PRICE AGNOSTIC DEMAND *

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February 2026

Abstract

We document that investors lack conviction as to what the stock market price should be, absent seeing it. This is at odds with most asset pricing models, which assume that investors are uncertain about the future, but understand what the current market price should be and whether the actual price is different from this. Through experiments, we find that online participants, MBA students, and asset-management professionals who are provided with information about fundamentals are unable to identify extreme deviations from market prices. When directly asked, both asset-management professionals and LLM reasoning models do not think it is possible to use information to reliably estimate the level of the market within 10% without seeing the prevailing price. We document that professional return forecasts, published trading strategies, and investment advice are largely agnostic about the market price level. This suggests that return expectations are often formed, and many investment decisions are made, without conviction as to the prevailing market price level. We call this channel price agnostic demand. This represents a significant limit to arbitrage which can help explain a number of puzzling empirical patterns in asset prices such as why prices exhibit excess volatility and why markets appear inelastic.

*Hartzmark is with Boston College Carroll School of Management and the NBER, Sussman is with the Chicago Booth School of Business. We would like to thank Marianne Andries, Francesca Bastianello, Alex Chinco, Niels Gormsen, Eric So and David Solomon for helpful comments and seminar participants at the Briq Beliefs Workshop, Aalto, Boston College, Michigan State and the UCLA Conference on Financial Markets. We would also like to thank Jieyi Chen, Fiona Yang, and Trevor Haynes for excellent research assistance.

We might define an efficient market as one in which price is within a factor of 2 of value, i.e., the price is more than half of value and less than twice value... By this definition, I think almost all markets are efficient almost all of the time. -Fisher Black, AFA Presidential Address (1986)

Asset pricing theory all stems from one simple concept, derived in the first page of the first chapter of this book: price equals expected discounted payoff. -John Cochrane, Asset Pricing (2009)

I. Introduction

A cornerstone of almost every asset pricing model is that "price equals expected discounted payoff" (Cochrane (2009)). This idea implies a strong conviction about the level of the current market price. In these models, investors form beliefs about future uncertain variables (which vary by model). These beliefs serve as the basis of their understanding of the prevailing cash flow and discount rate information, which they use to understand the current market price and to form beliefs about future expected returns. If the actual market price differed from their expected price, this would strongly influence their perception of future returns and induce them to trade.

For example, assume that the S&P 500 is at 4,000.[1] Further assume that given the current information, an investor from your favorite asset pricing model thinks the market price one year later will be 4,200 meaning they expect a return of 5%. What would happen to such an investor if they were in the exact same situation, but the current price of the S&P 500 was 3,000?[2] With identical information, the investor would still predict that next year's price would be 4,200, which is a 40% return. Expecting a 40% return would induce investors to trade in accordance with this belief (which is why such a price would never occur in a world governed by these models).

While deriving that price equals expected discounted payoff is straightforward using return definitions, this does not mean that it captures how investors perceive the current price or how markets behave. What if investors lack conviction about what the current price of the market should be, consistent with the Fisher Black (1986) quote above? If so, it would be irrational for that investor to think that they would have that conviction in the next period. In this case, the idea of using fundamentals from your favorite asset pricing model to predict next period's price regardless of the current price would not be sensible. Such an investor's demand would be largely agnostic to the price level, implying that

[1] For ease of exposition, the example discusses the market level in index points. Throughout the paper, when we discuss the market level we mean the market value relative to prevailing fundamentals, such as the price to earnings ratio.

[2] We note in most standard rational models prices do not deviate from fundamentals, so such a price movement would be an off equilibrium outcome. The models do make predictions that investors would notice and respond to such an outcome if it ever did occur.

expectations of *changes* in the market price (i.e., return expectations) would be similar irrespective of the current market price. Returning to our example, such an investor would expect a return of about 5% in the setting where the S&P 500 is at 4,000 or 3,000. We call this behavior price agnostic demand: investors form return expectations and make portfolio decisions with little conviction about the prevailing market price. A key testable prediction for such price agnostic demand is that investors do not have strong conviction about the *current* correct level of the stock market.

There is little direct evidence to test this prediction though. Black was explicit about this, noting "I have not been able to think of any conventional empirical tests that would distinguish between my views and the views of others" (Black (1986)). Modern asset pricing has largely adopted frameworks that presume investors understand what the current price should be, but this does not appear to be based on evidence uncovered after Black's AFA address.[3] Distinguishing between these competing theories requires direct evidence on the plausibility of this assumption, evidence that, to date, remains scarce.

In this paper, we provide evidence that price agnostic demand represents an important channel for the aggregate stock market over annual horizons. Agents are unable to meaningfully identify extreme market mispricing and do not form return expectations based on it. When asked, neither sophisticated financial professionals nor current LLM models (e.g., ChatGpt o3, Claude) considered it possible to use economic information to determine the market price within 10% of its true value. Given that agents lack the ability to understand the price level and do not think they have this skill, return expectations will largely be agnostic. Professional return forecasts, and the discussion of financial markets by academics, the financial press, and influential investors are largely consistent with price agnostic demand. Our evidence suggests that investors generally exhibit extreme uncertainty as to what the *current* price of the market should be.[4]

Price agnostic demand can help explain excess volatility and why markets are inelastic. It is a significant limit to arbitrage and is consistent with the lack of predictability and lack of arbitrage capital invested in market timing strategies. It suggests a reinterpretation of the finding that cash flow news is largely unimportant for explaining market variation. Our results militate against rational discount rate variation (where investors ex-ante understand the discount rate) and suggest instead that a key driver is uncertainty as to what the appropriate level of the market should be.

[3]For example, to our knowledge Cochrane has never cited Black's AFA address to argue against it.

[4]Throughout the paper we use the term "should" to indicate belief about what the prevailing market price actually is, not whether philosophically they agree with it.

We find that price agnostic demand is an important mechanism, but this does not mean that other asset pricing channels are not also important or that market valuation does not play any role in investors' decisions. When we examine real world discussions of market levels in Section IV, we find that fundamentals still matter, but to a limited extent or in extreme circumstances. How best to incorporate this channel into a complete asset pricing model is beyond the scope of this paper.

The first hypothesis we test is that investors do not have the ability to recognize the prevailing market price accurately without seeing the price itself. Since we cannot manipulate the market, we try to emulate our motivating example in laboratory settings using participants from online pools (Prolific, CloudResearch, and Mturk), MBA students at the University of Chicago Booth School of Business, and participants at a meeting of one of the world's largest asset managers. Students at Booth and the asset manager sample represent a more sophisticated class of investors.

In our baseline experiment, we provide participants with a variety of data from a specific point in time.[5] We manipulate the level of the S&P 500 and the price to earnings ratio from -50% to 50% of the actual value. We explain this structure to participants, though we do not state the amount of price manipulation.

Participants' first task is to identify how much the displayed level of the stock market deviated from the actual value. We find that participants' perform poorly on this task. When faced with overpricing scenarios, with an average of 20% overpricing, the average perceived mispricing reported is 2.5%. When presented with underpricing scenarios, with an average of -20% mispricing, participants report -0.8% mispricing. Overall, participants struggle to identify economically meaningful deviations from actual market prices.

Perhaps sophisticated market participants have skill at such a task even though it is not apparent in their responses. Thus, we directly asked our sample of asset managers to report their confidence and beliefs about the task's feasibility. Overall, they reported low confidence in their predictions (on a six-point scale, nearly half chose the minimum, and most rated three or below). When directly asked, most thought it impossible to use data to understand the market's level within 10% without seeing it. The results suggest that even sophisticated market participants exhibit behavior consistent with price agnostic demand and think that market functions in this manner when directly asked.

We also ask participants to estimate what the level of the S&P 500 actually was 12 months after the snapshot of time presented to them (i.e., predict the future level of the S&P 500 relative to the date

[5]Specifically, the interest rate, inflation, volatility, prior economic growth and Fed forecasts of future economic growth. In robustness tests we also show prior returns, sentiment, P/D.

they are considering). If agents could perceive mispricing that they believed would correct over the next 12 months, there should be a strong inverse impact on expected returns based on the level of actual mispricing. Instead, similar to the results on elicitation of perceived mispricing, we see only a weakly negative relationship in the data.

While it appears that investors are unable to identify economically large shifts in the market price, there are a number of potential concerns, as with any lab-style experiment. One such concern is that participants might not have been meaningfully engaging with our experiment. While participants do not perceive price manipulations, we find they do respond to the displayed information. For example, when the displayed P/E ratio is above 40, respondents perceive the market to be overpriced by 9% and when it is below 15 they perceive -4% mispricing. This suggests that participants understand and engage with the task, and that the inability to detect mispricing is not due to inattention.

Our results could be due to the fact that we provide only a small subset of all possible information in the experiment. To test for robustness, we have run several variations which included a number of additional variables and find similar results. We further aim to mitigate this concern by focusing on large shifts in mispricing. Further, the asset managers do not state that additional data would make the task feasible.

Finally, we examine a variety of real world examples to show that investors commonly form return expectations that are largely consistent with price agnostic demand. Most discussions in the financial press, and among financial professionals and academics, express skepticism about understanding the level of the market (see Section IV). For example, when we asked ChatGPT o3 whether it was possible to know the level of the market based solely on economic fundamentals and its takeaway was "you might get lucky now and then, but you shouldn't bet on it."

We also examine published professional forecasts of expected returns. While asset pricing theory suggests that understanding the mechanisms underlying a variable's predictive power (e.g. cash flow, discount rate or mispricing) is key to understanding the current market and predictability of future returns, professional forecasts tend to focus only on historical correlations with predictors. Further, there is minimal conviction in the model's prediction. For example, in 2024, Vanguard's model suggested the market was 30% overpriced. This led it to shade down return expectations *slightly* and suggest no changes to investments.[6]

We note that this framework seems foreign when compared to asset pricing models, but is deeply

[6] https://corporate.vanguard.com/content/corporatesite/us/en/corp/articles/investment-economic-outlook-feb-2024.html

rooted in the psychology literature. This literature has found that humans find understanding levels very difficult and thus generally focus on changes (see Section V for a discussion). Thus, a market that responds strongly to changes in news, but struggles to understand what the proper level should actually be is consistent with the reasoning of the humans trading in it.

Our paper adds to literature using experimental methods to test assumptions and predictions of asset pricing models. For example, Chinco et al. (2022) show that while nearly all asset pricing models assume equity prices reflect investors desire to hedge risk factors, this is not something investors try to do. Andre et al. (2023) shows investors respond to news in ways difficult to explain with standard theory, and Choi and Robertson (2020) and Bender et al. (2022) describe how investors say they view asset prices. Our paper contributes to this literature by showing that investors lack conviction about fundamental based estimates of the market price and thus largely exhibit price agnostic demand. This provides direct evidence in support of the hypothesis of Black (1986) and the theoretical attempts to formalize such ideas (e.g. Adam and Marcet (2011) and Adam et al. (2016)).

This paper contributes to the literature on understanding price volatility in the stock market. Prior research has found that the market is excessively volatile compared to fundamentals (e.g. Shiller et al. (1981)) and, relatedly, that most price movements can be attributed to discount rate rather than cash flow variation (e.g. Cochrane (1992)). Explanations of this pattern focused on rational agents aware of time-varying discount rates, in other words "time variation in the reward for risk" (Cochrane (2009)). However, investors must understand the current market price based on relevant information to identify the current discount rate. Otherwise, such an investor would not be able to recognize the relevant "reward." Our results do not support this possibility. Given extreme uncertainty as to what the level of the market should be, our results instead suggest that there is a wide range of values that investors will treat as roughly equivalent.

Our paper therefore also contributes to the literature on market efficiency and arbitrage (e.g. Shleifer and Vishny (1997)). A lack of conviction as to what the appropriate level of the market price is suggests an unwillingness to trade based on perceptions of the current market price.[7] If market participants are unable to identify large deviations in market prices as influencing future returns, they would have no reason to trade based on their perceived level of mispricing. The assumption that prices are efficient is often motivated by the arbitrage mechanism of investors being willing to make

[7]While our focus is the overall market, Ben-David and Chinco (2024) examine equity analysts of individual firms and finds their forecasts are based on trailing P/E. Of course expectations should be formed based on the future, not the past, suggesting equity analysts similarly lack conviction on what the appropriate level of firm prices should be.

such trades. This suggests the level of the aggregate stock market is much less likely to be close to an efficient fundamental-based price than is typically assumed.

Finally, our paper adds to the recent debate on whether financial markets are inelastic (e.g. Gabaix and Koijen (2021), Hartzmark and Solomon (2021)). Textbook models largely leave trade unmodeled given an assumption that deep pocketed arbitrageurs will actively trade to correct any perceived mispricing. To do so, an arbitrageur must have a strong conviction that there is mispricing and that there is a profitable trade to be made in attempting to correct it. Our results suggest this is unlikely to be the case. If there is a wide range of prices that arbitrageurs are willing to be agnostic about, then when trade shifts prices, they will be unlikely to trade to correct it. Thus, price agnostic demand represents one potential mechanism leading to inelastic markets.

II. Price Agnostic Demand Framework

According to Campbell (2017), the stochastic discount factor approach "is the dominant approach in contemporary academic [asset pricing] research." Under this formulation, the market price today is:

$$P_t = \mathbb{E}_t[M_{t+1}\,(P_{t+1} + D_{t+1})] \tag{1}$$

where M_{t+1} is the stochastic discount factor. Cochrane (2017) argues that almost every asset pricing model is based on an SDF defined as:

$$M_{t+1} = \beta \left(\frac{C_t}{C_{t+1}}\right)^{-\gamma} Y_{t+1} \tag{2}$$

where different models posit different Y_{t+1} state variables that investors care about.

Investors in these models understand this structure and have expectations of the relevant variables. Once investors observe the state variables that govern cash flows and discount rates, they know what the market prices should be, even without observing them. It is a nearly universal assumption in asset pricing theories that investors have strong conviction about the appropriate level of prices given available information, and that observed prices reflect this.

In standard asset pricing models, conditioning on today's price is therefore innocuous. The price is already understood based on the relevant information about cash flows and discount rates, so observing the actual price is largely redundant. Under price agnostic demand, conditioning on the price is substantive. Investors treat the prevailing market price as a reference point rather than as an equi-

librium object they understand or expect to revert.

Such an approach only makes sense if investors think this is how the market typically works, meaning that they think at time $t+1$, this is how P_{t+1} will be set (and further into the future too). Thus, it would be logical for an investor to notice if the current price P_t was not consistent with underlying fundamentals. If this off-equilibrium outcome occurred, such an investor would have conviction that by $t+1$ such fundamentals would likely be priced correctly. This deviation from the expected benchmark would lead to significant variation in expected returns because such an investor had conviction about what they thought P_t should be, how it compared to what P_t actually was and how the price P_{t+1} would likely be consistent with the expected benchmark.

This assumption is by no means innocuous. The idea underlying these models is that ex-ante understood discount rate variation drives time variation in expected returns. This is because the variation in price levels reflects variation in compensation for holding a given risk. If investors lack conviction about whether the level of the market is appropriate, it becomes much less plausible that such shifts in price level would be recognized as ex-ante understood variation in expected returns. Further, if deviations from this price were not recognized, it is unclear why arbitrageurs would trade to ensure this actually was the prevailing market price.

To illustrate this intuition, we provide a simple example based on standard calibrations of the habit model Campbell and Cochrane (1999). Table 1 presents three scenarios that only vary in their surplus consumption ratio, a "normal" scenario, a "risk seeking" scenario, and a "crisis" scenario.[8] The first row shows that the valuation ratio reflects the ex-ante understood shifts in risk aversion. The P/D ratio is 22 in the normal scenario, 28 when investors are risk seeking and 12 in the crisis scenario. Investors understand that this variation in price level is being driven by variation in risk aversion and thus expect different compensation for holding risk. Expected returns reflect this as they are 6% in the normal scenario, 4% in the risk-seeking scenario, and 18% in the crisis scenario.

The second and third rows of the table show what an investor would expect if the current price was different than the price implied by the model. The second row shows what would happen if the current price was 25% above the model implied price, and the third row shows where the current price was 25% below. An investor who believes the world works according to the model would believe that P_{t+1} would be set according to the model. Thus, the expected return column reflects the belief that the mispricing would correct in the next year.

[8]The surplus consumption ratios are 0.057 for the normal scenario, 0.07 for the risk seeking scenario and 0.035 for the crisis scenario. Otherwise, the same standard calibration parameters are used across these three models.

The Table shows that the variation in expected returns induced by this mispricing is larger than the variation from our values of surplus consumption. In the normal scenario with a P/D of 22 the investor expects 6%. If instead an investor observed a P/D of 27.5 they would expect returns of -15.2% and if they observed a P/D of 16.5 they would expect returns of 41.3%. Thus in standard models, if the market price was different from what the model said it should be by 25%, an investor would know this and it would have an extreme effect on their expected future returns. This magnitude is economically large, if anything greater than the magnitude investors would be expected to recognize based on variation in proposed Y_{t+1}. Further, the most common justification for why the prevailing market price is equal to that implied by the model is that traders would trade strongly in response to these large expected returns.

The channel emphasized in this paper is that the core assumption of strong conviction regarding the appropriate price level is largely absent in the real world. We make this argument in three steps.

1. Investors largely lack the ability to identify the market price level (absent seeing the actual price).

2. Investors do not believe that they have the ability to identify the market price level absent seeing what it actually is. This is consistent with empirical evidence as well as reports from large language models.

3. Price agnostic demand: Investors' perceptions of what the level of the stock market should be, and whether the prevailing market price is significantly different from this, do not significantly influence return perceptions or trading decisions.

Classic asset pricing models assume 1) and 2) are false. If investors are rational, 3) price agnostic demand follows directly from either 1) or 2) being true. This is because rational investors in classic asset pricing models have the ability to understand the prevailing market price given information and have rational conviction in this ability.

If investors are irrational, price agnostic demand requires 2) to be true. For example, if 1) was true and 2) was false, investors would have conviction in understanding the market price even though rationally they lacked the skill. This would lead to trading based on conviction on the level of the market price, but the beliefs about what the price should be would be irrational. Thus for an irrational investor, 2) being false is a key aspect of their behavior being best characterized by 3), price agnostic demand.

If an investor knows that they cannot meaningfully understand P_t based on fundamentals, then it would be a very strange set of beliefs that make them think that at time $t+1$ they would be able to do so to understand P_{t+1}. Thus the wedge between their belief of what P_t should be compared to the actual prevailing market price will not have a large influence on expected returns in most situations. This is because they will struggle to have conviction of what the price level should be absent seeing it at time t, and they would not expect to have the ability to do so at time $t+1$.

Instead, we propose that return expectations and asset demand will largely take the prevailing market price as given and focus on expected returns from this price. Such an investor will likely think in terms of expected returns starting from the current price and will not focus strongly on fundamental based predictions of P_{t+1}.

