The Pricing of Earnings News*

Benjamin Marrow†

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Abstract

How does earnings news get priced into stock returns? I use a demand system approach to show that this passthrough depends on investor responses to both earnings and prices and that these sensitivities are heterogeneous across investors. A key identification challenge is that earnings news is rapidly incorporated into prices; as a result, it is difficult to distinguish whether investors react to the earnings news itself or the concurrent price change. Using a two-step procedure to isolate price from earnings responses, I identify an average asset-weighted earnings elasticity of 3, i.e. for a stock that beats earnings expectations by 1%, the average investor would increase his number of shares held by 3% if prices were held fixed. These estimates vary across sectors, with most institutional investors more earnings elastic and price inelastic compared to the residual ("household") sector. The stock-level sensitivities implied by their ownership account for heterogeneous earnings passthroughs, as stocks with higher earnings sensitivity and lower price sensitivity see larger return responses from the same earnings surprise. Extremes of price and earnings elasticities are also closely related to misreaction: a strategy that bets on subsequent reversal (momentum) in sensitive (insensitive) stocks in response to earnings news generates significant outperformance and alpha. These findings suggest that the pricing of earnings news is closely related to the ownership structure of stocks.

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†University of Chicago, Department of Economics and Booth School of Business; email: bmarrow@chicagobooth.edu.

1 Introduction

Models of asset pricing typically specify a close link between stock fundamentals (dividends, earnings, etc) and valuations. Because these models imply that shocks to, or news about fundamentals translate into changes in prices, they raise a set of empirical questions about how precisely fundamental news becomes incorporated into stock returns. In this paper, I adopt a demand-system approach to study the pricing of earnings news – an organizing source of fundamental news about firms – in the stock market. I show that investor-level responses to earnings news depend on elasticities to prices and fundamentals separately, and that these elasticities are heterogeneous across investors.

Moreover, because stocks vary in their ownership structure, stocks inherit the sensitivities of their investors: in the cross-section, stocks with investors who are more earnings sensitive, or less price sensitive, see a larger price impact from an earnings surprise of a given magnitude. This differential pricing is not a result of investors sorting across stocks that differ along other dimensions that explain these cross-sectional responses, but rather a feature of market mispricing: long-short directional strategies that bet on *reversal* in stocks expected to overreact to fundamental news (i.e., earnings sensitive or price insensitive stocks), and on *momentum* in stocks expected to underreact (i.e., earnings insensitive or price sensitive stocks stocks) generate a four-factor alpha on the order of 1.0-1.7% per quarter. The stock-level analysis implies that the ownership structure of stocks plays a key role in the pricing of earnings news, and that variation in both investor earnings and price sensitivities closely reflects misreaction to fundamental news.

The challenge in identifying investor-level responses to earnings is that such news is contemporaneous with returns induced by *other* investors' responses to those surprises. In short, an investor's general-equilibrium response to earnings news embeds both his response to the news itself (the "fundamental" response) as well as his response to the aggregate price impact (the "price" response). To understand the challenge this poses for identification, consider the case of a momentum trader who pays no direct attention to earnings news and instead trades on the past performance of various stocks. Such an investor will appear to buy those stocks that beat earnings expectations (and sell those that underperform), but only because stocks that beat earnings tend to rise in price as well. A naive regression of this investor's portfolio weights on earnings surprises will deliver a positive coefficient, even as the investor in question does not, by assumption, care about earnings news. A potential alternative solution – controlling for returns – is inadequate, since returns are endogenous to the quantity responses of *all* investors, who may share the demand function of the investor analyzed. In other words, controlling for returns in this case introduces the "bad control" problem that arises when the control variable (stock returns) is itself a consequence of the treatment (earning surprises) (Angrist and Pischke (2009)).

I instead address the identification problem through a two-step procedure that first adjusts an investor's trades to account for how that investor responds to prices. Intuitively, consider two investors who are equally sensitive to an earnings surprise, i.e. believe it has the same implications for future earnings and dividend growth, while the rest of the market believes it has a larger impact. Each investor's total trading response will then depend not only on their elasticity to the earnings news, but also on how they trade against the perceived overvaluation induced by the pricing wedge between their own perception of the earnings news and the market's. An investor who trades actively against perceived overvaluations – a price elastic investor – will reduce his net purchases of the asset by more than an equally earnings-sensitive investor who is less active in his trading against prices. Hence these two investors, who share the same earnings elasticity, may have different general equilibrium responses to the earnings news due to differences in their respective price elasticities.

More formally, I start with a simple model in which an investor's portfolio choice is expressed as a log-linearized function of earnings surprises and price movements (i.e., returns). Through the logic of market clearing, I show that the coefficient from a simple regression of quantities on earnings surprises equals the investor's true earnings elasticity, plus a price response: the investor's price elasticity, times the market-level price impact of the earnings surprise. To recover the true fundamental elasticity, it is necessary to net out the investor's response to the aggregate price change. While the formulation is specific to the linear model I write down, the necessity of adjusting trading responses for the associated market-induced price response applies more generally, both to alternative specifications of demand and a broader set of news and characteristics.

Estimating an investor's price response requires an estimate of price elasticities, i.e., how an investor's portfolio holdings respond to a pure price change unassociated with other changes in fundamentals. I identify price elasticities using the market equity instrument from Koijen and Yogo (2019). This instrument generates cross-sectional variation in prices by exploiting variation in the investment universes of large investors: stocks that are in the investment universes of more (or wealthier) investors have higher prices ceteris paribus, and the relationship between investors' portfolio weights and this implied market equity provide an estimate of their sensitivity (elasticity) to prices. Investors that tilt their holdings further away from stocks that have exogenously higher market equity due to their larger presence in the investment universes are more price elastic. This price elasticity provides an estimate of how an investor would respond if the price moved without any corresponding change in fundamentals. Any systematic residual change in holdings beyond this predicted amount can then be attributed to an investor's sensitivity to earnings news itself.

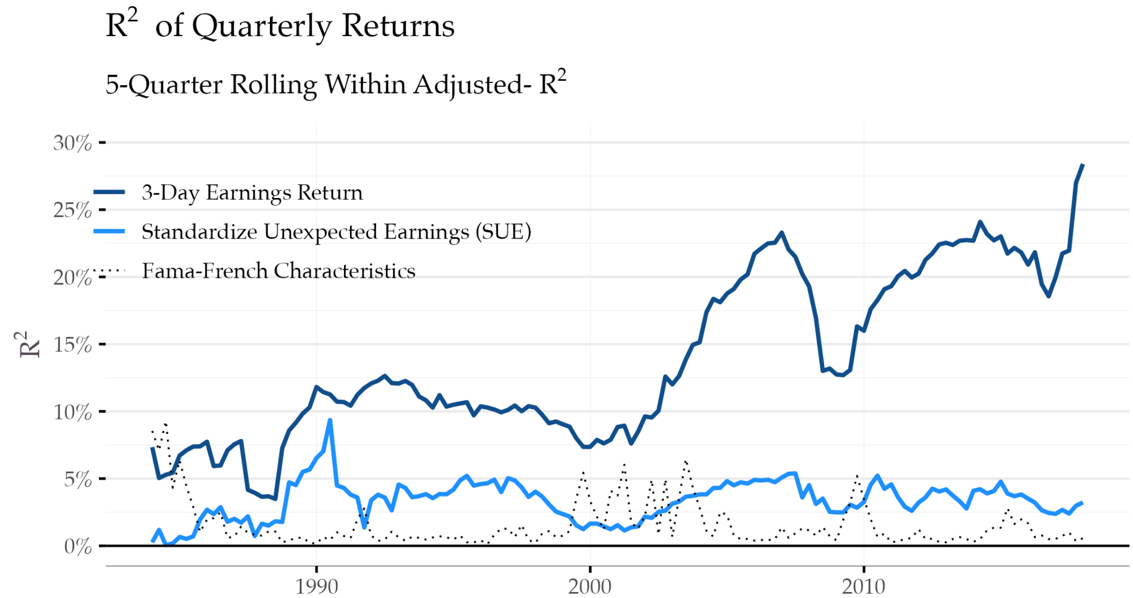
I estimate an earnings-augmented demand system on the full panel of 13-F investors 1980-2017. The average asset-weighted earnings elasticity is approximately 3, but ranges from slightly greater than 0 (in the late 1980s) to nearly 7 (in 2014). In other words, a stock that beats its expected earnings per share by 1% sees an asset-weighted increase in demand of around 3%. However, these responses vary significantly in the cross-section. Traditional institutional investors, including mutual funds and pension funds, tend to have the strongest sensitivity to earnings but are fairly price inelastic, while the 13-F residual "household" sector – the most price elastic of all investor types – is the least responsive to earnings. Meanwhile, investment advisers – which include large hedge funds – are price and earnings elastic. These investor-type estimates suggest that price sensitivity and earnings sensitivity are not well described as pure complements or substitutes: within institutional investors, they are positively correlated, but are negatively correlated unconditionally.[1]

In principle, the procedure I introduce for estimating earnings elasticities is not limited to earning news; it can be applied to any non-price characteristic. An investor's response to ESG-related news, for example, can be decomposed into their true sensitivity to ESG news plus an adjustment for how the market as a whole prices the ESG news. I focus on earnings news specifically not only for the prominent role that news about fundamentals plays in asset pricing models, behavioral theories, and earnings-related anomalies, but also for the simple empirical fact that earnings news accounts for a large component of variation in returns. To illustrate this point, figure (1) plots the time series of R^2 from quarterly cross-sectional regressions of log returns on various characteristics. In most periods, the variation in returns that can be attributed to characteristics associated with the 5 Fama-French factors (shown in the dotted line) is dominated by that from a single non-price characteristic, the standardized unexpected earnings (SUE) (shown in the light blue). Yet another measure of earnings news, the three day return around earning announcements days, is striking

[1] To clarify terminology, price elasticity by convention is defined as the *negative* partial derivative of quantities with respect to prices $-\partial \log Q/\partial \log P$, while earnings elasticity is defined as the *positive* partial derivative of quantities with respect to earnings news: $\partial \log Q/\partial SUE$. In other words, a price elastic investor shifts his holdings *away* from stocks that have exogenous increases in price, while an earnings elastic investor shifts his holding *toward* stocks with exogenous increases in earnings news.

not only for its relative dominance, but also for its ability, in absolute terms, to explain low frequency returns: close to 30% of variation in quarterly log returns is explained by the returns that span one day on either side of earnings announcements. An clear implication of this result is that earnings news must play an important role in investor demand for it to feature so saliently in aggregate returns.

Figure 1: $R^2$of Quarterly Log Returns on Characteristics



This figure shows the cross-sectional within-adjusted R^2 from three different models. The dotted line shows the in-sample R^2 from 5-quarter panel regresssions of $R_{nt} = \alpha_t + \boldsymbol{\beta}_t' \boldsymbol{X}_{nt} + \epsilon_{nt}$, where $\boldsymbol{X}_{nt}$ includes CAPM beta, asset growth, profitability, log book equity, log dividends-to-book-equity, and where R_{nt} is the return over the quarter. The light blue line shows the in-sample R^2 from 5-quarter panel regressions of $R_{nt} = \alpha_t + \beta_t SUE_{nt} + \epsilon_{nt}$. Finally, the dark blue line shows the in-sample R^2 from 5-quarter panel regressions of $R_{nt} = \alpha_t + \beta_t Ret_{nt}^{(-1,1)} + \epsilon_{nt}$, where $Ret_{nt}^{(-1,1)}$ is the total cumulative return of stock n from the open price the trading day prior to the earnings announcement through the close the trading day following the earnings announcement.

An advantage of using the demand system approach is that it gives interpretation to the earning passthrough, which has been a long object of study in asset pricing and accounting literature. In the linearized model I use, the earnings passthrough, i.e., the cross-sectional coefficient from a regression of log returns on standardized earnings surprises, equals an average ratio of two share-weighted elasticities: the asset-weighted earnings elasticity divided by the asset-weighted price elasticity. Intuitively, the earnings passthrough is larger if investors in aggregate become more responsive to earnings news (higher earnings elasticity) ceteris paribus or less responsive to price changes (lower price elasticity). I show that the ratio of these share-weighted elasticities, estimated from holdings data, well approximates the magnitudes and trends in the aggregate earnings passthrough estimated from simple pricing regressions. A longstanding question in asset pricing asks why the earnings passthrough varies over time; my approach allows me to decompose the time-series variation into the respective contributions of asset-weighted earning elasticities and price elasticities. The vast majority of the time-series variation in this coefficient is driven by investors' changing response to fundamentals rather than changing price elasticities.

In the second half of the paper, I connect measures of investor-level sensitivities to stock-level sensitivities. These measures are constructed as the weighted average sensitivities of a stock's investors, with weights equal to the ownership shares of the stock. I first show that these measures explain heterogeneous earnings passthroughs in the cross-section. Consistent with the implications of the model, in which the passthrough equals the ratio of stock-specific earnings elasticities to price elasticities, stocks with higher earnings sensitivity, or lower price sensitivity, see larger returns in the same quarter from a given earnings surprise. These effects are not spanned by many characteristics associated with heterogeneous passthroughs (such as size, value, leverage and market beta), and generate large relative improvements in R^2 compared to models that only use these stock characteristics to explain the passthroughs. The asset pricing results suggest that the demand-system measures capture important characteristics about the stock that are important for explaining the cross-sectional pricing of earnings news.

A natural question is whether these heterogeneous responses to earnings surprises are caused by variation in ownership, or are merely associated with it. For example, the observed cross-sectional results could occur if there are unobserved characteristics that are simultaneously associated with larger passthroughs and with the types of investors that hold the stock. Under this account, heterogeneous responses to earnings news could reflect rational market pricing insofar as they capture these omitted variables. If earnings news is more predictive of future earnings growth for tech stocks, for example, and if earnings elastic or growth-oriented investors (such as hedge funds) hold a comparatively larger share of tech stocks, then a larger response to earnings news for these stocks could be consistent with rational pricing.

I instead show that stock-level differences in ownership are more consistent with mispricing through over- and under-reaction. If stocks with the most earnings sensitive investors overreact to earnings news, the prices of these stocks may be expected to revert in the subsequent period. Likewise if stocks with earnings insensitive investors underreact, these stocks may be expected to exhibit momentum. To test this mechanism, I form two portfolios to capture earnings misreaction. These portfolios are constructed by first taking the intersection of 5 cross-sectional sorts on the earnings surprise (SUE) and 5 cross-sectional sorts on stock sensitivity – either for earnings or price. The "earning sensitivity" portfolio itself consists of two long-short portfolios to capture misreaction: one part of the earnings portfolio bets on momentum in stocks expected to underreact due to earnings insensitive investors. That is, it goes long in stocks with good earnings news with earnings insensitive investors – those expected to increase further – and short stocks with bad news and earnings insensitive investors – those expected to decrease further. The second earnings portfolio bets on subsequent reversal in stocks expected to overreact due to earnings over-sensitive investors. It goes long in stocks with bad earnings news and earnings sensitive investors (stocks presumed to have overreacted to the bad news) and short stocks with good news and sensitive investors (those presumed to have overreacted to the good news). The combined "earnings sensitivity" portfolio, constructed as the average return on these two portfolios, generates quarterly alpha of 1.7% equal weighted and 1.0% value weighted.

I also form a corresponding "price sensitivity" portfolio, constructed by intersecting earnings news sorts with stock *price*-sensitivity sorts. My model suggests that very price sensitive stocks should underreact to earnings news: price-elastic investors trade against any earnings-induced price movement they disagree with, dampening the contemporaneous response, but potentially generating a future "correction". Meanwhile, for price-inelastic stocks, there may not be enough capital to trade against earnings-induced price movements, leading to a contemporaneous overreaction corrected through a reversal pattern the following quarter. This logic calls for one portfolio that is long price-elastic stocks that have received good news and short price-inelastic stocks that have received good news, and a second portfolio that is long price-inelastic stocks that have received bad news and short price-elastic stocks that have received bad news. To ensure that both the earnings and price sensitivity portfolios are not driven by cross-sectional correlations of stock-level price sensitivity with stock-level earnings sensitivities, I first residualize each elasticity measure on the other before forming the portfolio. The combined "price sensitivity" portfolio – which does not use data on investor responses to earnings news, except in the orthogonalization step – generates quarterly alpha of 1.2% equal-weighted and 1.0% value-weighted.

