Dissecting Announcement Returns[*]

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Abstract

We develop a model with heterogeneous beliefs about a public and a private signal to understand return predictability around earnings announcements. We find evidence consistent with all of the model's key predictions: (1) Stock prices increase on average on earnings announcement days even though all signals are mean zero; (2) Firms with more fundamental uncertainty have higher announcement day returns on average; (3) Announcements day returns predict fundamental growth rates and stock returns; (4) The part of the announcement return *unrelated* to the public signal is more informative about future price drifts and fundamental growth rates than the part related to the public signal. Moreover, a factor based on announcement returns unrelated to the public signal should deliver significant returns that cannot be explained by standard risk factors. We find strong evidence for this and show that such a factor subsumes momentum returns.

JEL Classification: G12, G15

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1. Introduction

A key question in finance is how new information is impounded into asset prices. A prime example of such an information release is earnings announcements. Indeed, it is known from the earlier literature that earnings announcements strongly affect stock prices and generate return predictability in at least two ways: First, there is an *announcement day premium*, i.e., stock prices predictably increase on average on earnings announcement days even though these events are scheduled in advance. Second, there is a *price drift* following the announcement, i.e., stock prices of firms with positive (negative) earnings surprises tend to increase (decrease) for several months.[1]

Both of these patterns seem puzzling from the viewpoint of standard asset pricing models. Why should stock prices increase on announcement days on average if earnings surprises are zero on average? Why should earnings announcements be followed by a long price drift even though earnings announcements are public information?

We argue that that any explanation of these questions must jointly address both facts since they stem from the same information release and must be intricately linked. To do so, we present a stylized equilibrium asset pricing model with heterogeneous beliefs about a private and a public signal and then test the model's prediction empirically.

In a nutshell, our model works as follows. Investors have constant absolute risk aversion (CARA) utility and a normally distributed prior belief about the firm's fundamental (e.g., earnings). All investors receive the public signal and a small fraction of "informed" investors additionally receives a private signal. Both signals are mean zero, normally distributed, and informative about the future fundamental. We think of the public signal as an easily quantifiable and widely followed piece of information, such as the headline earnings per share announcement. The private signal comprises information on announcement days that is harder to quantify and less widely followed, such as the hard or soft information extracted from earnings calls (e.g., Matsumoto, Pronk, and Roelofsen, 2011; Druz, Petzev, Wagner,

[1] A large body of research has shown that asset prices tend to increase on average when new information is released. This includes earnings announcements (e.g., Savor and Wilson, 2016, for a recent study), scheduled macro news announcements (Savor and Wilson, 2013, 2014), or scheduled meetings of the Federal Open Market Committee (Lucca and Moench, 2015). Another strand of the literature has shown that earnings announcements are followed by strong and persistent price drifts (the so-called "post-earnings announcement drift", PEAD) (see, e.g., Kothari, 2001, for an early survey of the literature).

and Zeckhauser, 2017), from press releases (e.g., Demers and Vega, 2008), or more detailed financial statements released along with the raw earnings number. Investors agree to disagree, i.e., there is no learning by uninformed investors from informed investors. Based on this setup, the model delivers a number of testable predictions: (1) Stock prices increase on average on earnings announcement days even though all signals are mean zero. The reason for this effect is that any piece of new information, good or bad, lowers the uncertainty about a firm's fundamental. Hence, on average across firms, stock prices will increase on announcement days to reflect this resolution of uncertainty. Put differently, stocks trade at a discount prior to the announcement to compensate investors for the uncertainty that is not resolved until after the release of information.

(2) Firms with more fundamental uncertainty have higher announcement day returns on average. This follows from the same logic, since the effect of lowering uncertainty is stronger for firms that have more uncertain fundamentals. (3) Announcements day returns predict future stock prices and fundamental growth rates. This result follows from the assumptions that the signals are informative about future fundamentals and that investors agree to disagree so that the price underreacts to the private signal on announcement days. Importantly, even though the public and private signal are zero on average *across* firms (see (1) above) and thus wash out in the aggregate, the announcement day return of any *individual* firm still reflects the realizations of the two signals. (4) The part of the announcement day return *unrelated* to the public signal is more informative about future price drifts and fundamental growth than the part related to the public signal. The reason is that the public signal is impounded into the stock price immediately on the announcement day whereas the private signal is not. Hence, the part of the announcement day return *unrelated* to the public signal is a proxy for the private signal and has stronger forecast power. An additional, more subtle implication of this is that a factor based on the part of announcement day returns unrelated to the public signal should deliver significant returns which cannot be explained by its exposure to risk factors. The intuition for this result is that announcement returns unrelated to the public signal are proxies for the private information by informed investors. Hence, they do not represent a compensation for risk but a compensation for obtaining and processing private information by sophisticated investors. We find strong evidence for this and show that such a factor subsumes the returns to conventional momentum strategies.

To test the model's predictions empirically, we need a measure for the public signal and we need to split announcement day returns into a part related to the public signal and a part related to the private signal (i.e., unrelated to the public signal). We follow a large literature and use "standardized unexpected earnings" (SUE) as our starting point (e.g., Chan, Jegadeesh, and Lakonishok, 1996) for the public signal. For each firm and each announcement day, SUE is the year-over-year change in earnings per share divided by its standard deviation. We also make use of a de-trended SUE (denoted SUE*) which is defined as SUE minus the moving average of SUE over the previous eight quarters. We remove this trend term (denoted trend-SUE in the following) to account for the fact that some firms experience positive (or negative) earnings growth for prolonged time periods. Since we use SUE as a proxy for *unexpected* information, we need to guard against the possibility that such trends are partly predictable and thus remove the trend component from SUE. Importantly, adding trend-SUE and SUE* for any firm in a given quarter recovers the original SUE.

To capture announcement day returns, we follow the literature and compute cumulative abnormal stock returns (CAR), i.e., returns in a three-day window around an earnings announcement and in excess of the market return. Moreover, since our model makes predictions about announcement day returns related to and unrelated to the public signal, we decompose CAR into three economically distinct components: CAR related to trend-SUE, CAR related to SUE*, and CAR orthogonal to SUE. We do so by regressing CAR on a constant, SUE* and trend-SUE for all firms based on the most recent available data. The residual (plus the constant, which is the same for all firms) in this regression then identifies announcement day returns orthogonal to public information (SUE). The part of CAR associated with SUE* identifies the part of announcement day returns related to the public signal. The part of CAR associated with trend-SUE captures any effect due to trends in lagged SUE.[2]

Equipped with these empirical measures of public information and announcement day returns, which are very close to their theoretical counterparts, we take the model to the data and test its predictions on the CRSP sample of U.S. stocks from 1972 to 2016.

We find empirical support for all of the model's main predictions. (1) CARs are about 30

[2]This decomposition is exact in the following sense: The part of CAR related to trend-SUE plus the part of CAR related to SUE* plus the part of CAR unrelated to SUE always add up to the raw CAR of a firm. When necessary, e.g., for forming portfolios, we run these regressions in a rolling fashion to avoid any look-ahead bias.

basis points (bp) on average across all stocks and all earnings announcements in our sample even though the average earnings surprise is zero.[3] Importantly, this finding is almost fully driven by the component of CAR that is orthogonal to SUE, i.e., unrelated to the public signal. In other words, stock prices increase on average due to a resolution of uncertainty effect that is unrelated to the public signal, as predicted by our model. (2) This unconditional result masks important differences in the cross section and in the time series. When we split the sample into firms whose fundamentals are plausibly more (less) uncertain, we find significantly stronger (weaker) effects. For example, large stocks experience CARs of about 16 bp around earnings announcements whereas small stocks have CARs of 44 bp. As another example, the CAR of value stocks is 74 bp higher than the CAR of growth stocks. We provide evidence for other proxies of fundamental uncertainty based on leverage and industry and find similar results. In the time series, we find that CARs unrelated to SUE are significantly higher in times of high VIX readings (50 bp) compared to times when the VIX is low (16 bp). Overall, these findings suggest that the positive announcement premium observed in stock markets relates to a reduction of fundamental uncertainty which is unrelated to the new information itself.

Turning to the predictability of future fundamental growth rates and stock prices by announcement day returns, we find that (3) CAR positively predicts future earnings growth rates and the growth in gross profits over horizons of one to five years. Moreover, we find (4) that virtually all of this predictability stems from the part of CAR that is unrelated to SUE whereas the parts of CAR related to SUE either do not significantly forecast fundamental growth or forecast it with the wrong sign. We take this as strong evidence that the CAR unrelated to SUE identifies the private information about future fundamentals of informed investors as suggested by our model. To test for the predictability of future stock returns we first build portfolios based on (lagged) CAR. In line with the earlier literature, we find that a portfolio that goes long high CAR stocks significantly outperforms a portfolio comprised of low CAR stocks (69 bp per month). Turning to our decomposition of CAR into trend-SUE, SUE*, and the part of CAR orthogonal to SUE, we find that the orthogonal component accounts for almost all of the this spread in returns (54 bp per month) whereas the part of CAR due to SUE* and trend-SUE only accounts for the remaining $69 - 54 = 15$ bp per

[3] The same result obtains when we control for revenue surprises (e.g., Jegadeesh and Livnat, 2006) as well as surprises to other items that can be inferred from earnings and revenues.

month. In the context of our model, this result confirms that the private signal (proxied for by CAR unrelated to SUE) has more predictive power than the public signal (proxied for by SUE). Moreover, we find that the returns to a factor based on CAR unrelated to SUE are not spanned by standard risk factors but that they subsume returns to momentum strategies. In the context of our model, these findings suggest that momentum arises due to the diffusion of private information about future fundamentals in stock markets.

Our paper thus contributes to the literature on announcement premia (e.g. Beaver, 1968; Chari, Jagannathan, and Ofer, 1988; Ball and Kothari, 1991; Frazzini and Lamont, 2007) and the post-earnings announcement drift (e.g. Bernard and Thomas, 1989, 1990; Chan, Jegadeesh, and Lakonishok, 1996; Jegadeesh and Livnat, 2006) in a number of ways. First, we build an equilibrium asset pricing model with heterogeneous beliefs that *jointly* rationalizes the announcement premium *and* the post-earnings announcement drift (PEAD). Second, we provide novel empirical evidence, most notably that CAR *unrelated* to SUE is important for understanding both the announcement premium as well as the predictability of future returns and fundamental growth rates. Importantly, CAR and SUE do not capture the same information in the sense that CAR is more powerful than SUE in predicting future stock returns and fundamental growth rates (e.g., earnings growth and gross profitability growth). As such, our model and results rationalize Huo, Xue, and Zhang's (2015; 2017) finding that while their q-factor model fully explains the return to strategies based on SUE, it does not explain the returns to strategies based on CAR. Third, we also show empirically that CAR unrelated to SUE helps in understanding the puzzling returns to momentum strategies (Jegadeesh and Titman, 1993, 2001). Based on our model, CAR unrelated to SUE is a proxy for the unobserved private signal of informed investors. We show that the exposure of momentum to a portfolio based on CAR unrelated to SUE completely accounts for the returns to momentum and that the part of CAR unrelated to SUE is more important for understanding momentum returns than SUE itself. This extends the empirical findings in Novy-Marx (2015) and our model rationalizes these empirical findings.

A recent study on announcement premia that is closely related to ours is Savor and Wilson (2016). They propose a risk-based mechanism that can rationalize the announcement premium based on investors extracting information about aggregate earnings from individual firm's earning announcements. Consequently, they show that firms that announce earnings early earn a higher return than late announcers and find that announcement risk is priced in the cross section of stock returns. Our model reproduces a key feature of their main result, i.e., that the announcement premium is driven by discount rates (a resolution of fundamental uncertainty in our case). We go beyond their paper by also studying how earnings announcements can generate announcement premia and price drifts (PEAD) in a unified setup. Moreover, we propose a mechanism that allows us to disentangle the roles that public and private information play in driving these results and use this mechanism to better understand the returns to momentum strategies.

The rest of the paper unfolds as follows. Section 2 presents the model. Section 3 describes the data and summary statistics. Sections 4 and 5 present empirical tests of the model's prediction regarding announcement and post-announcement returns, respectively. Section 6 reports results on the relationship of announcement-based factors with momentum returns. Finally, Section 7 concludes.

2. Model

This section presents an equilibrium asset pricing model of heterogenous beliefs about a risky asset's fundamental value and derives our theoretical predictions. We show that following a release of information, there is an immediate reduction in fundamental uncertainty (discount rate effect) and a gradual diffusion of information about fundamentals in the aftermath of the announcement (cash flow effect). The first effect implies positive average announcement premia while the second implies that announcement returns have predictive power for future fundamentals and prices.

2.1. Model setup

There are three dates: $0-$, 0, and 1, where we think of date $0-$ as "just before" date 0. The model features a risk-free asset (i.e., a government bond) and a risky asset (i.e., a company's stock). The gross risk-free rate is fixed at $R_f = 1 + r_f > 1$ and the aggregate supply of the risky asset is fixed at $Z > 0$. At date 1, the risky asset has a fundamental value of $F_1 = \mu + A + B$, where $A \sim \mathcal{N}(0, \sigma_A^2)$ and $B \sim \mathcal{N}(0, \sigma_B^2)$; A and B are independent; and μ, σ_A, and σ_B are strictly positive constants. We call F_1's variance, $\sigma_A^2 + \sigma_B^2$, the risky asset's *fundamental uncertainty.* The distribution of F_1, including all parameters, is common knowledge to all investors. Without loss of generality, we assume that the entire amount corresponding to F_1 is paid out as a date-1 dividend.

At date 0, investors learn about F_1's unexpected components, A and B, from an earnings announcement. We think of A as a relatively quantifiable component that all investors learn about through, e.g., the headline earnings-per-share figure. In contrast, we think of B as a component that is harder quantify and/or process, so that only some investors choose to learn about B. This could be through (costly) research using additional hard or soft information extracted from the earnings call, the press release, or a more detailed financial statement released alongside the earnings-per-share figure (e.g., Demers and Vega, 2008; Matsumoto, Pronk, and Roelofsen, 2011; Druz, Petzev, Wagner, and Zeckhauser, 2017).

There is a continuum of investors with total (Lebesgue) measure 1. All investors are ex-ante identical, have CARA utility over terminal wealth with risk-aversion parameter $\gamma > 0$, and trade competitively (i.e., take prices as given). Heterogeneity across investors arises due to differences in beliefs about the risky asset's date-1 fundamental value.

We divide the investors into two groups: I is the group of relatively informed investors with measure $\iota \in (0, 1)$, while U is the group of relatively uninformed investors with measure $1 - \iota$. At date 0, each I- and U-investor receives an individual signal about A given by

$$a_i = A + \epsilon_{ia}, \quad i \in I \cup U, \tag{1}$$

where $\epsilon_{ia} \sim \mathcal{N}(0, \sigma^2_{\epsilon a})$ is independent of A and B and iid across investors. In addition to a signal about A, each I-investor also receives an individual signal about B given by

$$b_i = B + \epsilon_{ib}, \quad i \in I, \tag{2}$$

where $\epsilon_B \sim \mathcal{N}(0, \sigma^2_{\epsilon b})$ is independent of B, A, ϵ_{ia} for all i, and iid across I-investors. We refer to a_i as an investor's realization of the *public signal* (i.e., the headline earnings-per-share figure) and to b_i as an investor's realization of the *private signal* (i.e., additional information released alongside the earnings-per-share figure). Similar to Cespa and Vives (2015) and others, and without loss of generality, we adopt the convention that $\int_{I \cup U} a_i \, \mathrm{d}i = A$ and $\int_I b_i \, \mathrm{d}i = B$ almost surely, i.e., that individual signal-errors cancel out in the aggregate.

Following Banerjee, Kaniel, and Kremer (2009), we assume that investors have differences of opinion about the informativeness of other investors' signals, both within and across the two groups (see also Hong and Stein (1999, 2007)). That is, while investors agree about the distribution of F_1, they agree to disagree about the informativeness of their respective signals. For simplicity, we assume that each investor believes that no other investor holds information of any additional value. A less extreme setup where investors put some weight on other investors' signals, such as that in Banerjee and Green (2015), delivers qualitatively similar results. As a result, investors choose not to learn about other investors' signals from the date-0 equilibrium price. If all investors did use the price to infer other investors' signals, the model would reduce to that of Grossman (1976) where there is no price drift. Although none of the following results rely on this, it is useful to think of $\iota \ll 1$, so that most investors only receive a signal about A.