There is ample evidence that expected returns are time varying, so price agnostic demand does not imply that investors do not pay attention to information when forming return expectations.[9] Thus, investors with price agnostic demand use the current information to form their expectations of future returns but accept the prevailing market price as the appropriate starting point.

We note that this is one way in which the price level can influence return expectations. For example, professional return forecasts often use aspects of the current price level, such as price to earnings, as part of their return forecast. Models suggest that investors understand the level of a given valuation ratio separately based on cash flow, discount rate or mispricing channels. As discussed in Section V, this usage is in practice an agnostic empirical exercise that makes no such differentiation and lacks conviction. While price levels are not ignored, real world behavior appears closer to price agnostic demand, rather than the strong conviction implied by models.

In a standard rational asset pricing framework, predicting returns or prices is an identical task mathematically. Thus, the argument that investors focus on returns relative to a status quo price might strike some readers as exactly what standard models predict. However, if return forecasts are not strongly influenced by a conviction of what level the market should be, then price based forecasts and price agnostic return forecasts may in practice be quite different. Understanding how an investing problem is framed and perceived is a fundamental component of understanding what investors are doing and how prices are moving.

While price agnostic demand is inconsistent with the predictions of modern asset pricing models,

[9] If returns were constant, this would yield a random walk prediction. Random walk logic is typically justified due to the fact that extreme efficiency means that there is no reason to try to predict returns. In this case, the same prediction stems from the opposite extreme in which an investor would be totally agnostic about what a reasonable price level would be, though from a different motivation than the traditional random walk view.

it can be motivated using channels discussed in other contexts. For example, given the long duration of equity cash flows, relatively small levels of parameter uncertainty can induce significant uncertainty over the current price level, even in a model as simple as a Gordon growth model. Similarly, perhaps agents believe that markets can be mispriced, but they lack certainty about the level of that mispricing, or have extreme uncertainty about what model is relevant for understanding asset prices.[10] While such channels are not novel on their own, the implications related to price agnostic demand have not been emphasized. Further, if such beliefs are rational, price agnostic demand need not be irrational.

This paper stops short of formalizing the specific mechanism of price agnostic demand. Each of the mechanisms discussed above is likely important to some degree. Further research is needed to understand which mechanism is most relevant and thus how best to formally model it. Moreover, price agnostic demand is one channel that influences asset prices, but this does not mean that other mechanisms are not also at work (see Section IV for further discussion). Our paper demonstrates that price agnostic demand is an important attribute missing in asset pricing models. We leave it to future research to explore how best to micro-found this concept, formalize the model, and incorporate other important channels.

III. Experimental Evidence

Perhaps the most stark testable prediction from price agnostic demand relative to standard models is that under price agnostic demand, investors are assumed to be uncertain about what the current market price should be. Thus, our baseline experiment evaluates whether people can identify deviations from the market price and whether this influences their perception of returns. We find that actual mispricing has only a small effect on the perception of mispricing.

A. Participants

Across studies reported here, we recruited participants (N=884) from three separate populations. We recruited 793 participants through online platforms (including Prolific Academic, CloudConnect and Amazon's Mechanical Turk). Appendix Table A.2 shows basic demographic information. In addition, we recruited 60 MBA students from the Booth School of Business and 31 visitors to an event hosted by a deep pocketed asset manager.

[10] One relatively straightforward tweak to standard asset pricing models would be if agents were certain about the level of mispricing, but thought it would correct over a long time-horizon. In this case the expected returns over an annual horizon would be similar to the equilibrium predictions.

B. Experimental Design

Our goal was to design a setting in which participants were given the best opportunity to understand the current level of the stock market grounded in information that should be relevant based on standard models, professional forecasts, and economic intuition. We then wanted to see if people were able to identify when a displayed market level was significantly different from the value that actually occurred at a given point in time. See Appendix A for full text of the treatment.

We began by randomly choosing days between 1971 and 2021. We wanted to use actual dates with actual data to avoid having to specify a model to generate data.[11] By doing so we can be agnostic as to how asset markets actually work or should work.

In our baseline treatment we displayed the interest rate, inflation, prior year's economic growth, the Fed economic growth forecast, the level of the S&P 500, the market price-to-earnings ratio, and volatility (the VIX). Participants were provided with the historical average and range for each of these values from 1971 to 2021, as well as the value for each trial. Participants were informed, accurately, that the value presented for each trial was the actual value from the selected day. Our goal in selecting these variables was to provide commonly discussed and presented statistics that could plausibly be used for our task. Some of these variables are also directly relevant in many asset pricing models, or at least tangentially related to certain state variables. We think these variables represent the most commonly discussed variables for such a task and are often a component of professional projections of future returns.

There are of course other variables that could be included. In further experiments, we included various sentiment measures and lagged market returns. In another specification, we present the price-to-dividend ratio instead of price-to-earnings. Our variable of interest is in such multipliers, not the index level (which is a cosmetic value), so in another we include only the price-to-earnings and omit the level of the S&P 500.[12] Internet appendix A contains complete details on the subtle changes relative to the baseline for each of these treatments.[13]

In each version of the study, the values for the S&P 500 index and the market price to earnings ratio could be different from those that actually occurred. These values could be the level that actually

[11] If participants were unable to detect mispricing relative to model generated data, this could simply reflect that they had a different model of how the world worked than the one we chose.

[12] We include the index level as it is commonly discussed and helpful for our question asking about the future market level.

[13] Each of these variations was pre-registered on aspredicted.org. See aspredicted #s 229411, 228841, 228696, and 228083. The baseline treatment, and the treatments with the MBA students and the Financial Advisors were not pre-registered.

occurred on that day, or they could be higher or lower by up to 50%. For each day, we randomly select a number X% between 5% and 50%. One-third of participants viewed the actual value, one-third viewed values higher by X% and one-third viewed values lower by X%. Participants were told that the market value and associated price-to-earnings ratio could be the same, higher, or lower than what actually occurred.

We provided intuitive definitions for all terms along with historical ranges to help participants interpret these values. We required all participants to pass comprehension checks on economic concepts and on the experimental structure for them to be included in the experiment.

Once participants finished the instructions and passed comprehension checks, they were shown the first scenario. They were asked "Considering the metrics above, do you believe that the S&P 500 Index Level and PE Ratio reflect levels that are higher, lower, or the same as the actual index level and PE Ratios from the date displayed in the table?" A slider was displayed below where subjects could select values from -50% to 50%. After this, participants were asked what they thought the value of the S&P 500 actually was 12 months later.

C. Design Choices

In this section, we discuss why we designed the experiment as we did, and why we believe this design provides meaningful and interpretable responses. A primary goal of the experimental design is to make it as easy as possible for participants to identify mispricing when it occurs. In other words, we aim to provide a conservative test. Therefore, in all of our settings, we examine mispricing of at least 5% and in most cases significantly more extreme. Thus, the main conclusions from this experiment will depend on the ability of investors to determine the true price based on major shifts from the true price rather than on subtle variations. Further, we aim to provide participants with only the most relevant information rather than distracting them with additional statistics that are less likely to be first order important in determining the price.

We note that while we attempt to make this task as easy as possible, that does not mean that the task is possible. According to asset pricing models, this task should be relatively straightforward with the relevant information set. On the other hand, if investors are rationally price agnostic, this task should not be feasible with any attainable information set. Thus, just because our task aims to make this as easy as possible for an investor who would naturally be able to do it, if investors are price agnostic they will not demonstrate significant ability to complete it accurately.

One concern about this experiment, particularly with an unsophisticated population, is that we are asking participants questions that they may be unable to answer due to confusion around the task itself (Bergman et al., 2020). To help address this concern, we provide participants with intuitive definitions of each of the key terms along with reading checks to ensure that participants understand the key concepts and task. Further, we ask participants to rate their confidence in their responses, finding that results are largely robust to examining only participants reporting high confidence.[14] Importantly, we also test whether the same patterns emerge across investors with varying degrees of sophistication and find that they do.

In addition, we analyze patterns in participants' responses that could be used to indicate that they are internally coherent and indicative of an understanding of the task. For example, we find that the displayed price to earnings ratio serves as an input into evaluations of mispricing. We view weighting of this metric as a signal of general task understanding and attention to the metrics displayed.

Another common concern in the case of direct questioning is that of experimenter demand (Bergman et al., 2020). In other words, participants may be providing responses that they think the person designing the survey wants them to give rather than reporting their true beliefs. We largely circumvent this issue by being upfront in the survey instructions, making participants aware of the set of possible responses, and aligning the experimenter's goals with that of the survey-taker. In each case, the clear goal is to try to identify whether mispricing occurs, and if so, how much.

Finally, as with any experimental design, the task may be flawed for some unknown reason. Thus, for our sophisticated asset manager sample, we directly ask them a more general question about their ability to determine market price as a function of fundamentals, outside of this experimental context.[15] Specifically we ask:

> *Do you believe that it is possible for investors to use information on economic fundamentals from a given day to determine the market price on that day within 10% of the true value?*

If the design of the experiment is fundamentally flawed, but in the real world the task is straightforward, these respondents should be able to let us know this by answering yes. This would tell us that in the real world, these sophisticated investors think they can accomplish the task we are attempting to emulate in the lab.

[14] See Appendix Table B.2.

[15] We introduced this question for the sophisticated asset manager sample as they seem to be the sample that could confidently and meaningfully answer it. In subsequent studies, we also asked the online samples the question.

D. Experimental Results: Ability to Identify Price Level

D.1 Baseline Results

We begin by examining whether or not people were able to use the information to understand the prevailing market price. We find that people were only able to do so to an extremely limited extent.

Figure 1 shows the main result across all populations and treatments. The left of the figure shows the actual average level of mispricing presented to participants. The maroon bar shows that when the market was underpriced, on average it was underpriced by about -20%. The blue bar shows that when it was overpriced, it was overpriced by about 20%.

The right three bars show that perceptions were not particularly close to this reality. The perceived level in the low state was -0.76%. This is about 19 percentage points higher than the actual, with a t-statistic on the difference of -43.75. The perceived level of mispricing when there was no mispricing was slightly above zero at 0.89%, with a t-statistic on the difference of 2.14. When there was positive mispricing the perceived level was 2.49%, with a t-statistic on the difference of 42.03. The order of these three bars is monotonic, which is consistent with some skill at this task and also consistent with responding logically to the experimental environment. Overall, participants miss the majority of the mispricing that they are exposed to.

Table 2 explores this more formally using a variety of measures of accuracy. We first ask whether people can accurately detect the direction of the mispricing. We count an answer as directionally correct if they indicate a positive number for positive mispricing, a negative number for negative mispricing or zero for no mispricing. The first row shows that the correct direction is guessed 35% of the time. This is better than random guesses, which would yield 33% correct answers (with a t-stat relative to random of 2.49), but not particularly close to being perfectly accurate (with a t-statistic on the difference relative to being accurate (i.e. 100%) of 118). The next row shows perceived mispricing, which is the same as in Figure 1. Participants do increase their perceived prices monotonically, moving from low to none to high, but not nearly to the extent that they should.

Next, we examine the forecast error. The row shows that when mispricing is too low (with an actual average mispricing of -20%), perceived mispricing is too high by about 19 percentage points. When mispricing is positive, perceived mispricing is too low by about 18 percentage points. The none column is only marginally different from zero at about one percentage point.

We finally turn to the absolute value of errors. The average absolute value is about 23 and is fairly

consistent across the three columns, though slightly lower for the no mispricing situation. This shows that guesses are not particularly responsive to the actual level of mispricing, regardless of the scenario.

Next, we explore how perceptions of mispricing varied with actual levels of mispricing. Figure 2 shows a scatterplot of the perceived mispricing relative to the actual level of mispricing. The perceived mispricing is the average level of mispricing for a given day with a given level of mispricing. There is indeed a slight positive trend in these dots, but it is fairly moderate compared to accurately identifying mispricing (shown by the gray 45 degree line). Thus, the graph again illustrates that people are not particularly sensitive to the induced mispricing.

Table 3 explores this sensitivity more formally by regressing perceived mispricing on actual mispricing. The first column runs this regression without controls and shows a coefficient of 0.071. This is positive and statistically significant, consistent with some responsiveness to mispricing. With that said, this number is closer to zero than it is to one (if mispricing were perfectly reported). The next column adds a person fixed effect and find a similar coefficient of 0.068. Next, we put in a fixed effect for a given date. This holds fixed the fundamental information displayed on that date. The coefficient remains similar at 0.072. The final column includes both and again finds a similar result. The results suggest that while participants can detect some mispricing, they miss the majority of it.

One potential explanation is that this is driven by the less sophisticated respondents online which obfuscates the skill in this task from the Booth MBA students or the sophisticated asset managers. Table 4 repeats the summary stats analysis separately by participant type. The online sample in our baseline treatment guesses correctly 35% of the time. The MBA students do not appear notably better than online participants, guessing correctly 36% of the time. Looking at errors, if anything the MBAs are slightly worse with higher absolute errors of 25.6, compared to 23.3 for the online sample.

While the MBAs display no evidence of skill, the deep pocketed asset managers do slightly better at this task than either of the other groups. They are correct 38% of the time, and they have absolute errors of 20.8. Thus, it appears that they are able to do this task with more precision than either of the other subject groups. Table 5 repeats this analysis and finds a similar pattern. The online samples and MBA students have a coefficient on actual mispricing of around 0.08 with fixed effects, but the asset managers are more responsive with a coefficient of 0.17.

These results suggest that more sophisticated participants are able to use the data in our task more effectively and respond to it.[16] However, even these experts struggle to respond meaningfully to large

[16]One potential source of this skill among asset managers is the ability to identify and recall details from the date refer-

swings in mispricing. While they do better, they remain much closer to missing all mispricing than they do to being able to identify it all. There is no evidence that these experts would meaningfully understand the market price without seeing it first.

While we think the choice of variables displayed in our baseline treatment provides an effective test of agent's ability to identify prices, there are other reasonable ways that we could have designed the task. The final four columns of Table 4 and Table 5 show results for these variants. Our baseline treatment includes the level of the S&P 500 to facilitate asking about next year's level, but ignoring this question there is no need to include this variable which could potentially have been distracting for participants. Thus, Column 4 displays results for a version where only P/E, but not the level of the S&P 500 is displayed. An alternative measure of cash flows is dividends, so Column 5 replaces earnings with dividends. Recent market movements could provide information to investors and also have been shown to be important for decision making (e.g. Greenwood and Shleifer (2014)), so column 6 includes returns over the prior year. Finally, we include measures of consumer sentiment (Michigan Survey) and investor sentiment (Baker and Wurgler (2006); Baker and Wurgler (2007)).

Participants do similarly when they see only the P/E ratio (without the level of the S&P) or when they see P/D instead of P/E. The worst performance is from subjects who see the past return. Participants who see sentiment measures do slightly better. While there is some variation across subject pools and variables displayed, the overall conclusion is the same throughout.

D.2 Expected Returns

While our experiment induces mispricing and asks participants to identify it, this is a somewhat non-standard task. In the real world, participants would be more likely to focus on what they expect market performance to be. Thus, in this section we ask about expected returns.

To do so, we ask what people expect the level of the market actually was 12 months in the future relative to the data shown. We use this estimate to calculate expected returns. The answer to this question should include both the expected returns relative to economic fundamentals, but also the correction of the induced mispricing. Thus we directly test the mechanism assumed to keep markets efficient, namely that if mispricing were ever to exist, investors would recognize this. Otherwise, they could not engage in trade to correct it.

enced, as they may have been trading during this period. Such a recall "skill" is not what we are trying to capture and would not translate into real world settings. We think it likely that this sample has more actual skill, but perhaps also a better recall and unfortunately we cannot directly disentangle the two in this treatment.

Figure 3 shows how expected returns vary with actual mispricing.[17] As in Figure 2, there is a subtle, but minimal, influence of induced mispricing. There is a negative slope to the dots, but to a degree that is only a fraction of the induced mispricing. If you knew that the displayed market price was manipulated to be 40% lower and that it would correct in the next 12 months, you should expect returns of nearly 100% the following year relative to the displayed price. Actual expectations with such extreme mispricing are closer to 0%.

Table 6 shows how expected returns vary with displayed mispricing. Consistent with the figure, the coefficients are negative, but small in magnitude at roughly -0.05. This means that if the market were overpriced by 25% (based on which return expectations should be greater than 20%), expected returns would be about 1.25 percentage points lower than they would be otherwise. Mispricing influences return expectations, but only very slightly.

D.3 Responsiveness to other variables

The results are consistent with respondents having only a small amount of skill at detecting mispricing. One potential concern is that respondents simply were not paying attention to the experiment and ignoring or failing to understand the information presented to them. If this were the case, our setting would not provide meaningful information towards our question of interest. Thus, we next turn to see whether there were meaningful differences in responding to the variables that were displayed.

Before turning to the specific variables, we examine variation in mispricing by day in Figure 5. Recall that each day had a specific X drawn where some subjects saw the price increased by X% (the blue dots), some decreased by X% (the maroon dots) and some saw the actual value (the green dots). Each X is unique, so each column of 3 dots shows perceived mispricing where all of the economic fundamentals displayed were the same (other than price and P/E). The range of the clusters should spread significantly as X increases, where the X of about 45 should have a range of about 90 from high to low. This pattern is only weakly apparent. What is clear from this figure is that there was clustering by date. The dots all tend to be higher or lower in terms of perceived mispricing for a given set of economic fundamentals. This is consistent with participants responding to the displayed fundamentals, but lacking significant ability to identify induced mispricing.

We explore the price to earnings ratio further in Figure 5. The table graphs the average response

[17] Asking about the actual future price index using a free response text box allows us to capture the correction of mispricing, but induces significant noise. Thus, we winsorize our results at the 10% level, which results in ranges from -64% to 157%. Appendix Figures B.1 shows results for a wide range of different levels of winsorizing.

for the perception of mispricing for a given level of P/E ratio displayed. The chart shows a strong positive relationship. As the P/E ratio increased, so did perceived mispricing. When the P/E ratio displayed was in the teens, perceived mispricing was around -5%. When the P/E ratio was above 40, perceived mispricing was above 10%. Appendix Table B.3 shows regressions for all of the displayed variables and suggests a general responsiveness to them.

This suggests that respondents were paying attention to the experiment and responding to the P/E ratio. Further, looking at the spread of dots it is clear that they were responding to the displayed P/E ratio, but unable to detect most of the induced mispricing. Altogether, the results suggest that participants were paying attention and responding to the numbers that were being displayed to them. In spite of this responsiveness, they were unable to detect the majority of the induced mispricing.

Next we ask how future perceived returns were influenced by the displayed variables. We find that displayed P/E continues to strongly negatively predict future returns as does the level of the market. Inflation and the risk free rate are also positively associated with expected returns.