This paper is connected with several strands of literature, most closely to the literature on Demand-Systems Asset Pricing (DSAP) that endeavors to jointly explain asset prices alongside investor holdings (demand). As with my paper, Koijen and Yogo (2019), Koijen, Richmond, and Yogo (2023), Huebner (2023), and Van Der Beck (2022) among others, estimate demand functions for 13-F institutions, including the estimation of price elasticities over time and across investors. My contribution to this literature is two-fold: first, I introduce a new variable to the asset demand system – earnings surprises – that explains a greater proportion of returns than the typically modeled characteristics. Additionally, using the logic of demand systems, I closely illustrate the identification problem from reduced-form pricing regressions that do not account for price-inelastic investors.

My paper also addresses the behavioral finance literature that studies the existence, magnitude, and identity of "price" vs. "fundamental" investors. On the theoretical side, behavioral models typically model agents as *either* responding to fundamental (Barberis, Shleifer, and Vishny (1998), Fuster, Hebert, and Laibson (2012), Choi and Mertens (2019), Hirshleifer, Li, and Yu (2015)) *or* as responding to prices (Cutler, Poterba, and Summers (1990), Hong and Stein (1999), Barberis, Greenwood, et al. (2015)). On the empirical side, researchers use survey data (Dahlquist and Ibert (2023), Greenwood and Shleifer (2014)) to elicit beliefs and expectations, or study the behavior of specific subsets of investor like retail traders (Laarits and Sammon (2022)). Relative to this literature, I simultaneously estimate price vs. fundamental responses; I use trades rather than reported beliefs to study the passthrough of market-relevant beliefs into prices; and I study heterogeneity across a wider cross-section of investors (Banks, Mutual Funds, Investment Advisors, Pension Funds, Insurance Companies, and the residual "household" sector).[2] I also improve upon earlier estimation methods that either do not take into account the endogeneity of prices, or that naively control for returns to partial out the price response. I show that these approaches can misclassify the direction of the response to earnings news of entire sector types, such as the household sector.

My paper also relates to a long accounting and finance literature studying asset price responses to earnings news, and investor-level responses (e.g., Livnat and Mendenhall (2006); Bernard and Thomas (1989); Skinner and Sloan (2002); Barber et al. (2013); McClure and Nikolaev (2023)). Relative to papers that study asset prices at high frequency around earnings news, or even medium frequency (e.g. post-earnings announcement drift), I focus on the very low frequency component of earnings news that shows up in returns and holdings quarter to quarter. The method I use for constructing stock-level sensitivities is closely related to the approach in Blank, Kwon, and Tang (2023), which constructs a "holding gap" based on investor responses to earnings news. Since this approach does not distinguish whether investors' responses are due to a response to prices or to fundamentals, one contribution of the asset pricing section is to separately – and independently – estimate and form portfolios on these two different elasticities (indeed, the price sensitivity portfolio is, by construction, independent of investor responses to earnings news). Moreover, while their approach focuses on long run price run-ups and drawdowns, I focus purely on the impact of (non-price) earnings surprises. Finally, a contribution relative to this literature is to interpret earnings responses

[2]The elasticities I measure reflect contemporaneous responses that occur over the same quarter, whereas behavioral finance literature often focuses on "extrapolation," i.e. responses to past innovations. In appendix section (C), I develop a dynamic model that could be used to estimate the full term structure of elasticities.

through a demand system framework, which enables both proper identification of elasticities as well as a decomposition of the passthrough.

The remainder of the paper is as follows. Section II introduces the model of demand and the identification challenge associated with identifying price elasticities. Section III introduces the data and the construction of earnings surprises. Section IV estimates the model on a panel of 13-F investors, decomposes the (log) earnings passthrough, and discusses the heterogeneity by sector. Section V analyzes the implications of the investor-level responses for stock-level asset pricing in the cross-section and time-series. Section VI concludes.

2 A Model of Investor Demand

2.1 Investor Demand

In this section, I introduce a model of investor demand in order to illustrate the identification problem in traditional approaches to measuring earnings sensitivity.

I begin with a log-linearized demand curve for investor i over stock n in quarter t that expresses his trades as a function of earnings surprises and returns:

$$\Delta q_{int} = \alpha_{it} + \beta_{it} SUE_{nt} - \zeta_{it} \Delta p_{nt} + u_{int} \tag{1}$$

Here, Δq_{int} is the change in log shares demanded by investor i in stock n at quarter t; SUE_{nt} is the standardized unexpected earnings of stock n in quarter t (i.e., the earnings news), and Δp_{nt} is the quarterly log return. As a linearized approximation to the investor's true demand curve, this model does not impose that earnings and price news are the only determinants of an investor's demand: u_{int} captures all the other variables that drive changes in holdings.

In this model, the coefficients on earnings news and log returns, β_{it} and ζ_{it}, represent the investor's fundamental and price elasticity respectively. Crucially, they are partial derivatives of holdings with respect to characteristics: β_{it} is the percent change in demand associated with a stock that beats expected earning by 1%, holding all else – including prices – constant. ζ_{it} is the percent decrease in shares demanded associated with a stock that sees an exogenous price increase of 1%.

In standard models of portfolio choice, β_{it} and ζ_{it} are typically both nonnegative. To see this, consider the demand curve implied by an investor with CARA utility over one-period future returns. The quantity of shares demanded by investor i, Q_{it}, is given by:

$$Q_{it} = \frac{E_{it}\left[\left(P_{t+1} + D_{t+1}\right)/P_t\right]}{P_t A_{it} \sigma^2_{t+1}} := \frac{\pi_{it+1}}{P_t A_{it} \sigma^2_{t+1}} \tag{2}$$

where A_{it} is the investor's risk aversion and σ^2_{t+1} is the variance of returns. Taking logs of (2), the log number of shares demanded is

$$q_{it} = \log\left(\pi_{it}\right) - p_t - \log\left(A_{it}\sigma^2_{t+1}\right) \tag{3}$$

Assume that investors form expectations over future prices and dividends using conditional expectation functions f_i and g_i:

$$E_{it}\left[P_{t+1}\right] =: f_i\left(P_t, SUE_t\right)$$
$$E_{it}\left[D_{t+1}\right] =: g_i\left(P_t, SUE_t\right)$$

In other words, investors forecast future prices and future dividends as a function of current price levels and current earnings news. Investor i's price elasticity, ζ_{it}, is then given by:

$$\zeta_{it} := -\frac{\partial q_{it}}{\partial p_t} = \frac{1}{\pi_{it}}\left[\left(f_P + g_P\right) - \left(f + g\right) / \exp p_t\right]$$

where f_P and g_P are partial derivatives of f_i and g_i with respect to P_t. If prices do not affect expectations of future prices and future dividends, i.e. if $f_P = g_P = 0$, then the price elasticity simplifies to

$$\zeta_{it} = -\frac{1}{\pi_{it}}\left[-\left(f + g\right) / \exp p_t\right] > 0$$

Intuitively, if a stock has an exogenous increase in price, and investors do not change their views on *future* prices, dividends, or risk, then the expected returns for this stock are lower, and investors demand less, i.e. a positive price elasticity.

A similar logic applies to the earnings elasticity, defined as $\beta_{it} \equiv \partial q_{it} / \partial SUE_t$:

$$\frac{\partial q_{it}}{\partial SUE_t} = \frac{1}{\pi_{it}}\left(f_{SUE} + g_{SUE}\right)\frac{1}{\exp p_t}$$

where f_{SUE} and g_{SUE} are partial derivatives of f_i and g_i with respect to SUE_t. In many models, we may expect f_{SUE} and g_{SUE} to be greater than 0. Assume, for example, that all unexpected earnings are paid out as a dividend next quarter, then $g = E\left[D_{t+1} \mid SUE\right] = SUE \times P_t > 0$. Under many belief models (e.g. diagnostic expectations), agents may also change their expectation of future earnings growth, in which case they may also expect the price to increase ($f_{SUE} > 0$). Indeed if the estimated persistence is stronger, then f_{SUE} is larger. As with price elasticities, earnings elasticities are not guaranteed to be positive for all investors, but will depend on how earnings news affect expectations of future prices and fundamentals. Inattentive investors, for example, who do not pay attention to fundamental news, may exhibit a small passthrough of news to beliefs, in which case β_{it} will be close to 0. Alternatively, investors may decrease their expectations of future fundamentals if they associate the positive earnings surprise with discretionary earnings management, or if they expect the market to overreact to the earnings news.

2.2 Market Clearing

I next apply market clearing across individual investor demand curves. If stocks are in fixed net supply, market clearing implies that the share-weighted changes in quantities must sum to zero. Put differently, prices must adjust such that every investor's demand is offset by the residual supply provided by other investors in the market. Let S_{int} denote the fraction of shares outstanding of stock n held by investor i at time t:

$$S_{int} := Q_{int} / \sum_i Q_{int} \tag{4}$$

Market clearing imposes that $\forall n, t$,

$$\sum_i S_{int} \Delta q_{int} = 0 \tag{5}$$

Aggregating over all investor demands from (1), and solving for prices, we obtain

$$\Delta p_{nt} = \frac{\alpha_{Snt}}{\zeta_{Snt}} + \frac{\beta_{Snt}}{\zeta_{Snt}} SUE_{nt} + \frac{u_{Snt}}{\zeta_{Snt}} \tag{6}$$

where the S subscript denotes S_{int}-weighted sums: $X_S := \sum_i S_{int} X_i$. Equation (6) expresses that returns are related to earnings surprises through the ratio of ownership-weighted earnings elasticities (β_{Snt}) to similarly weighted price elasticities (ζ_{Snt}). If the market becomes more earnings elastic (higher β_{Snt}), the passthrough of earnings surprises to returns is larger. If the market becomes more price elastic (higher ζ_{Snt}), there is more capital to "undo" others investors' increased demand from a given earnings surprise, and the earnings passthrough is lower. Because β_{Snt} and ζ_{Snt} are share-weighted elasticities, time-series variation in these coefficients need not be driven by changing elasticities of each investor; a reallocation of capital from from less elastic to more elastic investors will increase the market-level elasticities.

Substituting the expression for prices in (6) back into investor demand provides the reduced-form investor demand function:

$$\begin{aligned}
\Delta q_{int} &= \alpha_{it} + \beta_{it} SUE_{nt} - \zeta_{it} \underbrace{\left(\frac{\alpha_{Snt}}{\zeta_{Snt}} + \frac{\beta_{Snt}}{\zeta_{Snt}} SUE_{nt} + \frac{u_{Snt}}{\zeta_{Snt}} \right)}_{\Delta p_{nt}} + u_{int} \\
&= \underbrace{\left(\alpha_{it} - \zeta_{it} \frac{\alpha_{Snt}}{\zeta_{Snt}} \right)}_{\tilde{\alpha}_{int}} + \underbrace{\left(\beta_{it} - \zeta_{it} \frac{\beta_{Snt}}{\zeta_{Snt}} \right)}_{\tilde{\beta}_{int}} SUE_{nt} + \underbrace{\left(u_{int} - \zeta_{it} \frac{u_{Snt}}{\zeta_{Snt}} \right)}_{\tilde{u}_{int}} \\
&= \tilde{\alpha}_{int} + \tilde{\beta}_{int} SUE_{nt} + \tilde{u}_{int}
\end{aligned} \tag{7}$$

Equation (7) illustrates the principle identification challenge: the passthrough $\tilde{\beta}_{int}$ relating earning surprises to trades is not the structural coefficient β_{it}, but rather the structural coefficient plus a stock-specific price adjustment.

$$\tilde{\beta}_{int} = \beta_{it} - \zeta_{it} \frac{\beta_{Snt}}{\zeta_{Snt}} \tag{8}$$

The price adjustment is the investor's response (ζ_{it}) to the price change arising from the market's asset-weighted response (β_{Snt}/ζ_{Snt}). While (7) is not properly a regression (due to the presence of investor$\times$stock$\times$quarter coefficients), the regression analog of (7) suffers from the same identification challenge. Suppose one were to estimate a regression of investor trades on earnings surprises:

$$\Delta q_{int} = \alpha_{it} + \tilde{\beta}_{it} SUE_{nt} + \epsilon_{int} \tag{9}$$

The coefficient $\tilde{\beta}_{it}$ from this regression would equal a weighted average of $\tilde{\beta}_{int}$ across stocks, with weights proportional to $\left(SUE_{nt} - \overline{SUE_{nt}}\right)^2$. Taking weighted averages by of (9), the estimated reduced-form coefficient would equal:

$$\tilde{\beta_{it}} = \beta_{it} + \zeta_{it}\gamma_t,$$
$$\gamma_t := \tilde{E}_t\left[\beta_{Snt}/\zeta_{Snt}\right]$$

,

where $\tilde{E}\left[\cdot\right]$ denotes the weighted average.

In effect, two things occur simultaneously in a period when a firm realizes an earnings surprise. First, the earnings surprise, isolated from any additional changes in price, affects the investor's demand for the asset. Second, the market as a whole responds to the earnings news and drives a price change in proportion to the ratio of aggregate elasticities. If the market response is much larger than the investor's individual earnings sensitivity, the investor should decrease the shares they hold due to the perceived overvaluation (assuming positive price elasticities). But how much this investor decreases their holdings in response to overvaluation depends on her price elasticity: more elastic investors will have a greater response to the overvaluation than less elastic investors. Investors with negative price elasticities, i.e. with upward sloping demand may even *increase* the shares they hold if the market response to the earnings news is larger than their individual sensitivities. This could occur for investors who learn from prices (about fundamentals) or for momentum traders, for example.

Rearranging, we can express an investor's true structural elasticity, β_{it}, as a function of his reduced-form coefficient, price elasticity, and market response:

$$\beta_{it} = \tilde{\beta}_{int} + \zeta_{it}\frac{\beta_{Snt}}{\zeta_{Snt}} \tag{10}$$

Without observing β_{it}, if the remaining terms $(\tilde{\beta}_{int}, \zeta_{it}, \beta_{Snt}, \zeta_{Snt})$ can be well-estimated, then one can recover the structural elasticity by adjusting the biased coefficient for the magnitude of the bias. Intuitively, this approach undoes the price response embedded in the reduced-form coefficient $\tilde{\beta}_{int}$.

$$\underbrace{\beta_{it}}_{\text{Earnings Elasticity}} = \underbrace{\tilde{\beta}_{int}}_{\text{Reduced-Form Response}} + \underbrace{\zeta_{it}}_{\text{Price Elasticity}} \times \underbrace{\gamma_{nt}}_{\text{Earnings Passthrough}} \tag{11}$$

Equation (11) clarifies how different types of investors may be expected to respond. For example, consider an index fund that holds the market portfolio. Since index funds hold the market portfolio, they do not trade $(\Delta q_{int} \equiv 0)$, so that the holdings regression implied by (9) will deliver a reduced-form $\tilde{\beta}_{it} = 0$. By the same token, these funds perfectly track market equity, i.e. are perfectly price inelastic, and so $\zeta_{it} = 0$. For any aggregate earnings passthrough γ_{nt}, an index fund's estimated structural earnings elasticity is $\beta_{it} = 0$. As expected, since index fund weights are only functions of market equity, there is zero sensitivity to earnings news when holding fixed prices.

Another insight of the identifying equation is that trade is not needed to identify an investor's demand for earnings. This is clearly true for the case of the index fund, which has no earnings elasticity, but can also hold for investors with positive earnings demand. An investor who shares the market elasticities for a given stock $\beta_{it} = \beta_{Snt}$, $\zeta_{it} = \zeta_{Snt}$ will have a reduced-form response of zero:

$$\tilde{\beta}_{it} = \underbrace{\beta_{it}}_{=\beta_{St}} - \underbrace{\zeta_{it}}_{=\zeta_{St}} \times \gamma_{nt} = \beta_{St} - \zeta_{St}\frac{\beta_{Snt}}{\zeta_{Snt}} = 0$$

A reduced-form response of zero – i.e., in which an investor does not trade at all in response to earnings news – does not imply that an investor has zero sensitivity to earnings. To the contrary, this investor by assumption shares the market's average response to earnings news, which must be positive since the earnings passthrough is, on average, positive. Precisely because the investor agrees with the market's elasticities, he does not need to trade at all; the price response perfectly tracks his views and make him indifferent to purchasing additional shares.

An additional insight reflected in equations (11) and (6) is that earnings passthroughs can be heterogeneous, even when each investor, by assumption, has elasticities that are common across all stocks. In the model, the earnings passthrough $\gamma_{nt} := \beta_{Snt}/\zeta_{Snt}$ depends on the stock (n), even as investor elasticities (ζ_{it}, β_{it}) do not. The heterogeneity arises because of the cross-variation in stock-*ownership*, which appears due to the stock-specific share-weighting of elasticities. If the ownership structure of each stock was identical across stocks, the model suggests there would be no cross-sectional variation in the earnings passthrough. If this does not hold, then earnings passthroughs are larger for stocks whose ownership consists of investors that are more earnings elastic or less price elastic. To be sure, there may be additional sources of heterogeneity in passthroughs, if, for example, investor elasticities depend on stock characteristics (e.g. industry). The log-linearized demand curve in (1) generalizes away from these stock-specific loadings, allowing heterogeneity only through variation in ownership structure. In section 5.1, I verify empirically that this ownership channel accounts for cross-sectional variation in the earnings passthrough.

