill)	50000
	51.1%	53.0%	50.7%	55.6%	51.9%	53.8%	45.5%	56.6%	54.1%	54.4%	49.0%	50.5%	Market Share	52.5%
	21.3%	21.6%	18.7%	18.0%	18.1%	16.7%	7.9%	16.0%	16.3%	14.4%	7.0%	7.5%	Operating Margin	12.0%
	494.8	556.7	654.1	712.6	729.1	765.8	821.5	873.1	912.4	902.9	900	925	Depreciation ($mill)	1300
	1734.8	2125.6	1793.4	1627.3	1731.9	1710.7	609.1	1935.7	2162.8	2398.1	855	1015	Net Income ($mill)	2620
	5.9%	5.8%	6.2%	6.3%	6.1%	6.0%	6.1%	6.1%	6.2%	5.8%	6.0%	6.0%	Depreciation Rate	6.0%
	47.2%	48.1%	45.2%	46.0%	50.9%	50.5%	21.8%	48.0%	48.8%	46.9%	43.0%	44.0%	Income Tax Rate	47.0%
	10.2%	10.3%	8.9%	8.1%	7.6%	7.0%	3.2%	6.8%	7.1%	6.7%	2.8%	3.0%	Net Income Margin	5.2%
	232.0	231.7	287.5	344.8	284.3	317.0	281.2	615.6	790.9	756.5	750	740	Funded Debt ($mill)	700
	7409.6	8030.1	8514.5	9048.3	9547.7	10020	9680.3	10650	11509	12391	12235	12250	Net Worth ($mill)	15050
	3651.0	3684.9	3608.0	4008.4	4230.3	4352.1	3010.5	4530.4	5564.8	6196.9	5600	5350	Working Cap'l ($mill)	7850
	23.4%	26.5%	21.1%	18.0%	18.1%	17.1%	6.3%	18.2%	18.8%	19.4%	7.0%	8.5%	% Earned Net Worth	17.5%
	74%	71%	73%	67%	72%	73%	162%	51%	59%	63%	115%	97%	% All Div'ds to Net Inc	67%

ANNUAL RATES of change (per sh)	Past 10 Yrs	Past 5 Yrs	Est '71-'73 to '77-'79
Sales	8.0%	8.5%	8.0%
"Cash Flow"	6.0%	5.0%	4.0%
Earnings	5.5%	5.0%	3.0%
Book Value	5.5%	5.0%	3.0%

CURRENT POSITION ($mill.)	1971	1972	12/31/73
Cash Assets	3317.0	2946.9	3046.1
Receivables	2724.2	2806.2	3082.5
Inventory (FIFO)	3991.6	4200.2	5176.9
Other	478.8	585.2	861.0
Current Assets	10511.6	10538.5	12166.5
Accts Payable	2206.3	2469.8	3275.7
Debt Due	—	—	—
Other	3774.9	2504.0	2693.9
Current Liab'ties	5981.2	4973.8	5969.6

CAPITAL STRUCTURE as of 12/31/73

Debt $756.5 mill. Interest $63.0 mill. Includes $371.3 mill. debt of foreign subsidiaries.

Pension Liab'ty $4.1 billion

Pfd Stock $283.6 mill. Pfd Div $12.9 mill. 1,000,000 shs. $3.75 cum. ($100 stated value) 1,835,644 shs. $5.00 cum. ($100 stated value)

Common Stock 285,730,153 shares

Calendar	QUARTERLY SALES ($ Millions) Mar. 31	June 30	Sept. 30	Dec. 31	Full Year
1971	7780	7592	5624	7268	28264
1972	7760	8457	5378	8820	30435
1973	9569	9606	7608	9015	35798
1974	6939	8277	6938	*8446*	*30600*
1975	*7700*	*9000*	*7500*	*10000*	*34200*

Calendar	EARNINGS AS REPORTED (per sh) Mar. 31	June 30	Sept. 30	Dec. 31	(A) Full Year
1971	2.12	1.97	.75	1.88	6.72
1972	2.26	2.52	.41	2.32	7.51
1973	2.84	2.78	.92	1.80	8.34
1974	.41	1.05	.05	*1.44*	*2.95*
1975	*.40*	*1.00*	*.40*	*1.70*	*3.50*

Calendar	QUARTERLY DIVIDENDS PAID Mar. 31	June 30	Sept. 30	Dec. 31	(B) Full Year
1971	.85	.85	.85	.85	3.40
1972	.85	1.10	.85	1.65	4.45
1973	.85	1.20	.85	2.35	5.25
1974	.85	.85	.85	.85	3.40
1975					

BUSINESS: General Motors is the world's largest automobile manufacturer. 1973 output was 54.4% of U.S. total. Automotive products account for 94% of sales. Also makes Chevrolet and GMC trucks; Frigidaire and Delco appliances; GM diesel locomotives and engines. Operates manufacturing and assembly plants in 17 foreign countries which make Vauxhall cars, Bedford trucks, and Opel and Holden cars and trucks. Foreign business acounts for about 16%, labor costs, 34% of 1973 sales. Has 811,000 employees, 1,306,000 stkhldrs. Insiders own 1% of stock. Chrmn.: T.A. Murphy. Pres.: E.B. Estes. Inc.: Del. Address: 3044 W. Grand Blvd., Detroit, MI 48202.

GM's yield is high, but is it secure? The $3.40 regular annual dividend was probably not earned last year and this may be the case through most of 1975 as well. Furthermore, the corporation's cash position is deteriorating as "cash flow" falls short of outlays for capital improvements, tooling, and dividends. Such a scenario would normally put the dividend in question. GM, though, has the means (and the borrowing power, if necessary) to maintain the payout for several quarters even if it exceeds earnings — as it did in the strike year of 1970. Its overall cash position (see table below) is the best by far of all the auto manufacturers. We believe a cut would come only if the directors were convinced that there was going to be a long-term reduction in the corporation's basic earning power. If industry and corporate prospects turn up later this year (see below), there would be no grounds for such an opinion. Accordingly, we think the dividend will hold.

The number one auto maker probably ended 1974 on a weak note. In addition to soft retail demand, factory auto sales also suffered by comparison with the prior year when output was accelerated to build dealer inventories in anticipation of a strike.

Earnings may remain depressed for a time. Domestic auto production in the first quarter is currently scheduled at about the year-earlier level reflecting the company's belief that retail demand will remain weak.

Some improvement is possible after midyear. Auto buyers (such as they are) have given a good reception to the company's new small car offerings. This may augur well for the luxury small car slated for a Spring introduction. In addition, its full-size cars, especially the luxury lines, have been returning to favor since the ending of the oil embargo. (A new gasoline tax and/or rationing could quickly reverse this trend, however.) The corporation may well garner a bigger share of the larger auto market we envision for the closing months of the year and earnings could benefit accordingly. *M.S.*

CASH POSITION	5-Year Av'g	12/31/73
Current Assets to Current Liabilities:	203%	204%
Cash & Equiv's to Current Liab'ties:	47%	51%
Working Capital to Sales:	17%	17%

(A) Based on avg. shs. outstanding. (B) Next div'd meeting about Feb. 3. Goes ex about Feb. 7. Div'd payment dates: Mar. 10, June 10, Sept. 10, Dec. 10. ■ Div'd reinvestment plan available. (C) Excludes intangible assets; in '73, $38 mill., 13¢ a sh. (D) In millions, adjusted for stock splits and div'ds.