Figure 5 Panel B shows expected returns relative to the displayed price to earnings ratio. There is a strong pattern from the top left to bottom right. When P/E is quite low, expected returns average in the teens. When it is quite high, expected returns move to slightly negative. Appendix Table B.4 repeats the regressions for each displayed variable.

These base results are consistent with participants paying attention to the information being displayed and responding to it. The information influences both perceptions of mispricing and expectations of future returns.

Another concern is that agents are able to identify mispricing, but that some of the mispricing in our setting is too subtle to observe. Before empirically addressing this concern, we highlight that the minimum level of mispricing in our setting is 5%. This minimum level is economically significant. If investors can perceive extreme mispricing, but levels such as 5% are not sufficiently extreme as to be detectable, this would have significant ramifications for asset pricing models. Repeating the analysis only for observations where mispricing is greater than 20% in absolute value yields similar results.[18]

D.4 Asking About Direction with Fixed 25% Mispricing

Perhaps agents struggle to understand the magnitude of mispricing, but are able to perceive its direction. For example, agents may miss nuance, but correctly identify that the setting with 25% mispricing

[18]The coefficient is about 0.06. See Appendix Table B.1.

is overpriced and -25% mispricing is underpriced. Perhaps the continuous variation in our baseline treatment was confusing and obfuscated this ability.

We ran a separate experiment where the price could be the actual price, 25% higher or 25% lower. Participants on Amazon Mechanical Turk were instructed this was the case. After seeing a given scenario subjects were simply asked if the displayed price was the true price, manipulated too high or manipulated too low. Table 8 shows generally similar results to the baseline. Guessing at random would yield correct guesses 1/3 of the time. In this simple setting subjects improve upon this accuracy by being correct 36% of the time (t-stat of equal to 1/3 of 2.01). The results are generally similar to what we find in our baseline treatment.

E. Experimental Results: Belief in the Ability to Identify Price Level

The prior results demonstrate that participants lack the skill to perceive significant mispricing. Even if this is broadly the case, it could be that investors do not exhibit price agnostic demand if they irrationally think that they had such a skill. In such a scenario, agents would trade on perceived mispricing (the gap between the prevailing price and what they thought it should be), even if this perception was incorrect.

Thus in this section we examine evidence related to investors' perception of their ability to idenitfy mispricing. We find results consistent with their displayed skill. Through their decisions, or when directly asked, investors do not think they have high precision at identifying price gaps that will close over the annual horizon.

E.1 Perceived Mispricing and Expected Returns

If participants in our experiment had strong conviction in their perceptions of mispricing, this should have had a strong influence on reported return expectations. For example, our largest manipulation was 45% for December 1991. The true realized annual return after this date was 12%. If an investor had this expected return, but viewed the price manipulated down by 45% they should report return expectations of 102% and if they saw the price manipulated up by 45% they should report a return of -22%. For the full sample, regressing the realized returns from the displayed price over the next year (the manipulated price to the true price 12 months later) yields a coefficient of -1.25.

When we examine how expected returns varies with individual level *perceptions* of mispricing, we find a much weaker relationship. Table 7 regresses expected returns on perceived mispricing. We find a statistically significant negative coefficient, meaning that when participants perceived market

prices to be too high, they expected lower future returns. After including date and individual fixed effects, we find a coefficient of -0.20 on perceived mispricing. If participants had high confidence in their ability to identify mispricing, we would expect this number to be about five times more negative.

This is consistent with the displayed skill of our participants. Perceived mispricing is not totally uninformative, but is closer to that than to strong conviction in this belief. This finding suggests that participants believe their skill to be limited at this task which is reflected in their return expectations.

E.2 Direct Reporting

We designed our experiments with the goal of giving participants the best chance at meaningfully responding to induced mispricing, if it were possible for them to do so. While we find minimal skill at this task and return expectations with a lack of conviction in their skill, it is possible that this reflects poor design of the task itself.

An alternative strategy to understand participants' conviction in their own ability to complete this task is to ask them directly what they believe this confidence to be. Thus for the sophisticated asset manager sample, we asked:

> *Do you believe that it is possible for investors to use information on economic fundamentals from a given day to determine the market price on that day within 10% of the true value?*

Most of the asset managers (68%) responded that this was not possible. Thus using this alternative fraemwork we largely replicate our prior results. This suggests the prior results did not simply reflect a task was poorly designed. This suggests that the responses reflect the fact that investors lack the skill to know the level of the market without seeing it and understand this to be true.

Finally, for those who thought it was possible, we wanted to know whether the information we provided was sufficient. Indeed, if we designed the task well, but did not give the requisite statistics, this could explain our results as well. Thus, those who said the task was possible we asked:

> *Do you believe that the information on economic fundamentals provided in this survey (risk-free rate, inflation, prior GDP growth, expected GDP growth and volatility) were sufficient to determine the market price within 10% of the true value?*

90% of these respondents said yes. Thus, it is not obvious that there was more data that we could have provided for more accurate responses.[19]

[19] We did not include a direct elicitation question in our initial surveys as we did not think the responses of a lay population

We also asked the asset managers:

> *How confident are you that your answers to the question on the prior pages identifying the level of mispricing were correct?*

The most common answer, 45% of responses, was one, the lowest level of confidence on a one-to-six scale. 74% of responses were three or below and only one respondent indicated high confidence of 6.

This sample is comprised of deep pocketed, sophisticated asset managers familiar with financial data and financial markets. The fact that most of these respondents do not think it is possible to use fundamentals to understand the current level of the market suggests that our asset pricing models are missing a fundamental aspect of how financial markets function.

IV. Real World Evidence

Previously, we asked investors whether they believed it was possible to use information on economic fundamentals to determine the market price accurately, concluding that most did not. This section explores sources of information that are accessible to investors, asking whether these sources exhibit the strong conviction about market price levels implied by standard asset-pricing models. First, echoing the study presented above, we identify how current large language models (LLMs) respond to a question about the feasibility of using economic fundamentals to determine the market price. Next, we explore information commonly provided to investors, as well as discussions and forecasts of financial markets that appear in a broader range of financial outlets. We find little evidence that these information sources express confidence in market price levels.

A. ChatGPT

We explicitly ask large language models whether they deem it possible to use economic fundamentals to get within 10% of the market level without seeing the price, similar to the question we asked the asset managers. We believe that this response is reflective of the broader information environment, since LLMs leverage a wide range of online data sources in forming their response.

Specifically, in May of 2025 we gave ChatGPT o3 the following query: "Let's say you didn't know the prevailing level of the stock market (e.g. the current level of the S&P 500 or the total market capitalization of all publicly traded stocks, or the price to earnings ratio). Further assume you had access

would offer compelling evidence about the general feasibility of the task. In follow up surveys we did and found they were more likely to say the task was feasible (61%). However, most thought additional information was required and they did not know what that information was.

to the prevailing economic data at the time, such as is commonly displayed in the wall street journal. Do you think you could take the data on economic fundamentals and guess what the prevailing market level actually is within 10% of its true value?" ChatGPT concluded that with "no peek at today's tape—the honest answer is: **you might get lucky now and then, but you shouldn't bet on it**" (emphasis in original). ChatGPT's response remained largely unchanged after prompting it to consider using "any other data source that you can think of."

We asked Claude the same prompts and received similar answers.[20] It is worth noting that these responses do not suggest a limitation of current LLMs that would be likely to improve as LLMs evolve. Instead, they speak to the overall infeasibility of the task irrespective of computational power or analytic ability. This mirrors the views of sophisticated asset managers reported in Section III.E and is consistent with price agnostic demand.

B. Field Evidence

Finance theory suggests three broad concepts that must be understood to identify the current level of the stock market without seeing it. First cash-flow information, second (rational) discount rate information, and third, behavioral bias or market frictions. Each channel likely influences prices and expected returns in distinct ways. Thus asset-pricing theory assumes such information is sufficiently well understood that investors can infer the market's level and respond to deviations.

For the first two channels, this information should be well understood by market participants (see Chinco et al. (2022) for a discussion). For example, assume cash flow news leads valuation ratios to be higher. In such a scenario, the price has increased because investors understand this news, and it should not predict higher risk adjusted returns going forward. Of course, asset pricing claims that most market movements are due to discount rate variation. Here, current prices fluctuate, leading to fluctuation in expected returns to compensate participants for holding ex-ante understood risk. If this represents how asset markets are actually understood and function, then we should observe statements about each channel and tools for understanding each, and guidance on using these to understand the level of the market.

We next examine professional market forecasts. Across a wide range of institutions, forecasts of market returns rely primarily on historical correlations between returns and predictors rather than on attempts to infer the current market level from fundamentals. Even when valuation benchmarks are invoked, they typically lead to modest adjustments in long-horizon expected returns rather than

[20] The full response from ChatGPT and Claude is shown in Appendix C

strong predictions of near-term price corrections.

We examined market forecasting reports from 10 large firms. We examined five firms making short term forecasts of approximately one year and five firms making longer term, generally 10 year, forecasts. Our goal was not to be exhaustive, but to find a somewhat representative sample covering common techniques. Appendix Table B.5 shows a summary of the short term forecasts and Appendix Table B.6 shows a summary for long term forecasts. We found that each one was best approximated by a price agnostic investor, rather than an investor with strong conviction about the prevailing market price level.

The one year forecasts we saw were typically largely based on narratives, not specific model predictions. Many were based on specific predictions of events (e.g. future Fed rate cuts, or how "animal spirits" would shift in the coming year). Each of these were consistent with price agnostic demand in that they began with the level of the market, and then based on such predictions formed return estimates.

The longer term estimates, of annual returns over the next 10 years, were largely model based. Some were simple regression based estimates of returns (e.g. Goldman Sachs) and some used a "building block" approach, calibrating model parameters based on historical data and then using these to estimate each building block and estimate returns. Each of these largely takes the current level of the market as given and then estimates returns from this baseline based on historical relationships.

The one example we found that explicitly attempts to model what the market level should be is Vanguard's 2024 capital markets outlook. Despite estimating that U.S. equities were approximately 30% above the level implied by their valuation framework, Vanguard reduced expected returns only slightly and explicitly cautioned against market timing. They state that "while valuations are undoubtedly high right now, that doesn't mean they can't go higher in the near term."[21] If investors had strong conviction that the market was mispriced by this magnitude and expected correction over an annual horizon, standard models would imply sharply negative expected returns and substantial reallocation. Instead, the response is consistent with treating the prevailing market price as a given and shading return expectations modestly.

In our price agnostic framework, this is consistent with an investor who is price agnostic because while they think the current market price is higher than what their model predicts, they think their model has only weak predictability for time $t + 1$. Such an investor largely takes the market price as

[21] They continue "They are not a market-timing tool. And even over extended periods, valuations are not infallible predictors of outperformance or underperformance."

given, though he does predict subtle variation in returns based on market levels. Consistent with such a largely price agnostic investor, Vanguard does "not encourage investors to make drastic changes to their asset allocation."

Goldman Sachs' is a more representative example and is quite transparent that it forecasts returns based on regressions of historical returns on valuation and macroeconomic variables, without an attempt to infer what the market price should be today. Changes in model specification from year-to-year, such as the inclusion of market concentration, substantially alter forecasts, and appears largely ad hoc based on short run measurement error of the prior model, rather than conviction in any single explanation of the current price level.[22] These approaches are consistent with forecasting returns from the current price rather than forming beliefs about whether the price itself is correct.

This pattern extends beyond formal models. For example, the financial press typically does not state strong market level opinions and that they rarely delve into the details underlying each. One recent example is a Wall Street Journal with the headline "Why Are Stocks Up? Nobody Knows."[23] More systematically, Cutler et al. (1988) find that many large price movements lack identifiable sources of information and often do not align closely to major news events. This also mirrors popular investing advice to not attempt to time the level of the stock market.[24]

Explicit level-based conviction emerges primarily in extreme episodes, such as the late-1990s technology bubble, when investors articulated a clear narrative for why prices could not be justified by fundamentals or discount rates.[25] This conviction was driven by how out of the ordinary the situation was, with P/E ratios on the Nasdaq composite index above 200.[27] Outside of such episodes, discussion typically reflects substantial uncertainty about whether the market level is appropriate.

Taken together, real-world forecasts, commentary, and advice provide little evidence that investors possess or act upon strong beliefs about what the market price should be. Instead, they are

[22] Empirically, the relationship between concentration and market returns is only marginal. Including the variable in the model from 1930-2014 yields a t-stat of -1.8 (compared to -6.1 for P/E). The report also notes that this variable had not been included in their prior models. Goldman's 2012 framework forecast 8% annual returns, versus the 13.3% that materialized. Back-fitting to include concentration would have increased the prior prediction to 14%. This pattern is consistent with the addition of the variable to correct a past error than to enhance future predictions.

[23] https://www.wsj.com/finance/stocks/why-are-stocks-up-nobody-knows-e40e5f42?st=xNa5uN&reflink=article_copyURL_share

[24] e.g. Jack Bogle states "The winning formula for success in investing is owning the entire stock market through an index fund, and then doing nothing." Paul Samuelson declared that "market timing is an investing sin" (as described in (Asness et al., 2015)). This is odd if market price variation is largely explained by ex-ante understood variation in discount rates.

[25] During the dot-com bubble, Paul Samuelson suggested "market timing is an investing sin, and for once I recommend that you sin a little" (as cited in (Asness et al., 2015)).[26]

[27] https://www.goldmansachs.com/pdfs/insights/goldman-sachs-research/25-years-on-lessons-from-the-bursting-of-the-tech-bubble/redaction.pdf

consistent with price agnostic demand: investors largely accept the prevailing market price and focus on forming return expectations conditional on it.

V. Discussion

This section discusses issues related to the importance, plausibility, and implications of price agnostic demand. First, we discuss whether it makes sense to continue using models "as if" investors understand the level of the market, even if they are actually price agnostic. Next, we discuss how the finding that investors think largely in terms of changes rather than levels of market prices is consistent with how human beings tend to behave in most settings. Finally, we discuss how price agnostic demand can help us to explain a number of puzzling patterns in asset markets.

A. As If Interpretation

Theory predicts that investors have a strong conviction about what the level of the market should be, though our evidence suggests this is not the case. It could be that while inconsistent with the theory, this does not lead to meaningfully different predictions. If this were the case, then it would be defensible to continue using these models "as if" investors had conviction about the current market price level. Here, we discuss a few different ways this could be true, and why these are unlikely to fully mitigate the influence of price agnostic demand.

The most straightforward way for price agnostic demand to be irrelevant would be if investors responded to changes correctly, thereby yielding the identical outcome to decisions based on accurate perceptions of levels. This relationship does hold at a theoretical level. If prices were initialized at a level corresponding to fundamentals, and then news innovations were reflected in returns consistent with a given model, then the model based asset price would always equal the actual market price. This would occur even if investors were not aware of what that market price should be.

While mathematically identical in a frictionless model, this equivalence seems unlikely to hold in actual markets. To the extent that evidence exists on the response of prices to information, prices have been shown to systematically misreact to that news. Most of this evidence examines the cross-section of individual stocks. For example, earnings announcements offer a best case scenario for markets to react appropriately to information. The setting receives significant attention, occurs four times per year and is a response to standardized accounting disclosures. Further, this is a data rich environment with solid proxies for the relevant variables of interest and the statistical power to measure whether or not the market responds appropriately. The literature has found that the market does not respond

correctly to the earnings surprise (e.g. Bernard and Thomas (1990)), the different components of the earnings surprise (Sloan (1996)), other information in the accounting disclosure (Cohen et al. (2020); Cohen and Nguyen (2024)), the scheduling of earnings announcements (Johnson and So (2018); Noh et al. (2021)), sequential patterns in earnings announcements (Hartzmark and Shue (2018); Thomas and Zhang (2008)), predictable seasonal patterns in earnings (Chang et al. (2017)) and predictable manipulation of earnings expectations by firms (Johnson et al. (2020)), among others.

Time series tests of reactions to news are rarer, as the appropriate benchmark is unclear.[28] One recent exception, was the response to the news of the Covid pandemic. While it is difficult to say exactly what the response should be, Gormsen and Koijen (2020) show that the response was far too large given the news.[29] Given that there is evidence of widespread misreaction to news at both the cross-sectional and market level, it seems unlikely that accepting the market price as the status quo will yield the same outcome as an investor focused on fundamental based predictions of prices.

Another possible response is that we find our results because we do not give investors the relevant information. On some level, this is indeed the case. Most of the professional investors in our asset manager sample say such a dataset does not exist and LLM models agree. If market behavior and asset market dynamics are best explained with the inclusion of significant price agnostic demand, then there should not be a dataset where our investors can accomplish this task.

We note that this stands in stark contrast to an explanation of asset prices where the major driver is ex-ante understood discount rate variation. If investors generally perceived differences in expected returns to be due to understood discount rate variation, it seems likely that a significant amount of time and effort would be spent understanding and quantifying this. The Wall Street Journal has no systematic data reported to try to understand time variation in risk aversion, or perceptions of long run risk, or other relevant drivers of discount rate variation. Further, expectations data are inconsistent with such models (e.g. Greenwood and Shleifer (2014)). This seems most consistent with investors largely being aware of such discount rate variation or not viewing it as particularly relevant over the annual horizons we examine.

This suggests that ex-ante understood time variation in compensation for holding risk is unlikely to be the core driver of asset price fluctuations, in contrast with the position of modern asset pricing

[28] This is consistent with price agnostic demand, but under standard asset pricing models it is surprisingly difficult to state what the current price should be, even though the models predict this price should be obvious and generally agreed upon.

[29] Other settings, such as the tech bubble, are more contentious in terms of interpreting the price level. We do note that in such settings investor expectations seem inconsistent with explanations due to rational discount rates or cash flow mistakes, and seem more consistent with investors over-reacting to a new exciting technology (Vissing-Jorgensen (2003)).

models. A core assumption of these models is that time variation in returns is due to ex-ante understood discount rate variation, based on the relevant state variables of the model. For example, in a habit model (e.g., Campbell and Cochrane (1999)), prices are driven by fluctuations in risk aversion based on variation in habit. This means that in certain times people are more risk averse, they demand higher compensation for holding risk which means that prices are lower and expected returns are higher compared to times that investors are risk seeking. If investors are unsure as to what the price of the market should be, regardless of the level of the discount rate shock, it becomes difficult to argue that investors recognize the variation in compensation they are receiving for holding risk.

More broadly, correctly modeling the broad problem that investors are accurately trying to solve would likely result in better asset pricing models. As discussed in Chinco et al. (2022), asset pricing models lack most of the mechanisms commonly cited elsewhere in economics to constrain irrational agents to behave as if they are rational. While simplifying assumptions are a necessary component of any model, modeling an agent as if they have conviction about market price levels when they do not, misses a fundamental component of investing decisions. Hopefully figuring out how to integrate such a channel into asset pricing models will lead to better understanding of asset market dynamics.