2.3 Estimation

Equation (10) is suggestive of a method to recover the earnings elasticity. If $\tilde{\beta}_{it}$ differs from the structural earnings parameter by a magnitude equal to the earnings passthrough times the investor's price elasticity, then one could estimate the $\tilde{\beta_{it}}$ from a reduced-form pricing of trades on earnings surprises, and correct it for the magnitude of the bias. The challenge with this approach is that the earnings passthrough in the correction, γ_{nt}, is stock- and time- specific, so cannot be estimated in a cross-sectional or time-series regression.[3] The alternative approach taken in this paper is to estimate a demand system that adjusts each investor's trading for her price response before estimating her response to prices. In words, this approach regresses the component of trades net of the price-induced response on the earnings surprises and controlling for changes in other characteristics that affect investor demand.

The first stage in the estimation procedure is to estimate investor-by-quarter level price elasticities, ζ_{it}. Identifying price elasticities in asset pricing setting is typically challenging due to the need for orthogonal drivers of changes in price. It is not sufficient to regress change in log quantities on prices, since prices themselves are endogenous to the trades (quantities) of investors. Nor is it possible to use asset-relevant news – such as earnings news – to identify price elasticities, since the investor's response to this news depends on both his price and earnings elasticity (as the demand system framework, and equation (6), make clear).

Instead, I use the "investment universe" approach from Koijen and Yogo (2019) to estimate price elasticities. This approach involves a two-stage estimation procedure that generates cross-sectional variation in the market equity of stocks by exploiting variation in the investment universes of asset managers. Formally, it constructs an instrument for market equity as the counterfactual market equity that would obtain at the market clearing price if every asset manager held an equal-weighted portfolio of all stocks in their investment universe, where a manager's investment universe is defined as the set of stocks held in the preceding or

[3] For estimation of a restricted model in which earnings passthroughs are assumed to be constant across stocks, i.e. $\gamma_{nt} = \gamma_t$, see Appendix section A.

subsequent 11 quarters. This instrument is defined as:

$$\hat{p}_{int} = \log\left(\sum_{j\neq i} A_{jt}\frac{\mathbb{I}_{jnt}}{1+\sum_{m=1}^{N}\mathbb{I}_{jmt}}\right) \tag{12}$$

where $\hat{p}_{int}$ is the log market equity of stock n at time t, implied by the investment universes of investors other than i. An advantage of using the price elasticity estimated from the investment universe of holdings is that it provides investor-by-quarter measures of elasticity, where alternative approaches typically only have sufficient statistical power for pooled estimation over the full sample. In addition to the standard exclusion restrictions and instrument relevance, the underlying assumption required to use this instrument in this demand system is that the price elasticities estimated from cross-sectional variation in price levels closely reflect the elasticity identified in the *time series* from a shift in price. In other words, it assumes that how an investor shifts his holdings of two stocks that differ in (exogenous) price levels at a point in time tracks how an investor would respond to an exogenous increase in the price level of a stock in a quarter.[4] An additional assumption is that price elasticities on earnings announcement days are identical to those on non-earnings announcement days. It is worth noting that for the purposes of recovering β_{it}, any measure of price elasticity that satisfies these assumptions will work; one could alternatively use measures estimated from other methods (e.g. Granular Instrumental variables, flow induced trading, benchmarking intensity, etc.). However, the evidence in section 5 demonstrates that the investment-universe instruments are able to account for several important asset pricing patterns consistent with theory.

Following Koijen and Yogo (2019) the procedure to estimate price elasticities ζ_{it} involves investor-by-quarter GMM estimation on moment condition:

$$\mathbb{E}\left[\epsilon_{int} \mid \hat{p}_{nt}, X_{nt}\right] = 1 \tag{13}$$

where $\hat{p}_{nt}$ is defined in (12), and ϵ_{int} is the residual of investor demand:

$$w_{int} = \exp\left\{(1-\zeta_{it})\,\hat{p}_{nt} + \boldsymbol{\Gamma}'_{it}\boldsymbol{X}_{nt}\right\}\epsilon_{int} \tag{14}$$

In estimation, ζ_{it} is bounded to be greater than 0 (i.e. downard sloping demand). In exercises in which ζ_{it} is unbounded, I estimate a 2SLS "log" version of (13)-(14) in which the first stage projects log market equity on the implied market equity in (12), and the second stage regresses log portfolio weights, $\log w_{int}$, on instrumented log market equity and the characteristics in $\boldsymbol{X}_{nt}$.

Once price elasticities are estimated, (1) can be rearranged to obtain the second estimating equation:

$$\Delta q_{int} + \zeta_{it}\Delta p_{nt} = \alpha_{it} + \beta_{it} SUE_{nt} + u_{int} \tag{15}$$

The left-hand side reflect a compensated measure, Δq^*_{int} that adjusts each investor's trades for the price response:

$$\Delta q^*_{int} := \Delta q_{it} + \zeta_{it}\Delta p_{nt} \tag{16}$$

Since Δq_{int} represents the general equilibrium (i.e., total response) of trades, it includes the response to both prices and other earnings news. The compensated measure Δq^*_{int} adjusts this quantity by subtracting

[4] One reason that these two elasticities could differ is if investors separately use price *levels* and price *changes* in forming expectations of future returns.

the investor's trading due to changes in market equity, $-\zeta_{it}\Delta p_{nt}$, where ζ_{it} is estimated from (13)-(14) and where Δp_{nt} is the actual – not instrumented – log return over the quarter. In the final estimating equation, I regress this "price-adjusted" response on the earnings news and control for innovations in the characteristics from (14) that determine the level of portfolio weights:

$$\underbrace{\Delta q_{it} + \zeta_{it}\Delta p_{nt}}_{\Delta q^*_{int}} = \alpha_{it} + \beta_{it} SUE_{nt} + \mathbf{\Psi}'_{it}\Delta \boldsymbol{X}_{nt} + \varepsilon_{int} \tag{17}$$

In the linearized demand curve in (1), $SUE_{nt} \perp u_{int}$, where u_{int} is latent demand. An identifying assumption to estimate (17) is thus that $E\left[\varepsilon_{int} \mid SUE_{nt}, X_{nt}\right] = 0$, i.e. mean independence of latent demand given the earnings surprise and the characteristics. It is known that earnings announcements are associated with a large amount of information beyond the earnings beat. They may contain, for example, forward guidance, information on firm activities, or other numbers (such as the revenue beat) relevant to future expectations. The identifying assumption needed to estimate (17) is not that investors ignore this other information, but rather that latent demand is mean zero conditional on a given realization of the earning surprise. For example, if investors associate the earnings surprise with future growth in fundamentals, or subsequent investment in the firm, the identification is still valid: investors change their quantities only due to the earning surprise itself, and indeed the elasticity is designed to capture the broad and heterogeneous ways in which investors interpret fundamental news. What is important for identification is that there are not other factors correlated and concurrent with the release of earnings that affect investor demand. For example, suppose investors have a "taste" for stocks associated with artificial intelligence, and in a given quarter, stocks that beat earnings surprises are systematically more likely to mention AI. Then the measured effect on trades is contaminated by the demand for AI, and the estimated coefficient β_{it} is biased. I assume that earnings surprises are close to randomly assigned, and so the assumption of mean independence is likely to hold.

3 Data and Summary Statistics

Earnings News: I use the standardized unexpected earnings ("SUE") based on I/B/E/S unadjusted reported analyst forecasts and actuals. The earnings surprise is constructed as

$$SUE_{nt} = \frac{\left(EPS^{Actual} - EPS^{Expected}\right)}{\text{Price per Share}}$$

where $EPS^{Expected}$ is the median analyst expectation among forecasts made in the 90 days prior to earnings. The sample begins in 1984Q1, but coverage in the early period is sparse: there are fewer than 1000 stocks until 1986Q1, and fewer than 2000 until 1994Q1. In most analyses, I filter to quarters where there at least 500 stocks in the cross-section ($\geq$1985Q1), or – for the asset pricing analysis in section 5 – post 1990, and I cross-sectionally winsorize the earnings variable at percentiles 3 and 97.[5] For stocks with multiple earnings announcements in a quarter, which occurs when there are annual releases and quarterly releases, I aggregate to a single stock–by-quarter SUE_{nt} within the quarter by taking a simple average across the earnings announcements. Summary statistics on the sample are below:

[5]I focus on post-1990 because the precision ($E\left[|SUE_{nt}|\right]$) and bias ($E\left[SUE_{nt}\right]$) of SUE stabilizes after this period, as seen in appendix figure 12.

Variable	P25	P50	P75	Mean	St. Dev
SUE_{nt}	-0.001	0.0003	0.002	-0.0005	0.010
$\lvert SUE_{nt}\rvert$	0.001	0.002	0.005	0.004	0.009

Holdings: I use holdings data from 13-F disclosures available from Thomson Reuters. All asset managers with >\$100M AUM are required to disclose quarterly positions of registered 13-F securities, which include common stocks. Common stock holdings by 13-F reporting institution account for 70% of total market capitalization at the end of the sample. Following Koijen and Yogo (2019), I classify 13-F managers into one of 6 types: Banks, Insurance Companies, Investment Advisers, Mutual Funds, Pension Funds, and Other. The residual sector – which includes non-13-F reporting institutions, and the aggregate short sector – are classified as the "household" sector. For sector- and aggregate-level measures (section 4), I construct Δq_{int} as the change in log quantities quarter to quarter. However, since holdings are sparse at the manager-level, the change in log quantities is not well defined when a stock position moves to or from zero portfolio weight. Therefore, for the construction of stock-level sensitivities, which require estimates for each investor in a stock, I use $\Delta q_{int} = (Q_{int} - Q_{int-1})/(2\,(Q_{int} + Q_{int-1}))$ in the estimation of the demand system, which approximates the percentage change in shares by normalizing by the average number of shares held across the two quarters. This measure closely tracks the log-constructed measure on the matched sample ($\rho = 0.87$).

Additional Stock Characteristics: Stock characteristics, such as returns and market equity, are from CRSP, while accounting data (including dividends, assets, profits, and book equity) are from Compustat. Most regressions use the set of (non-price) control variables from Koijen and Yogo (2019) that are designed to span the FF5 factors: profitability, dividend payout ratio, asset growth, beta, and log book equity.[6] For the heterogeneous earnings passthrough analysis, I also add assets-to-book equity, and log book-to-market equity. Section 5 examines the alpha of portfolios constructed on earnings sensitivity; I use data on factor returns available from Ken French's website. The matched sample of stocks that appear in 13-F reported securities and have a constructed measure of earnings surprises includes 276,680 stock-quarter observations from 1984Q1-2017Q4, including 10,652 distinct permnos.

4 Results

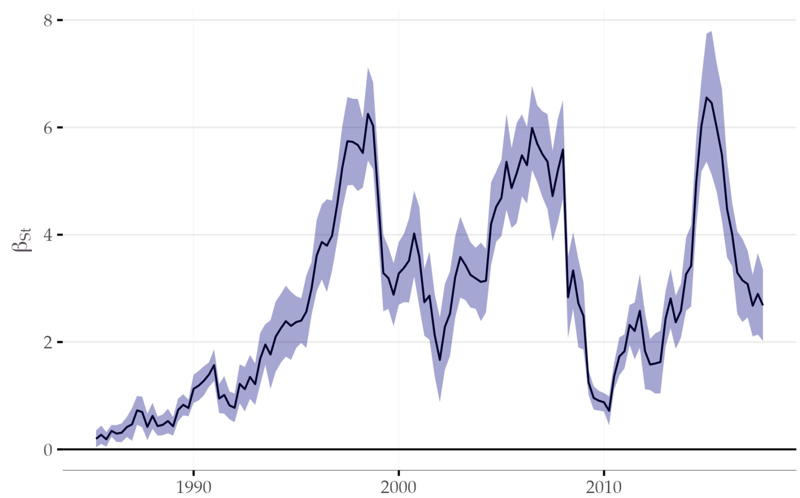
4.1 Market-Level Estimates

I estimate the earnings-augmented demand system from 1985Q1-2017Q4. While estimation at the investor-by-quarter level is, in principle, possible, trades are sparse at the manager level. I therefore conduct two types of pooling: first, following Koijen and Yogo (2019), I pool managers with below 1000 holdings into a size-by-type group (a form a group shrinkage). Second, I estimate the set of regressions over rolling four-quarter windows. I construct standard errors by jointly bootstrapping a common set of stock-quarter observations in the regressions, as described in appendix section B.

Figure (2) plots the asset-weighted earnings and price elasticities over this period.

[6]These 5 characteristics, along with (instrumented) market equity, explain a significant component of investor demand. Reduced-form IV regressions of log portfolio weights on the market equity instrument and the 5 characteristics deliver R^2 of $\geq 30\%$ for the majority of 13-F investors.

Figure 2: Aggregate Price and Earnings Elasticities



(a) Asset-Weighted Earnings Elasticity

(b) Asset-Weighted Price Elasticity

Panel (a) shows the asset-weighted earnings elasticity, computed by aggregating β_{it} (estimated from equation (17)) using AUM-weights. Standard errors are bootstrapped using the method in appendix section B. Panel (b) shows the asset-weighted price elasticity, computed by aggregating ζ_{it} (estimated from equation (13)) using AUM-weights. Following Koijen and Yogo (2019), price elasticity estimates are bounded below by zero and are estimated by pooling estimation for investors with fewer than 1,000 holdings a quarter at an investor by size-quantile level. Estimation uses rolling four quarter windows.

Panel (a) shows the asset-weighted earnings elasticity. The market-level elasticity averages around 3: in other words, for a stock that beats consensus expectations by 1%, the average investor would demand a 3% increase in the number of shares he holds if shares of that stock were available at the pre-news price. As noted, this elasticity is a partial equilibrium parameter that asks how quantities demanded would change if prices were held fixed. It does not itself imply that investors must (or do) change their holdings in equilibrium. Indeed, it is perfectly possible for no-trade to occur in equilibrium even as investors have high demand for earnings. The reason is that prices adjust such that investors are indifferent to keeping their current holdings at the new price and realization of earnings news.

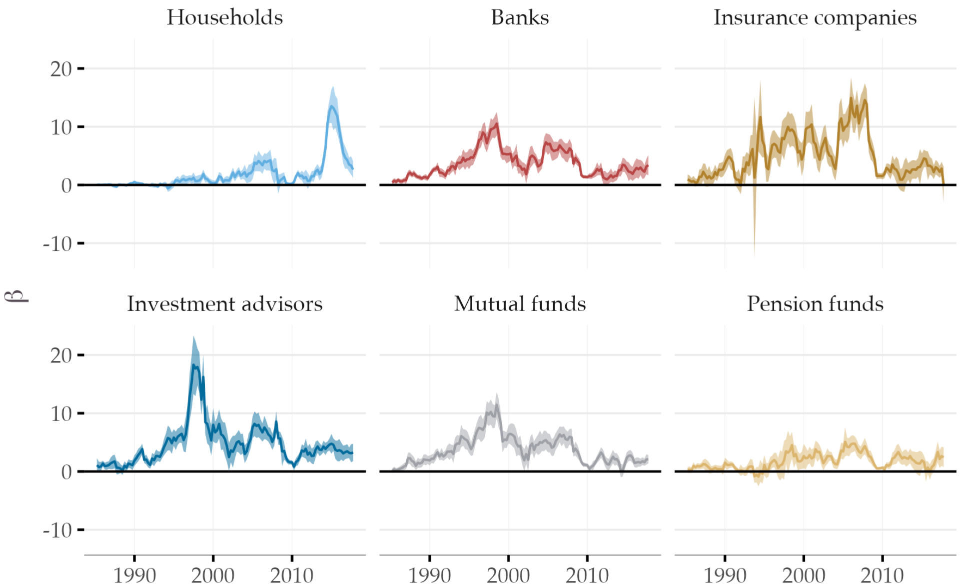
While earnings elasticities average near 3, there is significant low frequency variation over the time series. Toward the early part of the sample, pre 1990, earnings elasticities are small and close to zero (potentially a consequence of the smaller information content of consensus expectations in the early days of I/B/E/S forecasts). The highest earnings sensitivity observed over a sustained period is in the late 1990's and mid to late 2000's, when the average earnings elasticity was closer to 5.