In the following, we denote by $\mathbb{E}_i[\,\cdot\,]$, $\mathbb{V}_i[\,\cdot\,]$, and $\mathbb{COV}_i[\,\cdot\,,\,\cdot\,]$ the conditional expectation, variance, and covariance given investor i's information set. Furthermore, to simplify the notation, we define $\overline{\mathbb{E}}_G[\,\cdot\,] = \frac{1}{|G|}\int_G \mathbb{E}_i[\,\cdot\,]\,\mathrm{d}i$ and $\overline{\mathbb{V}}_G[\,\cdot\,] = \frac{1}{|G|}\int_G \mathbb{V}_i[\,\cdot\,]\,\mathrm{d}i$ as the *consensus expectation* and *consensus variance* in group G, where G is either I or U. Finally, we denote by $\mathbb{E}[\,\cdot\,]$, $\mathbb{V}[\,\cdot\,]$, and $\mathbb{COV}[\,\cdot\,,\,\cdot\,]$ the objective expectation, variance, and covariance, which is common to all investors and corresponds to the econometrician's information set.

2.2. *Pre-announcement market*

Similar to Ai and Bansal (2016) we assume that at date $0-$, i.e., just before the signals are received, there exists a *pre-announcement market* where the assets are traded. Before receiving their individual signals, all investors have common priors about the distribution of F_1. Denote by P_{0-} the pre-announcement price of the risky asset. The representative investor maximizes utility by optimally choosing the position, x, of the initial wealth, $W > 0$, to be invested in the risky asset. The remainder is invested in the risk-free asset. The representative investor's terminal wealth is thus $R_f W + x(F_1 - R_f P_{0-})$. Hence, given P_{0-}, the utility maximization problem becomes

$$\max_x \mathbb{E}\left[-e^{-\gamma(R_f W + x(F_1 - R_f P_{0-}))}\right] = \max_x -e^{-\gamma\left(x\mathbb{E}\left[F_1 - R_f P_{0-}\right] - \frac{\gamma x^2}{2}\mathbb{V}\left[F_1 - R_f P_{0-}\right]\right)}. \tag{3}$$

It follows that the optimal demand for the risky asset just before to the announcement is

$$x = \frac{\mathbb{E}\left[F_1\right] - R_f P_{0-}}{\gamma \mathbb{V}\left[F_1\right]} = \frac{\mu - R_f P_{0-}}{\gamma(\sigma_A^2 + \sigma_B^2)}. \tag{4}$$

The equilibrium pre-announcement price of the risky asset solves the market-clearing condition $\int_{I \cup U} x \, \mathrm{d}i = Z$, and is thus given by

$$P_{0-} = \frac{1}{R_f} \left(\mu - \gamma Z(\sigma_A^2 + \sigma_B^2)\right). \tag{5}$$

2.3. *Signals and updated beliefs*

At date 0, investors receive their individual signals about F_1's unexpected components, A and B. Each U-investor and each I-investor receives a realization of the public signal, a_i, about A. In addition, each I-investor receives a realization of the private signal, b_i, about B. All investors use Bayesian updating to form new beliefs about F_1, in that

$$\mathbb{E}_i[F_1] = \begin{cases} \mu + \lambda_a a_i & i \in U \\ \mu + \lambda_a a_i + \lambda_b b_i & i \in I \end{cases} \tag{6}$$

and

$$\mathbb{V}_i[F_1] = \begin{cases} (1 - \lambda_a)\sigma_A^2 + \sigma_B^2 & i \in U \\ (1 - \lambda_a)\sigma_A^2 + (1 - \lambda_b)\sigma_B^2 & i \in I \end{cases} \tag{7}$$

where $\lambda_a = \frac{\mathbb{COV}[a_i, A]}{\mathbb{V}[a_i]} = \frac{\sigma_A^2}{\sigma_A^2 + \sigma_{\epsilon a}^2} \in (0, 1)$ is the signal-to-noise ratio of each a_i, which is common to both groups of investors, and where $\lambda_b = \frac{\mathbb{COV}_I[b_i, B]}{\mathbb{V}_I[b_i]} = \frac{\sigma_B^2}{\sigma_B^2 + \sigma_{\epsilon b}^2} \in (0, 1)$ is the signal-to-noise ratio of each b_i from I-investors' perspective. Note that the assumption of disagreement across investor groups can be re-stated as assuming that U-investors believe that $\lambda_b = 0$, or, equivalently, that $\sigma_{\epsilon b}^2 = \infty$.

The updated beliefs highlight a *reduction in fundamental uncertainty*: Receiving a_i reduces each investor's beliefs about A's variance from σ_A^2 to $(1 - \lambda_a)\sigma_A^2$ regardless of the sign and magnitude of a_i, and, similarly, receiving b_i reduces each I-investor's beliefs about B's variance from σ_B^2 to $(1-\lambda_b)\sigma_B^2$ regardless of the sign and magnitude b_i. It follows that, after the announcement, the consensus beliefs of U-investors are

$$\overline{\mathbb{E}}_U[F_1] = \mu + \lambda_a A \qquad \text{and} \qquad \overline{\mathbb{V}}_U[F_1] = (1-\lambda_a)\sigma_A^2 + \sigma_B^2, \tag{8}$$

while the consensus beliefs of I-investors are

$$\overline{\mathbb{E}}_I[F_1] = \mu + \lambda_a A + \lambda_b B \qquad \text{and} \qquad \overline{\mathbb{V}}_I[F_1] = (1-\lambda_a)\sigma_A^2 + (1-\lambda_b)\sigma_B^2. \tag{9}$$

In the following, we refer to $\lambda_a A$ as the *public news* (about A) while we refer to $\lambda_b B$ as the *private news* (about B). As the signals about A become fully informative, i.e., as $\lambda_a \to 1$, the public news converges to the true value of A, and similarly for B as $\lambda_b \to 1$.

2.4. Announcement date equilibrium

Denote by P_0 the equilibrium price of the risky asset on the announcement date. Similar to the analysis of the pre-announcement market, we have that, given P_0, each investor's optimal demands of the risky asset is given by

$$x_i = \frac{\mathbb{E}_i[F_1] - R_f P_0}{\gamma \mathbb{V}_i[F_1]}. \tag{10}$$

By market clearing, i.e., by $\int_{I\cup U} x_i \,\mathrm{d}i = Z$, it follows that

$$P_0 = \frac{1}{R_f}\left(\underbrace{\kappa\overline{\mathbb{E}}_I[F_1] + (1-\kappa)\overline{\mathbb{E}}_U[F_1]}_{\text{Expectation}} - \underbrace{\gamma Z \cdot H(\sigma_A^2, \sigma_B^2)}_{\text{Uncertainty}}\right), \tag{11}$$

where $\kappa = \frac{\iota}{\overline{\mathbb{V}}_I[F_1]} H(\sigma_A^2, \sigma_B^2)$ and $1-\kappa = \frac{1-\iota}{\overline{\mathbb{V}}_U[F_1]} H(\sigma_A^2, \sigma_B^2)$ are weights in $(0,1)$ and where

$$H(\sigma_A^2, \sigma_B^2) = \frac{1}{\frac{\iota}{\overline{\mathbb{V}}_I[F_1]} + \frac{1-\iota}{\overline{\mathbb{V}}_U[F_1]}} \tag{12}$$

is the *weighted harmonic mean* of the two groups' consensus beliefs about F_1's variance, i.e., the risky asset's fundamental uncertainty.[4]

[4]Note that the pre-announcement price, P_{0-}, in Eq. (5) can alternatively be derived as the limit of P_0 as $(\lambda_a, \lambda_b) \to (0,0)$, i.e., as the signals become completely uninformative.

The date-0 price consists of two components: An expectation (or 'cash-flow') component and an uncertainty (or 'risk-premium') component. The expectation component is a weighted average of the consensus expectations, where the weight, κ, on the I-investors' consensus expectation is proportional to the inverse of I-investors' consensus variance, $\frac{1}{\overline{\mathbb{V}}_I[F_1]}$. The uncertainty component is the aggregate risk-aversion times the harmonic mean of the two groups' consensus beliefs about the asset's fundamental uncertainty.

Importantly, the expectation component can also be written as

$$\kappa\overline{\mathbb{E}}_I[F_1] + (1-\kappa)\overline{\mathbb{E}}_U[F_1] = \mu + \lambda_a A + \kappa\lambda_b B. \tag{13}$$

This shows that while the equilibrium price fully conveys public news (about A), it only partially conveys private news (about B) because $\kappa < 1$ when $\iota < 1$, i.e., as long as some investors do not receive a signal about B. It follows that P_0 *underreacts* to private news. The reason is that the two groups of investors agree-to-disagree about the informativeness of the private signals about B, and so, in equilibrium, the price only partially conveys the fraction κ of the information in the consensus expectation of B. As more and more investors receive a signal about B, i.e., as $\iota \to 1$, we have $\kappa \to 1$, and the underreaction disappears.

2.5. Announcement returns

We define the announcement return as the price change between dates $0-$ and 0, i.e.,

$$r_0 = P_0 - P_{0-} = \frac{1}{R_f}\left(\underbrace{\lambda_a A + \kappa\lambda_b B}_{\text{News}} + \underbrace{\gamma Z\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right]}_{\text{Uncertainty reduction}}\right). \tag{14}$$

The announcement return consists of a news- and an uncertainty-reduction component. The news component is the information about the unexpected fundamental, i.e., $A+B$, conveyed in P_0, while the uncertainty-reduction component is the risk aversion times the difference between the asset's fundamental uncertainty, $\sigma_A^2 + \sigma_B^2$, and the weighted harmonic mean of the consensus variances, $H(\sigma_A^2, \sigma_B^2)$. Note that while the news component can be positive or negative, the uncertainty reduction component is always positive because

$$H(\sigma_A^2, \sigma_B^2) < \sigma_A^2 + \sigma_B^2 \tag{15}$$

when each of ι, λ_a, and λ_b is in $(0,1)$.[5]

In addition to studying the total announcement return, r_0, we wish to study (i) the part of r_0 that can be explained by public news (i.e., by $\lambda_a A$) and (ii) the part of r_0 that cannot be explained by public news. By Eq. (14), the latter must capture a combination of the fraction of private news conveyed in the price (i.e., $\kappa\lambda_b B$) and the reduction in fundamental uncertainty. Hence, we write r_0 as

$$r_0 = \underbrace{\frac{1}{R_f}\lambda_a A}_{\widehat{r}_0} + \underbrace{\frac{1}{R_f}\Big(\kappa\lambda_b B + \gamma Z\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right]\Big)}_{r_0^{\perp}}. \tag{16}$$

Note that because A and B are uncorrelated, so are $\widehat{r}_0$ and $r_0^{\perp}$.[6]

We then have the following results (all proofs are in Appendix B).

Proposition 1 (Announcement returns and fundamental uncertainty)**.**

1. *The announcement return is positive if and only if the public news is not so negative that it undoes the always positive effect of the reduction in fundamental uncertainty:* $r_0 > 0$ *if and only if* $\lambda_a A > \underline{L}$*, where*

$$\underline{L} = -\kappa\lambda_b B - \gamma Z\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right],$$

   and it holds that $\mathbb{E}[\underline{L}] = -\gamma Z\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right] < 0$.

2. *The part of the announcement return unrelated to public news is on average positive because of the reduction in fundamental uncertainty:* $\mathbb{E}[r_0^{\perp}] = \frac{\gamma Z}{R_f}\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right] > 0$.

3. *The part of the announcement return unrelated to public news is on average higher when fundamental uncertainty is higher:* $\frac{\partial \mathbb{E}[r_0^{\perp}]}{\partial \mathbb{V}[F_1]} > 0$.

[5] This follows immediately from the properties of the weighted harmonic mean, since

$$H(\sigma_A^2, \sigma_B^2) < \iota\overline{\mathbb{V}}_I[F_1] + (1-\iota)\overline{\mathbb{V}}_U[F_1] = (1-\lambda_a)\sigma_A^2 + (1-\iota\lambda_b)\sigma_B^2 < \sigma_A^2 + \sigma_B^2$$

when each of ι, λ_a, and λ_b is in $(0,1)$.

[6] Formally, we decompose r_0 as

$$r_0 = \alpha + \beta(\lambda_a A) + \epsilon,$$

where α and β are constants and ϵ is a mean-zero random variable that is uncorrelated with $\lambda_a A$. Then $\alpha = \frac{1}{R_f}\gamma Z\left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right]$, $\beta = \frac{1}{R_f}$, and $\epsilon = \frac{1}{R_f}\kappa\lambda_b B$, and we set $\widehat{r}_0 = \beta(\lambda_a A)$ and $r_0^{\perp} = \alpha + \epsilon$.

The first part of the proposition shows that, because of the reduction in fundamental uncertainty, the announcement returns will in general be positive unless the public news is extremely negative.[7] Specifically, there exists a lower bound, $\underline{L}$, such that the announcement return is positive if and only if the public news, $\lambda_a A$, exceeds $\underline{L}$. The lower bound consists of two components: The negative of the fraction of private news conveyed in the price, $-\kappa\lambda_b B$, and the negative of the reduction in fundamental uncertainty. Since B has mean zero, the average $\underline{L}$ is strictly negative. Hence, for the announcement return to be negative, the public news needs to be so negative that it not only wipes out the effect of any positive private news but also the always positive effect of the reduction in fundamental uncertainty.

The second part of the proposition shows that the part of the announcement return unrelated to public news, $r^{\perp}$, is on average positive. This is, of course, because $r^{\perp}$ also captures the reduction in fundamental uncertainty and B has mean zero. Finally, the third part shows that this average $r^{\perp}$ is higher when fundamental uncertainty is higher. Intuitively, the reduction in fundamental uncertainty will be higher when fundamental uncertainty starts off from a higher level, leading to a higher average $r^{\perp}$.

2.6. *Announcement returns and future fundamentals*

Because the public and private signals are informative about F_1, and because the news embodied by the signals is (partly) reflected in the announcement return, a higher r_0 will naturally predict a higher value for F_1. The same is true for the part of r_0 unrelated to public news ($r_0^{\perp}$) and the part of r_0 related to public news ($\widehat{r}_0$) because they separate the effects of public and private news on r_0. Finally, because the price on the announcement date underreacts to private news (but not to public news), there is a gradual diffusion of the private information following the announcement. Since the magnitude of underreaction is captured by $r_0^{\perp}$, it will be a stronger predictor of F_1 compared $\widehat{r}_0$. The following proposition formalizes these considerations.

[7] We frequently refer to this increase in the precision about the distribution of the fundamental as a "resolution of uncertainty effect." Other papers in the literature use the same term but have somewhat different concepts in mind. For example, Schlag, Thimme, and Weber (2016) refer specifically to an "early versus late resolution of uncertainty" about cash flows, whereas Ai and Bansal (2016) refer to Knightian Uncertainty in the context of a pre-announcement drift.

Proposition 2 (Announcement returns and future fundamentals)**.**

1. *A higher announcement return predicts a higher future fundamental:* $\mathbb{E}[F_1 \,|\, r_0]$ *is increasing in* r_0*.*

2. *A higher value for either component of the announcement return predicts a higher future fundamental:* $\mathbb{E}[F_1 \,|\, r_0^{\perp}]$ *is increasing in* $r_0^{\perp}$ *and* $\mathbb{E}[F_1 \,|\, \widehat{r}_0]$ *is increasing in* $\widehat{r}_0$*.*

3. *As long as the informativeness of the public signal is not too low, a higher value for the component of the announcement return unrelated to public news predicts a higher fundamental than does the component related to public news: As long as* $\lambda_a > \kappa\lambda_b$*, it holds that* $\frac{\partial \mathbb{E}[F_1 \,|\, r_0^{\perp}]}{\partial r_0^{\perp}} > \frac{\partial \mathbb{E}[F_1 \,|\, \widehat{r}_0]}{\partial \widehat{r}_0}$*.*

The condition, $\lambda_a > \kappa\lambda_b$, in part 3 of the proposition is easily satisfied for a wide range of values for the volatility parameters $\sigma_A, \sigma_B, \sigma_{\epsilon a}$, and $\sigma_{\epsilon b}$ when $\iota < 1$, i.e., when some investors do not receive a signal about B. It ensures that the signal-to-noise ratio of the signals about A, i.e., λ_a, is not too low compared to that of the signals about B, i.e., λ_b. If $\lambda_a < \kappa\lambda_b$, the underreaction to private news is dwarfed by the low informativeness of the signals about A, which leads to a stronger relation between $\widehat{r}_0$ and F_1 compared to between $r_0^{\perp}$ and F_1.

2.7. *Post-announcement drift*

In addition to positively predicting the future fundamental, the announcement return also positively predicts the future return on the risky asset. That is, the model generates *post-announcement drift*: Expected future returns are increasing in the announcement day return, which leads the price to "drift" in a manner consistent with the sign and magnitude of the announcement return. To formally state this and related results, we define the post-announcement return as the price change between dates 0 and 1, i.e., $r_{0,1} = P_1 - P_0$. Since $P_1 = F_1 = \mu + A + B$, it follows that the post-announcement return is given by

$$r_{0,1} = \frac{1}{R_f}\Big(r_f\mu + (R_f - \lambda_a)A + (R_f - \kappa\lambda_b)B + \gamma Z \cdot H(\sigma_A^2, \sigma_B^2)\Big). \tag{17}$$

The following proposition states our results regarding post-announcement drift.