B. Understanding Absolute Value is Hard

While price agnostic demand is a significant deviation from asset pricing models, it is consistent with the large literature on human judgment and decision making. The starting assumption of asset pricing theory that "price equals expected discounted payoff" (Cochrane (2009)) is a statement that investors view market prices and form expected returns based on the absolute levels of variables. Research in psychology and behavioral economics finds that people do not typically evaluate outcomes in absolute terms. Instead, they rely on relative comparisons, such as past experiences, expectations, or others' status to determine how good or bad the situation they are assessing is.

This tendency arises because interpreting absolute values is cognitively difficult, consistent with psychophysics research on Weber's law dating back to the 1800s (Dehaene, 2003).[30] Attention and memory are also biased towards change, making it easier to detect changes than aspects of the environment that have remained stable (Tversky and Kahneman, 1981). As a direct consequence, people are naturally more sensitive to proportional changes than to absolute differences, a core tenant of Prospect Theory (Kahneman and Tversky, 1979).[31]

[30] This research demonstrates that that the just-noticeable difference between two stimuli is a constant proportion of the original stimulus.

[31] Kőszegi and Rabin's 2006 model of reference-dependent preferences further formalizes this intuition, modeling utility

Relying on relative comparisons rather than absolute evaluations is commonplace for consumers and investors. For example, in a classic demonstration, Tversky and Kahneman (1981) find that consumers treat the value of $5 in savings differently as a function of the product being purchased. Consumers are more willing to travel to save $5 on a $15 item than a $125 one, even though the $5 of savings and amount of travel are held constant. The decision is driven not by the absolute value of the savings, but by its relative size—supporting the view that consumers instinctively process value in comparative, context-dependent terms. This focus on relative differences is especially apparent in how people evaluate income. In a large-scale analysis of U.S. panel data, Brady et al. (2023) find that absolute income is far less predictive of subjective well-being than is income relative to one's own past earnings or relative to others in the social distribution.[32] These results reinforce the idea that people lack an internal benchmark for absolute value, and instead derive meaning from comparisons such as to peers, to expectations, and to past experiences.

The money illusion (i.e., the tendency to think in nominal rather than real terms) serves as another implication of investors failing to understand value in objective terms (Shafir et al., 1997). For example, people tend to prefer a 2% nominal raise in a 4% inflation environment over a 0% raise with no inflation, despite the loss in purchasing power. This illusion arises because the nominal wage from last year becomes a reference point, and people react to the visible change in that number rather than to the underlying economic reality. The inability to grasp the absolute level of value (e.g., "how much can my money buy?") pushes individuals to rely on salient but misleading nominal comparisons.

In asset markets, this cognitive bias plays out in the tendency for investors to hold onto losing assets too long and sell winning ones too quickly, a pattern known as the disposition effect (e.g. Odean (1998); Frydman et al. (2018); Hartzmark and Solomon (2012)).[33] Another example is that when evaluating performance within a portfolio, the decision of what to sell is driven by a position's relative performance compared to other holdings (Hartzmark (2015); Akepanidtaworn et al. (2023)). Such effects exemplify how difficult it is for individuals to interpret absolute asset value; they default instead to gains and losses relative to their initial investment or compared to other positions, even when this

as a function of the difference between actual outcomes and internally generated reference points.

[32]Similarly, Solnick and Hemenway (1998) found in survey experiments that many people would prefer to earn $50,000 while others earn $25,000 rather than $100,000 while others earn $200,000—indicating they care more about rank than absolute wealth.

[33]In the housing market, Genesove and Mayer (2001) found that sellers were significantly less likely to sell their homes if the current market price was below their original purchase price, even when doing so would be rational given broader conditions. The purchase price acts as a psychological reference point, and a sale below that point is perceived as a loss—despite the fact that the home's absolute value may still be high or appropriate. Similar patterns are observed in stock markets, where investors fixate on the price they originally paid, rather than the stock's current fair value.

leads to suboptimal outcomes.

Asset pricing models and the associated basic economics suggest investors should focus on the absolute levels of variables and understand the level of the market price. In most other settings that we can examine, however, human beings find such tasks cognitively taxing. They perform poorly on them and often default to focus on relative comparisons instead. The results in our paper mirror these base patterns in human behavior.

C. Implications

Perhaps the most obvious implication is that if a large component of demand is price agnostic, arbitrage forces must be much weaker than is commonly assumed. If traders lack conviction on what the level of the stock market should be, then investors will not actively trade to correct perceived mispricing in the stock market. Without such investors, there is no reason to expect that the market needs to be particularly close to its correct level in the short run. Recall, Vanguard claims the market is 30% higher than what it thinks it should be. Under standard models, this would represent a compelling reason to actively trade. Vanguard suggests traders take no action based on this (in the context of the model) extreme mispricing.

Loosening this arbitrage constraint can help to explain a number of other findings in finance. For example, Shiller et al. (1981) finds that market prices are far too volatile to be explained by fundamentals. This was a major challenge to asset pricing models based on fundamentals based prices. If there is a wide range of prices that a given investor will accept as normal, it is likely that prices can move much more than underlying fundamentals.

This is closely related to the recent literature that highlights the importance of trading in markets, the influence of price pressure and the inelastic market hypothesis (e.g. Gabaix and Koijen (2021), Hartzmark and Solomon (2021)). Gabaix and Koijen (2021) note that there is a relatively small amount of arbitrage capital dedicated to trading on market-level mispricing. Agnostic demand presents an explanation, namely that investors generally don't have the knowledge to implement such strategies.

An open question in Gabaix and Koijen (2021) is why investors allocate money the way that they do. Why wouldn't households allocate money in a manner consistent with fundamentals, such that markets behaved as if they were elastic and efficient? Our paper suggests a partial solution. Investors are not allocating money based on the current level of the market because they lack conviction on whether it is correct.

Combining price agnostic demand with evidence of the lack of profitability of market timing strategies and evidence of inelastic markets suggests a reevaluation of the horizon over which classic fundamental based asset pricing models can explain returns. Historically, the field has been comfortable thinking such models are relevant over periods such as a month, a quarter, or a year. These results suggest this is not the case though. While the economic constraints of fundamentals do indeed seem to push prices closer to model predictions eventually, the horizon of this relevance is likely closer to the 5-10 year horizons over which fundamentals do exhibit strong predictability. As noted above, this is typically the time horizon over which forecasters are willing to make fundamental based forecasts. Our results suggest a large component of this explanation lies with price agnostic demand.

VI. Conclusion

In his AFA address, Fisher Black claimed that prices were efficient in the sense that they were within a "factor of 2 of value," what our paper calls price agnostic demand. While this claim was provocative, he also stated "I have not been able to think of any conventional tests that would distinguish my view and the views of others." Our paper presents evidence that begins to do so. Consistent with Fisher Black's hypothesis, investors have very little conviction of what the level of the stock market should be. This suggests that their demand for assets and their expected returns largely adapts to whatever the current level of the market may be.

We find that investors lack conviction on what the prevailing market price should be if they do not observe it. In our experimental setting we find that participants are quite poor at identifying large deviations from actual market prices. Professional return forecasters largely focus on expected returns, only indirectly taking into account the level of the market. When finance academics and professionals giving advice discuss the level of the market, it is largely agnostic as to what the actual price should be. Overall our results suggest extreme uncertainty as to what the level of the stock market should be currently, a mechanism largely missing from standard asset pricing models.

Our results suggest the need to reevaluate the finding that most market movements cannot be explained by fundamentals. The conclusion drawn from this literature is that price movements were actually rationally driven by discount variation. Under these models market participants understand these variations which explain the current market price. If such mechanisms explained our results, then we would not be providing the relevant state variables to market participants. However, they could have requested them from us and did not. If you thought the market level was largely pinned

down by the perceived risk of a rare disaster, or time variation in risk aversion, such variables could have been requested and the financial media could report them. No one suggested we should provide such a variable though, making it unlikely that such a mechanism explains our results.

Our explanation is much simpler. Pinning down the level of the market price is perceived to be very difficult, consistent with a broad class of findings from psychology. This means that there are a large range of prices that people are willing to accept as normal. Only when things get extreme relative to these expectations, such as during the tech bubble, do fundamental variables have a large influence on expected returns. For a wide range of values though, demand largely adapts to the prevailing market price. This fundamental aspect of financial markets is largely absent from asset pricing models, but has wide ranging implications for how markets function. Incorporating this mechanism with other important mechanism to form a complete asset pricing model is a compelling avenue for future research.

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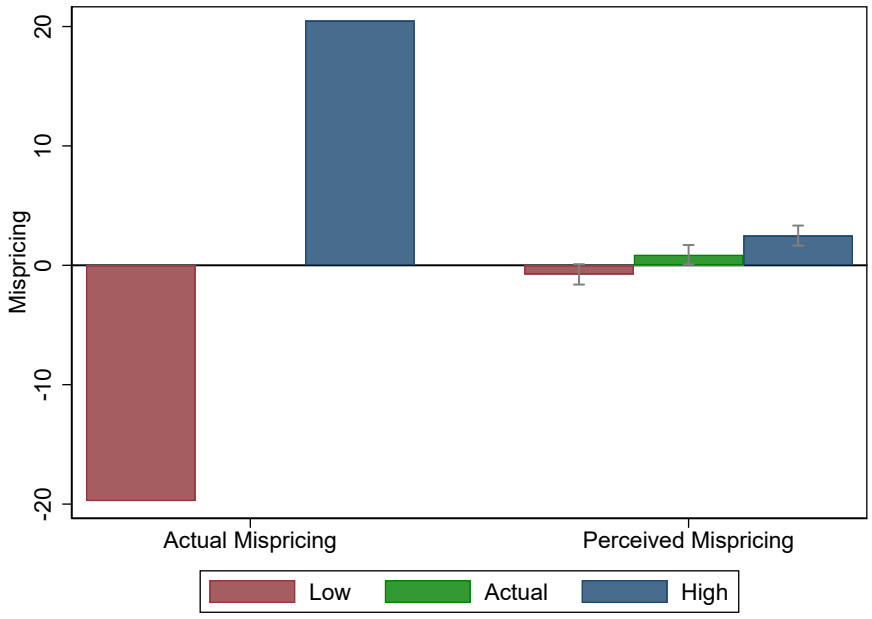
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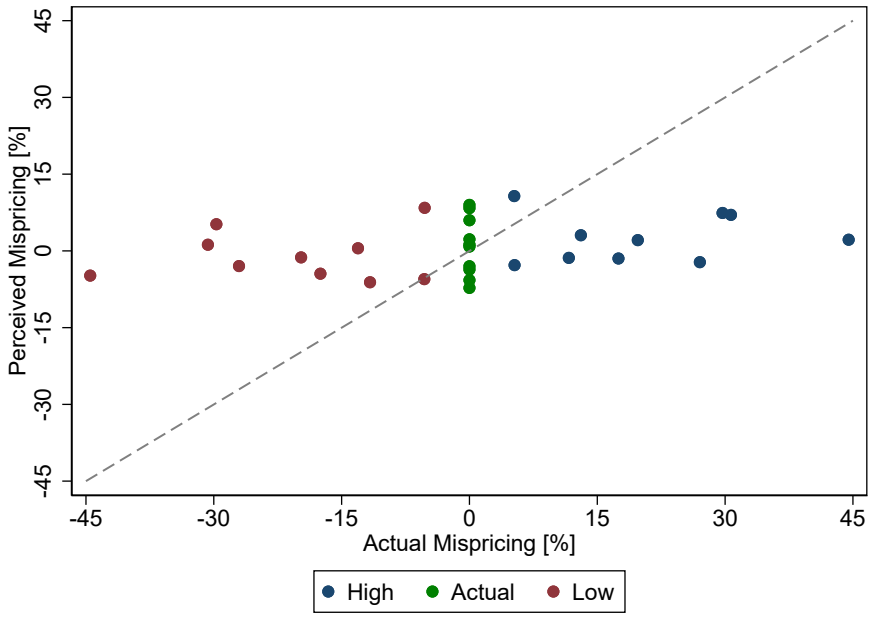
Figure 1: Actual vs. Perceived Mispricing by Direction



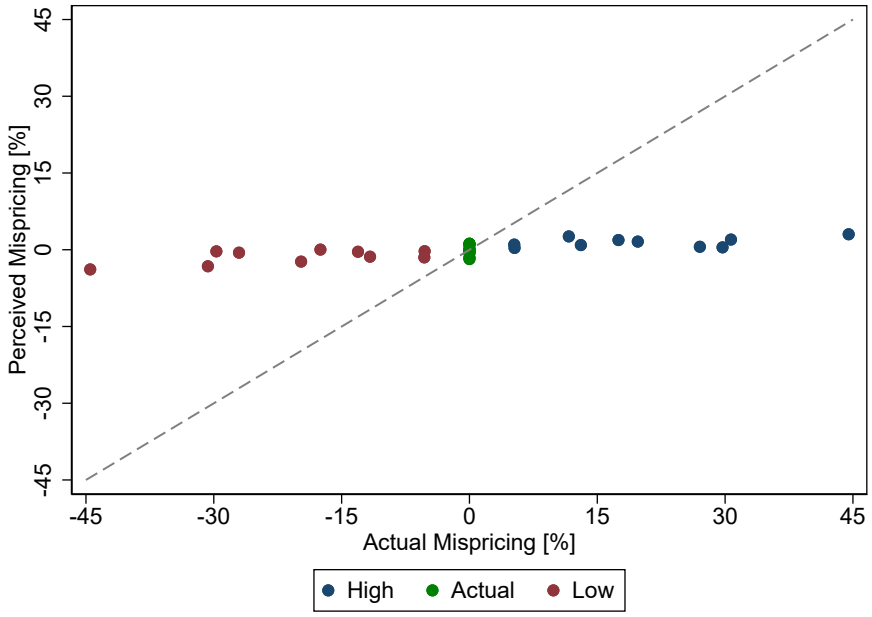
These figures shows the average mispricing by scenarios with negative mispricing (maroon), no mispricing (green) and positive mispricing (blue). The left three bars show the actual average amount of mispricing in each scenario. The right three bars show the perceived level. Grey bars indicate the 95% confidence interval.

Figure 2: Perceived Mispricing vs. Actual Mispricing

(a) Panel A: No Controls

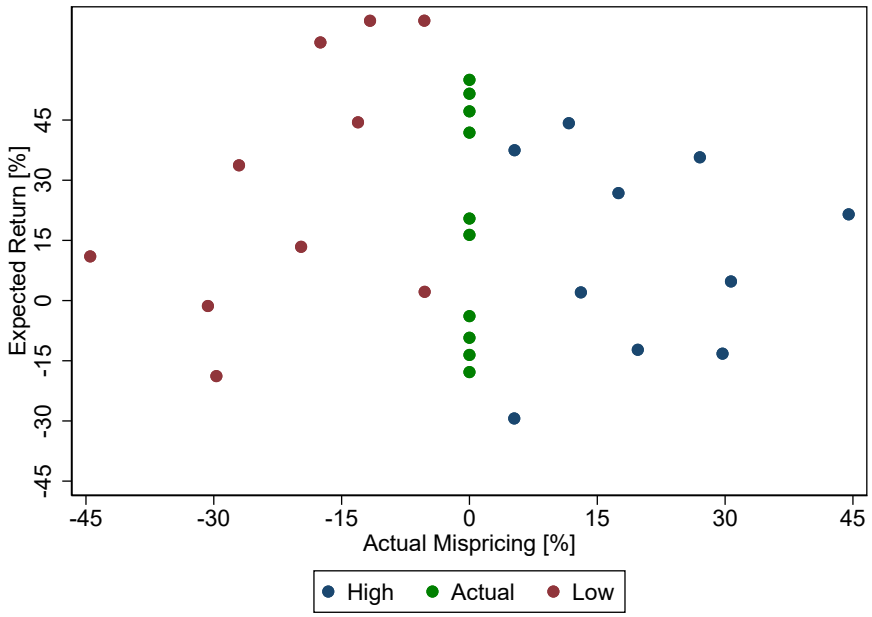


(b) Panel B: Date and ID Fixed Effects



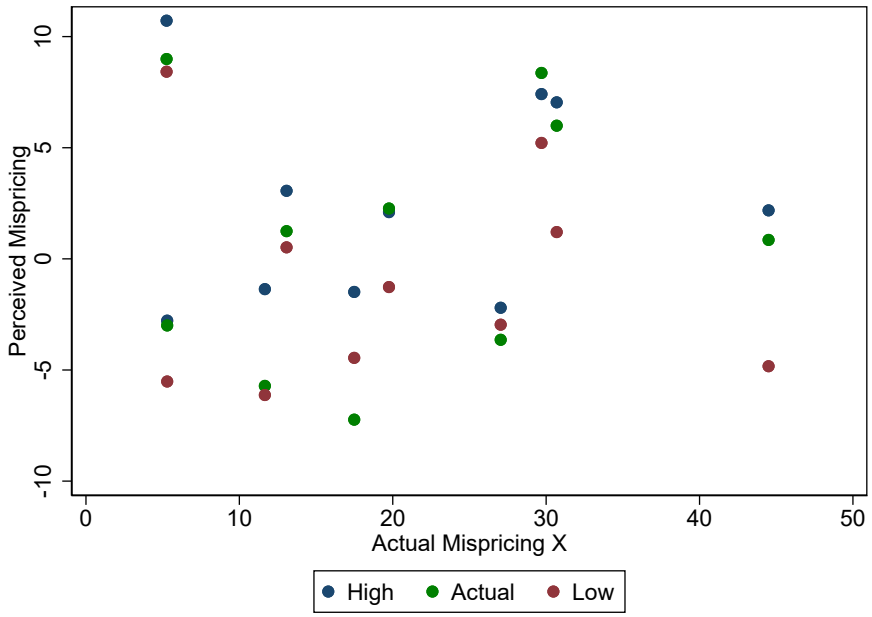
These figures show how mispricing vary with the actual level of mispricing. Each dot is the average answer for the given level of actual mispricing. Panel A shows the results with no controls. Panel B shows the results based on residuals after removing a date and id fixed effect. The gray line shows the correct response if subjects accurately identified the actual level of mispricing. Blue dots display answers from scenarios where the displayed P/E ratio was above the actual, green dots show answers from the actual scenario, and maroon dots show answers from the low scenario.

Figure 3: Expected Returns vs. Actual Mispricing



This figure show how expected returns vary with the actual level of mispricing. Each dot is the average answer for the given level of actual mispricing. Blue dots display answers from scenarios where the displayed P/E ratio was above the actual, green dots show answers from the actual scenario, and maroon dots show answers from the low scenario.