Panel (b) shows the asset-weighted price elasticity. The market-level price elasticity is small and close to 0.26 on average. The interpretation is that a price increase of 1% translates into a 0.26% decrease in the quantity of shares demanded. Equivalently, a 1% flow into stocks leads to a $1/0.26 \approx 3.85$ times multiplier in returns. As noted in Gabaix and Koijen (2022), these are well below the estimates implied by standard asset pricing models. Two features of Figure (2) stand out. First, pre-2010, the aggregate market elasticity is fairly stable, ranging from 0.21 (a multiplier of 4.76) to 0.47 (a multiplier of 2.13). Price elasticities during this period are far more stable than earnings elasticities. Second, during 2014, there is a large spike in elasticities for both prices and earnings that reverts soon after. The rise in earnings elasticity during 2014 is a consequence of large increase in *price* elasticities measured during this year, which itself is driven by a spike in the household sector's – and only the household sector's – price elasticity in 2014. Because the household sector is constructed as a residual to 13-F reporting institutions, and because it relies on an investment universe approach in the cross-section of holdings, this jump more likely represents measurement error rather than a true change in price elasticities. Alternative methods to estimate price elasticities may generate smoother measures of price elasticities and, by extension, earnings elasticities, during this period.

4.2 Estimates by Sector

The manager-level estimates from the demand system allow for alternative forms of aggregation that can provide some insight on how different investing sectors react to earnings news. I asset-weight quarterly manager level sensitivities within 6 13-F sectors: Banks, Pension Funds, Investment Advisors, Mutual Funds, Insurance Companies, and the residual "household" sector, and plot the earnings elasticities:

Figure 3: Earnings Elasticities by Sector



This figure shows the aggregate earnings elasticities by sector, 1985Q1-2017Q4. Earnings elasticities are estimated investor-by-quarter using equation (17) over rolling four-quarter periods, and are aggregated using AUM weights. Standard errors are bootstrapped using the method detailed in Appendix section B.

Consistent with the implications of the CARA model, all sectors have nonnegative earnings elasticity over the full sample. There is a common increase across sectors beginning in the 1990s, which begins to decline around 2000. However, investors differ in their trends. for example, investment advisors have small responses until the mid-to-late 1990s, whereas the sensitivity of mutual funds to earnings news starts several years prior. The household sector sees very little time-series variation in its earnings sensitivity.

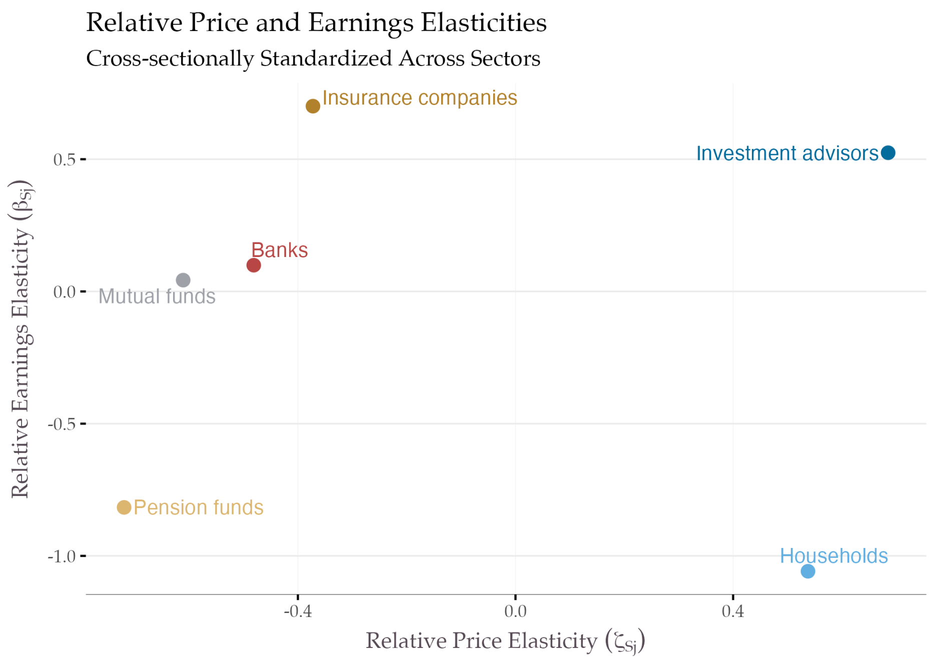
There are also important differences in the levels of sensitivities to prices and earnings. In Figure (4), I cross-sectionally standardize each sector's price and earnings elasticity, and take the time-series mean of these standardized earnings elasticities $\overline{\beta_{Sjt}}$ and price elasticities $\overline{\zeta_{Sjt}}$ within sector. Among institutional investors, there is a positive correlation between price elasticities and earnings elasticities. Of these 13-F investors, investment advisers and insurance companies are the more earnings sensitive, with an average elasticity half a standard deviation above average.[7] Pension funds are the least earnings elastic and price inelastic, which would be expected of less attentive or active traders. Investment advisers, meanwhile, are earnings and price elastic, consistent with the "rational" responses implied by the CARA model.

Compared to most institutional investors, the residual household sector is price elastic and earnings elastic. In line with previous literature (Koijen and Yogo (2019)), the household sector is among the most price elastic among sector types, with a price elasticity nearly 0.5 standard deviations above average.[8] But unlike for institutional sectors, this price elasticity does not coincide with higher earnings elasticity: households have the among the lowest sensitivities to earnings news, with magnitudes only slightly above

[7]Because estimates of earnings elasticity requires estimates of price elasticities, they are can be sensitive to estimation choices for ζ_{it} (and Δq_{it}). Sector-level estimates in which ζ_{it} is estimated without a requirement that demand is downward sloping yield the largest earnings and price elasticities for investment advisers among institutional investors.

[8]The price elasticity estimates for the household sector are still well below the price elasticities impled by standard asset pricing models.

Figure 4: Price vs. Earnings Elasticities by Sector



This figure shows relative price and earnings elasticities by 13-F sector type. Each quarter, I compute the asset-weighted price and earnings elasticity within sector, and then standardize these measures by quarter (i.e. across the investor types). The displayed results are the time-series means of these standardized measures, i.e. the axes represent the average number of standard deviations of a sector's elasticity relative to average. I omit 2014Q1-Q4 due to the large spike in household elasticity associated with the "investment universe" approach to measuring elasticities.

zero. A takeaway from Figure (4) is that price and earnings elasticities are not common across investors, as would be expected from a standard homogeneous investor agent model, but rather heterogeneous. Broadly speaking, investor types fall into one of four quadrants: price and earnings elastic (investment advisers, including hedge funds); price elastic and earnings inelastic (household sector); earnings elastic and price inelastic (banks, mutual funds, and insurance companies); and earnings and price inelastic (pension funds). To the extent stocks also differ in the relative proportion of their shares outstanding held by these different investor types, this investor heterogeneity will induce a stock-level heterogeneity in average elasticities, a property that will be explored in the subsequent section.

How important are price elasticity adjustments in estimating the demand for earnings? Recall that if price elasticities are zero, then there is no identification problem, in the sense that the reduced-form estimates perfectly recover the structural estimates. Intuitively, for an investor that has no response to price ($\zeta_{it} = 0$), the entire response to the earnings news can be attributed to the news itself rather than the contemporaneous price impact. For sectors with elasticities close to 0 – such as the insurance sector – this is indeed the case. Fig. (5) panel (a) compares the time series estimates of β_{it} to the reduced-form estimates $\tilde{\beta}_{it}$ one would obtain if they ran the following regression of trades on earnings surprises:

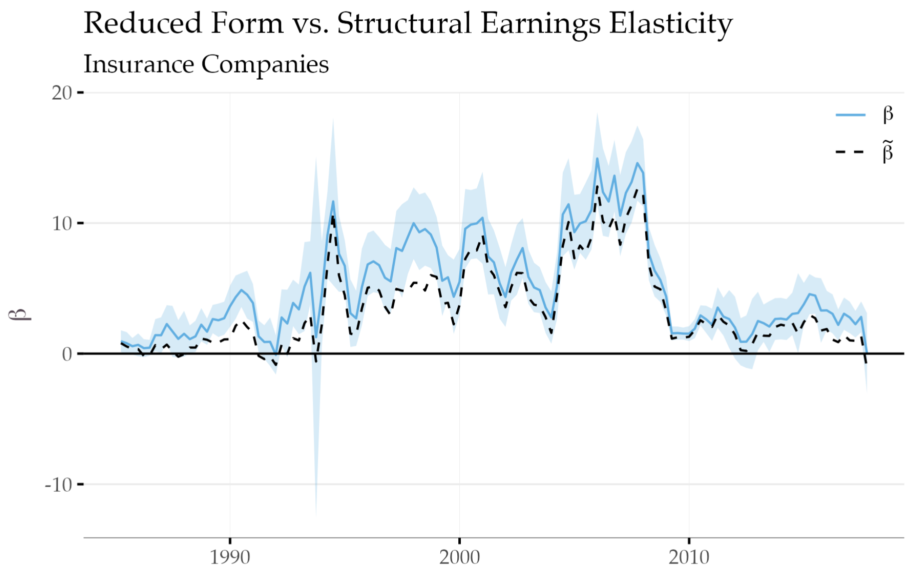
$$\Delta q_{int} = \alpha_{it} + \tilde{\beta}_{it} SUE_{nt} + \boldsymbol{\Psi}'_{it} \Delta \boldsymbol{X}_{nt} + u_{int} \tag{18}$$

While $\tilde{\beta}_{it}$ is always below β_{it} (since price elasticities are positive), the two estimates are close in levels and trends.

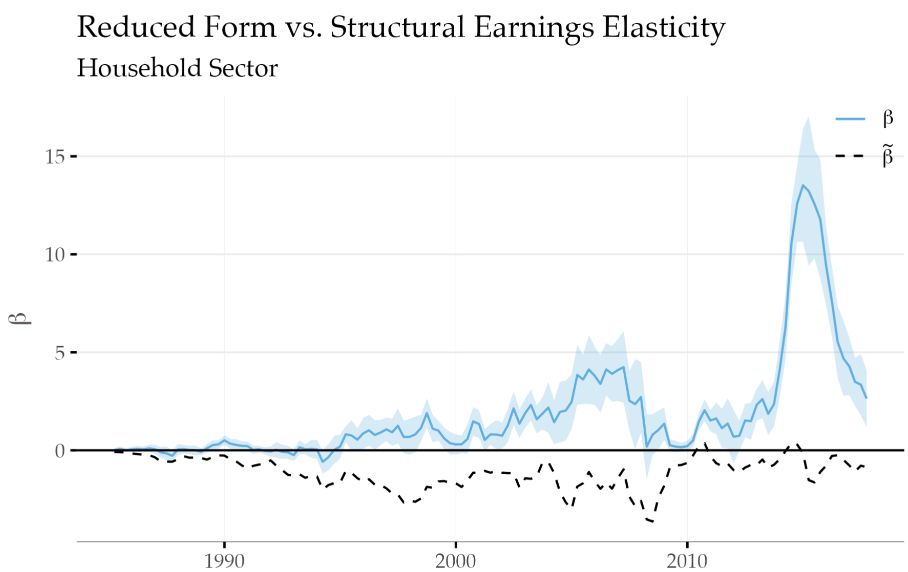
However, for investors with price elasticities sufficiently far from zero, such as the household sector, the wedge between reduced-form and structural elasticities can be much larger. Fig. (5) panel (b) compares the reduced-form coefficient to the structural coefficient for the household sector, where the reduced-form coefficient $\tilde{\beta}_{it}$ is estimated using (18) on the household sector's trades. Not only is the wedge between the two coefficients much larger, but the sign differs as well, with $\tilde{\beta}_{it} < 0$ and $\beta_{it} > 0$ in most periods. That the reduced-form coefficient is negative would otherwise suggest that this sector has *negative* sensitivity to earnings news. Rather, the household has positive demand sensitivity to earnings news, but is sufficiently price elastic that it sells shares in response to the price increase induced by the rest of the market's comparatively larger earnings elasticities. As noted, this problem is not addressed by controlling for returns: the coefficient from a regression of the household sector's demand on earnings surprises remains negative even after controlling for contemporaneous log stock returns over the quarter. While markets appear to be much more inelastic in the data than in standard asset pricing theory, the importance of adjusting estimates is still large: on average, the asset-weighted reduced-form elasticity $\tilde{\beta}_{St}$ is 22% the magnitude of the asset-weighted structural elasticity β_{St}, and ranges from -25% of the magnitude (when reduced-form estimates are negative) to 59% the magnitude (in 2001). Equivalently, the difference between $\tilde{\beta}_{St}$ and β_{St} is on average 77% of the magnitude of β_{St}. A full time-series of the discrepancy can be found in appendix figure (13).

Figure 5: reduced-form vs. Structural Earnings Elasticities

(a) Insurance Sector



(b) Household Sector



This figure compares reduced-form earnings elasticities, $\tilde{\beta}_{it}$, to structural elasticities, β_{it}. $\tilde{\beta}_{it}$ is estimated as in equation (18), and the adjustment to recover β_{it} uses bounded elasticities estimated from (13). In panel (a), manager level estimates within the Insurance sector are AUM-weighted to obtain a sector level measure. Panel (b) shows the analogous exercise for the household sector. Coefficients represent estimates over four-quarter rolling periods, with bootstrapped standard errors.

4.3 Decomposition of the Earnings Passthrough

An advantage of analyzing the pricing of earnings news using a demand system is that it provides a formula for the aggregate earnings passthrough in terms of investor-level price and earnings elasticities. Empirically, the passthrough of earnings surprises to stock returns exhibits substantial time series variation; figure (6) plots the rolling coefficient from cross-sectional pricing regressions of quarterly stock returns on standardized unexpected earnings.

Figure 6: Time Series of Raw Earnings Passthrough

This figure shows the time series of coefficients (β) from a 3-quarter rolling regression $Ret_{nt} = \alpha_t + \beta_t SUE_{nt} + \epsilon_{nt}$, where Ret_{nt} is the total return over the quarter. Standard errors are clustered by quarter; dates correspond to the midpoint of the 3-quarter window.

According to the model, this time series variation could be driven by any combination of three factors. First, it could be due to changing *fundamental* elasticities, as investors have become more sensitive to earnings news. This could occur, for example, if earnings surprises became more or less informative about future growth prospects over time, or if consensus expectations by sell-side analysts better reflected the expectations of asset managers. A second account could be due to changing *price* elasticities, that is, if investors became more or less responsive to price changes. An example of institutional changes that could drive changing price elasticities is the growing share of passive investors, who tend to have price elasticities close to zero, or momentum investors, who have negative price elasticities. If more momentum investors enter the market, even with no change in earnings sensitivity, the passthrough from a given earnings surprise will be larger because these momentum investors will augment the initial price impact of the earnings news. Finally, the change could be due to a *residual* term, capturing everything from estimation error to error in the underlying assumptions used to derive the model.[9]

Equation (6) implies that in the limit and under the model assumptions, the earnings passthrough, γ_{nt}

[9] These assumptions include linear demand curve with investor-by-quarter specific coefficients; zero mean expectation of latent demand conditional on the earnings surprise and characteristics; similarity between the price elasticities implied by the investment-universe instrument and those that occur on earnings-news days.

is:

$$\gamma_{nt} = \frac{\beta_{Snt}}{\zeta_{Snt}} \tag{19}$$

where β_{Snt} and ζ_{Snt} are the within-stock share-weighted earnings and price elasticities respectively. Taking cross-sectional expectations of (19) and then applying log transformations, we can express the log average treatment effect as:

$$\begin{aligned} \log E_t\left[\gamma_{nt}\right] &= \log E_t\left[\beta_{Snt}/\zeta_{Snt}\right] \\ \log \hat{\gamma}_t &= \log \hat{\beta}_{St} + - \log \hat{\zeta}_{St} + \hat{u}_t \end{aligned} \tag{20}$$

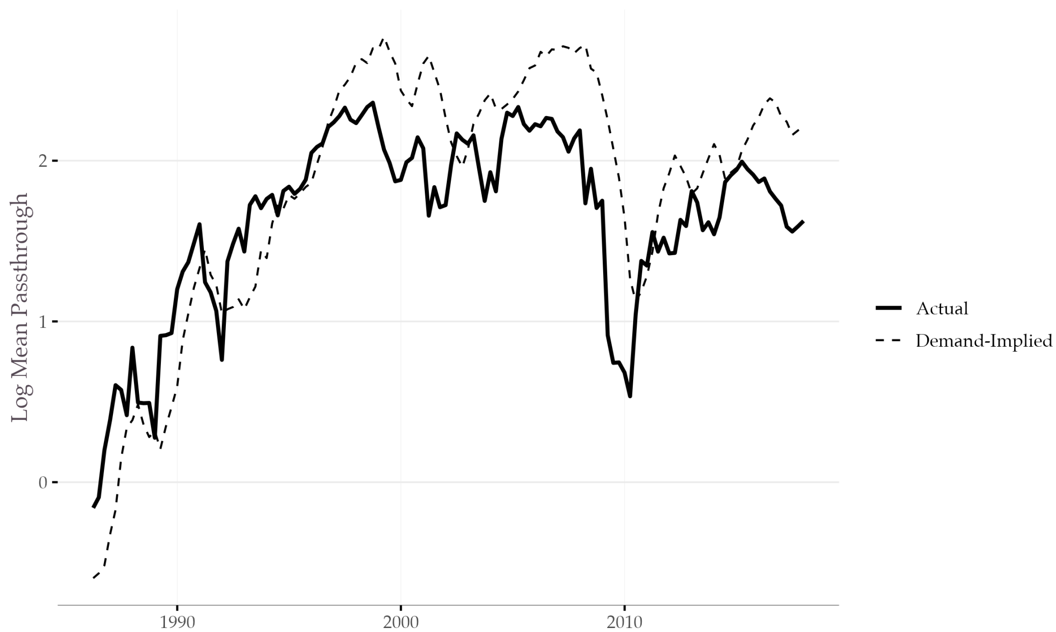
where u_t denote a residual arising from a Jensen term, model approximation error, and finite sample estimation.