Proposition 3 (Post-announcement drift)**.**

1. *A higher announcement return predicts a higher post-announcement return:* $\mathbb{E}[r_{0,1} \,|\, r_0]$ *is increasing in* r_0*.*

2. *A higher value for either component of the announcement return predicts a higher post-announcement return:* $\mathbb{E}[r_{0,1} \,|\, \widehat{r}_0]$ *is increasing in* $\widehat{r}_0$ *and* $\mathbb{E}[r_{0,1} \,|\, r_0^{\perp}]$ *is increasing in* $r_0^{\perp}$*.*

3. *As long as the informativeness of the public signal is not too low, a higher value for the component of the announcement return unrelated to public news predicts a higher post-announcement return than does the component related to public news: As long as* $\lambda_a > \kappa\lambda_b$*, it holds that* $\frac{\partial \mathbb{E}[r_{0,1} \,|\, r_0^{\perp}]}{\partial r_0^{\perp}} > \frac{\partial \mathbb{E}[r_{0,1} \,|\, \widehat{r}_0]}{\partial \widehat{r}_0}$*.*

Part 1 of the proposition mimics the results in Banerjee, Kaniel, and Kremer (2009): The announcement return predicts the post-announcement return positively (see also Hong and Stein (2007)). This follows from the underreaction to private news, leading to a gradual diffusion of private information following the announcement. Part 2 extends this result and shows that both components of the announcement return predict the post-announcement return positively. The orthogonal component, $r_0^{\perp}$, predicts $r_{0,1}$ positively because it captures the magnitude of underreaction to private news. One may wonder why the same holds for the projected component, $\widehat{r}_0$. This is because of (i) the disagreement among investors about the informativeness of the signals about A, and (ii) the fact that the public news, $\lambda_a A$, in general does not fully reveal the true A. These two effects imply that $\widehat{r}_0$ also predicts $r_{0,1}$ positively. Nonetheless, Part 3 shows that as long as the informativeness of the public signal is not so low that the underreaction is dwarfed by the low informativeness of the signals about A, $r_0^{\perp}$ is a stronger predictor of $r_{0,1}$ than is $\widehat{r}_0$.

Part 3 of the proposition implies that post-announcement drift is largely driven by the gradual diffusion of private information following the announcement. Hence, a higher expected post-announcement return is largely *not* a reflection of a higher risk-premium demanded, in equilibrium, by all investors. Rather, it is largely the compensation demanded by informed investors for obtaining an extra signal about B. A subtle but important testable implication of this is that the returns to trading strategies (or 'factors') based on the part of

Table I: Parameters used in the model simulation. This table shows the model parameters, the corresponding notation within the model, and the values used in the simulations. Panel A shows the exogenous parameters that we set. Panel B shows the implied parameters, which depend on the exogenous parameters.

Parameter	Notation	Value
Panel A: Exogenous parameters		
Risk-free rate	r_f	0.03
Aggregate supply	Z	1
Expected fundamental	μ	1
Risk-aversion	γ	1
Fraction of informed investors	ι	0.05
Volatility of quantifiable component (A)	σ_A	0.125
Volatility of unquantifiable component (B)	σ_B	0.150
Volatility of noise in signals about A	$\sigma_{\epsilon a}$	0.375
Volatility of noise in signal about B	$\sigma_{\epsilon b}$	0.120
Panel B: Implied parameters		
Informativeness of public news	λ_a	0.100
Informativeness of private news	λ_b	0.610
Fundamental uncertainty ($\mathbb{V}[F_1]$)	$\sigma_A^2 + \sigma_B^2$	0.038
U-investors' consensus variance	$\overline{\mathbb{V}}_U[F_1]$	0.037
I-investors' consensus variance	$\overline{\mathbb{V}}_I[F_1]$	0.023
Weighted harmonic mean of consensus variances	$H(\sigma_A^2, \sigma_B^2)$	0.035
Weight on I-investors' consensus expectation	κ	0.078

announcement returns unrelated to public news (i.e., $r_0^{\perp}$) should *not* be explained by standard risk-factors, because the returns to such strategies are inherently not a compensation for risk but rather compensation for information aquisation.

2.8. *Simulations*

We conclude our theoretical analysis with a simulation of the model. Table I, Panel A, shows the exogenous parameters used in the simulation. We set the risk-free rate to $r_f = 0.03$ and we normalize the supply of the risky asset and the expected fundamental by setting $Z = 1$ and $\mu = 1$. Similar to Banerjee and Green (2015), we set risk-aversion to $\gamma = 1$. Finally, we set $\iota = 0.05$, so that the informed investors (I) only constitute 5% of the market.

We set the volatilities of A and B to $\sigma_A = 0.125$ and $\sigma_B = 0.150$ to capture the idea that B is harder to quantify. On the other hand, we set the volatilities of the noise-terms in the signals about A and B to $\sigma_{\epsilon a} = 0.375$ and $\sigma_{\epsilon a} = 0.120$. This is to capture the idea that although B is harder to quantify, the signals about B, which are only received by I-investors, are more informative than the signals about A, which are received by all investors. These parameter values imply that the average announcement return in the simulations closely matches the one we document in the data.

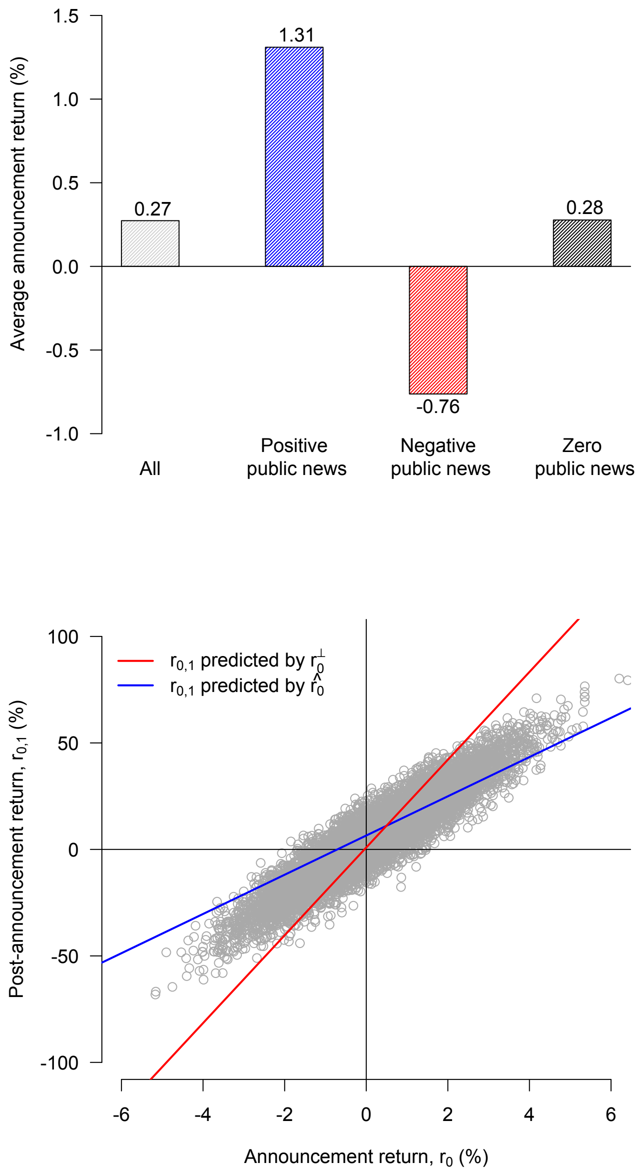

Figure 1: Simulated announcement and post-announcement returns. This figure shows announcement and post-announcement returns (in %) for a simulated sample of 10,000 firms. The top panel shows grouped averages of the firms' announcement returns (r_0), where the groups are defined according to the public news ($\lambda_a A$). The bottom panel shows firms' post-announcement returns ($r_{0,1}$) plotted against their announcement returns. It also shows the lines of best fit from univariate regressions of $r_{0,1}$ on the component of the announcement return unrelated to public news ($r_0^{\perp}$) and the component related to public news ($\widehat{r}_0$). The parameters used for the simulation are provided in Table I.

Table I, Panel B, shows additional parameters implied by the exogenous parameters. The informativeness of public news is $\lambda_a = 0.100$ while the informativeness of private news is a considerably higher $\lambda_b = 0.610$. Fundamental uncertainty, as measured by the variance of F_1, is $\sigma_A^2 + \sigma_B^2 = 0.038$. After receiving their signals about A, U-investors' consensus variance is a slightly lower $\overline{\mathbb{V}}_U[F_1] = 0.037$ due to the resolution of uncertainty. Because I-investors receive signals about both A and B, their consensus variance is a much lower $\overline{\mathbb{V}}_I[F_1] = 0.023$. The harmonic mean of these consensus variances is $H(\sigma_A^2, \sigma_B^2) = 0.035$ and is, of course, lower than fundamental uncertainty. The weight on I-investors' consensus expectation in the equilibrium price is $\kappa = 0.078$. This means that the price only reflects 7.8% of private news, which is close to the 6% market inefficiency estimate derived by Garleanu and Pedersen (2017). Finally, note that while $\lambda_b = 0.610$ is considerably higher than $\lambda_a = 0.100$, the condition $\lambda_a > \kappa\lambda_b$, which ensures that λ_a is not too low compared to λ_b, is still easily satisfied because $\kappa\lambda_b = 0.047$.

Figure 1 shows announcement and post-announcement returns (in %) for a simulated sample of 10,000 firms using the parameters in Table I. The top panel shows grouped averages of announcement returns (r_0), where the groups defined according to the public news ($\lambda_a A$). The average r_0 across all announcements is 0.27% despite the fact that all signals are mean-zero. The reason is the reduction in fundamental uncertainty. The average r_0 is 1.31% when public news is positive, but a magnitude-wise considerably lower -0.76% when public news is negative. This is because r_0 is only negative when public news is so negative that it wipes out any positive effect of private news as well as the always positive effect of the reduction in fundamental uncertainty. Finally, when public news is zero, the average r_0 is 0.28%, which, up to rounding errors, coincides with the average r_0 across all announcements.

The bottom panel shows post-announcement returns ($r_{0,1}$) plotted against r_0. It also shows the lines of best fit from univariate regressions of $r_{0,1}$ on the component of the announcement return unrelated to public news ($r_0^\perp$) and the component related to public news ($\widehat{r}_0$). Because of underreaction, there is a clearly positive relationship between $r_{0,1}$ and r_0. At the same time, the relationship between $r_{0,1}$ and $r_0^\perp$ is steeper than the one between $r_{0,1}$ and $\widehat{r}_0$ because $r_0^\perp$ captures the underreaction to private news. The corresponding figure of the future fundamental (F_1) plotted against r_0 with the lines of best fit is visually very similar, and is therefore omitted for brevity.

3. Data

Our sample consists of firms for which quarterly fundamentals data from Compustat and security data from CRSP are available. We consider firms traded on NYSE, Amex, and NASDAQ, and exclude all securities but ordinary common shares (CRSP's SHRCD 10 and 11). The sample starts in 1972Q1 and ends in 2016Q3, where the start date is determined by the availability of earnings announcement dates (Compustat's RDQ).

3.1. Measuring announcement returns and earnings surprises

We measure firms' announcement returns by their cumulative abnormal returns in the three-day window around earnings announcement dates (CAR_3). Specifically, CAR_3 is the return earned in excess of that on the value-weighted market portfolio (CRSP's VWRETD) starting one trading day before and ending one trading day after the announcement. We use a short window around the announcement to account for nonsynchronous trading and we subtract the market return from firms' returns to account for any market-wide news.

The literature has commonly measured earnings surprises using standardized unexpected earnings (SUE): Given a time-series model for firms' expected earnings, SUE is the standardized error from time-series regressions of current earnings on lagged earnings. Foster, Olsen, and Shevlin (1984) find that a seasonal random walk with a trend performs as well as more complex models of firms' expected earnings (see also Bernard and Thomas (1989, 1990)). Under this model, firm i's expected quarter-t earnings are given by

$$\mathbb{E}[e_{it}] = \delta_i + e_{i,t-4}, \tag{18}$$

and the corresponding SUE is thus

$$\frac{e_{it} - (\delta_i + e_{i,t-4})}{\sigma_{it}} \tag{19}$$

where σ_{it} is the standard deviation of the forecast error, i.e., of $e_{it} - \mathbb{E}[e_{it}]$.

However, since Chan, Jegadeesh, and Lakonishok (1996), most of the literature has ignored the trend term (δ_i) in Eq. (19) and simply measured SUE as the seasonal change earnings divided by its standard deviation (see, e.g., Novy-Marx (2015) and Huo, Xue, and

Zhang (2015)). We show below that this simple SUE measure may mistakingly conflate true earnings surprises with largely expected earnings growth.[8] We want to guard against this potential problem while still making our results comparable to the recent literature. We do so by defining a de-trended version of SUE, which we denote SUE*, as the simple SUE measure de-trended by its own moving average. Specifically, we define de-trended SUE for firm i in quarter t as

$$\text{SUE}^*_{it} = \text{SUE}_{it} - \overline{\text{SUE}}_{i,t-8,t-1}. \tag{20}$$

Here, SUE_{it} is the year-over-year change in quarterly earnings divided by the standard deviation of the year-over-year changes in quarterly earnings over the most recent 8 announcements, excluding the current announcement, with a requirement of at least six announcement to calculate the standard deviation, and $\overline{\text{SUE}}_{i,t-8,t-1}$ is the moving average SUE over the most recent 8 announcements, excluding the current announcement (denoted trend-SUE above). We measure earnings using basic earnings per share excluding extraordinary items (Compustat's EPSPXQ).

3.2. Surprises in revenues and related items

Jegadeesh and Livnat (2006) argue that the "vast majority of firms report revenues in addition to earnings in their preliminary quarterly earnings announcements" but that "many other potentially useful components of earnings (such as the components of accruals) and other financial statement information are likely to be available to market participants only after the SEC filing" (p. 148). If revenue surprises carry incremental information above earnings surprises about firms' future fundamentals, and this information is available to investors on earnings announcement dates, it is potentially important to incorporate such surprise measures in our analysis to avoid an omitted variable problem. Therefore, under the assumption that revenues are available on earnings announcement dates, we augment our analysis with the following standardized unexpected (SU) revenue-based surprise measures:

[8]Indeed, Novy-Marx (2015) finds that the time-series average of the monthly Spearman rank correlation between the simple SUE measure and prior year's cumulative monthly performance is 29.1%, and concludes that "This suggests that the earnings innovations scaled to create standardized unexpected earnings are actually largely expected" (p. 5). We show below that de-trending SUE strongly diminishes its correlation with past performance.

- SU Revenues, where revenues are measured on a dollar (not per share) basis (Compustat's REVTQ).

- SU Asset Turnover, where asset turnover is revenues scaled by lagged total assets (REVTQ scaled by one-quarter lagged ATQ). This measures the efficiency with which the firm converts its beginning-of-period assets into end-of-period revenues.

- SU Earnings Margin, where earnings margin is dollar earnings scaled by revenues (IBQ, i.e., income before extraordinary items, scaled by REVTQ). This is a measure of profitability in terms how much of each dollar of revenues that the firm can keep as earnings.

- SU Expenses, where expenses are revenues minus dollar earnings (REVTQ − IBQ).

Each SU item is defined as the year-over-year change in the defining variable divided by the standard deviation of the year-over-year changes in the defining variable over the most recent 8 announcements, excluding the current announcement, with a requirement of at least six announcements to calculate the standard deviation. Furthermore, similar to our de-trended version of SUE, we define a de-trended version of each of the above revenue-based surprise measures by subtracting its average over the most recent 8 announcements, excluding the current announcement.

3.3. Sample summary statistics and cross-sectional correlations

Table II shows summary statistics for the variables we employ in our study of announcement returns. For earnings announcements between 1972Q1 and 2016Q3, the average CAR_3 is 0.29% per announcement. We show below that this average is highly statistically significant, even when accounting for fixed effects at the firm, quarter, and industry levels. Furthermore, 0.29% is highly *economically* significant given that it is a return earned over a short 3-day holding period and *in excess* of the 0.13% average return earned by the market over the same three-day windows.

Table II also shows that the full-sample averages of the simple and de-trended earnings surprise measures (SUE and SUE^*) are both close to zero. However, this is not necessarily the case for individual firms over significant periods of time for the simple SUE measure. Moreover, de-trending helps bring the averages of the revenue-based surprise measures closer

Table II: Summary statistics. This table shows summary statistics for announcement returns, earnings surprises, standardized unexpected (SU) revenue-based surprise measures, and market-based variables.