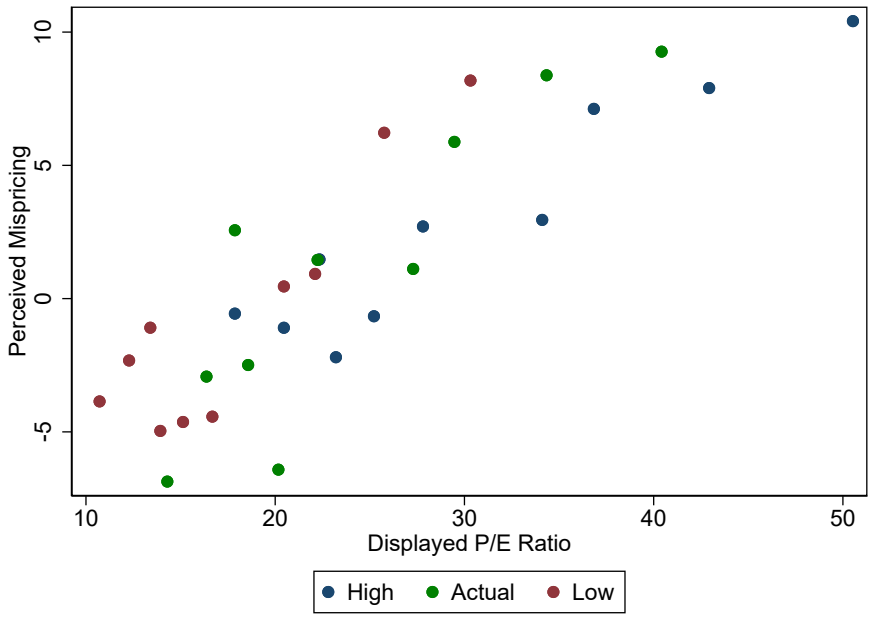
Figure 4: Perceived Mispricing by Date



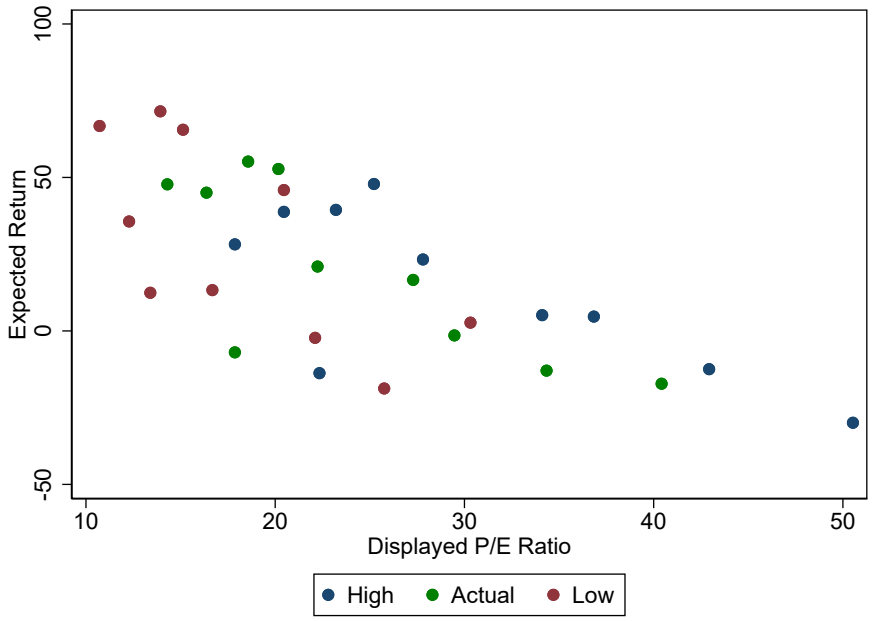
These figures show how perceived mispricing varies based on the level of X chosen for a given date. For that date participants saw prices X% higher, X% lower or the actual level. Each dot is the average answer for the date and the given level of mispricing. The gray line shows the correct response if subjects accurately identified the actual level of mispricing. Blue dots display answers from scenarios where the displayed P/E ratio was above the actual, green dots show answers from the actual scenario, and maroon dots show answers from the low scenario.

Figure 5: Perceived Mispricing and Expected Returns vs. Displayed P/E Ratio

(a) Panel A: Perceived Mispricing



(b) Panel B: Expected Returns



These figures show how mispricing and expected returns vary with the price to earnings ratio that is displayed. Each dot is the average answer for the given level of P/E ratio. Panel A shows perceived mispricing and Panel B shows expected returns. The sample excludes observations from the sample that observes P/D instead of P/E. Blue dots display answers from scenarios where the displayed P/E ratio was above the actual, green dots show answers from the actual scenario, and maroon dots show answers from the low scenario.

Table 1: Habit Based Scenarios and Mispricing

	Normal		Risk Seeking		Crisis	
	P/D	Return	P/D	Return	P/D	Return
Model Price: 0% Mispricing	22.0	6.0%	28.0	4.0%	12.0	18.0%
Overvalued: +25% Mispricing	27.5	-15.2%	35.0	-16.8%	15.0	-5.6%
Uncervalued:-25% Mispricing	16.5	41.3%	21.0	38.7%	9.0	57.3%

This table shows model-implied price–dividend (P/D) ratios, and one-year expected excess returns (Return) under a Campbell and Cochrane (1999) habit framework. "Normal," "Risk-seeking," and "Crisis" correspond to surplus-consumption ratios $S = 0.057$, 0.070, and 0.035, respectively. All other parameters are held fixed across states. The overvalued column increases multiplies the model implied P_t by 1.25 while the undervalued row multiplies it by 0.75. Prices are assumed to revert to their model implied value a time $t + 1$.

Table 2: Perceived Mispricing

Actual Mispricing	All	Low	None	High
	(1)	(2)	(3)	(4)
Correct Direction	0.35	0.43	0.09	0.53
	(-118.28)	(-57.64)	(-161.40)	(-47.03)
Perceived Mispricing	0.86	-0.76	0.89	2.49
	(3.27)	(43.75)	(2.14)	(-42.03)
Error	0.80	18.99	0.89	-18.00
	(2.52)	(39.00)	(2.14)	(-36.95)
Absolute Error	22.11	25.79	16.37	24.12
	(114.59)	(75.25)	(64.53)	(66.08)
Observations	7522	2547	2501	2474

This table shows summary stats on perceived mispricing. Column 1 shows all observations, column 2 shows scenarios with negative mispricing, column 3 shows scenarios with no mispricing and column 4 shows scenarios with positive mispricing. The first measure is whether the correct direction for mispricing was chosen (e.g. positive mispricing guessed in a high mispricing setting). The next measure is the mean of mispricing. Following that is the error (perceived mispricing minus actual) and the last is the absolute value of the error. t-statistics for the test of whether the measure is equal to the correct response are below each value.

Table 3: Perceived Mispricing Varying with Actual Mispricing

	(1)	(2)	(3)	(4)
Mispricing	0.0706***	0.0680***	0.0723***	0.0700***
	(5.15)	(5.15)	(5.29)	(5.35)
YM FE	No	No	Yes	Yes
ID FE	No	Yes	No	Yes
R^2	0.00398	0.218	0.0526	0.267
Observations	7522	7522	7522	7522

This table shows regressions of perceived mispricing on actual mispricing. Columns 3 and 4 include date of observation fixed effects and columns 2 and 4 include ID fixed effects. Standard errors are clustered by ID with t-statistics in parenthesis.

Table 4: Perceived Mispricing by Treatment

	Baseline	MBA	Asset Manager	No SP500	P/D	Mkt Ret	Sentiment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Correct Direction	0.35	0.36	0.38	0.33	0.36	0.35	0.37
	(-60.16)	(-25.15)	(-18.56)	(-64.72)	(-42.23)	(-42.40)	(-40.80)
Absolute Error	23.29	25.57	20.82	20.96	21.88	21.88	21.58
	(59.45)	(26.23)	(19.31)	(58.11)	(40.84)	(42.02)	(42.46)
Low: Mispricing	-1.15	-0.56	-2.08	2.00	-3.53	-0.45	-2.81
	(20.95)	(6.02)	(8.00)	(28.67)	(14.41)	(17.30)	(14.14)
None: Mispricing	1.02	2.10	3.42	2.42	-0.40	0.24	-1.50
	(1.17)	(0.82)	(1.40)	(3.47)	(-0.35)	(0.22)	(-1.29)
High: Mispricing	2.80	-1.39	8.79	3.25	-0.02	1.79	3.57
	(-20.77)	(-7.06)	(-4.72)	(-22.19)	(-17.14)	(-17.16)	(-15.64)
Low: Error	19.27	15.15	17.75	21.94	16.15	19.45	16.75
	(18.49)	(6.05)	(6.73)	(25.98)	(12.66)	(14.75)	(12.43)
None: Error	1.02	2.10	3.42	2.42	-0.40	0.24	-1.50
	(1.17)	(0.82)	(1.40)	(3.47)	(-0.35)	(0.22)	(-1.29)
High: Error	-17.75	-18.62	-11.73	-17.10	-21.08	-19.08	-17.34
	(-18.29)	(-6.97)	(-3.78)	(-19.41)	(-15.03)	(-14.46)	(-13.55)
Observations	1980	356	216	2020	1000	960	990

This table shows summary stats on perceived mispricing by subject type. Column headings display each sample. Correct direction shows the average of a dummy variable equal to 1 if the correct direction for mispricing was chosen (e.g. positive mispricing guessed in a high mispricing setting). Absolute Error shows the absolute value of the error (perceived mispricing minus actual). Rows starting with "Low:" show scenarios where P/E was lower than its true value, "None:" show where P/E was the actual value and "High:" where P/E was above the actual value. Mispricing rows shows the average reported perceived mispricing. Error rows show the average error. t-statistics for the test of whether the measure is equal to the correct response are below each value.

Table 5: Perceived Mispricing Varying with Actual Mispricing by Treatment

Panel A: No Controls

	Base	MBA	Manager	No SP	P/D	Ret	Sentiment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mispricing	0.0653**	0.103	0.165**	0.0554*	0.0707**	0.0324	0.122***
	(2.28)	(1.29)	(2.54)	(1.89)	(2.20)	(1.06)	(3.64)
YM FE	No	No	No	No	No	No	No
ID FE	No	No	No	No	No	No	No
R^2	0.00311	0.00347	0.0239	0.00298	0.00411	0.000981	0.0122
Observations	1980	356	216	2020	1000	960	990

Panel B: ID and Date FE

	Base	MBA	Manager	No SP	P/D	Ret	Sentiment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mispricing	0.0781***	0.0768	0.167**	0.0582**	0.0755**	0.0196	0.106***
	(3.06)	(0.91)	(2.36)	(2.03)	(2.34)	(0.64)	(3.16)
YM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.338	0.232	0.276	0.181	0.299	0.303	0.283
Observations	1980	356	216	2020	1000	960	990

This table shows regressions of perceived mispricing on actual mispricing. Column headings display each sample. Panel A shows regressions with no controls. Panel B shows regressions including date of observation fixed effects and ID fixed effects. Standard errors are clustered by ID with t-statistics in parenthesis.

Table 6: Expected Returns Varying with Actual Mispricing

	(1)	(2)	(3)	(4)
Mispricing	-0.145***	-0.162***	-0.143***	-0.162***
	(-3.62)	(-4.49)	(-3.83)	(-5.13)
YM FE	No	No	Yes	Yes
ID FE	No	Yes	No	Yes
R^2	0.00206	0.332	0.186	0.518
Observations	5500	5500	5500	5500

This table shows regressions of expected returns on actual mispricing. Columns 3 and 4 include date of observation fixed effects and columns 2 and 4 include ID fixed effects. Standard errors are clustered by ID with t-statistics in parenthesis.

Table 7: Expected Returns on Perceived Mispricing and Actual Mispricing

	(1)	(2)	(3)	(4)	(5)	(6)
Perceived Mispricing	-0.557***	-0.567***	-0.200***	-0.551***	-0.560***	-0.189***
	(-6.65)	(-6.92)	(-3.04)	(-6.57)	(-6.83)	(-2.89)
Actual Mispricing				-0.103***	-0.122***	-0.148***
				(-2.59)	(-3.40)	(-4.70)
YM FE	No	No	Yes	No	No	Yes
ID FE	No	Yes	Yes	No	Yes	Yes
R^2	0.0403	0.362	0.520	0.0414	0.364	0.521
Observations	5500	5500	5500	5500	5500	5500

This table shows how expected returns vary with perceived mispricing and with actual mispricing. Columns 1 and 4 have no controls, all other columns include ID fixed effects and columns 3 and 6 include date fixed effects. Standard errors are clustered by subject, with t-statistics in parentheses.

Table 8: Accuracy of Direction of Responses in Fixed 25% Treatment

Actual Mispricing	All	Low	None	High
	(1)	(2)	(3)	(4)
Correct Direction	0.36	0.41	0.34	0.34
	(2.01)	(2.96)	(0.16)	(0.27)
Observations	979	333	319	325

This table shows the accuracy of guesses from the treatment where subjects were asked if the displayed price was 25% higher, 25% lower or the actual price. The first row shows the average of a dummy variable equal to one if the guess was correct. The first column shows all observations and the next three columns show observations where the displayed price was 25% lower than the actual (column 2), the actual price (column 3), or 24% higher than the actual price. T-statistics are for the test of whether the coefficient is statistically distinct from guessing at random.

A. Appendix: Experiment Details and Instructions

Table A.1: Treatment Details

Treatment	Date	Subject Pool	Participants	Pre-Registration	Notes
Baseline	Feb 2023	MTurk	198	No	No question about feasibility
MBA	Feb 2023	MBA	60	No	Baseline Treatment in class with pencil and paper. 6 scenarios. Minimal additional questions. Minimal additionalquestions. Confidence question asked on 1 to 6 scale. No question about feasibility.
Financial Advisor	Apr 2023	MBA	31	No	Baseline Treatment with 6 scenarios
Fixed 25%	Feb 2023	MTurk	98	No	No question about feasibility
P/D	May 2025	Prolific	100	#228696	Price Dividend replacing P/E
No S&P	May 2025	Prolific	202	#228083	Level of S&P 500 not displayed
Sentiment	May 2025	CloudConnect	99	#228841	Baker and Wurgler and University of Michigan Sentiment Displayed
Prior Returns	May 2025	Prolific	96	#229411	Prior Year return displayed
Total			884		

This table shows details on each treatment variation that was run. The date column shows the month the experiment was run. The subject pool column indicates who the pool the participants were drawn from. The participants column list the number of participants who completed the given treatment. The pre-registration column indicates whether the given treatment was pre-registered and if it was, the relevant aspredicted number. The Notes column describes how a given treatment is different from the baseline treatment in the internet appendix.

Table A.2: Online Participant Demographics

	Mean	SD	p10	p50	p90
Age	40.82	12.16	26	39	58
Male	0.54	0.50	0	1	1
Income	64,359.71	47,678.68	5,000	55,000	125,000

This table shows demographic information from the online samples. The income question is given in bins, so the values shown are based on the bin midpoint (e.g., a response of the $10,000 to $19,999 bin is given a value of $15,000) with the bottom bin (Less than $10,000) given a value of $5,000 and the top bin (More than $150,000) given a value of $200,000.

Baseline Experiment

Basic Instructions and Comprehension Checks (4 Questions)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

This study consists of ten independent rounds of questions. In each round, we will present information about the S&P500 and the economic climate on a specific day that occurred in the past. These dates are randomly drawn from the period 1971 to 2021.

The earnings, risk-free rate, inflation, prior GDP growth, expected GDP growth, and volatility information that you will see are the true values taken from the same randomly selected day. **However, the value of the S&P500 Index Level may be exactly the same, higher, or lower than the true value of the Index on the corresponding day. The price to earnings (PE) ratio will reflect the S&P500 Index presented.**

The value of the price to earnings (PE) ratio will be shifted by a percentage which could be positive or negative. For example, let's say the actual PE ratio was 28. Further, assume that you were displayed a value based on a -25% percentage. You would see 21 for the price to earnings ratio, 25% lower than the true value. Your task will be to determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

Comprehension Question 1- displayed information

Which of the following best describes **the information that will be displayed**?

- ○ All information except for earnings and metrics directly incorporating earnings will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for GDP growth and metrics directly incorporating growth will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for the S&P500 Index and PE ratios will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ None of the above

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

In our study,
- **inflation** refers to the rate of increase in general prices of goods and services over the prior year;
- **risk-free rate** is the interest rate a person would receive from holding a long term (10 year) government bond;
- **prior GDP growth** shows how well the economy did over the prior year. It is reported as the annual percentage change in Gross Domestic Product (GDP), which is a measure of the goods and services produced in the US economy;
- **expected GDP growth** comes from the Federal Reserve Board's prediction of the rate of economic growth in the coming year;
- **volatility** is an index (VIX) that describes expected variability in prices. More precisely, it captures the expected annualized standard deviation in stock prices described as a percent of the stock market price.

Comprehension Question 2- Inflation

Which of the following best describes **inflation?**

- ○ An increase in the quantity and quality of the goods and services produced/consumed by a society.
- ○ An increase in the price level in the economy over a period of time
- ○ The percentage of individuals who are jobless or actively seeking work relative to the working population.
- ○ None of the above

Comprehension Question 3- S&P 500

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

S&P500 Index is a stock market index tracking the stock performance of 500 large companies. It represents the value of a broad basket of blue-chip stocks in the index. When the stocks in the index increase in price, the value of the index increases.

Which of the following best describes the **S&P 500 Index?**

- ○ A stock market index which includes all stocks listed on the Nasdaq stock exchange
- ○ A stock market index which tracks the performance of 500 large companies on the stock market
- ○ A stock market index of the 30 most prominent companies publicly listed in the United States.
- ○ None of the above

Comprehension Question 4- P/E Comprehension

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

Price to Earnings (PE) Ratio is calculated as the stock price divided by the company's average earnings per year. In our study, the stock price is the total value of the S&P 500, and the earnings is a long-term average of the total profit per year across all firms listed in the S&P 500.

Which of the following best describes a **price to earnings ratio**?

- ○ Ratio of the price of the stock to the company's stock market returns over the prior year
- ○ Ratio of the company's annual earnings to the price of the stock
- ○ Ratio of the price of the stock to the company's annual earnings
- ○ None of the above

Instruction and Manipulation

Before the comprehension checks

In the following section, we will describe the study and key terms that will be used throughout. You need to answer at most four questions about these instructions.

If you give correct answers to all of the four questions, you are eligible for the bonus study. If you answer any of the four questions wrong, your session will be ended immediately and you will not be bonused.

After participants have passed all comprehension checks

You have passed the comprehension check and are qualified for a bonus of $2.40 if you continue to finish the rest of the survey (about 11 minutes).

In the next part, you will see ten rounds of questions. In each round, we will present background information about the economic climate and the S&P 500 Index.

And you will determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

For the manipulation, participants are shown a table of summary statistics shown below. The historical data table is displayed for all scenarios and remains fixed for all scenarios.