Equation (20) not only provides an intuitive decomposition of the (log) earnings passthrough as a difference of (log) asset-weighted price and fundamental elasticities, but also allows for an additional test of the estimated asset demand system. Since the earnings passthrough (estimated from pricing regressions) should equal the ratio of share-weighted elasticities (estimated from holdings regressions), comparing the implied passthrough to the actual passthrough is an untested moment. I construct the demand-implied analog of the earnings passthrough by share-weighting investor-level β_{it} and ζ_{it} within-stock each quarter and taking the ratio of these objects.

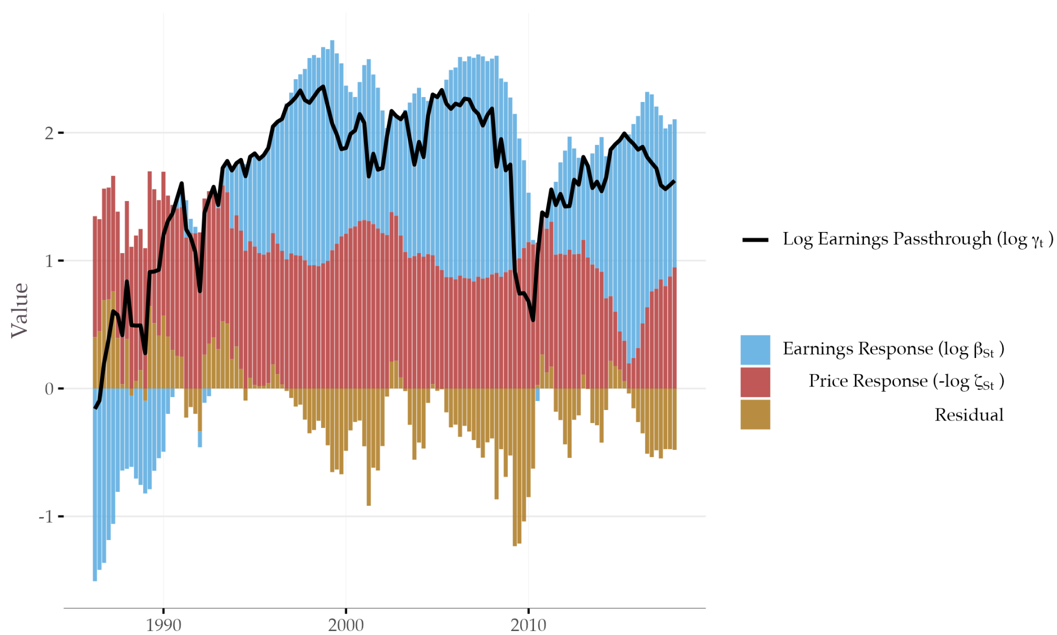
Figure (7) shows the results from estimates. The solid line indicates the actual log earnings passthrough, estimated from cross-sectional pricing regressions of log returns on earnings surprises; the dotted line, by contrast, shows the demand-implied analog from averaging the ratio of share-weighted elasticities across stocks, and taking a log. The demand-implied passthrough approximates the actual passthrough in level in changes. In particular, it captures the low frequency rise in the 1990s, the high frequency variation around the turn of the century, and the drop and subsequent recovery around the recession. However, it overshoots the magnitude of the earnings passthrough throughout the 2000's.

Figure 7: Earnings Passthrough Decomposition

(a) Actual vs. Demand-Implied Log Mean Earnings Passthrough



(b) Decomposition of Log Mean Earnings Passthrough



These figures compare the earnings passthrough estimated from pricing regressions to the earnings passthrough implied by taking the ratio of share-weighted elasticities estimated from the demand system. In panel (a), the solid black line plots the time series of $\log \gamma_t$ from quarterly regressions of $\Delta p_{nt} = \alpha_t + \gamma_t SUE_{nt} + \mathbf{\Gamma}'_t \Delta \boldsymbol{X}_{nt} \epsilon_{nt}$, where Δp_{nt} is the quarterly log return , SUE_{nt} is the standardized earnings surprise, and $\Delta \boldsymbol{X}_{nt}$ is the change in control characteristics . The dotted line plots $\log E_t \left[\beta_{Snt}/\zeta_{Snt}\right]$, where β_{Snt} and ζ_{Snt} are calculate by share-weighting, within stock, estimates of β_{it} and ζ_{it} from equations (11) and (13) respectively. Parameters are estimated over rolling four quarter windows. Panel (b) presents an analogous plot where $\log \gamma_t$ (the solid black line) is decomposed into the sum of $\log E_t \left[\beta_{Snt}\right]$, $-\log E_t \left[\zeta_{Snt}\right]$, and a residual u_t. The blue bars plot the earnings response $\log E_t \left[\beta_{Snt}\right]$, the red bars plot the price response $-\log E_t \left[\zeta_{Snt}\right]$, and the bronze bars plot the residual u_t.

In addition to showing the demand-implied passthrough, Figure (7)(b) also shows the relative contribution of the two weighted share-weighted elasticities. Log aggregate earnings elasticities, shown in red bar, sum with (negative) log aggregate price elasticities, shown in blue bars, and the residual (bronze bars) to yield the demand-implied coefficient. While the aggregate price elasticities are fairly constant over the time series, the aggregate earnings response moves in tandem with the pricing passthrough, suggesting that earnings elasticities play a comparatively larger role in explaining the time-series variation of γ_t. To quantify these relative contributions, I estimate a time series variance decomposition of the log earnings passthrough, by taking covariances of each component of equation (20) with $\log \gamma_t$:

$$1 = \underbrace{\frac{Cov\left(\log \hat{\beta}_{St}, \log \hat{\gamma}_t\right)}{Var\left(\log \hat{\gamma}_t\right)}}_{0.96} + \underbrace{\frac{Cov\left(-\log \hat{\zeta}_{St}, \log \hat{\gamma}_t\right)}{Var\left(\log \hat{\gamma}_t\right)}}_{-0.13} + \underbrace{\frac{Cov\left(\hat{u}_t, \log \hat{\gamma}_t\right)}{Var\left(\log \hat{\gamma}_t\right)}}_{0.17}$$

Close to 96% of variation in the earnings passthrough is driven by changing earnings elasticities; 17% is driven by the residual term; and a smaller -13% is driven by changing price elasticities. While the specific magnitudes are somewhat dependent on the estimation approach (e.g., the size of the rolling window, construction of Δq_{int}), the relative magnitudes consistently point to the primacy of changing earnings elasticities. These estimates are not surprising given the previously discussed stability of price elasticities over time, but they suggest that the vast majority of the variation earnings passthrough is well captured by the aggregate price and fundamental elasticities implied by the demand system.[10]

5 Asset Pricing Implications

So far, the analysis in this paper has considered heterogeneity in elasticities across investors and over time. But the implications for this variation in elasticities for asset pricing are not immediately clear: heterogeneity across investors may be unimportant to the extent that these differences "wash out" in the cross-section, and the documented time-series variation in elasticities does not reveal the economic reason for this evolution. In this section, I analyze the role that heterogeneous elasticities play in cross-sectional asset pricing. I first connect investor-level elasticity estimates to stock-level estimates, by exploiting variation in the ownership structure of stocks. The logic for this approach is that stocks inherit the sensitivities of their investors. If owners of an asset play a more salient role in pricing an asset at a point in time than investors who do not own the asset, then variation in the sensitivities of a stock's owners will determine its response to earnings news. I first confirm that these stock-level measures of elasticity account for some variation in heterogeneous passthroughs. In section 5.1, I show that stocks with earnings-sensitive investors see a larger response to earnings news than stocks with less earnings-sensitive investors, while price-sensitive stocks see smaller passthroughs than price insensitive stocks. These effects are not spanned by many stock characteristics that explain expected returns and heterogeneous passthroughs.

In section 5.2, I then examine whether differences in earnings responses persist in the longer run. If ownership-induced differences in earnings passthroughs reflect frictions in external investors' ability to respond to news at the same frequency as the owners of a stock, then passthroughs may be corrected as this

[10] The small contribution of price elasticities to time series *variation* in the log earnings passthrough does not imply that price elasticities are unimportant for matching the *levels* of the earnings passthrough. Because price elasticities feature in the denominator of the earnings passthrough, small changes in price elasticity are still able to generate large changes in the passthrough.

friction is eased over time. However, ownership-differences could alternatively reflect unobserved characteristics that are informative about future earnings growth, in which case they can reflect rational pricing of the same news. Frictions may also be sufficiently strong such that differences in pricing are not corrected over a horizon observable to the econometrician. To test these channels, I form a set of two portfolios that each bet on long-run correction to ownership-induced responses to news. First, an "earnings sensitivity" combines a long-short portfolio that bets on reversal in earnings sensitive stocks (those expected to overreact to earnings news), with a long-short portfolio that bets on momentum in earnings insensitive stocks (those expected to underreact to earnings news). Second, a "price sensitivity" portfolio combines a long-short portfolio that bets on reversal in price inelastic stocks (those expected to overreact) with a long-short portfolio that bets on momentum in price elastic stocks (those expected to underreact). Each portfolio generates positive returns unconditionally and relative to standard factor models, consistent with the misreaction channel of ownership-related pricing of earnings news.

5.1 Heterogeneous Earnings Passthrough

A long literature in accounting endeavors to understand "earning response coefficients" (ERCs), i.e. why the market responds more strongly to the same earnings beat for some firms compared to others. In this literature, heterogeneous responses are often attributed to differences in characteristics of the underlying *firm*; for example, differences in market beta, capital structure, earnings quality, growth opportunities, price informativeness, and analyst dispersion (Scott and Scott (2015)). I consider an alternative account of heterogeneous earnings responses based on the sensitivities of a stock's owners. Specifically, I compare the passthrough of earnings surprises for stocks with more earnings sensitive investors to those with less earnings sensitive investors.

For each stock-quarter, I construct a measure of the weighted earnings and price elasticities of its owners. That is, I construct measures $\breve{\beta}_{Snt}$ and $\breve{\zeta}_{Snt}$ that give the share-weighted elasticities of the owners of stock n. First, at the investor level, I construct the average sensitivity of investor i over the preceding year $\bar{\beta}_{it} := \frac{1}{4}\sum_{k=0}^{3}\beta_{it-k}$, $\bar{\zeta}_{it} := \frac{1}{4}\sum_{k=0}^{3}\zeta_{it-k}$. To aggregate to the stock level, I take weighted averages of investor-level earnings sensitivities at the stock level:

$$\breve{\beta}_{Snt} := \sum_i w_{int}\bar{\beta}_{it}, \quad w_{int} := \frac{Q_{int}}{\sum_i Q_{int}} \tag{21}$$

I construct an analogous measure of price elasticities,

$$\breve{\zeta}_{Snt} := \sum_i w_{int}\bar{\zeta}_{it}, \quad w_{int} := \frac{Q_{int}}{\sum_i Q_{int}} \tag{22}$$

An important feature of these stock-level measures is that they use very little information on either a stock's past responses to earnings, or on the investor's response to that stock's history of beating earnings. Because investors hold many stocks, the measures of $\breve{\beta}_{Snt}$ and $\breve{\zeta}_{Snt}$ will be primilary driven by how investors respond to *other* stocks in their portfolio (in other words, omitting stock n from the computation of the investor-level sensitivities used to generate $\breve{\beta}_{Snt}$ and $\breve{\zeta}_{Snt}$ will have little effect on the investor-level or stock-level sensitivities).

I then estimate earnings response panel regressions of the form:

$$\Delta p_{nt} = \boldsymbol{\alpha}_t + \boldsymbol{\alpha}_n + \delta_1 SUE_{nt} + \delta_2 \breve{\beta}_{Snt-1} + \delta_3 SUE_{nt} \times \breve{\beta}_{Snt-1} + \boldsymbol{\Gamma}' \left(\boldsymbol{X}_{nt} + \boldsymbol{X}_{nt} \times SUE_{nt} \right) + \epsilon_{nt} \tag{23}$$

where Δp_{nt} is quarterly log returns. The coefficient of interest is δ_3: if $\delta_3 > 0$, stocks with more earnings-sensitive investors see a higher passthrough from a given earnings surprise. In all specifications, I include stock and date fixed effects and control for the same set of characteristics used in estimation: firm size (log book equity), profitability, asset growth, market beta, and dividends to book equity. I use the lagged measure of share-weighted earnings elasticities, $\breve{\beta}_{Snt-1}$, such that the sorting variable is known ex ante and does not use any information from the contemporaneous earnings surprise. Finally, I cross-sectionally standardize $\breve{\beta}_{Snt-1}$ so that δ_3 does not capture time series differences in the aggregate earnings passthrough.

Table (1) displays the results from estimating versions of (23). In column (1), log returns are regressed on earnings surprises without any interactions; as expected, stocks with higher earnings surprises have higher log returns (i.e., there exists a positive earnings passthrough). But crucially, this passthrough depends on the earnings sensitivity of its owners. Column (2) indicates that stocks with higher cross-sectional earnings elasticity see a higher earnings passthrough as well. Column (3) controls for the share weighted price elasticity, $\breve{\zeta}_{Snt-1}$, as well as its interaction with the earnings surprise, $SUE_{nt} \times \breve{\zeta}_{Snt-1}$. Consistent with the implications of the static model, in which higher price elasticity translates into a smaller earnings passthrough (since investors are more sensitive to price increases and dampen any price response from the earnings news), the coefficient on the interaction of earnings surprise with price elasticity is negative. In other words, the earnings passthrough is smaller for stocks that with more price elastic investors.

In column (4), I show that these effects are are not spanned by other characteristics that commonly explain heterogeneous earnings response coefficients. In addition to the controls used in estimation with the demand system (log book equity, profitability, asset growth, market beta, and dividends to book equity), I include measures of value (log book-to-market) and leverage (assets-to-book equity). I include these control variables as standalone characteristics and as interactions of each with the earnings surprise, for a total of 14 control variables beyond the date and stock fixed effects. The ceofficient on the interaction of the earnings elasticity with SUE_{nt} remains positive and similar in magnitude, while the interaction with price elasticity remains negative and significant. Finally, in columns (5) and (6) I include the "total" heterogeneous passthrough implied by the demand system, $\breve{\gamma}_{Snt-1} := \breve{\beta}_{Snt-1}/\breve{\zeta}_{Snt-1}$. Consistent with the model, passthroughs are larger when the ratio of share-weighted earnings elasticities to share-weighted price elasticities is larger.