Earnings announcement dates are Compustat's RDQ. CAR_3 is cumulative 3-day return in excess of the return on the value-weighted market market portfolio around the announcement date in %. CMR_3 is cumulative 3-day return on the value-weighted market portfolio (CRSP's VWRETD) around the announcement date in %. The surprise measures are defined as the year-over-year change in the defining variable divided by the standard deviation of the changes in the defining variable over the most recent 8 announcements, excluding the current announcement, and with a requirement of at least 6 announcements to calculate the standard deviation. The defining variables in the surprise measures are earnings per share (Compustat's EPSPXQ), revenues (REVTQ), asset turnover ($REVTQ/ATQ_{-1}$), earnings margin (IBQ/REVTQ), and expenses (REVTQ − IBQ). A "*" indicates a surprise measure de-trended by firms' moving average for the measure over the most recent 8 announcements excluding the current announcement. $r_{12,2}^{RDQ}$ is the compounded daily returns from 12 months to 2 months before the announcement and $r_{2,1}^{RDQ}$ is the compounded daily returns from 2 months to 1 month before the announcement, both in %. $\log(M_{-1})$ is the logarithm of the market value of equity from the previous quarterly statement (one-quarter lagged PRCCQ × CSHOQ) and $\log(B_{-1}/M_{-1})$ is the logarithm of the book-to-market equity ratio from the previous quarterly statement.

The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3.

			Percentile				
Variable	Mean	Standard deviation	1st	25th	Median	75th	99th
CAR_3	0.29	9.22	−23.89	−3.28	−0.03	3.48	27.77
CMR_3	0.13	1.92	−5.31	−0.83	0.25	1.19	4.72
SUE	−0.01	1.58	−5.63	−0.54	0.06	0.67	4.13
SUE*	−0.02	1.68	−5.70	−0.68	0.04	0.81	4.02
SU Revenues	1.18	2.47	−3.35	−0.16	0.60	2.08	10.13
SU Revenues*	−0.06	2.15	−5.96	−1.07	−0.03	0.90	6.24
SU Asset Turnover	0.03	1.53	−3.73	−0.76	−0.01	0.69	4.85
SU Asset Turnover*	−0.01	1.58	−4.16	−0.83	0.00	0.79	4.35
SU Earnings Margin	−0.18	1.61	−6.46	−0.60	0.01	0.52	3.08
SU Earnings Margin*	−0.01	1.73	−6.11	−0.64	0.04	0.82	3.93
SU Expenses	1.16	2.33	−2.93	−0.14	0.60	1.99	9.72
SU Expenses*	−0.07	2.09	−5.61	−1.08	−0.06	0.86	6.28
$r_{12,2}^{RDQ}$	12.81	67.41	−78.72	−19.44	4.87	30.67	237.50
$r_{2,1}^{RDQ}$	1.01	17.01	−38.05	−6.38	0.00	6.86	54.17
$\log(M_{-1})$	4.96	2.18	0.50	3.40	4.83	6.42	10.39
$\log(B_{-1}/M_{-1})$	−0.54	0.90	−3.15	−1.03	−0.45	0.05	1.30

to zero. For instance, the simple revenue surprise measure has an average of 1.18 standard deviations, which raises concerns regarding its validity as a measure of a 'surprise.' De-trended revenue surprises, on the other hand, have an average of just −0.06 standard deviations.

Table III: Cross-sectional correlations. This table shows time-series averages of cross-sectional Spearman rank correlations between firms' announcement returns, earnings surprises, standardized unexpected (SU) revenue-based surprise measures, and market-based variables, all measured on earnings announcement dates (Compustat's RDQ). Test-statistics (in parentheses) are computed using standard errors clustered at the yearly level.

The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3

	SUE	SUE*	SU Revenues	SU Revenues*	SU Asset Turnover	SU Asset Turnover*	SU Earnings Margin	SU Earnings Margin*	SU Expenses	SU Expenses*	$r^{\mathrm{RDQ}}_{12,2}$	$r^{\mathrm{RDQ}}_{2,1}$	M_{-1}	B_{-1}/M_{-1}
CAR_3	0.18	0.16	0.10	0.11	0.10	0.08	0.18	0.15	0.06	0.05	0.03	0.00	0.01	0.02
	(28.01)	(27.76)	(37.82)	(34.04)	(15.44)	(15.94)	(28.09)	(27.71)	(15.89)	(13.27)	(6.22)	(0.69)	(3.63)	(6.81)
SUE		0.79	0.33	0.30	0.32	0.23	0.79	0.62	0.07	0.05	0.23	0.08	0.04	−0.06
		(171.22)	(34.62)	(43.89)	(36.57)	(34.79)	(101.46)	(79.15)	(3.19)	(2.82)	(36.51)	(17.23)	(4.98)	(−7.21)
SUE*			0.19	0.29	0.30	0.30	0.65	0.78	−0.03	0.00	0.09	0.05	−0.03	0.03
			(25.59)	(36.06)	(45.00)	(35.30)	(87.52)	(135.33)	(−1.89)	(0.18)	(16.86)	(14.77)	(−4.89)	(4.65)
SU Revenues				0.61	0.50	0.35	0.20	0.09	0.85	0.51	0.26	0.06	0.20	−0.24
				(68.29)	(36.57)	(32.46)	(20.00)	(12.04)	(68.85)	(42.01)	(36.17)	(13.47)	(22.13)	(−36.76)
SU Revenues*					0.55	0.57	0.21	0.17	0.49	0.79	0.20	0.06	−0.01	−0.02
					(60.93)	(47.94)	(33.61)	(23.66)	(38.01)	(50.97)	(38.63)	(15.36)	(−0.61)	(−3.27)
SU Asset turnover						0.76	0.21	0.21	0.37	0.41	0.13	0.05	−0.05	0.00
						(119.68)	(9.65)	(13.09)	(18.74)	(27.09)	(12.99)	(7.86)	(−4.63)	(−0.42)
SU Asset turnover*							0.15	0.21	0.26	0.42	0.05	0.04	−0.02	0.03
							(9.06)	(10.14)	(17.37)	(21.57)	(6.52)	(7.23)	(−2.67)	(4.32)
SU Earnings margin								0.77	−0.07	−0.04	0.25	0.08	0.02	−0.05
								(134.92)	(−5.71)	(−3.55)	(45.13)	(20.21)	(3.04)	(−6.69)
SU Earnings margin*									−0.13	−0.13	0.09	0.05	−0.04	0.06
									(−13.17)	(−9.46)	(13.09)	(13.39)	(−8.87)	(9.09)
SU Expenses										0.62	0.19	0.04	0.19	−0.23
										(68.39)	(24.56)	(8.03)	(19.54)	(−30.27)
SU Expenses*											0.17	0.04	0.01	−0.03
											(37.48)	(11.70)	(0.53)	(−4.23)
$r^{\mathrm{RDQ}}_{12,2}$												0.02	0.20	−0.20
												(2.80)	(10.42)	(−12.12)
$r^{\mathrm{RDQ}}_{2,1}$													0.05	0.02
													(6.31)	(2.59)
M_{-1}														−0.31
														(−16.19)

Table III shows time-series averages of cross-sectional Spearman rank correlations between the variables. The pairwise correlations between CAR_3 and each of the surprise measures range from 8% to 15% and are all highly statistically significant, although CAR_3 is most strongly correlated with surprises to earnings and earnings margins. Furthermore, the pairwise correlations between CAR_3 and each of the surprise measures are similar for the simple and the de-trended measures. The differences between SUE and SUE^* are much more apparent from the correlations than from the summary statistics in Table II. While the correlation between prior year's performance ($r_{12,2}^{\text{RDQ}}$) and SUE is 23%, the correlation between $r_{12,2}^{\text{RDQ}}$ and SUE^* is a comparably much lower 9%. Furthermore, while the correlation between SUE and lagged book-to-market equity is -6% ($t = -7.21$), the correlation between SUE^* and book-to-market equity is 3% ($t = 4.65$).[9] This suggests that the simple SUE measure might mistankingly classify the plausibly higher earnings-growth of firms with lower book-to-market as 'surprising' and that SUE^* appears to be a more plausible measure of true earnings surprises. Similar arguments can be made for the de-trended versions of the revenue-based surprise measures.

4. Announcement returns

This Section provides evidence for the model's predictions about announcement returns.

4.1. *Announcement returns and public news: Benchmark results*

Parts 1 and 2 of Proposition 1 predict (i) that announcement returns are more positive for good public news than they are negative for bad public news of the same magnitude and (ii) that the part of the announcement return unrelated to public news is on average positive because of the resolution of uncertainty effect. Figure 2, which is the empirical counterpart of top panel of Figure 1, presents benchmark evidence in line with these predictions using

[9] We use a quarterly version of the book-to-market equity ratio defined similar to the the annual version employed by Fama and French (2015) and many others. Book equity, B, is shareholder's equity plus deferred taxes minus preferred stock. Shareholder's equity is SEQQ. If SEQQ is missing, we substitute it by common equity, CEQQ, plus preferred stock (defined below), or else by total assets minus total liabilities, ATQ − LTQ. Deferred taxes is deferred taxes and investment tax credits, TXDITCQ, or else deferred taxes, TXDBQ. Preferred stock is redemption value, PSTKRQ, or else carrying value, PSTKQ. Book-to-market equity is B divided by market capitalization, M, from the latest quarterly statement (PRCCQ×CSHOQ). We lag book-to-market equity one quarter (B_{-1}/M_{-1}) to ensure that it is the ratio available to investors on any given earnings announcement date.

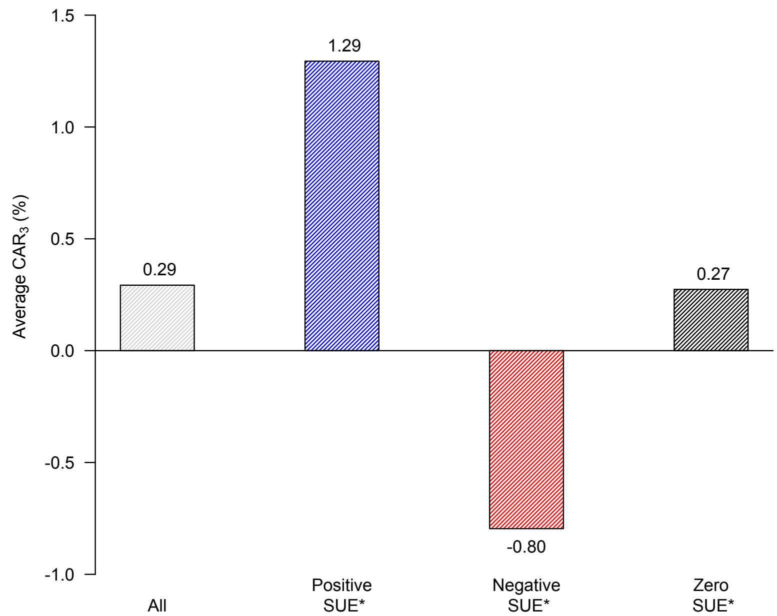

Figure 2: Announcement returns and public news. This figure shows averages of firms' cumulative three-day abnormal returns in excess of the return on the value-weighted market portfolio around earnings announcement dates (CAR_3) grouped according to firms' de-trended standardized unexpected earnings (SUE^*). The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3.

the de-trended earnings surprise measure, SUE^*, as the proxy for public news.

The figure shows averages of CAR_3 across different groups defined according to SUE^*. The left-most bar shows the average CAR_3 for the full sample, i.e., the 0.29% per announcement documented in Table II. The second and third bars show the average CAR_3 for announcements with a positive SUE^* and for announcements with a negative SUE^*. The average CAR_3 for good-news announcements is 1.29% per announcement while the average CAR_3 for bad-news announcements is -0.80% per announcement. This difference between the average CAR_3 for good-news and bad-news announcements is in line with the model's prediction that announcement returns are only negative if the public news is so bad that it wipes out the effect of any positive private news as well as the always positive effect of the aggregate reduction in fundamental uncertainty.

The right-most bar provides shows the average CAR_3 for announcements with a zero SUE^*, i.e., the part of the announcement return unrelated to public news. This orthogonal component of CAR is positive on average and close to the overall CAR_3 (since the average SUE^* is close to zero). Since the public signal is zero, the 0.27% average return is an estimate of the aggregate reduction in fundamental uncertainty across all announcements in our sample. It confirms our model's prediction that the part of the announcement return unrelated to public news is on average positive because of the resolution of uncertainty effect.

In the following subsection, we show that the same results continue to hold in a more detailed analysis of announcement returns where we proxy for public news using SUE* in combination with the revenue-based surprise measures.

4.2. Announcement returns and public news: More detailed evidence

Table IV presents more detailed evidence for parts 1 and 2 of Proposition 1. It shows results from pooled regressions of firms' abnormal returns around earnings announcements (CAR_3) on de-trended earnings surprises (SUE*) and de-trended standardized unexpected (SU) revenue-based surprises.

To proxy for non-accounting based information that might influence announcement returns, the regressions include controls for return-based variables at the firm- and market-level. At the firm-level, we control for one- and four-quarter lagged CAR_3 as well as past performance 12-to-2 months ($r_{12,2}^{\text{RDQ}}$) and 2-to-1 month ($r_{2,1}^{\text{RDQ}}$) before the announcement. At the market level, we control for cumulative 3-day returns for the Fama and French (2015) factors including the three past-performance factors.[10] To avoid undue influence of outliers, independent variables, excluding the factor returns, are trimmed at the 1st and 99th percentiles. Test-statistics are computed using standard errors triple-clustered at the firm, industry, and quarter levels, where the industries are the Fama and French 49.

[10] The factors are the market factor (MKT), the small-minus-big size factor (SMB), the high-minus-low value factor (HML), the robust-minus-weak profitability factor (RMW), the conservative-minus-aggressive investment factor (CMA), the momentum factor (MOM), the short-term reversal factor (STRev), and the long-term reversal factor (LTRev). The factor returns are from Ken French's Data Library. Replacing the cumulative 3-day returns for the Fama and French factors with cumulative 3-day returns for the factors from Huo, Xue, and Zhang's (2015) *q*-factor model produces essentially identical results (untabulated). Furthermore, controlling for Pástor and Stambaugh's (2003) liquidity factor, Frazzini and Pedersen's (2014) betting-against-beta (BAB) factor, or Asness, Frazzini, and Pedersen's (2014) quality-minus-junk (QMJ) factor, which are available at the monthly frequency, has no effect on the results (untabulated).

Table IV: Announcement returns and public news. This table shows results from pooled regressions of firms' cumulative 3-day abnormal returns around earnings announcements (CAR_3, in %) on de-trended standardized unexpected earnings (SUE*), standardized unexpected (SU) revenue-based surprise measures, and return-based controls.

The revenue-based surprise measures are de-trended by firms' moving average over the most recent 8 announcements excluding the current announcement. The return controls at the firm-level are one- and four-quarter lagged CAR_3 as well as past performance 12-to-2 months ($r_{12,2}^{RDQ}$) and 2-to-1 month ($r_{2,1}^{RDQ}$) before the announcement. The return controls at the market level are cumulative 3-day returns for the Fama and French (2015) factors (MKT, SMB, HML, RMW and CMA) including the three past performance factors (MOM, STRev, and LTRev). Independent variables, excluding the factor returns, are trimmed at the 1st and 99th percentiles. Test-statistics (in parentheses) are computed using standard errors triple-clustered at the firm, industry, and quarter levels, where the industries are the Fama and French 49. R^2 is adjusted for degrees of freedom. $\%R^2$ due to SUE* is based on a Shapley-value decomposition of the total R^2.

The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3.