The definitions and historical data are provided for reference:

Term	Definition	Historical Average (1971-2021)	Historical Range (1971-2021)
PE Ratio	Price to Earnings Ratio is the stock price divided by the company's average earnings per year.	24	10 to 49
S&P500 Index	S&P500 Index tracks the stock performance of 500 large companies.	949	67 to 4,675
Risk-Free Rate	The annual interest rate a person would receive from holding a long-term (10-year) government bond.	6.1%	0.6 to 15.8%
Inflation	The rate of increase in general prices of goods and services over the prior year.	3.9%	-2.1 to 14.8%
Prior GDP Growth	The annual percentage change in Gross Domestic Product (GDP) which is a measure of the goods and services produced in the US economy.	2.8%	-8.4 to 12.5%
Expected GDP Growth	The Federal Reserve Board's prediction of the economic growth rate in the coming year.	3.0%	0.7 to 5.8%
Volatility	The volatility index (VIX) describes the expected annualized volatility of stock prices.	20	9 to 69

Below is an example scenario. The numbers in this table changed with each scenario. All Prolific and Mturk samples saw ten scenarios. The MBA and financial advisor samples saw six scenarios.

Question:

Metric	Value
PE Ratio	27
S&P500 Index	559
Risk-Free Rate	6.3%
Inflation	2.6%
Prior GDP Growth	2.7%
Expected GDP Growth	2.6%
Volatility	14

Considering the metrics above, do you believe that the S&P500 Index and PE Ratio reflect levels that are higher, lower, or the same as the actual index and PE Ratio from the date displayed in the table? Please indicate your response on the slider below.



What do you think the actual level of the S&P 500 was 12 months from the date displayed in the table?

How confident are you in your response?

Very Unconfident 1	2	3	Neutral 4	5	6	Very Confident 7
○	○	○	○	○	○	○

Investor and demographic questions after the main experiment

Do you believe that it is possible for investors to use information on economic fundamentals from a given day to determine the market price on that day within 10% of the true value?

Economic fundamentals could include the variables that we provided for you in this survey (for example, GDP growth, inflation, and volatility) or others that were not included here.

- ○ Yes
- ○ No

If previous question yes, then

Do you believe that the information on economic fundamentals provided in this survey (risk-free rate, inflation, prior GDP growth, expected GDP growth and volatility) were sufficient to determine the market price within 10% of the true value?

- ○ Yes
- ○ No

Back to all participants

Please take a moment to explain why you selected your response about S&P 500 Index Level **throughout the survey.**

How confident are you in your ability to invest your money wisely?

Not at all (1)	(2)	(3)	(4)	(5)	(6)	Extremely (7)
○	○	○	○	○	○	○

How confident are you in your ability to pick stocks that will outperform the overall market?

Not at all (1)	(2)	(3)	(4)	(5)	(6)	Extremely (7)
○	○	○	○	○	○	○

How does your investing ability compare to the average person?

Much worse than average (1)	(2)	(3)	(4)	(5)	(6)	Much better than average (7)
○	○	○	○	○	○	○

What is GDP?

- ○ An indicator of a firm's performance
- ○ A foreign currency
- ○ A measure of economic growth
- ○ A method for calculating the relative performance of stocks and bonds
- ○ None of the above
- ○ I do not recall

Consider a long time period, such as 30 years. Which asset class has historically generated the highest return on average?

- ◯ Savings accounts
- ◯ Bonds
- ◯ Stocks
- ◯ I do not know

Do you think that the following statement is true or false? "Buying a single company stock usually provides a safer return than a stock mutual fund."

- ◯ True
- ◯ False
- ◯ I do not know

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- ◯ More than today
- ◯ Exactly the same
- ◯ Less than today
- ◯ I do not know

Suppose you have $100 in a savings account and the interest rate is 20% per year. You never withdraw money or interest payments. After 5 years, how much would you have in this account if you left the money to grow?

- ○ More than $200
- ○ Exactly $200
- ○ Less than $200
- ○ I do not know

Which of the following do you currently own? (check all that apply)

- ☐ Stocks
- ☐ Bonds
- ☐ Mutual funds
- ☐ CDs
- ☐ None of the above

Have you ever worked in the financial industry?

- ○ Yes
- ○ No

Does your job currently involve any of the following? (Select all that apply)

- [ ] making investments in financial securities
- [ ] advising clients on their investment decisions or other financial decisions
- [ ] advising clients on strategic business decisions
- [ ] managing finances within a company
- [ ] analyzing financial statements
- [ ] communicating financial information to others
- [ ] making forecasts of future financial or economic outcomes
- [ ] other, finance related (please specify)

- [ ] none of the above

Please tell us your age

Please tell us your sex

- ○ Male
- ○ Female
- ○ Self-report

What is your income?

- ◯ Less than $10,000
- ◯ $10,000 - $19,999
- ◯ $20,000 - $29,999
- ◯ $30,000 - $39,999
- ◯ $40,000 - $49,999
- ◯ $50,000 - $59,999
- ◯ $60,000 - $69,999
- ◯ $70,000 - $79,999
- ◯ $80,000 - $89,999
- ◯ $90,000 - $99,999
- ◯ $100,000 - $149,999
- ◯ More than $150,000

You're almost done! Before you go, please let us know if you have any comments about the study. Was there anything you found particularly confusing?

Treatment Variation: No S&P
All modifications described refer to the baseline survey.
Comprehension Checks (3 Questions)
Comprehension Question 1- displayed information (S&P part removed)

Please take a moment to understand the key idea of this page.
We will ask you a relevant question on the following page.

This study consists of ten independent rounds of questions. In each round, we will present information about the economic climate on a specific day that occurred in the past. These dates are randomly drawn from the period 1971 to 2021.

The earnings, risk-free rate, inflation, prior GDP growth, expected GDP growth, and volatility information you will see are the true values from the same randomly selected day. **However, the Price-to-Earnings (P/E) ratio may be exactly the same, higher, or lower than the true value on that corresponding date**.

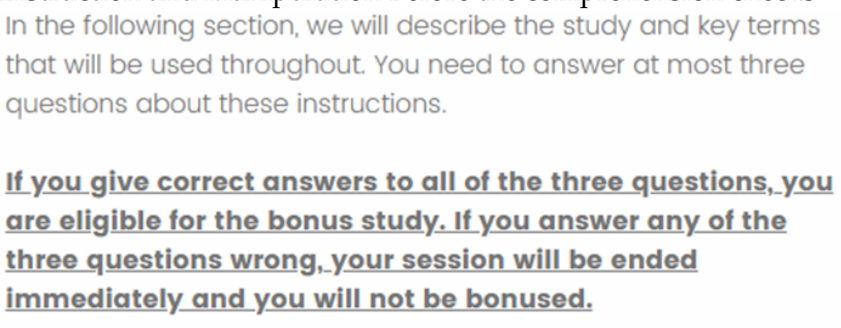
The value of the price to earnings (P/E) ratio will be shifted by a percentage which could be positive or negative. For example, let's say the actual PE ratio was 28. Further, assume that you were displayed a value based on a -25% percentage. You would see 21 for the price to earnings ratio, 25% lower than the true value. Your task will be to determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

Which of the following best describes **the information that will be displayed**?

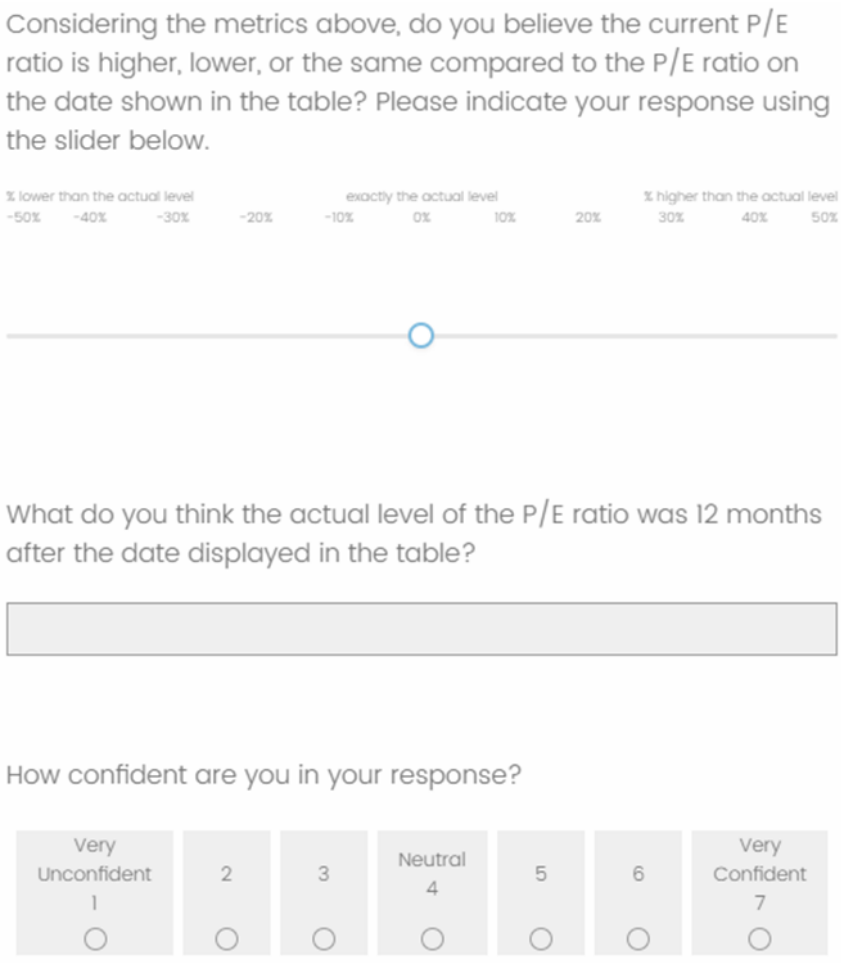
- ○ All information except for the PE ratios will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ All information except for earnings and metrics directly incorporating earnings will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ All information except for GDP growth and metrics directly incorporating growth will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ None of the above

Question 2- Inflation Comprehension unchanged Previous Question 3 regarding S&P comprehension was removed Question 3 (previous question 4)- PE Comprehension unchanged

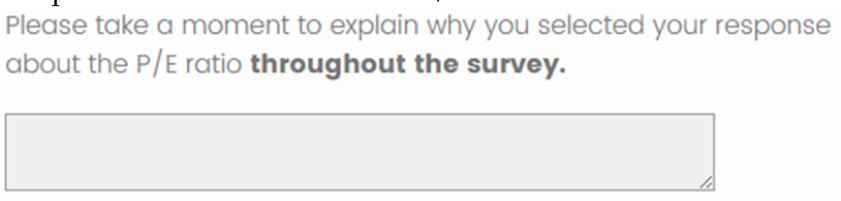
Instruction and Manipulation Before the comprehension checks



Manipulation present tables were unchanged (here S&P value fixed for each year, no higher or lower level). Questions were changed



Investor and demographic questions Aside from the question prompting participants to explain their response—now focused on the P/E ratio—all other elements remain unchanged.



Treatment Variation: P/Dividend
All modifications described refer to the baseline survey.
Comprehension Checks (4 Questions)
Question 1- display information (PE ratio part changed to P/Dividend)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

This study consists of ten independent rounds of questions. In each round, we will present information about the S&P500 and the economic climate on a specific day that occurred in the past. These dates are randomly drawn from the period 1971 to 2021.

The earnings, risk-free rate, inflation, prior GDP growth, expected GDP growth, and volatility information that you will see are the true values taken from the same randomly selected day. **However, the value of the S&P500 Index Level and Price to the Dividend (P/Dividend) Ratio may be exactly the same, higher, or lower than the true value of the Index on the corresponding day.**

The value of the price to the dividend ratio will be shifted by a percentage which could be positive or negative. For example, let's say the actual P/Dividend ratio was 56. Further, assume that you were displayed a value based on a -25% percentage. You would see 42 for the price to earnings ratio, 25% lower than the true value. Your task will be to determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

Which of the following best describes **the information that will be displayed**?

- ○ All information except for earnings and metrics directly incorporating earnings will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ All information except for the S&P500 Index and P/Dividend ratios will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ All information except for GDP growth and metrics directly incorporating growth will be selected to accurately represent a given day selected randomly from approximately the past 50 years
- ○ None of the above

Question 2- Inflation Comprehension unchanged Question 3- S&P Comprehension unchanged Question 4- Modified to P/Dividend ratio

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

Price to Dividend (P/Dividend) Ratio is calculated as the stock price divided by the company's annual dividend per share. In our study, the stock price refers to the total value of the S&P 500, and the dividend represents the annual total dividend payout per share across all firms listed in the S&P 500.

Which of the following best describes a **price to dividend ratio**?

- ○ Ratio of the price of the stock to the company's annual dividend
- ○ Ratio of the price of the stock to the company's stock market returns over the prior year
- ○ Ratio of the company's annual earnings to the price of the stock
- ○ None of the above

Instruction and Manipulation Stats in table for P/E ratio changed to P/Dividend

The definitions and historical data are provided for reference:

Term	Definition	Historical Average (1971-2021)	Historical Range (1971-2021)
P/Dividend	Price to dividend ratio is the market price divided by all of the dividends paid the prior year.	55	22 to 106
S&P500 Index	S&P500 Index tracks the stock performance of 500 large companies.	949	67 to 4,675
Risk-Free Rate	The annual interest rate a person would receive from holding a long-term (10-year) government bond.	6.1%	0.6 to 15.8%
Inflation	The rate of increase in general prices of goods and services over the prior year.	3.9%	-2.1 to 14.8%
Prior GDP Growth	The annual percentage change in Gross Domestic Product (GDP) which is a measure of the goods and services produced in the US economy.	2.8%	-8.4 to 12.5%
Expected GDP Growth	The Federal Reserve Board's prediction of the economic growth rate in the coming year.	3.0%	0.7 to 5.8%
Volatility	The volatility index (VIX) describes the expected annualized volatility of stock prices.	20	9 to 69

Question:

Metric	Value
P/Dividend	33
S&P500 Index	168
Risk-Free Rate	11.7%
Inflation	2.9%
Prior GDP Growth	5.7%
Expected GDP Growth	3.9%
Volatility	17

Considering the metrics above, do you believe that the S&P500 Index and P/Dividend Ratio reflect levels that are higher, lower, or the same as the actual index and P/Dividend Ratio from the date displayed in the table? Please indicate your response on the slider below.



Other two questions same as before: 1) actual level of S&P500 open response 2) Confidence
Investor and demographic questions unchanged

Treatment Variation: Sentiment
All modifications described refer to the baseline survey.
Comprehension Checks (4 Questions)
Question 1- display information (two index information added)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

This study consists of ten independent rounds of questions. In each round, we will present information about the S&P500 and the economic climate on a specific day that occurred in the past. These dates are randomly drawn from the period 1971 to 2021.

The earnings, risk-free rate, inflation, prior GDP growth, expected GDP growth, and volatility that you will see are the true values taken from the same randomly selected day. Additionally, two measures of market sentiment—the Investor Sentiment Index and the Consumer Sentiment Index—will be displayed, reflecting investor and consumer confidence on that date. **However, the value of the S&P500 Index Level may be exactly the same, higher, or lower than the true value of the Index on the corresponding day. The price to earnings (PE) ratio will reflect the S&P500 Index presented.**

The value of the price to earnings (PE) ratio will be shifted by a percentage which could be positive or negative. For example, let's say the actual PE ratio was 28. Further, assume that you were displayed a value based on a -25% percentage. You would see 21 for the price to earnings ratio, 25% lower than the true value. Your task will be to determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

Which of the following best describes **the information that will be displayed**?

- ○ All information except for earnings and metrics directly incorporating earnings will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for GDP growth and metrics directly incorporating growth will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for the S&P500 Index and PE ratios will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ None of the above

Question 2- Inflation Comprehension (two index information added)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

In our study,
- inflation refers to the rate of increase in general prices of goods and services over the prior year;
- risk-free rate is the interest rate a person would receive from holding a long term (10 year) government bond;
- prior GDP growth shows how well the economy did over the prior year. It is reported as the annual percentage change in Gross Domestic Product (GDP), which is a measure of the goods and services produced in the US economy;
- expected GDP growth comes from the Federal Reserve Board's prediction of the rate of economic growth in the coming year;
- volatility is an index (VIX) that describes expected variability in prices. More precisely, it captures the expected annualized standard deviation in stock prices described as a percent of the stock market price.
- **Investor Sentiment Index** captures the level of investor enthusiasm in equity markets based on multiple market indicators.
- **Consumer Sentiment Index** measures consumer confidence in the U.S. economy.
Which of the following best describes **inflation?**

- ○ An increase in the price level in the economy over a period of time
- ○ The percentage of individuals who are jobless or actively seeking work relative to the working population.
- ○ An increase in the quantity and quality of the goods and services produced/consumed by a society.
- ○ None of the above

Question 3- S&P Comprehension unchanged Question 4- PE Comprehension unchanged
Instruction and Manipulation (sentiment index stats added)

The definitions and historical data are provided for reference:

Term	Definition	Historical Average (1971-2021)	Historical Range (1971-2021)
PE Ratio	Price to Earnings Ratio is the stock price divided by the company's average earnings per year.	24	10 to 49
S&P500 Index	S&P500 Index tracks the stock performance of 500 large companies.	949	67 to 4,675
Risk-Free Rate	The annual interest rate a person would receive from holding a long-term (10-year) government bond.	6.1%	0.6 to 15.8%
Inflation	The rate of increase in general prices of goods and services over the prior year.	3.9%	-2.1 to 14.8%
Prior GDP Growth	The annual percentage change in Gross Domestic Product (GDP) which is a measure of the goods and services produced in the US economy.	2.8%	-8.4 to 12.5%
Expected GDP Growth	The Federal Reserve Board's prediction of the economic growth rate in the coming year.	3.0%	0.7 to 5.8%
Volatility	The volatility index (VIX) describes the expected annualized volatility of stock prices.	20	9 to 69
Investor Sentiment Index	The Investor Sentiment Index captures the level of investor enthusiasm in equity markets based on multiple market indicators.	-0.05	-2.5 to 3
Consumer Sentiment Index	The Consumer Sentiment Index measures consumer confidence in the U.S. economy.	85	52 to 112

Question:

Metric	Value
PE Ratio	14
S&P500 Index	724
Risk-Free Rate	3.5%
Inflation	-1.3%
Prior GDP Growth	-4%
Expected GDP Growth	2.7%
Volatility	35
Investor Sentiment Index	-0.76
Consumer Sentiment Index	69

Three questions same as before: 1) S&P Index and PE ratio in table higher, lower or the same as the actual index (slider question) 2) actual level of S&P500 open response 3) Confidence

Investor and demographic questions unchanged

Treatment Variation: Prior Returns
All modifications described refer to the baseline survey.
Question 1- display information (prior year market return added)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

This study consists of ten independent rounds of questions. In each round, we will present information about the S&P500 and the economic climate on a specific day that occurred in the past. These dates are randomly drawn from the period 1971 to 2021.