That interactions of elasticity measures with earnings news retain their sign and significance in the presence of alternative characteristics suggests that the ownership measures are not spanned by existing characteristics. However, they do not speak to the relative importance of these measures to explaining heterogeneous passthroughs. In figure (8), I compare the in-sample, within-adjusted R^2 of the earnings passthrough implied by different models. The left-most bars indicate the R^2 from a base model that only uses characteristic controls and fixed effects. Adding interactions of the seven stock-level characteristics with the earnings surprise slightly improves the adjusted R^2, consistent with the notion that these characteristics account for some variation in the earnings response coefficient. Finally, I also add the interaction of the elasticity measures ($\breve{\beta}_{Snt}$ and $\breve{\zeta}_{Snt}$) with the earnings surprise, and chart the R^2 in the red bars. Here the improvement is large relative to only adding the stock characteristic variables. These results point to an additional channel driving hetereogeneous earnings passthroughs. In addition to characteristics associated

Table 1: Earnings Passthrough and Stock Level Sensitivities

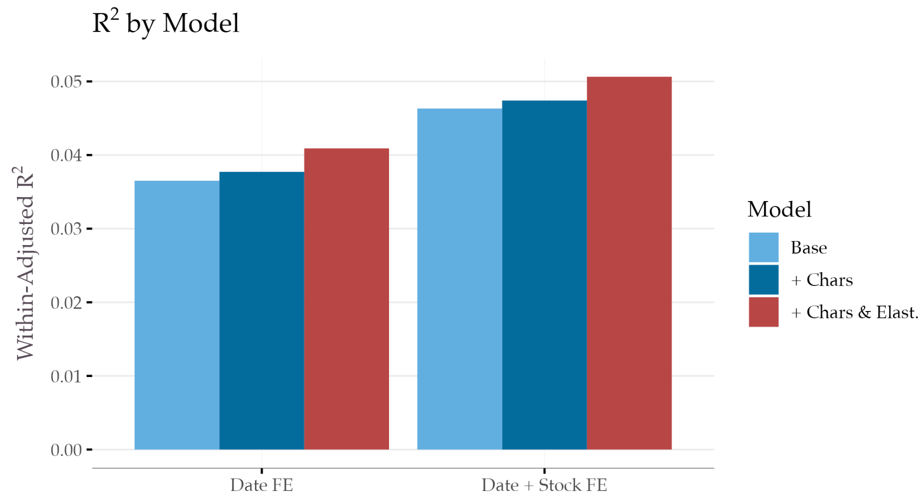
	(1)	(2)	(3)	(4)	(5)	(6)
SUE_{nt}	3.814***	4.038***	4.156***	6.611***	4.180***	5.867***
	(5.774)	(5.535)	(5.540)	(8.887)	(5.238)	(6.494)
$SUE_{nt} \times \breve{\beta}_{Snt-1}$		0.493**	0.472*	0.326*		
		(2.834)	(2.400)	(2.593)		
$SUE_{nt} \times \breve{\zeta}_{Snt-1}$			−0.312***	−0.420**		
			(−3.785)	(−3.162)		
$SUE_{nt} \times \breve{\gamma}_{Snt-1}$					0.657*	0.646**
					(2.611)	(3.052)
Num.Obs.	233 762	233 762	233 762	233 762	233 762	233 762
Controls	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓
Controls × SUE_{nt}				✓		✓

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows estimates from regressions of the form $\Delta p_{nt} = \alpha_t + \alpha_n + \delta_1 SUE_{nt} + \delta_2 \breve{\beta}_{Snt-1} + \delta_3 SUE_{nt} \times \breve{\beta}_{Snt-1} + \mathbf{\Gamma}' \left(\boldsymbol{X}_{nt} + \boldsymbol{X}_{nt} \times SUE_{nt}\right) + \epsilon_{nt}$. All columns use date and stock fixed effects, include the earnings surprise SUE_{nt}, and control for log book equity, log book-to-market, asset growth, profitability, dividends to book equity, CAPM beta, and assets-to-book equity. Column (2) adds $\breve{\beta}_{Snt-1}$ and the $\breve{\beta}_{Snt-1} \times SUE_{nt}$, and column (3) additionally adds $\breve{\zeta}_{Snt-1}$ and $\breve{\zeta}_{Snt-1} \times SUE_{nt}$, where $\breve{\beta}_{Snt-1}$ and $\breve{\zeta}_{Snt-1}$ are constructed as in (21)-(22) and are then cross-sectionally standardized within quarter. Column (4) includes interactions of the seven control variables with SUE_{nt}. Column (5) includes $\breve{\gamma}_{Snt-1}$ and $\breve{\gamma}_{Snt-1} \times SUE_{nt}$, where $\breve{\gamma}_{Snt-1}$ is the cross-sectionally standardized $\breve{\beta}_{Snt-1}/\breve{\zeta}_{Snt-1}$. t-statistics associated with standard errors clustered two-way at the date and stock level are in parentheses.

with the underlying firm and investor expectations, heterogeneous ownership structures drive variation in responses to earnings news.

Figure 8: Improvements to R^2 from Elasticity Measures



This figure shows the within-adjusted R^2 from different models associated with equation (23). The "base" model shows the R^2 from estimating $\Delta p_{nt} = \boldsymbol{\alpha} + SUE_{nt} + \boldsymbol{\Gamma}'\boldsymbol{X}_{nt} + \epsilon_{it}$ where $\boldsymbol{\alpha}$ is α_t in the model with date fixed effects and is $\alpha_t + \alpha_n$ in the date and stock fixed effects model. $\boldsymbol{X}_{nt}$ includes log book equity, log book-to-market, asset growth, profitability, dividends to book equity, CAPM beta, and assets-to-book equity. The "+ Chars" model shows the R^2 from estimating $\Delta p_{nt} = \boldsymbol{\alpha} + SUE_{nt} + \boldsymbol{\Gamma}'\left(\boldsymbol{X}_{nt} + \boldsymbol{X}_{nt} \times SUE_{nt}\right) + \epsilon_{nt}$. Finally, the "+ Chars & Elast" shows the R^2 from estimating $\Delta p_{nt} = \boldsymbol{\alpha} + SUE_{nt} + \boldsymbol{\Gamma}'\left(\boldsymbol{X}_{nt} + \boldsymbol{X}_{nt} \times SUE_{nt}\right) + \boldsymbol{\lambda}'\left(\mathcal{E} + \mathcal{E} \times SUE_{nt}\right) + \epsilon_{nt}$, where $\mathcal{E} := \left(\breve{\beta}_{Snt-1}, \breve{\zeta}_{Snt-1}\right)$.

5.2 Earnings Surprises and Misreaction

Cross-sectional variation in investor sensitivity to earnings news could arise from investors sorting into stocks that differ in the price-informativeness of their earnings news. However, it could also reflect a role for over or underreaction in the dynamic response of returns to earning news, particularly if sensitivities are orthogonal to future fundamentals. In this section, I address whether the heteregeneous passthroughs documented in the previous section are consistent with the market "correctly" pricing earnings news.

The central finding of this exercise is that variation in earnings sensitivity does not reflect rational investor sorting into stocks, but misreaction to earnings news. Consider a stock with earnings-insensitive investors, that realizes a large positive earnings surprise in quarter t. Because the investors of this stock do not respond much to earnings news, the return response is likely to be small. However, as time passes, sensitive external investors may internalize the news and bid up the price of the asset. Likewise, a stock with an extremely earnings sensitive investor base may overreact to news, generating a stock response that is later corrected. These effects imply a pattern of earnings momentum for stocks held by earnings-insensitive investors, and a pattern of earnings reversal for stocks held by earnings-sensitive investors.

To test this channel, I construct 25 cross-sectional portfolios as the intersection of 5 cross-sectional SUE quintiles and 5 cross-sectional earnings-sensitivity quintiles on the set of I/B/E/S covered stocks. For stocks in the highest quintile of earnings surprises, the candidate strategy goes long stocks in the lowest quintile of earnings sensitivity and short stocks in the highest quintile of earnings sensitivity. For stocks in the lowest quintile of earnings news, the strategy is reversed: long stocks in the highest quintile of earnings sensitivity, short stocks in the lowest quintile of earnings sensitivity. These portfolios are formed at the end of the quarter, and are held through the subsequent quarter. Formally, let $R^{j,k}_{nt+1}$ denote the return of a stock in SUE quintile j and $\breve{\beta}$ quintile k,

$$
\begin{aligned}
R^{GoodNews}_{t+1} &:= \overbrace{\sum_n w^{5,1}_{nt} R^{5,1}_{nt+1}}^{\text{Good News + Earnings Insensitive}} - \overbrace{\sum_n w^{5,5}_{nt} R^{5,5}_{nt+1}}^{\text{Goods News + Earnings Sensitive}} \\
R^{BadNews}_{t+1} &:= \underbrace{\sum_n w^{1,5}_{nt} R^{1,5}_{nt+1}}_{\text{Bad News + Earnings Sensitive}} - \underbrace{\sum_n w^{1,1}_{nt} R^{1,1}_{nt+1}}_{\text{Bad News + Earnings Insensitive}}
\end{aligned}
$$

For the equal-weighted portfolio, the stocks are weighted equally within each leg of the portfolio, i.e.$w^{j,k}_{nt} = 1/\sum_n \mathbf{1}\{n \in j,k\}$. For the value-weighted portfolio, the stocks are weighted by lagged market equity in each leg of the portfolio, i.e. $w^{j,k}_n = me^{j,k}_{nt}/\sum_n me^{j,k}_{nt}$. The total earnings sensitivity portfolio return is then formed as the simple average of these two portfolios:

$$
R^{\beta}_{t+1} = \frac{1}{2}\left(R^{GoodNews}_{t+1} + R^{BadNews}_{t+1}\right) \tag{24}
$$

As detailed above, one way of thinking about this portfolio is a pair of "convergence" trades on two stocks that receive the same earnings news, but differ in the sensitivity of their owners. $R^{GoodNews}_{t+1}$ is a convergence trade conditional on good news, while $R^{BadNews}_{t+1}$ is a convergence trade conditional on bad news. An equivalent way of thinking about the returns on the total portfolio is as a pair of momentum and reversal strategies. That is, we can equivalently write the returns on the total portfolio as:

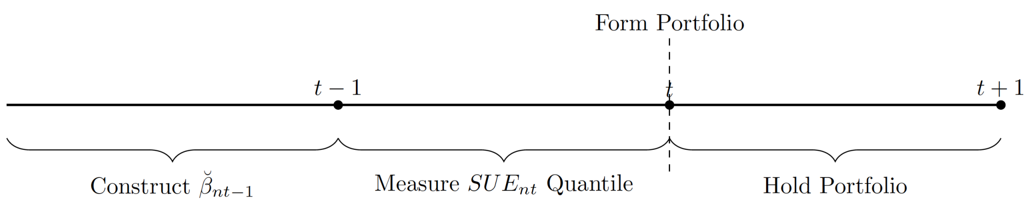
$$
\begin{aligned}
R^{\beta}_{t+1} &= \frac{1}{2}\left(R^{Insensitive}_{t+1} + R^{Sensitive}_{t+1}\right), \\
R^{Insensitive}_{t+1} &= \sum_n w^{5,1}_{nt} R^{5,1}_{nt+1} - \sum_n w^{1,1}_{nt} R^{1,1}_{nt+1} \\
R^{Sensitive}_{t+1} &= \sum_n w^{1,5}_{nt} R^{1,5}_{nt+1} - \sum_n w^{5,5}_{nt} R^{5,5}_{nt+1}
\end{aligned}
$$

The earnings insensitive portfolio, $R^{Insensitive}_{t+1}$, conditions on earnings insensitive investors and goes long stocks that have received good news and short stocks that have received bad news: this is similar to a post-earnings announcement drift portfolio, in that it bets on momentum in these stocks, but at a lower frequency. The earnings sensitive portfolio, $R^{Sensitive}_{t+1}$, conditions on an earnings sensitive investors, and bets long stocks that have received bad news and short stocks that have received good news, i.e. it bets on reversal in these stocks. Expressing the total portfolio this way highlights the fact that there should be no aggregate loading of this portfolio on the well-documented tendency of stocks to exhibit earnings momentum (Novy-Marx (2015), Chan, Jegadeesh, and Lakonishok (1996)). Because the portfolio takes an equal weight in momentum and reversal it does not simply load on this momentum factor.

Figure (9) illustrates the timing of the portfolio. The stock-level elasticities are estimated using ownership data prior to the release of news using data on $t-4$ from $t-1$. This not only ensures the strategy is feasible – since 13-F reporting requirements allow a delay between the end of the quarter and the period of disclosure – but also avoids using the end-of-period ownership shares, which are endogenous to responses to the earnings announcement itself. Between periods $t-1$ and t the firm realizes its earnings news, and is sorted into SUE quintiles based on its relative surprise during this period. At the end of period t, the portfolios are formed using quintiles from the earnings news as of t and the elasticities as of $t-1$. The portfolio is then held for a quarter from t to $t+1$.

It is important to note that theories of over- and under-reaction do not directly speak to the timing over which correction must occur. When to form the portfolio and how long to hold it are ultimately empirical questions that depend on the degree of overreaction and correction.[11] In this exercise, the portfolio is formed at the *end* of the quarter in which the earnings announcement occurs, even though the earnings announcement can happen at any point during the quarter. The portfolio is then held for a single quarter, even though misreaction can be corrected over a shorter horizon (including before the end of the quarter) or longer horizons (e.g. a year). While coarse, this approach has several advantages. First, since portfolios are formed once per quarter and are unique to the entire quarter, they reduce turnover relative to a portfolio that is resorted at the frequency at which earnings announcements occur (e.g. monthly). Second, since the elasticities are constructed using quarterly data on trades and holdings, they measure sensitivities at this frequency and suggest an analogous period for misreaction. Third, positive returns formed even on coarse measures – quarterly formation, and quarterly holding period – likely reflect conservative measures of the true returns achievable. More sophisticated strategies could analyze the timing over which over/underreaction peaks, the timing with which it corrects, and the differences in these properties over the four legs of the strategy.

Figure 9: Portfolio Timing

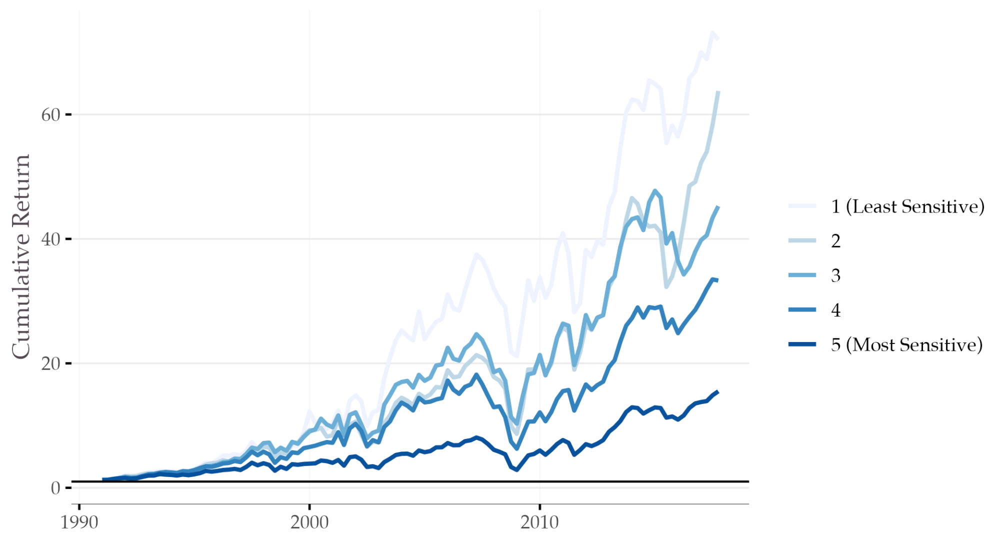


Before tracking the returns of the aggregate portfolio, I illustrate graphical evidence of misreaction patterns by tracking the *future* returns of stocks in different quantiles of earnings sensitivity after very positive (and negative) earnings news. In Fig. (10) I condition on stocks in the highest (panel (a)) and lowest (panel (b)) quintiles of earnings news respectively, and I track the cumulative returns in the *subsequent* quarter. For stocks in the highest quintile of earnings news, displayed in panel (a), the future returns are inversely related to earnings sensitivity: among stocks with good earnings news, those with the most earnings sensitive investors have the lowest future returns, consistent with contemporaneous overreaction that is later corrected. By contrast, high earnings news stocks with the least earnings-sensitive investors have the highest returns. This pattern is consistent with contemporaneous *under*reaction by these investors, that is later corrected.