	Intercepts, slopes, and test-statistics (in parentheses) from regressions of the form $CAR_{3,it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$						
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept (%)	0.29 (5.54)	0.28 (5.29)	0.33 (6.17)	0.32 (6.10)	0.27 (5.98)	0.36 (6.97)	0.35 (6.95)
SUE*		0.79 (13.50)		0.45 (8.65)	0.77 (12.15)		0.43 (8.19)
SU Revenues*			0.27 (5.34)	0.22 (4.73)		0.28 (5.09)	0.22 (4.51)
SU Asset turnover*			0.21 (6.43)	0.17 (5.63)		0.17 (6.66)	0.14 (5.80)
SU Earnings margin*			0.64 (16.58)	0.33 (9.95)		0.64 (16.04)	0.35 (11.28)
SU Expenses*			−0.04 (−1.35)	−0.01 (−0.54)		−0.01 (−0.47)	0.01 (0.49)
$r_{12,2}^{RDQ}$					0.00 (−2.56)	−0.01 (−5.50)	0.00 (−5.30)
$r_{2,1}^{RDQ}$					−0.01 (−4.30)	−0.01 (−6.42)	−0.01 (−6.43)
$\text{lag}_1(CAR_3)$					0.02 (6.05)	0.02 (4.23)	0.01 (3.64)
$\text{lag}_4(CAR_3)$					0.01 (6.04)	0.01 (5.10)	0.02 (5.76)
MKT_3					−0.10 (−2.80)	−0.11 (−2.80)	−0.11 (−2.84)
SMB_3					0.69 (12.03)	0.69 (11.62)	0.69 (11.51)
HML_3					0.04 (0.47)	0.05 (0.64)	0.05 (0.65)
RMW_3					0.08 (0.93)	0.14 (1.89)	0.14 (1.84)
CMA_3					0.07 (1.15)	0.08 (1.60)	0.08 (1.60)
MOM_3					−0.11 (−4.41)	−0.11 (−3.90)	−0.11 (−3.82)
$STRev_3$					0.06 (2.46)	0.05 (1.83)	0.05 (1.72)
$LTRev_3$					0.08 (1.95)	0.09 (1.98)	0.09 (1.98)
R^2		1.5%	1.8%	2.0%	2.7%	3.0%	3.2%
$\%R^2$ due to SUE*				38.2%	62.9%		25.8%

The first specification shows that the 0.29% average CAR_3 for the full sample has a t-statistic of 5.54 and is thus highly significant. The second specification shows that SUE* has significant explanatory power for announcement returns. Higher earnings surprises are associated with higher announcement returns, but the average announcement return unrelated to SUE*, as measured by the intercept, is 0.28% with a t-statistic of 5.29, and is thus about as large and as strong as the unconditional average announcement return for the full sample. Moreover, the R^2 is just 1.5%, suggesting that the bulk of the total variation in announcement returns cannot be explained by earnings surprises.

The third specification shows that, with the exception of surprises to expense, the revenue-based surprise measures also have some power explaining announcement returns. However, only earnings-margin surprises have power comparable to that of SUE*, which is to be expected given that Table III shows that their cross-sectional correlation is 0.78. When significant, higher values for the revenue-based surprises are associated with higher announcement returns. Nonetheless, the intercept is slightly larger and stronger than in the specification that only employs SUE*, and the R^2 is only marginally higher (1.8% vs. 1.5%). The fourth specification shows that controlling for revenue-based surprises results in an only moderate decrease in the power of SUE* while having virtually no effect on the magnitude or strength of the intercept. Furthermore, combining earnings surprises with revenue-based surprises implies an R^2 of just 2.0%, and the *Shapley-value decomposition* reported in the last row shows that SUE* can by itself account for 38.2% of this R^2.[11]

The last three specifications show that essentially the same results continue to hold when controlling for the return-based variables. The intercepts are all of the same magnitude as the unconditional average CAR_3 and are statistically even stronger. This confirms that there is a large part of the average CAR_3 unrelated to earnings surprises or revenue-based surprises, even when controlling for the return-based variables. The fifth specification shows

[11] A Shapley-value decomposition (named after the corresponding concept from game theory) of a regression model's goodness-of-fit statistic, such as R^2, decomposes the total goodness-of-fit statistic into the contributions of the individual explanatory variables. It does so by successively removing individual explanatory variables from the full model according to a particular ordering. The change in the goodness-of-fit statistic due to the removal of a given explanatory variable is then a measure of the variable's marginal contribution to the total goodness-of-fit statistic in this particular ordering. Under the assumption that all orderings are equally probable, the variable's Shapley value for the goodness-of-fit statistic is then defined as its average marginal contribution across all possible orderings (of which there are 2^k in total, where k is the number of explanatory variables). See Huettner and Sunder (2012) for a review and additional references, and see Begenau and Palazzo (2017) for a recent application on Compustat data.

that adding the return-based variables alongside SUE* has virtually no effect on the power of SUE*. While the addition of the return-based variables alongside SUE* increases the R^2 from 1.5% to 2.7%, SUE* can still account for 62.9% of this higher R^2. The sixth specification shows that, with the exception of surprises to expenses, revenue-based surprises also have power beyond that in the return-based variables. The seventh and final specification shows that the combination of earnings surprises, revenue-based surprises, and return-based variables results in an R^2 of just 3.2%, and that SUE* can by itself account for 25.8% of this R^2. In fact, SUE* is the variable with the highest incremental contribution to the total R^2 in this specification (untabulated).

Because earnings surprises appear to be the proxy for public news with the most power explaining announcement returns, and because the revenue-based surprises and return-based variables only add negligible incremental power on top of earnings surprises, we focus on earnings surprises as the proxy for public news for the remainder of the paper. Focusing on earnings surprises has the additional advantage of alleviating any concerns about whether or not revenues are available on earnings announcement dates. Table IA.1 in the Internet Appendix compares the explanatory power of SUE* with that of the simple SUE measure and with that of the trend in earnings surprises, $\overline{\text{SUE}}_{8,1}$. It shows that SUE* and SUE have similar power and that $\overline{\text{SUE}}_{8,1}$ has incremental power above that in SUE*. To make our results comparable to the extant literature employing the simple SUE-measure, we employ $\overline{\text{SUE}}_{8,1}$ as an auxiliary variable alongside SUE* when studying announcement returns.

4.3. Announcement returns and fundamental uncertainty

Part 3 of Proposition 1 predicts that the part of announcement returns unrelated to public news is on average higher when fundamental uncertainty is higher. To test this prediction, we group firms according to characteristics that plausibly proxy for fundamental uncertainty and estimate the part of the announcement return unrelated to public news. Building on the results of Table IV, we proxy for public news using earnings surprises, which we measure using de-trended standardized unexpected earnings (SUE*), and we add the trend in earnings surprises ($\overline{\text{SUE}}_{8,1}$) as an auxiliary control variable that accounts for the difference SUE* and the simple SUE-measure.

Table V: Announcement returns and fundamental uncertainty. This table shows grouped averages of firms' 3-day abnormal returns around earnings announcement dates (CAR_3, in %). It also shows the corresponding averages of standardized unexpected earnings (SUE), de-trended standardized unexpected earnings (SUE^*), and the trend in standardized unexpected earnings ($\overline{SUE}_{8,1}$). Finally, it shows grouped averages of the orthogonal component ($CAR_3^{\perp}$) and the projected components ($\widehat{CAR}_3 \,|\, SUE^*$ and $\widehat{CAR}_3 \,|\, \overline{SUE}_{8,1}$) from pooled regressions of CAR_3 on SUE^* and $\overline{SUE}_{8,1}$ within the groups.

At the end of each calendar quarter, firms are grouped into deciles based on NYSE-breakpoints. The reported group-estimates are for the extreme deciles and the corresponding test-statistics (in parentheses) are computed using standard errors triple-clustered at the firm, quarter, and industry levels, where the industries are the Fama and French 49. The "Diff"-rows report the differences in estimates for the extreme deciles along with the corresponding Welch t-test statistic based on the triple-clustered standard errors. All accounting variables are lagged one financial-quarter relative to the earnings announcement date (RDQ).

Size is market equity from firms' accounting statements (PRCCQ×CSHOQ). B/M is the book-to-market equity ratio. Market leverage is total liabilities (LTQ) divided by total liabilities plus market equity. Book leverage is total liabilities divided by total assets (ATQ). Operating leverage is cost of goods sold plus selling, general, and administrative expenses net of R&D expenditures divided by total assets ((COGSQ + XSGAQ − XRDQ)/ATQ). The utility industry is Compustat SIC codes 4900-4999 and the finance industry is SIC codes 6000-6999.

The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3.

			Earnings surprises, de-trended earnings surprises, and the trend in earnings surprises			Components from regressions of CAR_3 on SUE^* and $\overline{SUE}_{8,1}$		
		CAR_3	SUE	SUE^*	$\overline{SUE}_{8,1}$	$CAR_3^{\perp}$	$\widehat{CAR}_3 \,\vert\, SUE^*$	$\widehat{CAR}_3 \,\vert\, \overline{SUE}_{8,1}$
Size	Big	0.16	0.10	−0.04	0.14	0.15	−0.01	0.02
		(5.23)	(3.59)	(−1.72)	(5.55)	(4.96)	(−1.72)	(5.55)
	Small	0.44	−0.07	0.03	−0.10	0.48	0.03	−0.07
		(6.09)	(−4.83)	(2.60)	(−6.99)	(6.26)	(2.60)	(−6.99)
	Diff	0.28	−0.17	0.07	−0.24	0.33	0.04	−0.09
		(3.56)	(−5.39)	(2.76)	(−8.29)	(3.99)	(3.04)	(−8.49)
B/M	Growth	−0.09	0.10	−0.02	0.12	−0.12	−0.01	0.04
		(−1.19)	(4.75)	(−1.31)	(4.88)	(−1.64)	(−1.31)	(4.88)
	Value	0.74	−0.19	0.07	−0.26	0.91	0.07	−0.23
		(8.35)	(−8.34)	(2.83)	(−12.23)	(9.17)	(2.83)	(−12.23)
	Diff	0.84	−0.30	0.08	−0.38	1.03	0.08	−0.28
		(7.07)	(−9.37)	(3.10)	(−11.73)	(8.28)	(3.08)	(−13.16)
Market leverage	Low	−0.14	0.01	−0.10	0.11	−0.13	−0.06	0.04
		(−1.98)	(0.49)	(−5.23)	(4.21)	(−1.75)	(−5.23)	(4.21)
	High	0.61	0.01	0.05	−0.04	0.60	0.03	−0.01
		(3.67)	(0.31)	(1.42)	(−0.47)	(3.55)	(1.42)	(−0.47)
	Diff	0.76	0.00	0.15	−0.15	0.72	0.09	−0.06
		(4.15)	(0.08)	(3.76)	(−1.81)	(3.95)	(3.92)	(−2.11)
Book leverage	Low	0.03	−0.08	−0.10	0.02	0.09	−0.08	0.01
		(0.38)	(−4.00)	(−5.75)	(1.45)	(1.26)	(−5.75)	(1.45)
	High	0.49	0.08	0.09	−0.01	0.45	0.04	0.00
		(6.48)	(4.68)	(1.62)	(−0.14)	(6.78)	(1.62)	(−0.14)
	Diff	0.46	0.16	0.19	−0.03	0.36	0.12	−0.01
		(4.45)	(6.07)	(3.39)	(−0.51)	(3.61)	(4.06)	(−0.66)
Operating leverage	Low	0.24	0.02	−0.03	0.05	0.23	−0.01	0.01
		(3.06)	(0.40)	(−1.89)	(1.39)	(3.46)	(−1.89)	(1.39)
	High	0.60	0.05	0.04	0.02	0.54	0.04	0.01
		(9.71)	(3.13)	(1.86)	(1.02)	(8.20)	(1.86)	(1.02)
	Diff	0.36	0.03	0.06	−0.03	0.31	0.05	0.00
		(3.64)	(0.75)	(2.63)	(−0.77)	(3.24)	(2.22)	(0.12)
Industry	Utility	0.10	−0.01	−0.01	0.00	0.10	−0.01	0.00
		(1.14)	(−0.51)	(−4.38)	(0.25)	(1.09)	(−4.38)	(0.25)
	Finance	0.34	0.05	−0.02	0.07	0.33	−0.01	0.02
		(15.39)	(2.36)	(−1.61)	(4.41)	(13.88)	(−1.61)	(4.41)
	Diff	0.24	0.06	−0.01	0.07	0.23	0.00	0.02
		(2.79)	(2.03)	(−0.57)	(2.99)	(2.37)	(−0.46)	(2.44)

Table V shows grouped averages of firms' announcement returns, earnings surprises, de-trended earnings surprises, and the trend in earnings surprises. It also shows results from pooled regressions of firms' announcement returns on the de-trended earnings surprises and the trend in earnings surprises within the groups. At the end of each calendar quarter, firms are grouped into deciles based on NYSE-breakpoints. For each grouping variable, the table shows the group-estimates for the extreme deciles as well as the differences in estimates for the extreme deciles. The corresponding t-statistics are computed using standard errors triple-clustered at the firm, quarter, and industry levels.

4.3.1. Size and book-to-market

Our first proxies for fundamental uncertainty are size and book-to-market equity (B/M). There is much evidence that smaller firms are more financially fragile and have less productive assets than big firms. The same applies to value firms with high B/M compared to growth firms with low B/M.[12] Hence, according to the model, the average announcement return unrelated to public news should be significantly higher for small firms compared to big firms and for value firms compared to growth firms.

Table V's first column shows grouped averages of CAR_3. Small firms earn an average CAR_3 of 44 bp per announcement while big firms earn an average CAR_3 of just 14 bp per announcement. Furthermore, this 28 bp small-minus-big spread in average CAR_3 has a t-statistic of 3.56. Similarly, the value-minus-growth spread in average CAR_3 is 84 bp with a t-statistic of 7.07. With four announcements per year, the latter is over two-thirds of the 4.91% average annualized return of the Fama and French value factor (HML) over our sample period (July 1972 to December 2016).

The next three columns show the corresponding averages of SUE, SUE^*, and $\overline{\text{SUE}}_{8,1}$. The small-minus-big and value-minus-growth differences in average SUE are both negative and significant, suggesting, counterfactually, that big firms and growth firms outperform on earnings announcement dates. The reason is, of course, that the simple SUE measure conflates earnings surprises with largely expected growth in earnings. This is evident from the fact that the small-minus-big and value-minus-growth differences in average $\overline{\text{SUE}}_{8,1}$ are both

[12] For instance, Fama and French (1995) find that "High BE/ME [...] signals sustained low earnings on book equity" and that "small stocks tend to have lower earnings on book equity than do big stocks" (p. 132).

negative and highly significant. Because SUE^* subtracts $\overline{\text{SUE}}_{8,1}$ from SUE, the small-minus-big and value-minus-growth differences in average SUE^* are both positive and significant, in line with corresponding spreads in announcement returns.

The last three columns show grouped averages of the orthogonal component and the projected components from pooled regressions of CAR_3 on SUE^* and $\overline{\text{SUE}}_{8,1}$ within the groups. To mimic the model's decomposition of the announcement return in Eq. (16), we decompose CAR_3 for firm i in quarter t as

$$\text{CAR}_{3,it} = \underbrace{\beta_1 \times \text{SUE}^*_{it}}_{\widehat{\text{CAR}}_{3,it}\,|\,\text{SUE}^*_{it}} + \underbrace{\beta_2 \times \overline{\text{SUE}}_{i,t-8,t-1}}_{\widehat{\text{CAR}}_{3,it}\,|\,\overline{\text{SUE}}_{i,t-8,t-1}} + \underbrace{\alpha + \varepsilon_{it}}_{\text{CAR}^{\perp}_{3,it}} \tag{21}$$

using a pooled regression for each group that employs the most recently available data for firm i in quarter t. We thus have the decomposition

$$\text{CAR}_{3,it} = \text{CAR}^{\perp}_{3,it} + \widehat{\text{CAR}}_{3,it}\,|\,\text{SUE}^*_{it} + \widehat{\text{CAR}}_{3,it}\,|\,\overline{\text{SUE}}_{i,t-8,t-1} \tag{22}$$

and, since $\text{SUE}^*_{it} + \overline{\text{SUE}}_{i,t-8,t-1} = \text{SUE}_{it}$, we also have the decomposition

$$\text{CAR}_{3,it} = \text{CAR}^{\perp}_{3,it} + \widehat{\text{CAR}}_{3,it}\,|\,\text{SUE}_{it}, \tag{23}$$

for each firm i and each quarter t within a given group. The same decompositions hold when we average across firms within a given group. Hence, the regressions decompose a given group's average CAR_3 into a part unrelated to public news ($\text{CAR}^{\perp}_3$), a part related to public news ($\widehat{\text{CAR}}_3\,|\,\text{SUE}^*$), and a part related to the trend in public news ($\widehat{\text{CAR}}_3\,|\,\overline{\text{SUE}}_{8,1}$).

The decomposition of the 28 bp small-minus-big spread in average CAR_3 suggests that 33 bp ($t = 3.99$) are unrelated to public news, 4 bp ($t = 3.04$) are due to earnings surprises, and a *negative* 9 bp ($t = -8.49$) are due to earnings growth. Taking the sum of the spreads in the two projected components shows that a negative 5 bp can be explained by the simple SUE measure. Similarly, of the 84 bp value-minus-growth spread in average CAR_3, the decomposition suggests that 103 bp ($t = 8.28$) are unrelated to public news, 8 bp are due to earnings surprises, and -28 bp are due to earnings growth. The results from these decompositions are consistent with Part 3 of Proposition 1.