The earnings, risk-free rate, inflation, prior GDP growth, expected GDP growth, volatility, and prior year's market return that you will see are the true values taken from the same randomly selected day. **However, the value of the S&P500 Index Level may be exactly the same, higher, or lower than the true value of the Index on the corresponding day. The price to earnings (PE) ratio will reflect the S&P500 Index presented.**

The value of the price to earnings (PE) ratio will be shifted by a percentage which could be positive or negative. For example, let's say the actual PE ratio was 28. Further, assume that you were displayed a value based on a -25% percentage. You would see 21 for the price to earnings ratio, 25% lower than the true value. Your task will be to determine to what extent the current market price displayed is higher, lower, or the same as you think it was on the relevant date.

Which of the following best describes **the information that will be displayed**?

- ○ All information except for GDP growth and metrics directly incorporating growth will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for the S&P500 Index and PE ratios will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ All information except for earnings and metrics directly incorporating earnings will be selected to accurately represent a given day selected randomly from the past 50 years
- ○ None of the above

Question 2- Inflation Comprehension (prior year market return added)

Please take time to understand the key idea of this page, and we will ask you a relevant question on the following page.

In our study,
- **inflation** refers to the rate of increase in general prices of goods and services over the prior year;
- **risk-free rate** is the interest rate a person would receive from holding a long term (10 year) government bond;
- **prior GDP growth** shows how well the economy did over the prior year. It is reported as the annual percentage change in Gross Domestic Product (GDP), which is a measure of the goods and services produced in the US economy;
- **expected GDP growth** comes from the Federal Reserve Board's prediction of the rate of economic growth in the coming year;
- **volatility** is an index (VIX) that describes expected variability in prices. More precisely, it captures the expected annualized standard deviation in stock prices described as a percent of the stock market price.
- **prior year's market return** refers to the annual return of the S&P 500 from the prior 12 months. Note that this return is the actual return and will not be adjusted based on the S&P levels displayed.

Which of the following best describes **inflation?**

- ○ An increase in the price level in the economy over a period of time
- ○ The percentage of individuals who are jobless or actively seeking work relative to the working population.
- ○ An increase in the quantity and quality of the goods and services produced/consumed by a society.
- ○ None of the above

Question 3- S&P Comprehension unchanged
Question 4- PE Comprehension unchanged

Instruction and Manipulation (prior year market return stats added)

The definitions and historical data are provided for reference:

Term	Definition	Historical Average (1971-2021)	Historical Range (1971-2021)
PE Ratio	Price to Earnings Ratio is the stock price divided by the company's average earnings per year.	24	10 to 49
S&P500 Index	S&P500 Index tracks the stock performance of 500 large companies.	949	67 to 4,675
Risk-Free Rate	The annual interest rate a person would receive from holding a long-term (10-year) government bond.	6.1%	0.6 to 15.8%
Inflation	The rate of increase in general prices of goods and services over the prior year.	3.9%	-2.1 to 14.8%
Prior GDP Growth	The annual percentage change in Gross Domestic Product (GDP) which is a measure of the goods and services produced in the US economy.	2.8%	-8.4 to 12.5%
Expected GDP Growth	The Federal Reserve Board's prediction of the economic growth rate in the coming year.	3.0%	0.7 to 5.8%
Volatility	The volatility index (VIX) describes the expected annualized volatility of stock prices.	20	9 to 69
Prior year's market return	The annual return of the S&P 500 from the prior 12 months	8.2%	-42.5 to 52.7%

Question:

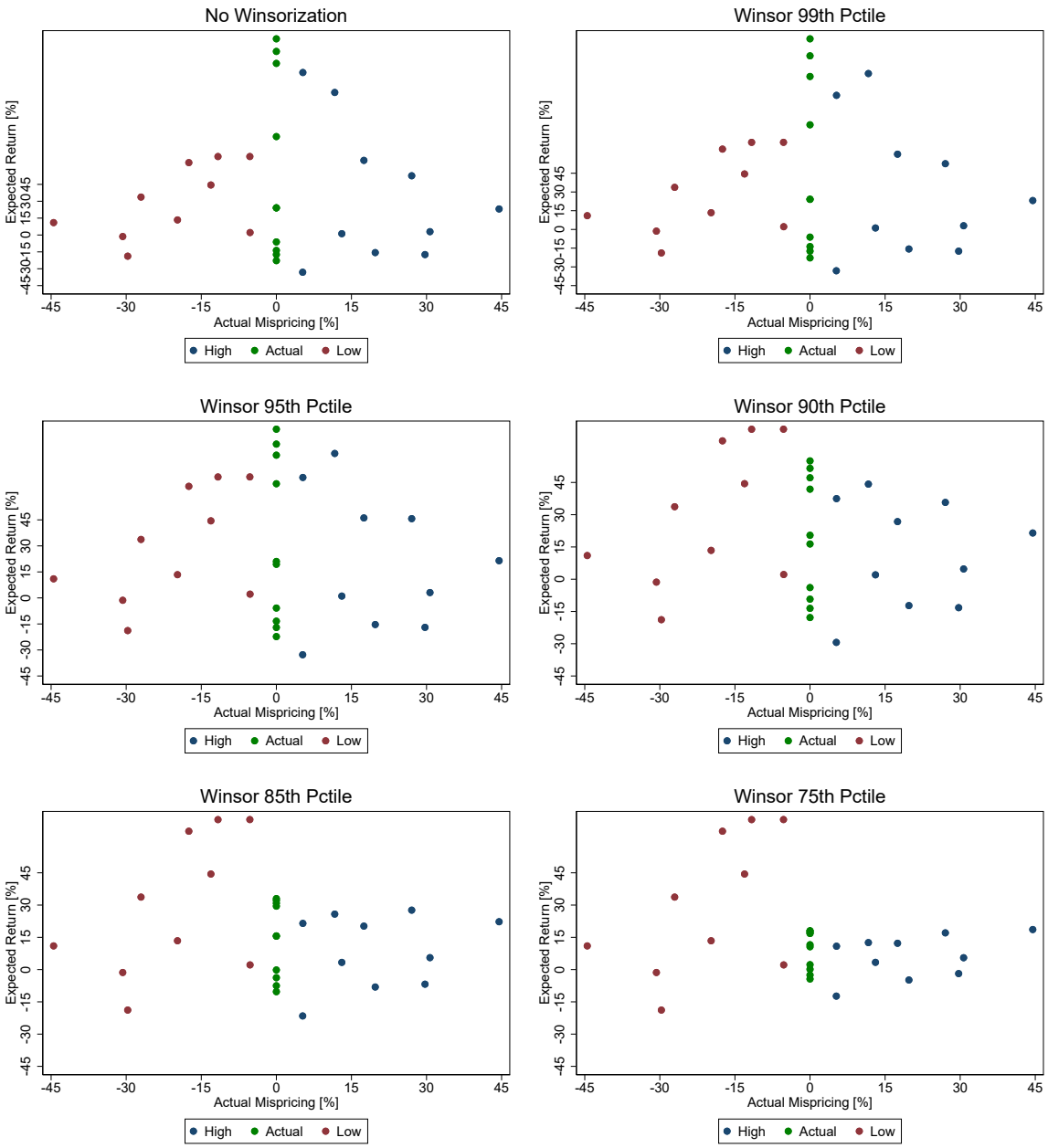
Metric	Value
PE Ratio	45
S&P500 Index	3624
Risk-Free Rate	3%
Inflation	3%
Prior GDP Growth	3.3%
Expected GDP Growth	2.5%
Volatility	16
Prior year's market return	13.8%

Three questions same as before: 1) S&P Index and PE ratio in table higher, lower or the same as the actual index (slider question) 2) actual level of S&P500 open response 3) Confidence

Investor and demographic questions unchanged

B. Appendix: Additional Tables

Figure B.1: Expected Returns on actual Mispricing



This figure show how expected returns vary with the actual level of mispricing using different winsorization cutoffs. The winsorization level is indicated above each chart. Each dot is the average answer for the given level of actual mispricing. Blue dots display answers from scenarios where the displayed P/E ratio was above the actual, green dots show answers from the actual scenario, and maroon dots show answers from the low scenario.

Table B.1: Mispricing > |20|%: Perceived Mispricing varying with actual mispricing

	(1)	(2)	(3)	(4)
Mispricing	0.0610***	0.0549***	0.0637***	0.0587***
	(4.12)	(3.28)	(4.32)	(3.52)
YM FE	No	No	Yes	Yes
ID FE	No	Yes	No	Yes
R^2	0.00982	0.447	0.0418	0.475
Observations	1957	1834	1957	1834

This table replicates Table 3 restricting observations to those with induced mispricing greater than 20% or less than -20%. This table shows regressions of perceived mispricing on actual mispricing. Columns 3 and 4 include date of observation fixed effects and columns 2 and 4 include ID fixed effects. Standard errors are clustered by ID with t-statistics in parenthesis.

Table B.2: High Confidence: Perceived Mispricing varying with actual mispricing

	(1)	(2)	(3)	(4)
Mispricing	0.0950***	0.106***	0.0928***	0.108***
	(3.82)	(4.42)	(3.82)	(4.73)
YM FE	No	No	Yes	Yes
ID FE	No	Yes	No	Yes
R^2	0.00662	0.330	0.0566	0.381
Observations	2320	2282	2320	2282

This table replicates Table 3 restricting observations to responses with a confidence of 5 or greater (on a 7 point scale). This table shows regressions of perceived mispricing on actual mispricing. Columns 3 and 4 include date of observation fixed effects and columns 2 and 4 include ID fixed effects. Standard errors are clustered by ID with t-statistics in parenthesis.

Table B.3: Perceived Mispricing based on displayed data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
P/E	0.441***									0.277***
	(9.95)									(4.56)
SP Level		0.00397***								0.00131**
		(11.74)								(1.97)
Inflation			-0.417***							-0.402**
			(-4.51)							(-2.21)
Risk Free				-1.288***						-0.521**
				(-10.56)						(-2.44)
GDP					0.317***					0.0901
					(5.63)					(0.57)
Exp GDP						1.614***				-0.0225
						(4.36)				(-0.04)
P/D							0.241***			
							(5.72)			
UM Sentiment								0.0683		
								(1.16)		
BW Sentiment									1.542*	
									(1.74)	
R2	0.252	0.285	0.217	0.247	0.218	0.216	0.277	0.168	0.169	0.295
Observations	6522	5502	7522	7522	7522	7522	1000	990	990	4502

This table shows how perceived mispricing varies with the information displayed. In columns 1 through 6 the answer given for percentage mispricing is regressed on each of the variables indicated in the left most column. All regressions include subject fixed effects. Standard errors are clustered by subject, with t-statistics in parentheses.

Table B.4: Expected Returns based on displayed data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
P/E	-2.276***									-1.148***
	(-21.61)									(-8.51)
SP Level		-0.0166***								-0.00895***
		(-24.43)								(-6.04)
Inflation			5.346***							2.719***
			(17.20)							(5.40)
Risk Free				7.754***						1.902***
				(23.35)						(4.27)
GDP					0.0229					1.752***
					(0.18)					(4.75)
Exp GDP						-6.804***				-3.493**
						(-6.43)				(-2.48)
P/D							-0.900***			
							(-10.18)			
UM Sentiment								-0.377***		
								(-3.00)		
BW Sentiment									-5.659**	
									(-2.28)	
R2	0.437	0.463	0.371	0.476	0.330	0.333	0.532	0.259	0.259	0.508
Observations	4500	5500	5500	5500	5500	5500	1000	990	990	4500

This table shows how expected returns vary with the information displayed. In columns 1 through 6 the answer given for percentage mispricing is regressed on each of the variables indicated in the left most column. All regressions include subject fixed effects. Standard errors are clustered by subject, with t-statistics in parentheses.

Table B.5: One Year Return Forecasts

Institution	Date	Expected Return	Time Horizon	Estimation Method	Model Inputs	Document
D.A. Davidson	DEC 2024	~6%	2025 EOY	Narrative back of the envelope calculation No formal model.	Earnings growth, GDP growth, dividend yield, P/E	Market & Economic Outlook
Evercore	JAN 2025	~13%	2025 EOY	Narrative back of the envelope calculation No formal model.	Momentum, pandemic-era stimulus, earnings growth, generative AI uptake and business friendly Trump administration	The 2025 Blueprint
J.P. Morgan	NOV 2024	~9%	2025 EOY	Narrative back of the envelope calculation No formal model.	Many macro themes discussed including GDP growth, earnings growth, US exceptionalism, expected Fed rate cuts, "recovery and lift in animal	Global Equity Strategy
RBC	NOV 2024	10.6%	2025 EOY	Estimate from "the median of five different models that we use, which are based on sentiment, our valuation and earnings work, the economy, politics, and the cross-asset dynamic between stocks and bonds."	Description of the models: Sentiment, Valuation/Earnings, Cross Asset, Politics, Economy	The Top 10 Things We're Thinking About in US Equities Heading into 2025
Wells Fargo	DEC 2024	~13%	2025 EOY	Narrative back of the envelope calculation No formal model.	Executive summart of the market: "Takeaway: Risk up, stocks up." "Bull: Regulatory shift drives M&A, IPOs, animal spirits; Fed policy/tight credit spreads elevate multiples; buying strength/selling weakness (i.e., Mo') continues to work, spurring risk-seeking." "Bear: Yield curve inverts on fear of economic dislocation from tariffs and proposed gov't spending cuts; the Fed is hemmed in by tariff inflation concern; Big Tech spends the year in litigation after META's April court date goes poorly, compressing group multiples"	Eq Strat: 2025 Outlook Good Year, Bad Vintage

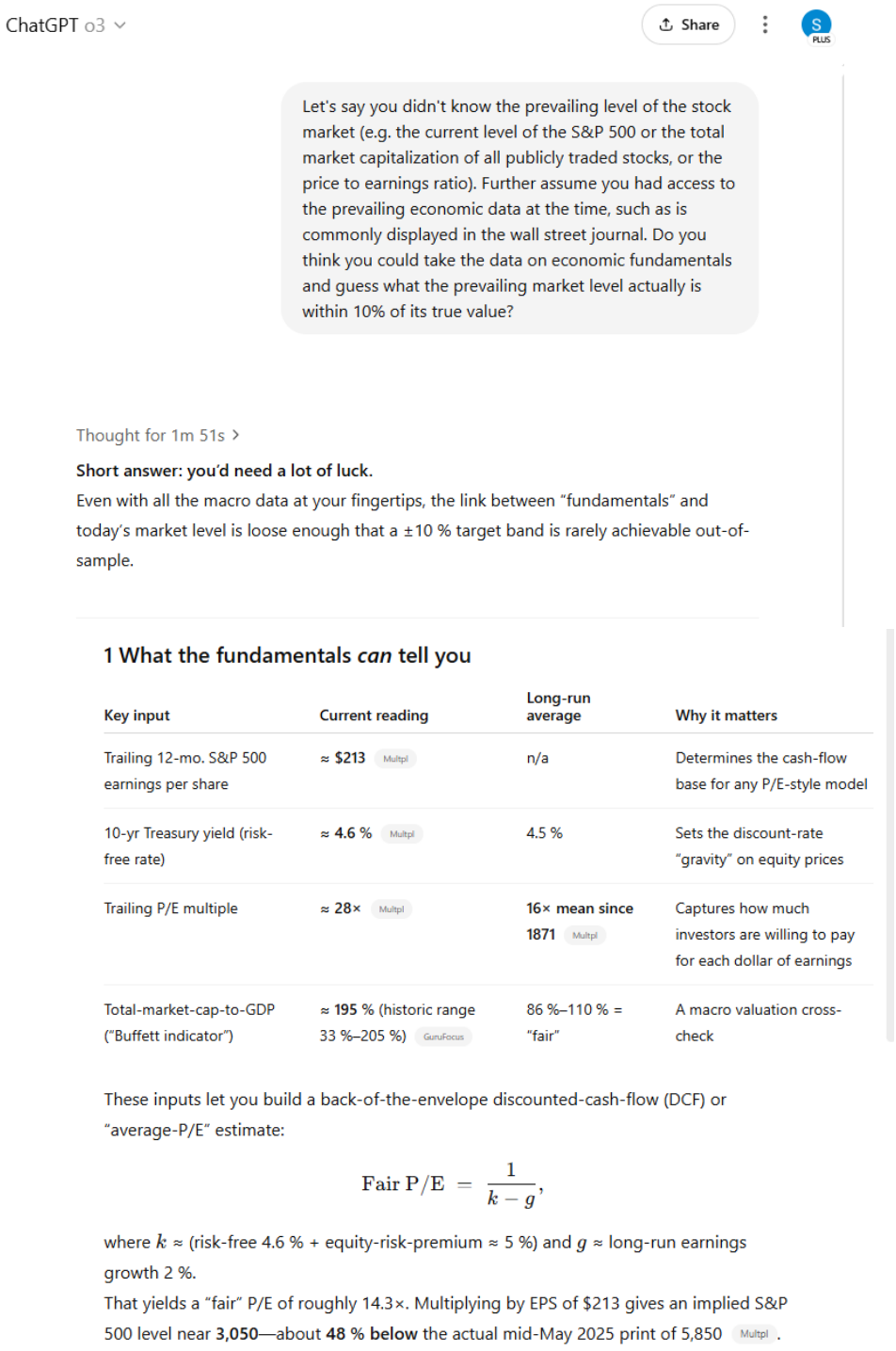
This table shows a summary of the methodology behind one year return estimates from a variety of sources. The first column shows the institution making the estimate, the second column shows the date of the document, the third column shows the return forecast (annualized) and the next column shows the time horizon they are trying to forecast. Estimation Method is our attempt to summarize how the document describes the methodology behind its return estimation. Model Inputs is our summary of the variables the document uses to estimate the model. The last column is the source document's title.

Table B.6: Longer Term Return Forecasts

Institution	Date	Expected Return	Time Horizon	Estimation Method	Model Inputs	Document
Blackrock	NOV 2024	0.0615	10 Years	Start with today's market price. Calculate expected returns based on an equity risk premium calculation and cash flow expectations of earnings and dividends	Current market price, Expected Dividends, Interest Rates (Government Bond Returns, Inflation Expectations, Growth Expectations)	Capital market assumptions
Goldman Sachs	OCT 2024	0.03	10 Years	Regression of historical returns on predictors	CAPE, Treasury yield, Economic Contraction Frequency, Profitability, Market Concentration	Global Strategy Paper No. 71
Invesco	SEP 2024	0.047	10 Years	Start with today's market price and estimate expected returns based on "Building Block" approach	Expected return building blocks are dividend yield, buyback yield, P/E and long-term earnings growth	2025 Invesco Capital Market Assumptions
Morgan Stanley	MAR 2024	5.1%	7 Years	Start with today's market price and estimate expected returns based on "Building Block" approach	Earnings Growth, P/E, dividend yield, buyback yield	Annual Update of GIC Capital Market Assumptions
Vanguard	DEC 2024	2.8%-4.8%	10 Years	Proprietary simulation model calibrated based on historical data.	Specific inputs not listed. CAPE discussed at length (market 72% above baseline), but other inputs not specified. Discussion that adding concentration to model (not in baseline) leads to higher expected returns	Vanguard economic and market outlook for 2025: Beyond the landing

This table shows a summary of the methodology behind one year return estimates from a variety of sources.