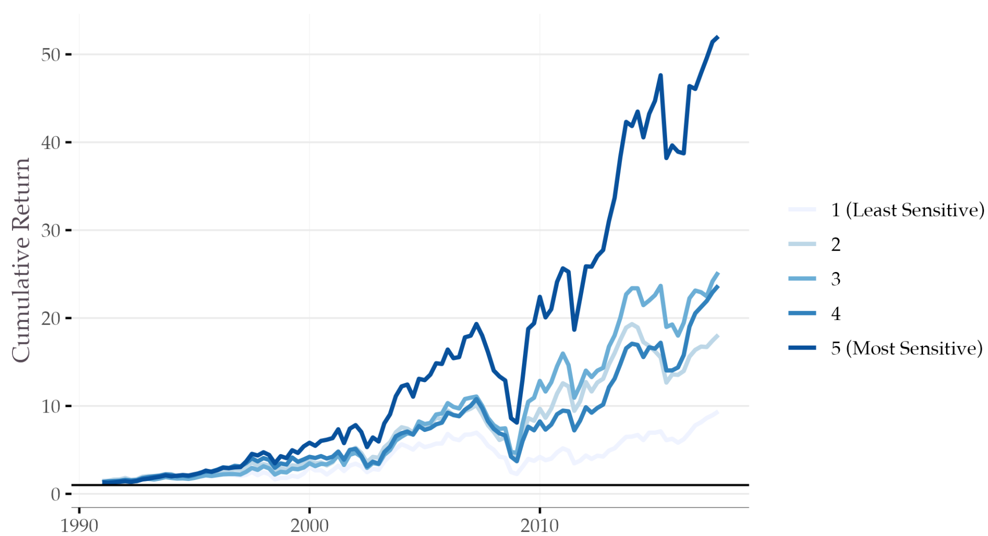
[11] The momentum vs. reversal portfolio, and the good earnings news vs. bad earnings news portfolios may also differ from each other in their dynamics.

Figure 10: Future Returns by SUE and Beta Quintile

(a) Future Returns of **Highest** SUE Quintile Stocks



(b) Future Returns of **Lowest** SUE Quintile Stocks

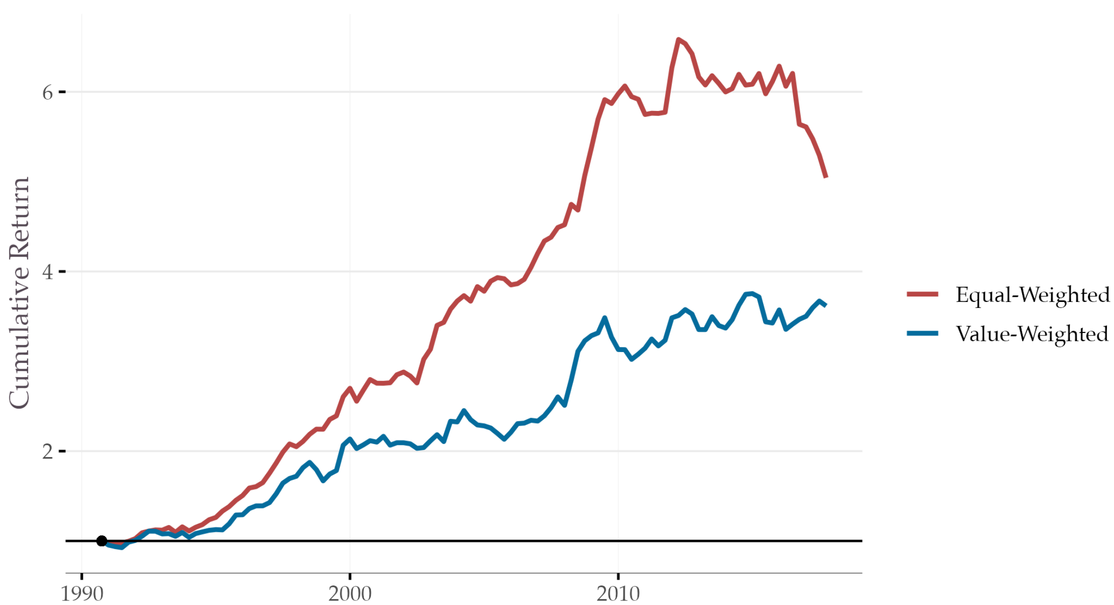


This figure shows future returns of stocks sorted on earnings news and investor earnings sensitivity. At the end of each quarter t, stocks are sorted into the intersection of 5 quintiles of earnings news that quarter (on SUE_{nt}) and 5 quintiles of earnings sensitivity measured at the beginning of the quarter ($\breve{\beta}_{Snt-1}$), where $\breve{\beta}_{Snt-1}$ is first cross-sectionally orthogonalized on $\breve{\zeta}_{Snt-1}$. Panel (a) conditions on stocks in the top quintile of earnings news (SUE quintile 5) and looks at the (equal-weighted) average returns the subsequent quarter ($t+1$) for stocks in each quintile of $\breve{\beta}_{Snt-1}$. The lines chart the cumulative returns from this strategy. Panel (b) conditions on stocks in the lowest quintile of earnings news (SUE quintile 1) and similarly plots the cumulative average return in $t+1$ of stocks associated with each $\breve{\beta}_{Snt-1}$ quintile. Consistent with overreaction, for good earnings news, future returns are inversely related with earnings sensitivity, while for bad earnings news, future returns are positively related to earnings sensitivity.

As noted, an alternative explanation for this pattern is that stocks held by earnings sensitive investors have properties associated with higher average returns. According to this narrative, stocks with the most sensitive investors might be expected to underperform stocks with high sensitive investors in any quarter. To test this, Fig. 10b considers the same strategy, but for stocks in the lowest quintile of earnings news; that is, those stocks that severely underperform analyst earning expectations. For these stocks, the pattern is reversed: low earnings news stocks with the most earnings-sensitive investors have high future returns, compared to those with the least earnings sensitive investors. This pattern is again consistent with stories of under and overreaction. High-earnings sensitive investors that see poor earnings news overreact to the news, causing a contemporaneous drop in stock price that is too large. The next quarter, this overreaction is corrected by other investors, leading to large future returns. For low-earnings sensitive investors, the logic is similar: these investors underreact to the low earnings news, causing a drop in the stock price that is too low. The subsequent quarter, the remaining investors correct this underreaction to poor news, and drive down the stock price further.

Figure (11) plots the cumulative raw returns of the aggregate earnings sensitivity portfolio for the 1990-2017 sample. To ensure that differences are not driven by correlations with stock-level price elasticities, I first orthogonalize $\breve{\beta}_{Snt-1}$on $\breve{\zeta}_{Snt-1}$ in each quarter and form the earnings portfolio on the intersection of the earnings surprise and the orthogonalized earnings sensitivity. This earnings-sensitivity portfolio generates large positive returns, with a quarterly return of 1.57 ($t = 4.80$) for the equal weighted portfolio, and 1.28% ($t = 3.27$) over the 27 year period.

Figure 11: Earnings-Sensitivity Portfolio Returns



This figure shows the cumulative returns to the earnings sensitivity portfolio described in equation (24). The red line plots the cumulative quarterly equal-weighted returns, while the blue line plots the cumulative quarterly value-weighted returns. Since the elasticity measures use data from 4 quarters prior to the portfolio formation quarter, the sample period begins in 1990Q4 and extends to the 2017Q4.

Since this portfolio bets equally on reversal on momentum within each SUE quintile – and since the

Table 2: Earnings Sensitivity Portfolio Alpha

	Equal-Weighted				Value-Weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.016***	0.014***	0.015***	0.017***	0.013***	0.011***	0.011***	0.010**
	(4.792)	(4.274)	(4.464)	(4.704)	(3.272)	(2.756)	(2.748)	(2.390)
MKT_t		0.054	0.051	0.033		0.075	0.059	0.071
		(1.305)	(1.149)	(0.706)		(1.522)	(1.096)	(1.268)
SMB_t			−0.040	−0.057			0.062	0.074
			(−0.530)	(−0.751)			(0.695)	(0.808)
HML_t			−0.074	−0.093*			−0.023	−0.011
			(−1.398)	(−1.707)			(−0.363)	(−0.164)
UMD_t				−0.060				0.040
				(−1.419)				(0.773)
Num.Obs.	108	108	108	108	108	108	108	108

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the quarterly alpha associated with the earnings sensitivity portfolio described in equation (24). Columns (1)-(4) show the alpha of the equal-weighted portfolio while columns (5)-(8) show the alpha the value-weighted portfolio. Robust t-statistics are shown in parentheses.

total portfolio return is an average of the two SUE quintile portfolio returns – the positive returns observed are not simply a case of earnings momentum. Nor are the returns explained by differential loadings on common factors. In table (2), I evaluate the alpha of this strategy again the market, Fama-French 3, and FF3/Carhart momentum model. The alpha remains positive and significant across specifications (with small loadings on existing factors). The smaller returns on the value-weighted portfolio (compared to the equal-weighted portfolio) are consistent with the notion that the market is more accurate at correctly pricing the earnings news of large stocks.

The model of investor demand does not only relate earnings passthroughs to earnings elasticities, but also relates them to price elasticities. In particular, when price elasticities are larger, earnings passthroughs are smaller. The implication for a trading strategy based on misreaction is that very price sensitive stocks see a muted contemporaneous reaction to earnings news that may be expected to grow in the following period. Price insensitive stocks do not have sufficient active capital to trade against earnings-sensitive investors, which would lead to a too-large response that reverts in the following period. As before, I form four strategies that together combine to make a "price sensitivity" portfolio as:

$$R^{\zeta}_{t+1} = \frac{1}{2}\left(R^{GoodNews}_{t+1} + R^{BadNews}_{t+1}\right), \tag{25}$$

$$\begin{aligned} R^{GoodNews}_{t+1} &= \overbrace{\sum_n w^{5,5}_{nt} R^{5,5}_{nt+1}}^{\text{Good News + Price Sensitive}} - \overbrace{\sum_n w^{5,1}_{nt} R^{5,1}_{nt+1}}^{\text{Goods News + Price Insensitive}} \\ R^{BadNews}_{t+1} &= \underbrace{\sum_n w^{1,1}_{nt} R^{1,1}_{nt+1}}_{\text{Bad News + Price Insensitive}} - \underbrace{\sum_n w^{1,5}_{nt} R^{1,5}_{nt+1}}_{\text{Bad News + Price Sensitive}} \end{aligned}$$

Table 3: Price-Sensitivity Portfolio Returns

	Equal-Weighted				Value-Weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.014***	0.012***	0.012***	0.012***	0.012**	0.008*	0.009*	0.010*
	(4.776)	(4.094)	(3.930)	(3.979)	(2.617)	(1.817)	(1.871)	(1.982)
MKT_t		0.076**	0.070*	0.061		0.159***	0.165***	0.153**
		(2.130)	(1.804)	(1.506)		(2.906)	(2.765)	(2.455)
SMB_t			0.040	0.032			−0.053	−0.064
			(0.617)	(0.484)			(−0.529)	(−0.628)
HML_t			0.016	0.007			−0.035	−0.047
			(0.352)	(0.151)			(−0.495)	(−0.642)
UMD_t				−0.029				−0.039
				(−0.784)				(−0.675)
Num.Obs.	108	108	108	108	108	108	108	108

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the quarterly alpha associated with the price sensitivity portfolio described in equation (25). Columns (1)-(4) show the alpha of the equal-weighted portfolio while columns (5)-(8) show the alpha the value-weighted portfolio. Robust t-statistics are shown in parentheses.

where $R^{j,k}_{nt+1}$ denotes the return of a stock in SUE quintile j and price elasticity quintile k. As before, a challenge with this approach is that earnings elasticities are correlated with price elasticities in the cross-section. Because the household sector has large price elasticities and small earnings elasticities, high household sector ownership of a stock will induce variation both in price elasticities and in earning elasticities that will work in opposite directions. To ensure that the price sensitivity portfolio is not indirectly picking up variation in earnings sensitivity, I first cross-sectionally residualize the stock-level measure of $\breve{\zeta}_{Snt}$ on $\breve{\beta}_{Snt}$, and use the residuals as the sorting variable for the price-elasticity quintile. Because these residuals are independent from $\breve{\beta}_{Snt}$ (by construction) and from SUE_{nt} (by random assignment of earnings news) the sorts of this portfolio are independent from the sorts of earnings news portfolio in the limit. [12]Moreover, since the sorts for this portolio only depend on relative price elasticities, not their magnitude, I use measures of price elasticity that are not bounded below by zero in estimation in order to induce maximum variation in price sensitivities.

Table (3) displays the cumulative returns from the "price sensitivity" portfolio 1990-2017. As with the earnings sensitivity portfolio, both the equal- and value-weighted portfolios display positive and significant alpha over the sample period. The four-factor equal-weighted alpha is 1.36% equal-weighted ($t = 4.78$) and 1.17% value-weighted ($t = 2.62$). The returns of both portfolios suggest that extremes of earnings and price sensitivities are associated with market mispricing in the cross-section that is resolved in the time-series.

6 Conclusion

Understanding how different investors respond to fundamentals is central to understanding the pricing of earnings news. This paper documents that the observed general equilibrium responses of investors to earnings news reflect not only their sensitivity to the earnings news itself, but also how they react to the price impact

[12] An alternative approach is conduct a triple sort by taking the intersection of portfolios sorted on SUE, β, and ζ. Unfortunately, there is not a sufficient number of stocks in the cross-section to deal with this additional dimensionality.

induced by the market's response. When price elasticities also vary across investors, two investors may share similar general equilibrium responses but differ in their sensitivity to earnings.

In the first half of this paper, I develop a method for recovering earnings elasticities by adjusting each investor's total trading response for their response for prices, and then measuring the sensitivity of this compensated measure to earnings news. Intuitively, this method uses countefactual price elasticities to estimate how an investor would respond to the difference in pricing between the investor's perceived assessment of the earnings news and the market's. Using quarterly 13-F holdings data, I apply this method to estimate investor-by-quarter price and earnings elasticities over a 30-year period. These estimates reveal significant heterogeneity across investor types on both measures of elasticities, with the largest margin of variation between most institutional sectors (price inelastic, earnings elastic); investment advisers (price and earnings elastic); and the residual household sector (price elastic, earnings inelastic).

Because stocks vary in their ownership structure, *investor*-level heterogeneity in sensitivity to prices and fundamentals translates to *stock*-level variation in price and earnings sensitivity. In the second half of this paper, I show that these stock-level measures explain many properties associated with the pricing of earning news. More earnings sensitive and less price sensitive stocks see larger contemporaneous passthroughs from a given earnings surprise. This differential sensitivity appears to capture mispricing rather than unboserved characteristics that would justify a differential response for rational reasons. Ultimately, this cross-sectional mispricing is resolved in the time series: extremes of earnings sensitivity tend to revert the following quarter, such that strategies that bet on momentum in earnings insensitive (price sensitive) stocks and reversal in earnings sensitive (price insensitive) stocks generate profitable returns. Together, these results suggest that the ownership structure of stocks, through heterogeneous sensitivities to prices and fundamentals, determines the pricing of earnings news in the market.

The importance of adjusting holdings responses for price elasticities is particularly important for price-relevant news (such as earnings news), but it applies more generally to any news that affects investor demand. The methodology in this paper could be extended to understanding investor demand for other sorts of news, such as news about macroeconomics, sentiment and uncertainty, ESG, regulatory and legal landscapes, and corporate actions. As with the analysis in this paper, this approach can be used not only to understand investor heterogeneity in demand for each type of news, but also to decompose the (average) passthrough of this news to aggregate prices and track the cross-sectional and time-series implications of stock-level heterogeneous responses.

Finally, while this paper focuses on the estimation and asset pricing implications of heterogeneous elasticities, it does not speak to the sources of this variation. Why earnings elasticities have changed over time (and what has been the impact of e.g., the rise in passive investing); how the estimated elasticities relate to the perceived persistence of future earnings growth and other behavioral models; and what information – beyond standardized earnings surprises – is contained in the earnings announcement is a ripe area for future research.