4.3.2. *Financial and operating leverage*

Our next three proxies for fundamental uncertainty are based on firms' financial and operating leverage. More levered firms, whether this is financial or operating leverage, give up a larger fraction of their revenues to financial or operating expenses, and their fundamentals are thus plausibly more uncertain.[13]

The results are consistent with model's prediction and remarkably similar for all three leverage ratios. The levered-minus-unlevered spread in average CAR_3 is positive and significant for all three ratios, though it is highest for the market leverage ratio (76 bp per announcement with $t = 4.15$). For all three leverage ratios, the spread is mostly driven by the fact that levered firms have large, positive and highly significant average announcement returns. The corresponding differences in average earnings surprises are also positive, but cannot account for the spread in average CAR_3: The levered-minus-unlevered spread in the average orthogonal component, $\text{CAR}_3^{\perp}$, is positive, significant, and about as large as the spread in average CAR_3 for all three leverage ratios.

4.3.3. *Industry*

Lastly, we consider industry classification as a proxy for fundamental uncertainty. To identify industries with a plausibly large difference in fundamental uncertainty, we focus on financials and utilities. While firms in both industries are subject to regulatory supervision, the fundamentals of financial firms are typically much more cyclical than those of utility firms, whose fundamentals are quite insensitive to business cycle fluctuations. As such, utility firms should have higher fundamental uncertainty than financial firms.[14]

The finance-minus-industry spread in average CAR_3 is a modest but significant 24 bp per announcement ($t = 2.79$). Financial firms earn an average announcement return of 34 bp which, while not large, is highly statistically significant ($t = 15.39$) and dwarfs the insignificant 10 bp ($t = 1.14$) earned on average by utility firms around announcement dates.

[13] For financial leverage, we use both the market leverage ratio (total liabilities, LTQ, relative to market equity) and the book leverage ratio (total liabilities relative to total assets, ATQ). For operating leverage, we use the ratio of total operating costs to total assets. Similar to Novy-Marx (2011), we define operating costs as costs of goods sold plus selling general and administrative expenses (COGSQ + XSGAQ), but we follow Ball, Gerakos, Linnainmaa, and Nikolaev (2015) and subtract research and development expenditures (XRDQ) from operating costs to avoid conflating the cost measure with intangible investments.

[14] An alternative would be to use, e.g., technology firms instead of financial firms. However, these make up a large fraction of the growth firms used in the book-to-market split, so we opt for financials here.

The corresponding differences in the earnings surprise measures are, however, extremely small. As a result, the earnings surprise measures can only account for a combined 2 bp of the financial-minus-utility spread in average CAR_3, leaving behind a spread in average $\text{CAR}_3^{\perp}$ which, in line with the model, is positive and significant.

4.3.4. Market-wide uncertainty

So far, we focused on cross-sectional differences in fundamental uncertainty. We now show that similar results hold in the time-series, i.e., that the average announcement return unrelated to public news is higher during times with higher market-wide uncertainty. We proxy for the latter using the commonly employed S&P 500 implied volatility index (VIX).[15]

Figure 3 shows grouped averages of the components of firms' announcement returns where the groups are tertiles of VIX. At the end of each calendar quarter, we estimate the orthogonal component ($\text{CAR}_3^{\perp}$) and the projected components ($\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$ and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$) from cross-sectional regressions of CAR_3 on SUE^* and $\overline{\text{SUE}}_{8,1}$. We then split the sample according to VIX tertiles and compute the averages of the components within each tertile.

The figure shows evidence strongly consistent with Part 3 of Proposition 1: The part of the announcement return unrelated to public news is on average positive across all three VIX tertiles and is monotonically increasing with VIX (from 16 bp in the lowest tertile to 50 bp in the highest). The projected components are essentially zero across the three VIX tertiles (between 3 and negative 4 bp), though there is a slight indication that the component due to earnings growth ($\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$) decreases as VIX increases.

[15] In our model's expression for the equilibrium post-announcement price in Eq. (11), the 'uncertainty' (or 'risk-premium') component is the product of (i) the aggregate risk aversion and (ii) the weighted harmonic mean of U- and I-investors' beliefs about fundamental uncertainty. We use the VIX as a summary measure of this product and simply refer to 'market-wide uncertainty' above. However, since the VIX empirically behaves in a similar way to the SVIX measure proposed by Martin (2017) and Martin and Wagner (2017), another interpretation of splitting the sample into VIX tertiles is that this allows us to capture different levels of the market risk premium. The latter interpretation is, in fact, also in line with our model, as the market risk premium is driven by aggregate risk aversion.

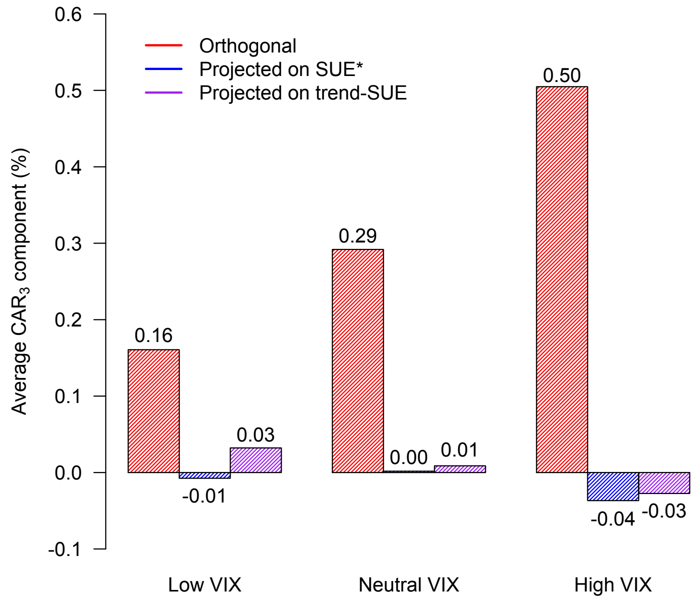

Figure 3: Announcement returns and market-wide uncertainty. This figure shows grouped averages of the components of firms' cumulative 3-day abnormal returns around earnings announcement days (CAR_3) where the groups are tertiles of the S&P 500 implied volatility index (VIX). At the end of each calendar quarter, we estimate the orthogonal component ($\mathrm{CAR}_3^{\perp}$) and the projected components ($\widehat{\mathrm{CAR}}_3 \,|\, \mathrm{SUE}^*$ and $\widehat{\mathrm{CAR}}_3 \,|\, \overline{\mathrm{SUE}}_{8,1}$) from cross-sectional regressions of firms' cumulative 3-day abnormal returns around earnings announcement days (CAR_3) on de-trended standardized unexpected earnings (SUE^*) and the trend in standardized unexpected earnings ($\overline{\mathrm{SUE}}_{8,1}$). We then split the sample according to VIX tertiles and compute the averages of components within each tertile. The sample covers earnings announcements between fiscal 1990Q1 and fiscal 2016Q3, with the start date determined by the availability of VIX data.

4.4. Announcement returns and future fundamentals

Proposition 2 states (i) that a firm's announcement return predicts its future fundamentals positively, (ii) that the part of the announcement return related to public news, as well as the part unrelated to public news, predicts future fundamentals positively, and, finally, (iii) that the part of the announcement return unrelated to public news has more power predicting future fundamentals than does the part related to public news. This subsection presents evidence consistent with these predictions.

Table VI shows pooled regressions of firms' 1-year, 3-year, and 5-year growth in fundamentals on CAR_3. It also shows the corresponding regressions with CAR_3 replaced by the orthogonal component ($\mathrm{CAR}_3^{\perp}$) and the projected components ($\widehat{\mathrm{CAR}}_3 \,|\, \mathrm{SUE}^*$ and $\widehat{\mathrm{CAR}}_3 \,|\, \overline{\mathrm{SUE}}_{8,1}$) from calendar quarterly cross-sectional regressions of CAR_3 on SUE^* and $\overline{\mathrm{SUE}}_{8,1}$. We proxy for future fundamentals using the growth in earnings scaled by beginning-of-period book equity. However, following Novy-Marx (2013), we also employ the growth in gross profits scaled by beginning-of-period assets as an additional proxy for future fundamentals.

Table VI: Announcement returns and future fundamentals. This table shows results from pooled regressions of firms' 1-year, 3-year, and 5-year growth in fundamentals on cumulative 3-day abnormal returns around announcements (CAR_3). It also shows the corresponding regressions with CAR_3 replaced by the orthogonal component ($\text{CAR}_3^{\perp}$) and the projected components ($\widehat{\text{CAR}_3}\,|\,\text{SUE}^*$ and $\widehat{\text{CAR}_3}\,|\,\overline{\text{SUE}}_{8,1}$) from calendar-quarter cross-sectional regressions of CAR_3 on de-trended standardized unexpected earnings (SUE^*) and the trend in standardized unexpected earnings ($\overline{\text{SUE}}_{8,1}$). In panel A, the dependent variable is growth in earnings (IBQ) scaled by beginning-of-period book equity. In panel B, the dependent variable is growth in gross profits (GPQ = REVTQ − COGSQ) scaled by beginning-of-period total assets (ATQ).

All regressions control for gross profits-to-assets (GP/A), earnings-to-book equity (IB/B), dividends and repurchases-to-book equity (Div/B, where Div is DVPSPQ×CSHOQ plus quarterly PRSTKCY), book-to-market equity ($\log(B/M)$), size ($\log(M)$), and compounded daily returns 12-to-1 month prior to the announcement ($r_{12,1}^{\text{RDQ}}$). Test-statistics (in parentheses) are computed using standard errors triple-clustered at the firm, year, and industry levels, where the industries are the Fama and French 49. R^2 is adjusted for degrees of freedom. The regressions exclude microcaps, defined as firms with a market capitalization below the 20th percentile of the quarterly NYSE market capitalization distribution. Dependent and independent variables are trimmed at the 1st and 99th percentiles.

The sample covers earnings announcement between fiscal 1972Q1 and fiscal 2016Q3.

	Slope coefficients and test-statistics (in parentheses) from regressions of the form $y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$					
	CAR_3 as independent variable			CAR_3 components as independent variables		
Independent variables	(1) 1-year	(2) 3-year	(3) 5-year	(4) 1-year	(5) 3-year	(6) 5-year
Panel A: Dependent variable is growth in earnings, $y_{it} = \frac{\text{IBQ}_{i,t+u} - \text{IBQ}_{it}}{B_{it}}$						
CAR_3	0.02	0.03	0.03			
	(5.71)	(7.97)	(4.69)			
$\text{CAR}_3^{\perp}$				0.02	0.03	0.03
				(8.20)	(9.39)	(6.12)
$\widehat{\text{CAR}_3}\,\|\,\text{SUE}^*$				−0.37	−0.36	−0.46
				(−6.12)	(−4.26)	(−4.09)
$\widehat{\text{CAR}_3}\,\|\,\overline{\text{SUE}}_{8,1}$				−0.26	−0.32	−0.22
				(−2.41)	(−1.56)	(−0.78)
GP/A	0.03	0.02	0.02	0.03	0.02	0.01
	(1.95)	(1.04)	(0.51)	(1.87)	(0.92)	(0.46)
IB/B	−0.21	−0.31	−0.30	−0.17	−0.26	−0.24
	(−5.47)	(−6.68)	(−5.09)	(−4.86)	(−5.58)	(−4.23)
Div/B	0.02	−0.01	−0.04	0.02	−0.02	−0.05
	(2.90)	(−0.35)	(−1.36)	(1.99)	(−0.94)	(−1.77)
$\log(B/M)$	0.00	−0.01	−0.02	0.00	−0.01	−0.02
	(−2.11)	(−6.37)	(−10.16)	(−2.21)	(−6.38)	(−10.60)
$\log(M)$	0.00	0.00	−0.01	0.00	0.00	−0.01
	(−1.87)	(−4.56)	(−6.90)	(−2.01)	(−4.65)	(−7.19)
$r_{12,1}^{\text{RDQ}}$	0.01	0.00	0.00	0.01	0.00	0.00
	(6.21)	(1.88)	(−0.18)	(7.67)	(2.61)	(0.23)
R^2	5.5%	5.6%	5.3%	5.6%	5.2%	5.2%

(Continued)

(Continued)

Independent variables	(1) 1-year	(2) 3-year	(3) 5-year	(4) 1-year	(5) 3-year	(6) 5-year
	Slope coefficients and test-statistics (in parentheses) from regressions of the form $y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$					
	CAR_3 as independent variable			CAR_3 components as independent variables		
Panel B: Dependent variable is growth in gross profits, $y_{it} = \frac{\text{GPQ}_{i,t+u} - \text{GPQ}_{it}}{\text{ATQ}_{it}}$						
CAR_3	0.02 (6.86)	0.05 (7.06)	0.07 (6.69)			
$\text{CAR}_3^{\perp}$				0.02 (7.51)	0.04 (6.98)	0.07 (6.47)
$\widehat{\text{CAR}}_3 \mid \text{SUE}^*$				−0.08 (−2.64)	0.00 (0.02)	−0.04 (−0.37)
$\widehat{\text{CAR}}_3 \mid \overline{\text{SUE}}_{8,1}$				0.00 (−0.03)	0.45 (2.37)	1.05 (3.17)
GP/A	0.08 (8.20)	0.25 (7.93)	0.45 (8.14)	0.08 (8.40)	0.25 (7.99)	0.45 (8.18)
IB/B	−0.06 (−3.88)	−0.13 (−4.76)	−0.21 (−4.50)	−0.05 (−3.65)	−0.13 (−4.73)	−0.21 (−4.33)
Div/B	−0.08 (−8.62)	−0.28 (−8.02)	−0.49 (−7.02)	−0.08 (−8.54)	−0.28 (−7.88)	−0.49 (−6.87)
$\log(B/M)$	−0.01 (−7.58)	−0.03 (−8.36)	−0.05 (−7.41)	−0.01 (−7.63)	−0.03 (−8.38)	−0.05 (−7.43)
$\log(M)$	0.00 (−6.02)	−0.01 (−6.74)	−0.01 (−7.08)	0.00 (−6.07)	−0.01 (−6.72)	−0.01 (−7.04)
$r_{12,1}^{\text{RDQ}}$	0.01 (7.23)	0.01 (4.90)	0.01 (3.66)	0.01 (7.56)	0.01 (5.15)	0.01 (3.61)
R^2	12.2%	20.0%	23.7%	12.2%	20.0%	23.8%

The regressions include controls for gross profits-to-assets (GP/A), earnings-to-book equity (IB/B), dividends and repurchases-to-book equity (Div/B), book-to-market ($\log(B/M)$), size ($\log(M)$), and compounded daily returns 12-to-1 month prior to the announcement ($r_{12,1}^{\text{RDQ}}$). Test-statistics are computed using standard errors triple-clustered at the firm, year, and industry levels.[16] Similar to Fama and French (2006), and in order to avoid undue influence of small firms, the regressions exclude microcaps, defined as those with a market capitalization below the 20th percentile of the quarterly NYSE market capitalization distribution. Finally, to avoid undue influence of outliers, dependent and independent variables are trimmed at the 1st and 99th percentiles.

[16] In untabulated tests, we re-produced all specifications in Table VI using Fama and MacBeth (1973) cross-section regressions at the quarterly frequency and computed test-statistics using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with a lag-length corresponding to the prediction horizon in quarters minus one quarter. In general, the test statistics in Table VI, computed using triple-clustered standard errors, are slightly lower and thus more conservative than the ones from the Fama and MacBeth regressions.

In Panel A, the dependent variable is growth in earnings. The first three specifications show that CAR_3 has power predicting earnings growth 1, 3, and 5 years after the announcement, with higher CAR_3 associated with significantly higher earnings growth. At the 1-year horizon, the power of CAR_3 is almost three times that of gross profitability (t-statistics of 5.71 and 1.95, respectively) and only slightly lower than that of past performance (t-statistic of 6.21). Furthermore, while gross profitability and past performance loose their power for 3- and 5-year earnings growth, CAR_3 does not (t-statistics of 7.97 and 4.69, respectively). In line with our model, the orthogonal component ($\text{CAR}_3^{\perp}$) is a much stronger predictor of earnings growth than the projected components ($\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$ and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$).[17] Moreover, the latter components, as well as earnings-to-book equity, forecast earnings growth negatively, highlighting the strong mean-reversion in earnings.

Panel B repeats these tests, but using the growth in gross profits instead of the growth in earnings as the dependent variable. The first three specifications show that CAR_3 has power predicting gross profit growth up to 5 years after the announcement. In fact, the power of CAR_3 is only slightly lower than that of gross profitability for all three horizons (t-statistic ranging between 6.69 and 7.06 and between 7.93 and 8.20, respectively). The last three specifications show that the orthogonal component, $\text{CAR}_3^{\perp}$, has about the same power as CAR_3 itself predicting gross profit growth for all three horizons. Different from the results for earnings growth in Panel A, $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$ predicts significantly higher gross profit growth at the 3- and 5-year horizons, while $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$ is insignificant at those horizons. Still, when $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$ predicts gross profit growth positively, it does so with considerably lower power than that in $\text{CAR}_3^{\perp}$ (t-statistic of 2.37 and 3.17 vs. 6.98 and 6.47, respectively). Hence, when the growth in gross profits is used as the proxy for future fundamentals, the results are even more in line with Proposition 2.