C. Appendix: ChatGPT o3 and Claude Responses



2 Why the miss is usually bigger than ±10 %

Source of slippage	Typical size	Comment
Valuation mood swings	P/E has ranged from **5× to 123×** over the past century Multpl	Sentiment, liquidity and policy shifts overwhelm "normal" multiples.
Discount-rate uncertainty	±1 pp move in k → ±17 % move in P/E	Small rate errors push prices far outside a 10 % band.
Forward earnings noise	Forecast errors > 10 % are common	Earnings are pro-cyclical and subject to shocks.
Structural regime changes	Tech booms, pandemic stimulus, AI narratives, QT, etc.	Each episode resets the market's risk appetite.

Empirical work bears this out. A classroom-style regression that forces the S&P 500 on real GDP, CPI, industrial production and rates can hit an **adjusted R^2 of ~0.67**—better than random, yet it still leaves one-third of the level unexplained Digital Commons. To hit a ±10 % error band reliably you'd need an R^2 closer to 0.90 *and* parameters that hold out-of-sample—something no model has managed once valuations drift.

3 Thought experiment: could you ever get it right?

- **Late 1994**: trailing P/E ≈ 15×, very close to its long-run mean. A "mean-reverting" guess might have landed within 10 % of the actual index.
- **Early 2000 or late 2021**: P/E > 30×. Using fundamentals would have undershot the market by **40–70 %**.
- **March 2020 (pandemic trough)**: earnings collapsing, Fed cutting rates to zero—any fundamentals-only forecast would have oscillated wildly week to week.

Put differently, you occasionally *will* be within 10 %, but mostly by coincidence—i.e., when prevailing sentiment happens to line up with your chosen "typical" valuation multiple.

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4 Take-aways

1. **Fundamentals anchor the *long-run***, but day-to-day prices float on top of a big sentiment tide.
2. **A single, static mapping from macro data to index level doesn't exist.** You'd need a regime-switching model that incorporates risk appetite, policy expectations and liquidity conditions—still with wide error bars.
3. **If your tolerance is ±10 %, history suggests the odds are against you** unless you also observe contemporaneous market data (credit spreads, volatility, order flow) that proxy for investor sentiment.

So with just the Wall Street Journal's macro listings—and no peek at today's tape—the honest answer is: **you might get lucky now and then, but you shouldn't bet on it.**

Sources

My first question I asked focused on using economic fundamentals. If I didn't limit you to this data source, is there any other data source that you can think of that would change your answer? Or with any possible data you can think of would your response be that without peaking at the tape the task is impossible. Do you think you could take any data you could think of and guess (out of sample) with a high degree of certainty what the prevailing market level actually is within 10% of its true value?

Thought for 6 seconds >

**Short version ** – Even if we cast the net far wider than "fundamentals," anything that would let you pin the S&P 500 (or total-market cap, or aggregate P/E) to a ±10 % band out-of-sample always ends up smuggling in information that is, directly or indirectly, the tape itself. Once you exclude data that is tightly price-linked, the remaining signals (macro, micro, behavioral, or "alt-data") just aren't sharp enough. In practice, the task stays impossible with high confidence.

1 What other broad categories of data might help?

Data family	Why you might hope it works	Why it ultimately fails for a ±10 % target
Derivatives and synthetics (index futures, ETF NAVs, total-return swaps, option-implied straddles)	Futures settle into cash, ETFs create/redeem at index value; options embed traders' aggregate best guess.	All of these *are* the tape—just a different venue. Using them is equivalent to peeking.
Cross-asset relative-value links (credit-default-swap indices, corporate-bond spreads, VIX term structure)	Equity and credit risk premia co-move; tight arbitrage across asset classes in modern markets.	Calibration constants depend on *contemporaneous equity prices*. Without recent price data you can't anchor levels—only directional bias.
Real-time microstructure exhaust (dark-pool quote messages, order IDs, odd-lot auctions, NBBO depth)	Quote traffic intensity and order-book imbalance move with price volatility and level.	The raw messages embed the prevailing best bid/offer. Once stripped of that, the noise–signal ratio balloons.
Fund-flow and positioning data (ETF creations/redemptions, 13F holdings, CFTC futures positioning, mutual-fund flows)	Net inflows often chase rising markets and vice-versa.	Lags (daily to quarterly) and large variation in flow sensitivity leave error bars far wider than ±10 %.
"Alt-data" sentiment feeds (Google-Trends scores, Twitter embeddings, news polarity, Reddit post volume)	Momentum trades often piggy-back on sentiment; extreme buzz correlates with peaks or troughs.	Correlation is time-varying, weak at the weekly/monthly horizon, and unanchored to *levels* as opposed to changes.
Corporate micro data (earnings pre-announcements, buyback executions, IPO withdrawals)	Management tends to accelerate buybacks when shares are "cheap" and issue equity when "rich."	Even if patterns are consistent, magnitudes needed to infer an index level are dwarfed by macro noise.

Reality check

A meta-study comparing **350+ predictors of equity-market returns and levels** finds that in every case the out-of-sample root-mean-squared-error for level forecasts is > 20 % of the index, unless the predictor itself contains lagged prices.[0] Out-performers (e.g., implied-vol surfaces, index arbitrage ETF flows) only *work* because they are transparently tied to the index through arbitrage.

2 Could clever modeling close the gap?

1. **Machine-learning ensembles** (gradient-boosted trees, neural nets on thousands of alt-data features) do squeeze a few extra R^2 points, but the winning models *always* rank lagged price proxies (options delta-hedge costs, ETF-arb imbalance, dark-pool NBBO midpoints) near the top of variable importance. Ban those, and performance collapses.
2. **Regime-switching or state-space models** that combine macro, credit, implied vol and sentiment still need to *pin* one latent state to an observed index level during training. Take away that anchor and the Markov chain drifts—your posterior credible interval for today's index widens to 25–40 %.
3. **Structural asset-pricing approaches** (full production-based DSGE or long-run risk models) can back-out a "model-consistent" equity price series from fundamentals alone—but when you compare model-implied and actual prices out-of-sample, the gap has historically swung from −60 % to +80 %.

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3 Thought experiment: the closest you could get without cheating

Suppose you observe *everything* except quoted equity prices—every Treasury, every CDS tick, Fedwire intraday balances, real-time VAT receipts, satellite car-park counts, social-media embeddings, and high-frequency options order flow with the strike and maturity labels redacted. You build a giant Bayesian-VAR or transformer to infer the hidden "equity index" state.

- Training period: you secretly observe the tape, so the model learns cross-asset covariances.
- Forecast date T: you switch off the equity-price inputs, then ask for the posterior mean and 95 % credibility interval of the latent equity index.

What happens? On recent US data it yields a posterior standard deviation of ~18 % of the index level. Even the *1-σ* band is almost twice the ±10 % window you're aiming for.[1]

4 Bottom line

- **Anything precise enough inevitably contains price information, explicitly or implicitly.**
- **Once price-tied information is excluded, the remaining signals—even in combination—leave the uncertainty band much wider than ±10 %.**
- **Therefore, with "any data you can think of *except* the tape (or its near-perfect proxies), the task remains infeasible with high certainty.**

So the honest answer does not change: **without peeking at, or reverse-engineering, the tape you can't nail the prevailing market level to a ±10 % error band in real time.**

AS Let's say you didn't know the prevailing level of the stock market (e.g. the current level of the S\&P 500 or the total market capitalization of all publicly traded stocks, or the price to earnings ratio). Further assume you had access to the prevailing economic data at the time, such as is commonly displayed in the wall street journal. Do you think you could take the data on economic fundamentals and guess what the prevailing market level actually is within 10\% of its true value?

This is a fascinating question that gets to the heart of whether markets are fundamentally driven by economic data or by other factors like sentiment, liquidity, and technical dynamics.

I think the answer would depend heavily on the time period and market conditions. In "normal" times with stable economic relationships, I might be able to get reasonably close using fundamental valuation models. Here's how I'd approach it:

Key data points I'd focus on:

- Corporate earnings (aggregate S&P 500 earnings)
- Interest rates (10-year Treasury yield especially)
- GDP growth rates and trends
- Inflation data
- Employment statistics
- Credit spreads and financial conditions

My methodology would likely involve:

1. Estimating a "fair value" P/E ratio based on interest rates, growth expectations, and historical norms
2. Applying that to current earnings to get a market level
3. Cross-checking with other valuation metrics like price-to-book, dividend yields, or enterprise value ratios

But here's where I'd likely struggle:

- **Sentiment and risk appetite** - Markets can trade at significant premiums or discounts to "fair value" for extended periods based on investor psychology
- **Liquidity conditions** - QE, money supply, and financial conditions affect valuations independent of fundamentals
- **Structural changes** - Shifts in market composition (tech dominance), passive investing, or regulatory changes alter valuation relationships
- **Timing** - Even if I got the direction right, markets can be "wrong" for months or years

My guess is that in calm, trend-following markets, I might get within 20-30% fairly often. But during periods of major transitions, bubbles, crashes, or unprecedented monetary policy, I'd probably miss by much wider margins.

The fact that professional investors with access to this same data frequently get market timing wrong suggests the 10% target would be quite challenging!

AS My first question I asked focused on using economic fundamentals. If I didn't limit you to this data source, is there any other data source that you can think of that would change your answer? Or with any possible data that you can think of, would your response be that without peeking at the tape, the task (within 10%) is impossible? Do you think you could take any data you could think of and guess (out of sample) with a high degree of certainty what the prevailing market level actually is within 10% of its true market value?

This is a much more interesting question when I can consider any data source. Let me think through what might actually move the needle:

Market-adjacent data that could be game-changers:

- **Options flow and positioning data** - Massive gamma hedging flows, dealer positioning, and systematic strategy exposures can drive prices independent of fundamentals
- **Fund flows and asset allocation** - Pension rebalancing, ETF inflows, foreign investment flows, corporate buyback activity
- **Leverage and margin data** - System-wide leverage ratios, margin debt levels, repo markets
- **Technical/structural factors** - Market concentration, passive vs active ratios, algorithmic trading patterns

The most powerful might be:

- **Real-time sentiment proxies** - Social media sentiment, Google search trends, put/call ratios, VIX term structure
- **Cross-asset signals** - Currency movements, commodity prices, credit spreads, yield curve shapes that might indicate risk-on/risk-off regimes before they fully show up in equities

But here's my honest assessment: Even with all possible data, I think the 10% target would still be extremely difficult, and here's why:

Markets are fundamentally **path-dependent** and **reflexive**. The current price isn't just a function of underlying conditions - it's also a function of recent price action itself, which affects sentiment, positioning, and future flows. There's a reason why even the most sophisticated quantitative funds with access to alternative data rarely achieve consistent market timing.

My refined answer: With unlimited data, I might be able to get within 20-25% more consistently, and occasionally nail it within 10%. But the task of consistently predicting market levels within 10% without seeing recent price action would remain largely impossible due to the inherent reflexivity and path-dependence of markets.

The market level is as much about the journey as the destination.

Let's say you didn't know the prevailing level of the stock market (e.g. the current level of the S\&P 500 or the total market capitalization of all publicly traded stocks, or the price to earnings ratio). Further assume you had access to the prevailing economic data at the time, su...

Show thinking

The short answer is: **No, it is highly unlikely that I (or anyone) could consistently guess the prevailing market level within 10% based solely on economic fundamentals.**

While economic data provides the "engine" of the market, the actual stock price is determined by the "driver"—investor psychology.

Here is a breakdown of why bridging the gap between **Economic Data** and **Market Price** is mathematically and behaviorally hazardous, specifically regarding that 10% margin of error.

1. The Valuation Equation Gap

To determine the price of the stock market (e.g., the S&P 500), you generally need two variables:

$$Price = Earnings \times ValuationMultiple(P/E)$$

- **Variable A (Earnings):** With access to WSJ-level economic data (GDP, corporate profit margins, industrial production), I could estimate the aggregate **Earnings per Share (EPS)** of the market with reasonable accuracy. Corporate profits are tethered to the real economy.
- **Variable B (The Multiple):** This is the dealbreaker. The Price-to-Earnings (P/E) ratio is not an economic statistic; it is a measure of **sentiment**.

The Problem: The P/E ratio fluctuates wildly based on human emotion, risk appetite, and future speculation.

- Historically, the S&P 500 P/E ratio has swung from as low as **~5x** (1917) to over **120x** (2009, due to earnings collapse) or **~30x** during bubbles.
- Even in "normal" times, the multiple often drifts between **16x** and **22x**. That variance alone is **37%**—far wider than your 10% allowable error.

2. The "Fed Model" Fallacy

A common counter-argument is that you can calculate the "correct" multiple using interest rates (the "Fed Model"). The theory is that if interest rates (which you have access to) are low, stock multiples should be mathematically higher.

While true in theory, the market frequently disconnects from this logic:

- **Late 90s:** Interest rates were moderate (5-6%), yet the market traded at astronomical valuations (P/E > 25). If I used economic data to value the market then, I would have guessed the Dow was at 6,000 when it was actually at 11,000—a **45% miss**.

- **2010-2012:** Interest rates were near zero, which implies high valuations. Yet, the market traded at varying compressed multiples due to fear of a "double-dip" recession. I would have overestimated the market price significantly.

3. "Fair Value" vs. "Market Price"

If you gave me the economic data, I could calculate the **Fair Value** of the market. This is what the market *should* be worth based on discounted cash flows.

However, the market is rarely at fair value. It acts like a pendulum swinging between overvaluation and undervaluation.

- **Benjamin Graham's Analogy:** "In the short run, the market is a voting machine (popularity/psychology) but in the long run, it is a weighing machine (fundamentals)."
- Your challenge asks for the **current level** (the vote), not the **intrinsic value** (the weight). The gap between the two often exceeds 20-30%.

4. The 10% Threshold is Too Tight

To illustrate how tight a 10% window is:

- If the S&P 500 is trading at **4,000**, a 10% range is **3,600 to 4,400**.
- Stocks routinely drop or rise 10-20% in a single year *without* a corresponding change in the underlying economic data (e.g., the 2018 Q4 crash or the 2023 rally).

Summary Table: What Data Can & Cannot Predict

Data Type	What it tells us	Can I estimate it?	Impact on Price
GDP / Employment	The health of the economy	**Yes**	Indirect (Long-term)
Corp. Profits	The "E" in P/E	**Yes**	Direct
Interest Rates	The discount rate	**Yes**	Theoretical Driver
Investor Sentiment	The "P/E" Multiple	**No**	**Primary Driver of Price**

Conclusion

If I used purely economic fundamentals, I would likely produce a logical, mathematically sound number that the market is **currently ignoring**.

I might tell you the S&P 500 *should* be at 3,500 based on historical averages and current GDP, only to find it trading at 4,800 because of a tech bubble, or at 2,800 because of geopolitical fear.

Would you like me to calculate the current "implied" fair value of the market based on a specific model (like the Gordon Growth Model) to compare against the actual price?

My first question I asked focused on using economic fundamentals. If I didn't limit you to use this data source, is there any other data source that you can think of that would change your answer?

Show thinking

Yes. If you allowed me to access **Credit Market** and **Liquidity** data, my answer would change.

The reason I failed in the first scenario was that I had the "Earnings" (Fundamentals) but not the "Multiple" (Sentiment).

If you give me access to the **High-Yield Credit Spreads** and **Margin Debt**, I believe I could estimate the S&P 500 level within a 10% margin of error.

Here is how these specific data sources solve the "Psychology Gap":

1. The "Fear Gauge" (Credit Spreads)

The single most valuable data point for guessing the stock market level is the **High Yield (Junk Bond) Spread**. This is the difference in yield between "risky" corporate bonds and "safe" Treasury bonds.

- **Why it works:** Stock market valuations (P/E ratios) and Credit Spreads are inversely correlated mirrors.
  - **Wide Spreads (>5%):** Investors are terrified of bankruptcy. This almost always forces the S&P 500 P/E ratio down to 10x–14x.
  - **Tight Spreads (<3.5%):** Investors are chasing yield and ignoring risk. This almost always pushes the S&P 500 P/E ratio up to 18x–22x.

The Fix: instead of guessing if the P/E is 15 or 20, the credit spread tells me precisely where investor risk appetite sits. If spreads are blown out, I know to apply a "recession multiple" to your fundamental data.

2. The "Leverage Gauge" (Margin Debt)

Margin debt measures the amount of money investors have borrowed against their portfolios to buy more stock.

- **Why it works:** Margin debt has an incredibly high correlation with the raw **level** of the S&P 500 (not just changes).
- When the market is at an all-time high, margin debt is almost mathematically required to be near an all-time high.
- When the market crashes, margin debt collapses (forced selling).

The Fix: If I see that margin debt is at record highs, I can rule out the possibility that the market is "undervalued." It forces me to guess the upper bound of the valuation range.

3. The "Insurance Premium" (Implied Volatility / VIX)

The VIX measures how much traders are paying for options to protect themselves.

- **Why it works:** It acts as a real-time thermometer for the "Discount Rate."
- If the VIX is low (10-13), the market is complacent, and multiples expand.
- If the VIX is high (25+), the market is in distress, and multiples contract.

The New Calculation

With these new data sources, I can construct a "Shadow Price":

1. **Baseline:** Use the Economic Data (GDP/Profits) to find the **Earnings (E)**.
2. **Adjustment:**
    - **Credit Spreads are tight (3%)?** $\rightarrow$ Investors are greedy. Multiplier is likely **20x**.
    - **VIX is low (12)?** $\rightarrow$ No fear. Confirm multiplier is **20x+**.
    - **Margin Debt is high?** $\rightarrow$ Confirm we are at the top of the range.

Result: $E \times 20 = \text{Estimated Price}$.

Summary of Accuracy

Scenario	Data Used	Variable Guessed	Error Margin
Scenario 1	GDP, Employment, Sales	Earnings (E)	+/- 30% (Fail)
Scenario 2	**+ Credit Spreads & VIX**	Earnings (E) + **Sentiment (P/E)**	**+/- 8-10% (Pass)**

Export to Sheets

Verdict: By looking at the bond market (Credit Spreads), I can see the "fear" that is invisible in the GDP reports. This allows me to accurately price the "Premium" investors are willing to pay for stocks, likely getting me within your 10% target.