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A Specialized Model with Homogeneous Earnings Passthrough

This section discusses estimation of a model with homogeneous earnings passthroughs. In effect, if elasticities are independent from relative ownership shares, then variation in ownership will not induce variation in the sensitivities of stocks. In this case, one can recover the structural earnings elasticity by adjusting the reduced-form coefficient by the average earnings passthrough identified from pricing regressions. Estimation of this model requires the following proposition:

Proposition. *Let s_{it} denote any investor-by-quarter component, and let η_{int} be the residual in $S_{int} = s_{it} + \eta_{int}$, where $S_{int} = Q_{int}/\sum_i Q_{int}$. If $\forall n \in N, \forall t \in T$, $\eta_{int} \perp (\beta_{it}, \zeta_{it})$, then $\hat{\gamma}_t$ in the cross-sectional regression $\Delta p_{nt} = \delta_t + \gamma_t SUE_{nt} + \epsilon_{nt}$ is consistent estimator of β_{Snt}/ζ_{Snt}.*

Proof. Imposing market clearing on (1),

$$\begin{aligned}
0 &= \sum_i \left(s_{it} + \varepsilon_{int}\right)\left(\alpha_{it} + \beta_{it} SUE_{nt} - \zeta_{it}\Delta p_{nt} + u_{itn}\right) \\
&= \alpha_{St} + \beta_{St} SUE_{nt} - \zeta_{St}\Delta p_{nt} + u_{Stn} + \left(\sum_i \varepsilon_{int}\alpha_{it} + \sum_i \varepsilon_{int}\beta_{it} SUE_{nt} - \sum_i \varepsilon_{int}\zeta_{it}\Delta p_{nt} + \sum_i \varepsilon_{int} u_{itn}\right)
\end{aligned}$$

$$\Delta p_{nt} = \frac{1}{\zeta_{St} + \sum_i \zeta_{it}\varepsilon_{int}}\left[\alpha_{St} + \beta_{St} SUE_{nt} + u_{Stn} + \left(\sum_i \varepsilon_{int}\alpha_{it} + \sum_i \varepsilon_{int}\beta_{it} SUE_{nt} + \sum_i \varepsilon_{int} u_{itn}\right)\right]$$

Suppose $\forall n \in \mathcal{N}, t \in \mathcal{T}, \quad \epsilon_{int} \perp (\zeta_{it}, \beta_{it})$. In words, this says that knowing an investor's elasticity is uninformative for whether they hold more or less of a given stock (in advance of earnings surprises). This condition implies that $\sum_i \zeta_{it}\varepsilon_{int} = 0$ and $\sum_i \beta_{it}\varepsilon_{int} = 0$. Then we have:

$$\begin{aligned}
\Delta p_{nt} &= \frac{\alpha_{St}}{\zeta_{St}} + \frac{\beta_{St}}{\zeta_{St}} SUE_{nt} + \frac{u_{Snt}}{\zeta_{St}} + \frac{1}{\zeta_{St}}\left(\sum_i \varepsilon_{int}\alpha_{it} + \sum_i \varepsilon_{int}\beta_{it} SUE_{nt} + \sum_i \varepsilon_{int} u_{itn}\right) \\
&= \frac{\alpha_{St}}{\zeta_{St}} + \frac{\beta_{St}}{\zeta_{St}} SUE_{nt} + \frac{u_{Snt}}{\zeta_{St}} + \frac{SUE_{nt}}{\zeta_{St}}\underbrace{\sum_i \varepsilon_{int}\beta_{it}}_{=0} + \underbrace{\left(\frac{1}{\zeta_{St}}\sum_i \varepsilon_{int} u_{itn} + \frac{1}{\zeta_{St}}\sum_i \varepsilon_{int}\alpha_{it}\right)}_{\check{u}_{nt}} \\
&= \frac{\alpha_{St}}{\zeta_{St}} + \frac{\beta_{St}}{\zeta_{St}} SUE_{nt} + \frac{u_{Stn}}{\zeta_{St}}
\end{aligned}$$

□

This proposition decomposes ownership shares into an investor-by-quarter component, s_{it} and a residual component, η_{int}. A natural candidate for the investor-by-quarter component s_{it} is the fractional ownership, or AUM-weights in the market: i.e. $s_{it} = A_{it}/\sum_i A_{it}$, where $A_{it} = \sum_n P_{nt}Q_{int}$ is the AUM held in 13-F securities. The proposition then asserts that if the deviations of ownership shares from these AUM-weights are uncorrelated with investor-level elasticities, the earnings passthrough coefficient is a consistent estimator of the ratio of asset-weighted elasticities.

The assumption allows estimation of the following specialized model. First, one can estimate a "quantity" regression using investor holdings data to obtain investor-by-quarter reduced-form elasticities, $\tilde{\beta}_{it}$:

$$\Delta q_{int} = \alpha_{it} + \tilde{\beta}_{it} SUE_{nt} + \boldsymbol{\Psi}'_{it}\Delta \boldsymbol{X}_{nt} + \epsilon_{int} \tag{26}$$

Second, one can estimate price elasticities ζ_{it} using (13). Finally, one can directly use the pricing passthrough coefficient γ_t, by running a series of cross-sectional pricing regressions of log returns on earnings surprises:

$$\Delta p_{nt} = \alpha_t + \gamma_t SUE_{nt} + \mathbf{\Upsilon}_t' \Delta \boldsymbol{X}_{nt} + \varepsilon_{nt} \tag{27}$$

Under these assumptions, one can then recover the structural earnings elasticity as:

$$\hat{\beta}_{it} = \hat{\tilde{\beta}}_{it} + \hat{\zeta}_{it}\hat{\gamma}_t$$

B Bootstrap Details

I bootstrap standard error using the following procedure over 4-quarter rolling windows:

1. In iteration k, sample with replacement from the set of stock-quarters over $(t-4):t$. Denote this set $\Omega_t^{(k)}$.
2. Estimate the GMM regression, i.e. equation (13), on the full sample of manager i's holdings in quarter t.
3. Construct Δq_{int}^* on the set of stock quarters in $\Omega_t^{(k)}$ as in (16).
4. For manager i, construct the kth draw of β_{it} as in (17):

$$\Delta q_{int}^{*(k)} = \alpha_{it}^{(k)} + \beta_{it}^{(k))} SUE_{nt} + \mathbf{\Psi'}_{it}^{(k)} \Delta \boldsymbol{X}_{nt} + \varepsilon_{int}^{(k)}, \quad \forall n, t \in \Omega_t^{(k)}$$

5. Aggregate to 13-F sector level (j) as:

$$\beta_{Sjt}^{(k)} = \sum_{i \in \mathcal{J}(i)} \frac{AUM_{it}}{\sum_{i \in \mathcal{J}(i)} AUM_{it}} \beta_{it}^{(k)}$$

6. Repeat steps (1)-(5) K times to obtain the empirical distribution of β_{Sjt}.

C Dynamic Model and Earnings Momentum

Consider a dynamic demand curve in which investor demand depends not only on current earnings news and prices (SUE_{nt},Δp_{nt}) but also those that occurred at a lag: SUE_{nt-1}, Δp_{nt-1}. We can write investor demand as:

$$\Delta q_{int} = \alpha_{it} + \beta_{it}^{st} SUE_{nt} + \beta_{it}^{lt} SUE_{nt-1} - \zeta_{it}^{st} \Delta p_{nt} - \zeta_{it}^{lt} \Delta p_{nt-1} + u_{int} \tag{28}$$

where "st" and "lt" superscript denote "short-term" and "long-term" respectively.

Imposing market clearing, we solve for prices:

$$\Delta p_{nt} = \frac{1}{\zeta_{Snt}^{st}} \left(\alpha_{Snt} + \beta_{Snt}^{st} SUE_{nt} + \beta_{Snt}^{lt} SUE_{nt-1} - \zeta_{Snt}^{lt} \Delta p_{nt-1} + u_{Snt} \right) \tag{29}$$

Substituting back into investor demand,

$$\begin{aligned}
\Delta q_{int} = & \underbrace{\left(\alpha_{it} - \frac{\zeta_{it}^{st}}{\zeta_{Snt}^{st}}\alpha_{Snt}\right)}_{\tilde{\alpha}_{int}} + \underbrace{\left(\beta_{it}^{st} - \zeta_{it}^{st}\frac{\beta_{Snt}^{st}}{\zeta_{Snt}^{st}}\right)}_{\tilde{\beta}_{int}^{st}} SUE_{nt} + \underbrace{\left(\beta_{it}^{lt} - \zeta_{it}^{st}\frac{\beta_{Snt}^{lt}}{\zeta_{Snt}^{st}}\right)}_{\tilde{\beta}_{int}^{lt}} SUE_{nt-1} \\
& - \underbrace{\left(\zeta_{it}^{lt} + \frac{\zeta_{Snt}^{lt}}{\zeta_{Snt}^{st}}\right)}_{\tilde{\zeta}_{int}^{lt}} \Delta p_{nt-1} + \underbrace{\left(u_{int} - \zeta_{it}^{st}\frac{u_{Snt}}{\zeta_{Snt}^{st}}\right)}_{\tilde{u}_{int}} \\
= & \tilde{\alpha}_{it} + \tilde{\beta}_{int}^{st} SUE_{nt} + \tilde{\beta}_{int}^{lt} SUE_{nt-1} - \tilde{\zeta}_{it}^{lt}\Delta p_{nt-1} + \tilde{u}_{int} \qquad (30)
\end{aligned}$$

As before, reduced-form coefficients are structural coefficients adjusted by a ratio of elasticities:

$$\tilde{\beta}_{int}^{st} = \beta_{it}^{st} - \zeta_{it}^{st}\frac{\beta_{Snt}^{st}}{\zeta_{Snt}^{st}} \qquad (31)$$

$$\tilde{\beta}_{int}^{lt} = \beta_{it}^{lt} - \zeta_{it}^{st}\frac{\beta_{Snt}^{lt}}{\zeta_{Snt}^{st}} \qquad (32)$$

$$\tilde{\zeta}_{int}^{lt} = \zeta_{it}^{lt} + \frac{\zeta_{Snt}^{lt}}{\zeta_{Snt}^{st}} \qquad (33)$$

Inspecting (28), the ratios of share-weighted elasticities, in turn, correspond to stock-specific passthroughs. $\beta_{Snt}^{st}/\zeta_{Snt}^{st}$ is the contemporaneous earnings passthrough; $\beta_{Snt}^{lt}/\zeta_{Snt}^{st}$ is the passthrough of lagged earnings (controlling for lagged returns) to current prices, i.e. "fundamental momentum"; and $-\zeta_{Snt}^{lt}/\zeta_{Snt}^{st}$ is the passthrough of lagged return to current returns, i.e. "price momentum". Fundamental momentum – the momentum associated with higher earnings in the past, controlling for past prices – is higher when investors are more sensitive to earnings last quarter or less sensitive to prices today. Price momentum depends on the term structure of price elasticities; if investors are less *long-term* price elastic – e.g., if they extrapolate past returns in which case $\zeta_{Snt}^{lt} < 0$, then the passthrough is larger. If, at the same time the market is more short-term price elastic, it can better absorb demand shocks contemporaneously, dampening any momentum effects.

Unlike in the static model, the reduced-form regression in (30) is not solely a function of earnings surprises. Nor can elasticities be recovered simply by estimating (30) with earnings surprises and *realized* past returns. Instead, it requires instruments for price changes Δp_{nt-1} as well. This is because market clearing was imposed only at time t, not $t-1$, so $Cov\left(\Delta p_{nt-1}, \tilde{u}_{int}\right) \neq 0$ (e.g. if there are correlated demand shocks over time). One way to solve this is using instruments for longer term price changes, as in Huebner (2023), who uses flow-induced trading. Under this approach, one could measure long and short term price elasticities using chosen price instruments; adjust the trades this quarter for the term structure of elasticities, and then regress these compensated trades on current and past earnings surprises.

Alternatively one can impose market clearing at $t-1$ as well and solve for prices Δp_{nt-1}, i.e. solve for the endogenous variable. Since Δp_{nt-1} is a function of Δp_{nt-2}, this introduces the need for an instrument for $t-2$ prices as well:

$$\Delta p_{nt-1} = \frac{1}{\zeta^{st}_{Snt-1}} \left(\alpha_{Snt-1} + \beta^{st}_{Snt-1} SUE_{nt-1} + \beta^{lt}_{Snt-1} SUE_{nt-2} - \zeta^{lt}_{Snt-1} \Delta p_{nt-2} + u_{Snt-1} \right)$$
$$\Delta q_{int} = \tilde{\alpha}^{(1)}_{it} + \tilde{\beta}^{st(0)}_{int} SUE_{nt} + \tilde{\beta}^{lt(1)}_{int} SUE_{nt-1} + \tilde{\beta}^{lt(2)}_{int} SUE_{nt-2} - \tilde{\zeta}^{lt(1)}_{it} \Delta p_{nt-2} + \tilde{u}^{(1)}_{int}$$

One can iterate recursively to solve for current prices as:

$$\Delta p_t = \tilde{\alpha} + \frac{\beta^{st}_S}{\zeta^{st}_S} SUE_{nt} + \sum_{k=1}^{\infty} \tilde{\beta}^{(k)} SUE_{nt-k} + \tilde{u}_{nt}$$

where

$$\tilde{\beta}^{(k)} = \frac{1}{\zeta^{st}_S} (-1)^k \left[\left(\frac{\zeta^{lt}_S}{\zeta^{st}_S} \right)^k \beta^{st}_S - \left(\frac{\zeta^{lt}_S}{\zeta^{st}_S} \right)^{k-1} \beta^{lt}_S \right]$$
$$\tilde{\alpha} = \frac{1}{\zeta^{st}_S} \sum_{k=0}^{\infty} (-1)^k \left(\frac{\zeta^{lt}_S}{\zeta^{st}_S} \right)^k \alpha_{St-k}$$
$$\tilde{u}_{nt} = \frac{1}{\zeta^{st}_S} \sum_{k=0}^{\infty} (-1)^k \left(\frac{\zeta^{lt}_S}{\zeta^{st}_S} \right)^k u_{St-k}$$

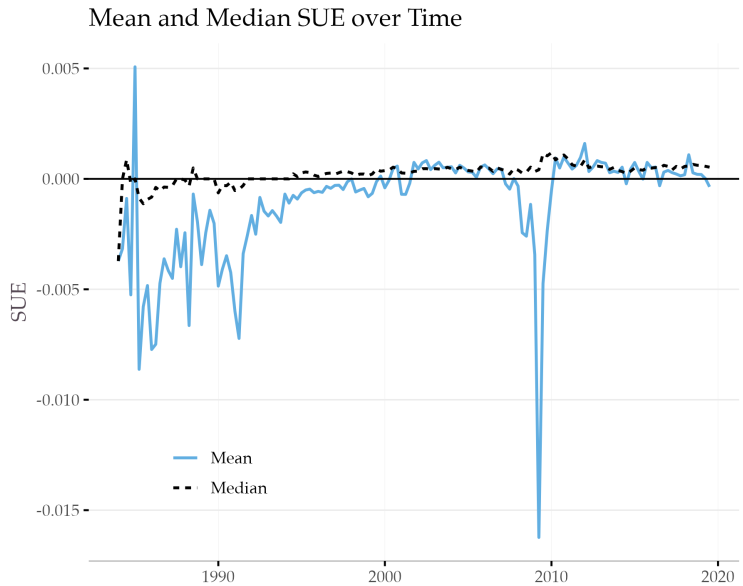
In the limit, no price instruments are needed; however, estimation may suffer from low power.

D Additional Figures

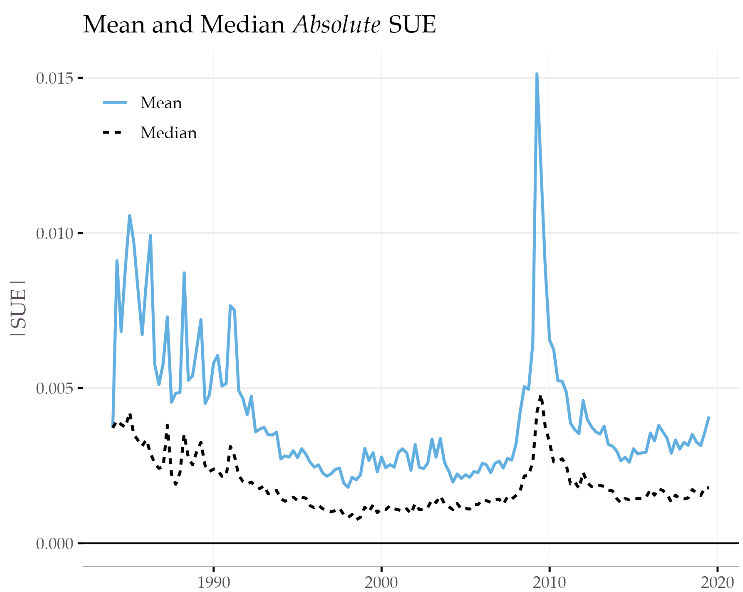
D.1 Bias and Precision of Standardized Unexpected Earnings

Figure 12: Bias and Precision of Standardized Unexpected Earnings

(a) $E\left[SUE_{nt}\right]$



(b) $E\left[|SUE_{nt}|\right]$



D.2 Reduced-Form vs. Structural Earnings Elasticities

Figure 13: Discrepancy Between $\tilde{\beta}_{St}$ and β_{St}

This figure shows the time series of the magnitude of the difference between the asset-weighted reduced-form earnings sensitivity, $\tilde{\beta}_{St}$, and the asset-weighted structural elasticity, β_{St}. $\tilde{\beta}_{St}$ is computed b estimating (18) for each investor×quarter, and aggregating using AUM weights. β_{St} is computed by estimating β_{it} according to (17) and aggregating using AUM weights. The y-axis plots the difference between these quantities as a percentage of the magnitude of the structural earnings elasticity, i.e. it plots $\left(\tilde{\beta}_{St} - \beta_{St}\right)/\beta_{St}$. On average across the time series, the difference is 77% of β_{St}.