[17] Sadka and Sadka (2009) also find some predictability of fundamentals by announcement day returns. Our results suggest that using the orthogonal component of CAR_3 strengthens predictability considerably, because $\text{CAR}_3^{\perp}$ and the projected components $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$ and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$ forecast earnings growth with opposite signs.

5. Post announcement returns

This section presents tests of the model's predictions about post-announcement returns.

5.1. *Announcement returns and PEAD*

Part 1 of Proposition 3 is the theoretical counterpart of the well-documented post earnings announcement drift (PEAD) phenomenon: On average, prices drift after earnings announcements in a manner consistent with the sign and magnitude of the announcement return. Two important questions are (i) what is the magnitude of the price drift, and (ii) for how long do prices drift after earnings announcement dates?

To answer these questions, we form portfolios on CAR_3 and study their post-formation returns. The portfolios are from a decile-sort, using NYSE-breakpoints, and are value-weighted and rebalanced at the end of each month. Quarterly fundamentals data is employed starting from the end of the month following the earnings announcement date (RDQ). Figure 4 shows the average cumulative excess return, from 1 to 60 months after formation, to the CAR_3 strategy that buys the top and sells the bottom deciles. The detailed performance of the underlying portfolios, as well as that of the corresponding portfolios formed on SUE^*, is given in Table IA.2 in the Internet Appendix. The table shows that the CAR_3 strategy's average excess return is 0.88% one month after formation (t-statistic of 6.94, calculated using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags). The figure shows that this positive average return persists for just over 24 months after formation. At its peak, the strategy's cumulative performance reaches just over 3%.

5.2. *Dissecting PEAD using double-sorts on announcement returns and earnings suprises*

Parts 2 and 3 of Proposition 3 predict (i) that the part of the announcement return unrelated to public news, as well as the part related to public news, predict a higher post-announcement return, and (ii) that the part of the announcement return unrelated to public news is the stronger predictor of post-announcement returns.

Preliminary evidence in line with these predictions can be seen from the univariate sorts on CAR_3 and SUE^* reported in Table IA.2 in the Internet Appendix. Consistent with the model's predictions, the univariate SUE^* strategy earns an average excess return of 0.37%

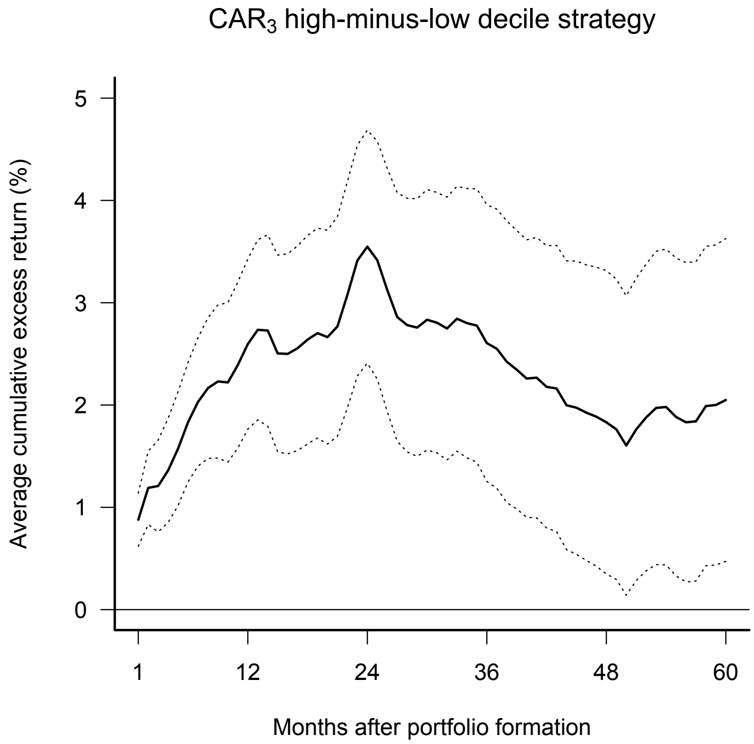

Figure 4: Post earnings announcement drift. This figure shows average cumulative excess returns to a high-minus-low CAR_3 strategy from 1 to 60 months after portfolio formation along with a 95% confidence band. The strategy buys the top portfolio and shorts the bottom portfolio from sorts on CAR_3. The portfolios are constructed using a decile sort, based on NYSE-breakpoints, and are value-weighted and rebalanced monthly. The detailed performance of the portfolios and the high-minus-low strategy is given in Table IA.2 in the Internet A ppendix. Data are monthly and cover July 1972 to December 2016.

per month with a t-statistic of 3.57, which is both lower and statistically weaker than that of the CAR_3 strategy (0.88% per month with t-statistic of 6.94).[18] However, as is evident from the average portfolio characteristics also shown in Table IA.2, a univariate sort on CAR_3 produces a high-CAR_3 portfolio polluted with high-SUE^* firms and a low-CAR_3 portfolio polluted with low-SUE^* firms. We address this issue by studying the performance of portfolios double-sorted on CAR_3 and SUE^*, which allow us to study how post-announcement returns vary with either variable while keeping the other variable fixed.

[18]Furthermore, while the SUE^* strategy earns insignificant abnormal returns relative to the Fama and French (2015) factors as well as the Huo, Xue, and Zhang (2015) factors, the corresponding abnormal returns for the CAR_3 strategy are about as large and as strong as its average return. This is consistent with the findings of Huo, Xue, and Zhang (2015). They find that a decile strategy based on the simple SUE-measure earns an average excess return of 0.45% per month with a t-statistic of 3.59, which falls to an insignificant 0.16% per month with a t-statistic of 1.12 when risk-adjusted with their q-factor model. However, they also find that a decile-strategy based on announcement returns earns an average excess return of 0.73% per month with a t-statistic of 5.50, which is neither explained by the Fama and French three-factor model (with or without the momentum factor) nor by their q-factor model (q-factor abnormal return of 0.64% per month with a t-statistic of 4.07). Huo, Xue, and Zhang (2017) reaffirm these results, as they find that strategies based on announcement returns are among the small list of anomalies that survive their replication study.

Table VII: Double sorts on announcement returns and earnings surprises. This table shows average excess returns to portfolios double-sorted on CAR_3 and SUE^*. The portfolios are constructed from independent quintile sorts, using NYSE-breakpoints, and are value-weighted and rebalanced monthly. It also shows the performance of conditional CAR_3 strategies within SUE^*-quintiles and the performance of conditional SUE^* strategies within CAR_3 quintiles, both in terms of average excess returns ($\mathbb{E}[r^e]$) as well as abnormal returns (α) relative to the CAPM, the Fama and French tree-factor and five-factor models, including the momentum factor, and the q-factor model. Finally, it shows portfolios' average value-weighted characteristics (CAR_3 and SUE^*) as well as equal-weighted average market capitalization and number of firms. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags.

Data are monthly and cover July 1972 to December 2016.

Panel A: Portfolio excess returns and strategy performance

	CAR_3 quintiles					CAR_3 strategy performance				
	Low	2	3	4	High	$\mathbb{E}[r^e]$	α_{CAPM}	$\alpha_{FF3+MOM}$	$\alpha_{FF5+MOM}$	α_q
SUE^* quintiles										
	Portfolio excess return					High minus low CAR_3 within SUE^* quintiles				
Low	0.27	0.34	0.43	0.46	0.61	0.34	0.35	0.32	0.27	0.22
	(0.97)	(1.49)	(1.88)	(2.04)	(2.25)	(3.03)	(3.08)	(2.66)	(2.14)	(1.70)
2	0.22	0.53	0.50	0.36	0.53	0.31	0.32	0.22	0.21	0.18
	(0.76)	(2.30)	(2.47)	(1.70)	(1.85)	(2.48)	(2.48)	(1.55)	(1.46)	(1.22)
3	0.39	0.43	0.69	0.63	0.62	0.23	0.27	0.23	0.37	0.38
	(1.58)	(1.89)	(3.48)	(3.18)	(2.72)	(1.62)	(1.86)	(1.62)	(2.36)	(2.34)
4	0.50	0.71	0.56	0.72	0.93	0.43	0.48	0.34	0.37	0.44
	(2.06)	(3.72)	(2.70)	(3.54)	(4.16)	(2.69)	(3.06)	(2.11)	(2.21)	(2.62)
High	0.29	0.57	0.72	0.71	1.05	0.76	0.81	0.77	0.79	0.84
	(1.16)	(2.45)	(3.62)	(3.67)	(4.55)	(5.94)	(6.66)	(4.88)	(4.61)	(5.36)
SUE^* strategy performance										
	High minus low SUE^* within CAR_3 quintiles									
$\mathbb{E}[r^e]$	0.02	0.23	0.29	0.25	0.44					
	(0.15)	(1.71)	(2.24)	(1.94)	(2.87)					
α_{CAPM}	0.01	0.26	0.31	0.29	0.47					
	(0.07)	(1.95)	(2.30)	(2.24)	(3.11)					
$\alpha_{FF3+MOM}$	−0.22	0.15	0.37	0.07	0.23					
	(−1.33)	(1.02)	(2.40)	(0.53)	(1.55)					
$\alpha_{FF5+MOM}$	−0.30	0.04	0.32	0.04	0.23					
	(−1.62)	(0.28)	(2.26)	(0.32)	(1.56)					
α_q	−0.44	−0.04	0.25	0.00	0.18					
	(−2.38)	(−0.25)	(1.53)	(0.01)	(1.05)					

Panel B: Portfolio characteristics

	CAR_3 quintiles					CAR_3 quintiles				
	Low	2	3	4	High	Low	2	3	4	High
SUE^* quintiles										
	Portfolio SUE^*					Portfolio CAR_3				
Low	−2.21	−2.22	−2.11	−2.17	−2.19	−7.07	−2.08	0.11	2.32	7.36
2	−0.49	−0.47	−0.48	−0.47	−0.49	−6.98	−2.08	0.10	2.37	7.34
3	0.04	0.05	0.05	0.05	0.06	−6.58	−2.02	0.13	2.36	7.13
4	0.58	0.57	0.57	0.58	0.59	−6.66	−2.04	0.13	2.39	7.30
High	1.87	1.86	1.85	1.88	1.98	−6.76	−2.05	0.14	2.42	7.71
	Average market capitalization ($ millions)					Average number of firms				
Low	976	2,170	2,388	2,441	1,443	265	155	137	121	148
2	1,101	2,066	2,122	2,196	1,300	206	145	139	123	147
3	1,235	2,221	2,494	2,412	1,391	159	134	137	129	154
4	1,153	2,420	2,717	2,508	1,375	154	126	135	137	193
High	1,103	2,126	2,273	2,486	1,151	169	129	139	150	260

Table VII reports average excess returns for these double-sorted portfolios, which are constructed from independent quintile sorts, using NYSE-breakpoints, and are value-weighted and rebalanced at the end of each month. The table also shows the performance of conditional CAR_3 strategies within SUE^*-quintiles and the performance of conditional SUE^* strategies within CAR_3-quintiles. Finally, it shows average value-weighted characteristics, equal-weighted average market capitalization, and the number of firms for each portfolio.

For a given SUE^*-quintile, the portfolios exhibit very little variation in average SUE^* across CAR_3-quintiles. Similarly, for a given CAR_3-quintile, the portfolios exhibit very little variation in average CAR_3 across SUE^*-quintiles. This indicates that the double-sorts do a good job in isolating the effect of CAR_3 on post-announcement returns while keeping SUE^* fixed, and vice-versa. We can thus interpret the return-spread due to CAR_3 within a given SUE^*-quintile as driven by the part of CAR_3 unrelated to SUE^*, and vice-versa. As such, these double-sorts allow us to non-parametrically identify the model's $\mathbb{E}[r_{0,1} \,|\, r_0^{\perp}]$ and $\mathbb{E}[r_{0,1} \,|\, \widehat{r}_0]$, where the post-announcement return is measured at the horizon of one month.

The average return spread due to CAR_3 across the SUE^*-quintiles is 0.41% per month, which, consistent with the model's predictions, is higher than the 0.25% per month average return spread due to SUE^* across the CAR_3-quintiles. In fact, a t-test rejects that the average difference in return spreads across quintile-pairs is zero (t-statistic of 2.31). These results are only strengthened when looking at abnormal returns. For instance, the average q-factor abnormal return due to CAR_3 across the SUE^*-quintiles is 0.41% per month, while the average q-factor abnormal return due to SUE^* across the CAR_3-quintiles is just -0.01% per month, and a t-test strongly rejects that the average difference across quintile-pairs is zero (t-statistic of 3.85). Finally, note that while 3 out of 5 CAR_3 strategies generate significant q-factor abnormal returns, all of which are positive, only one SUE^* strategy generates a significant q-factor abnormal return which, nonetheless, is *negative.*

5.3. Dissecting PEAD using linear-weighted CAR_3-factors

The double-sorted portfolios from the previous subsection show that varying CAR_3 within SUE^*-quintiles generates larger spreads in post-announcement returns than when varying SUE^* within CAR_3-quintiles. In this subsection, we provide more direct evidence in support of Proposition 3 by constructing *linear-weighted factors* that allow for an *exact* decomposition of post-announcement returns into the components of CAR_3.

We construct these factors by employing the same procedure as the one used by Menkhoff, Sarno, Schmeling, and Schrimpf (2017). We start by estimating the orthogonal component ($\text{CAR}_3^{\perp}$) and the projected components ($\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$ and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$) from monthly cross-sectional regressions of firms' CAR_3 on SUE^* and $\overline{\text{SUE}}_{8,1}$ that use the most recently available quarterly data for all firms. More specifically, we estimate the same regression equation as shown in Eq. (21). However, a key difference is that we here run cross-sectional regressions using rolling windows (instead of pooled, full-sample regressions), which always use the most recent announcement data for each firm. This ensures that our portfolios are implementable in real time and do not suffer from look-ahead bias.

The linear CAR_3-factor is then the long-short strategy that weighs firms in proportion to their cross-sectional values for CAR_3 minus its cross-sectional average. We scale the weights of the linear CAR_3-factor such that it is one dollar long and one dollar short and we rebalance it at the end of each month. To avoid undue influence from small firms, the factor excludes microcaps, defined as firms with a market capitalization below the 20th percentile of the monthly NYSE market capitalization distribution.[19] Appendix A gives a mathematical description of the factor construction and portfolio weights.

Similarly, the linear CAR_3 factor components are the long-short strategies that weigh firms in proportion to their cross-sectional values for the components of CAR_3 (i.e., $\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}$) minus their cross-sectional averages. Microcaps are again excluded. We scale the weights of these factor-components such that they in total are one dollar long and one dollar short and we rebalance them at the end of each month. By construction, the returns to the linear CAR_3 factor-components sum to the returns of the linear CAR_3-factor, allowing for an exact decomposition.[20]

Table VIII shows the performance of the linear CAR_3-factor that excludes microcaps as

[19] Two advantages of linear-weighted factors is that they use the entire cross-section of firms and that they allow us to do exact decompositions. A drawback, however, is that they are not value-weighted, which raises the concern that their performance is disproportionality driven by small firms. To alleviate this concern, we focus in the main text on factors that exclude microcaps. In robustness tests (Table IA.3 and Figure IA.1 in the Internet Apppendix), we show that very similar results continue to hold when we construct the linear-weighted factors excluding all smallcaps, defined as firms with a market capitalization below the 50th percentile of the monthly NYSE market capitalization distribution.

[20] Asness, Moskowitz, and Pedersen (2013) employ a similar procedure to construct their value and momentum factors, except that they use the ranks of the sorting variables instead of their raw values. Using ranks mitigates the influence of outliers but does not allow for an exact decomposition.

Table VIII: Linear-weighted CAR_3-factors. This table shows average excess return to the linear-weighted CAR_3-factor. It also the average excess returns to corresponding linear-weighted factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). Finally, it shows results from time-series regressions of these factors' returns on the factors from the Fama and French (2015) five-factor model, including the momentum factor, and the Huo, Xue, and Zhang (2015) q-factor model. The linear-weighted factors exclude microcaps, defined as firms with a market capitalization below the 20th percentile of the monthly NYSE market capitalization distribution, and are rebalanced at the end of each month. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags.

The factor returns are monthly and cover July 1972 to December 2016.

		Component factors from CAR_3 decomposition		
	CAR_3	$\text{CAR}_3^{\perp}$	$\widehat{\text{CAR}}_3 \,\|\, \text{SUE}^*$	$\widehat{\text{CAR}}_3 \,\|\, \overline{\text{SUE}}_{8,1}$
Panel A: Average excess returns				
$\mathbb{E}[r^e]$	0.69	0.54	0.13	0.02
	(8.44)	(7.19)	(6.58)	(2.72)
Panel B: Time-series regression results from FF5+MOM model				
$\alpha_{\text{FF5+MOM}}$	0.61	0.49	0.10	0.02
	(8.49)	(6.42)	(5.45)	(3.18)
β_{MKT}	−0.03	−0.04	0.01	0.00
	(−1.56)	(−1.97)	(2.98)	(−2.30)
β_{SMB}	0.03	0.05	−0.02	0.00
	(1.07)	(1.70)	(−2.06)	(1.27)
β_{HML}	−0.08	−0.06	−0.01	−0.01
	(−2.31)	(−1.75)	(−1.01)	(−1.62)
β_{RMW}	−0.07	−0.07	−0.01	0.02
	(−1.34)	(−1.31)	(−1.03)	(5.76)
β_{CMA}	0.09	0.06	0.05	−0.02
	(1.26)	(0.82)	(3.37)	(−3.03)
β_{MOM}	0.17	0.13	0.03	0.01
	(7.94)	(6.16)	(5.49)	(4.09)
Panel C: Time-series regression results from q-factor model				
α_q	0.60	0.51	0.08	0.01
	(5.65)	(4.98)	(4.51)	(1.98)
β_{MKT}	−0.04	−0.05	0.01	0.00
	(−1.51)	(−1.93)	(2.77)	(−1.76)
β_{ME}	0.09	0.09	0.00	0.01
	(1.30)	(1.26)	(−0.06)	(3.58)
β_{ROE}	0.17	0.08	0.06	0.03
	(4.12)	(2.18)	(4.06)	(7.66)
$\beta_{\text{I/A}}$	−0.02	−0.04	0.04	−0.02
	(−0.26)	(−0.61)	(3.19)	(−4.48)

well as the performance of the corresponding factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). The CAR_3 factor earns an average excess return of 69 bp per month with a t-statistic of 8.44. This average return is thus slightly below that of the value-weighted strategy that trades the extreme CAR_3-deciles (Table IA.2 in the Internet Appendix), but is statistically stronger because the linear-weighted portfolios trade in all firms and are therefore

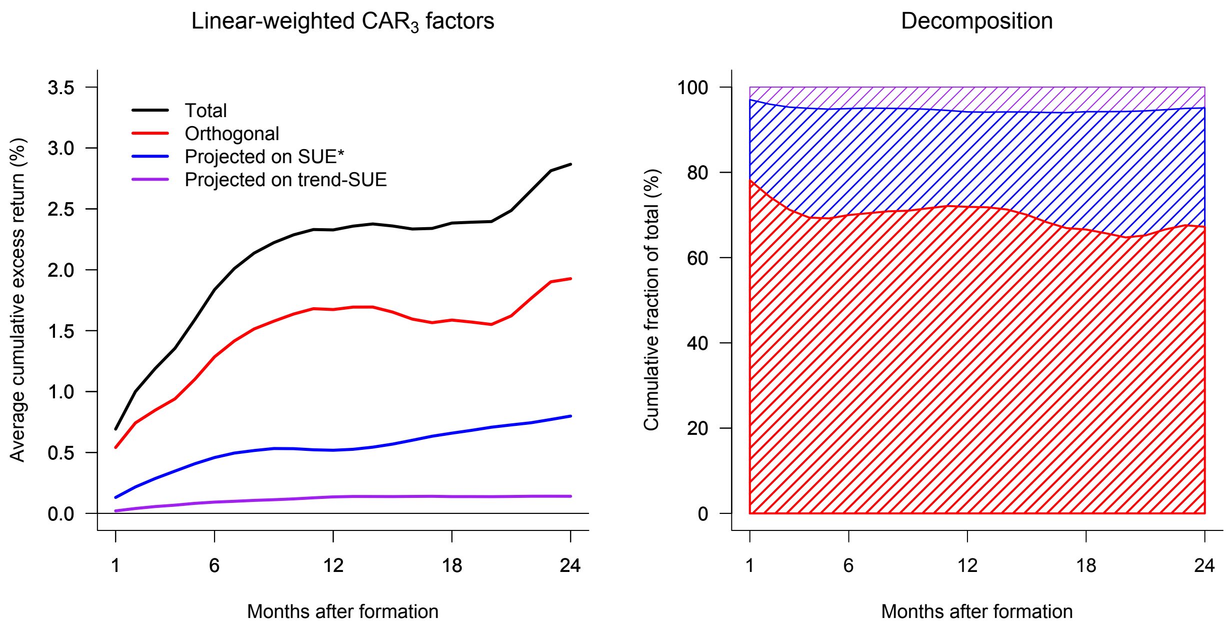

Figure 5: Dissecting PEAD using linear-weighted CAR_3-factors. The left panel shows average cumulative excess returns, from 1 to 24 months after portfolio formation, to the linear-weighted CAR_3-factor as well as the corresponding linear-weighted factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). The right panel shows a decomposition of the linear-weighted CAR_3-factor's average cumulative excess returns from 1 to 60 months after portfolio formation into the fractions that are due to the linear-weighted factor components. The linear-weighted factors exclude microcaps, defined as firms with a market capitalization below the 20th percentile of the monthly NYSE market capitalization distribution. The factor returns monthly and cover January 1972 to December 2016.

better diversified. Decomposing these 69 bp shows that 54 bp (t-statistic of 7.19) are due to the orthogonal component, $\text{CAR}_3^{\perp}$, while a combined 15 bp are due to the projected components. That is, just under 80% of the average post-announcement return one month after the announcement date are due to the component of announcement returns unrelated to public news.

Essentially the same results hold for abnormal returns relative to Fama and French's (2015) five-factor model, including the momentum factor, and Huo, Xue, and Zhang (2015) q-factor model. The CAR_3-factor's abnormal returns are in both cases around 60 bp ($t_{\text{FF5+MOM}} = 8.49$ and $t_q = 5.65$), of which around 50 bp are due to the orthogonal component ($t_{\text{FF5+MOM}} = 6.42$ and $t_q = 4.98$). The fact that the average returns to the CAR_3 factor are largely due to the orthogonal component and cannot be explained by standard risk-factors is in line with the model's implication that post-announcement returns are largely a manifestation of the gradual diffusion of private information, not a compensation for risk.

Figure 5 shows the average cumulative excess returns, from 1 to 24 months after portfolio formation, to the linear CAR_3-factor and the corresponding factor components. The right panel shows that the CAR_3-factor's the average post-formation returns are around 300 bp 24 months after formation, which is very similar to what we observed in Figure 4 for the value-weighted deciles strategy. Out of these 300 bp, just under 200 bp are due to the orthogonal factor-component. The right panel shows that between 70 and 80% of the CAR_3-factor's post-formation returns due to the orthogonal component.

Taken together, the results in Table VIII and Figure 5 are strongly supportive of Proposition 3.

6. Dissecting momentum with announcement returns

In our model, post-announcement returns are largely driven by the gradual diffusion of private information about future fundamentals, which is strongly supported by the evidence we provide in previous sections. Related to this, Novy-Marx (2015) shows that the returns to momentum strategies (Jegadeesh and Titman, 1993, 2001) are essentially driven by earnings momentum, in the sense that the Fama and French momentum factor (MOM) is subsumed by PEAD factors constructed using either SUE or CAR_3. Since our model offers a way to disentangle public and private news about fundamentals, it is natural to to ask which of these components of news, if either, drives the profitability of momentum strategies. The decomposition results we present in this section indicate that the lion's share of momentum returns is due to the gradual diffusion of private information following earnings announcements whereas public news are much less important.

We base our tests on value-weighted conditional announcement factors constructed using the same basic procedure as the strategies from the double-sorts on SUE^* and CAR_3 in Table VII. However, we add an additional control for size to bring these factors as close as possible to their counterparts from the five-factor and q-factor models. Specifically, the factors are constructed from independent $2 \times 3 \times 3$ triple-sorts on size, SUE^*, and CAR_3, using NYSE-breakpoints. The sorts on size use the median market capitalization as the breakpoint while the sorts on SUE^* and CAR_3 use the 30th and 70th percentiles as breakpoints. These sorts produce 12 portfolios, which are value-weighted and rebalance at the end of each month.

From these portfolios, we construct a conditional CAR_3-factor, denoted by $\text{CAR}_3 \,|\, \text{SUE}^*$, as the long-short strategy that buys the 6 high-CAR_3 portfolios in equal weights and shorts the 6 low CAR_3 portfolios in equal weights. We also construct a conditional SUE^* factor, denoted by $\text{SUE}^* \,|\, \text{CAR}_3$, as the long-short strategy that buys the 6 high-SUE^* portfolios in equal weights and shorts the 6 low-SUE^* portfolios in equal weights.

We take the $\text{CAR}_3 \,|\, \text{SUE}^*$ factor as a proxy for post-announcement returns largely unrelated to public news, and similarly, we take the $\text{SUE}^* \,|\, \text{CAR}_3$ as a proxy for post-announcement returns largely related to public news. The performance of these conditional announcement factors is given in Table IA.4 in the Internet Appendix. The correlation between the two factors is just 14%, suggesting that they capture largely distinct variations in average returns. Both factors earn highly significant average excess returns of just over 0.40% per month with t-statistics exceeding 7.50. The t-statistics for the abnormal returns of the $\text{CAR}_3 \,|\, \text{SUE}^*$ factor are $t_{\text{FF5+MOM}} = 7.25$ and $t_q = 5.67$, while they are $t_{\text{FF5+MOM}} = 5.71$ and $t_{\text{FF}} = 3.55$ for the $\text{SUE}^* \,|\, \text{CAR}_3$ factor. Hence, these conditional announcement factors are non-redundant in both the five-factor model and the q-factor model, even by the higher t-statistic threshold of 3.00 advocated by Harvey, Liu, and Zhu (2016). Nonetheless, these t-statistics show that, of the two, $\text{CAR}_3 \,|\, \text{SUE}^*$ has the highest information ratio relative to the two factor models.

Table IX shows factor spanning tests that explore the pricing power of the conditional announcement factors for the momentum anomaly. The dependent variable is in all specifications the Fama and French momentum factor (MOM). In Panel A, the independent factors are the conditional announcement factors and the factors from the Fama and French (2015) five-factor model. The first specification shows that MOM earns an average excess return of 0.65% per month with a t-statistic of 3.30. The second specification shows that controlling for the Fama and French factors results in a slightly higher abnormal return of 0.72% per month but with a lower t-statistic of 2.84. The total R^2 from this specification is 10.2%, and a Shapley-decomposition shows that 56.3% of this total R^2 is due to HML. The third specification shows that $\text{CAR}_3 \,|\, \text{SUE}^*$ completely explains the average returns to MOM with an R^2 of 17.2%. The fourth specification shows that controlling for the Fama and French factors has no effect on the pricing power of $\text{CAR}_3 \,|\, \text{SUE}^*$, which, furthermore, accounts for 64.5% of the total R^2 in this specification. The fifth specification shows that a horse race between $\text{CAR}_3 \,|\, \text{SUE}^*$ and $\text{SUE}^* \,|\, \text{CAR}_3$ in explaining MOM results in 68.4% of the total R^2

Table IX: Dissecting momentum with value-weighted announcement factors. This table shows results of time-series regressions of the Fama and French momentum factor (MOM) on the conditional announcement factors ($CAR_3 \,|\, SUE^*$ and $SUE^* \,|\, CAR_3$) as well as the factors from the Fama and French (2015) five-factor model and the Huo, Xue, and Zhang (2015) q-factor model.

The conditional announcement factors are from independent $2 \times 3 \times 3$ triple-sorts on size, SUE^*, and CAR_3 using NYSE-breakpoints. The sorts on size use the median market capitalization as the breakpoint while the sorts on SUE^* and CAR_3 use the 30th and 70th percentiles as breakpoints. The resulting 12 portfolios are value-weighted and rebalance at the end of each month. The $CAR_3 \,|\, SUE^*$ factor is the long-short strategy that buys the 6 high-CAR_3 portfolios in equal weights and shorts the 6 low CAR_3 portfolios in equal weights. The $SUE^* \,|\, CAR_3$ is the long-short strategy that buys the 6 high-SUE^* portfolios in equal weights and shorts the 6 low-SUE^* portfolios in equal weights. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags. R^2 is adjusted for degrees of freedom. $\%R^2$ is based on a Shapley-value decomposition of the total R^2.

The factor returns are monthly and cover July 1972 to December 2016.

	Estimates, test-statistics (in parentheses), and R^2 decomposition from time-series regressions of the form $MOM_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$									
	(1)	(2)		(3)	(4)		(5)		(6)	
Independent variable		Estimate	$\%R^2$		Estimate	$\%R^2$	Estimate	$\%R^2$	Estimate	$\%R^2$
Panel A: Additional regressors are from the FF5 model										
Intercept	0.65	0.72		0.04	0.15		−0.26		−0.11	
	(3.30)	(2.84)		(0.17)	(0.56)		(−1.00)		(−0.39)	
$CAR_3 \,\|\, SUE^*$				1.49	1.29	64.5%	1.37	68.4%	1.19	48.0%
				(5.31)	(5.63)		(5.29)		(5.49)	
$SUE^* \,\|\, CAR_3$							0.80	31.6%	0.81	25.1%
							(2.61)		(3.38)	
MKT		−0.14	20.5%		−0.09	7.1%			−0.13	6.5%
		(−1.67)			(−1.31)				(−1.87)	
SMB		0.04	0.6%		0.05	0.3%			0.11	0.7%
		(0.30)			(0.44)				(0.96)	
HML		−0.60	56.3%		−0.45	19.3%			−0.37	14.1%
		(−3.26)			(−2.73)				(−2.08)	
RMW		0.22	8.8%		0.23	4.3%			0.21	3.2%
		(0.86)			(1.02)				(0.88)	
CMA		0.52	13.9%		0.38	4.5%			0.16	2.4%
		(1.63)			(1.35)				(0.63)	
Total R^2		10.2%	100%	17.2%	22.4%	100%	22.9%	100%	27.8%	100%
Panel B: Additional regressors are from the q-factor model										
Intercept	0.65	0.14		0.04	−0.24		−0.26		−0.35	
	(3.30)	(0.51)		(0.17)	(−1.06)		(−1.00)		(−1.51)	
$CAR_3 \,\|\, SUE^*$				1.49	1.04	34.7%	1.37	68.4%	0.99	31.0%
				(5.31)	(4.34)		(5.29)		(4.13)	
$SUE^* \,\|\, CAR_3$							0.80	31.6%	0.50	13.2%
							(2.61)		(2.29)	
MKT		−0.09	5.2%		−0.06	3.0%			−0.08	3.2%
		(−1.35)			(−0.99)				(−1.36)	
ME		0.27	5.3%		0.23	3.5%			0.24	3.5%
		(1.59)			(1.70)				(1.72)	
ROE		0.92	89.3%		0.79	58.7%			0.71	48.7%
		(4.98)			(4.22)				(3.72)	
I/A		−0.04	0.2%		0.00	0.1%			−0.10	0.4%
		(−0.16)			(0.01)				(−0.46)	
Total R^2		27.7%	100%	17.2%	35.3%	100%	22.9%	100%	37.1%	100%

coming from $\text{CAR}_3 \mid \text{SUE}^*$. The sixth specification shows that when we control for the Fama and French factors in addition to $\text{SUE}^* \mid \text{CAR}_3$, the marginal contribution of $\text{CAR}_3 \mid \text{SUE}^*$ to the total R^2 is still 48.0%, and it remains the factor with the highest marginal contribution to the total R^2.

Panel B repeats these tests but with the factors from the Fama and French (2015) five-factor model replaced by the factors from the Huo, Xue, and Zhang (2015) q-factor model. The second specification shows that the q-factor model explains the average returns to MOM (abnormal return of 0.14% per month with a t-statistic of 0.51) because of MOM's large and positive loading on ROE. In fact, ROE by itself accounts for 89.3% of the specification's total R^2, which is 27.7%. The fourth specification shows that when we add $\text{CAR}_3 \mid \text{SUE}^*$ alongside the q-factors, the marginal contribution of ROE to the total R^2 falls to 58.7% and that $\text{CAR}_3 \mid \text{SUE}^*$ has a marginal contribution of 34.7% to the total R^2. The sixth specification shows that adding $\text{SUE}^* \mid \text{CAR}_3$ brings the marginal contribution of ROE to the total R^2 further down to 48.7%. In this specification, $\text{CAR}_3 \mid \text{SUE}^*$ accounts for 31.0% of the total R^2 while $\text{SUE}^* \mid \text{CAR}_3$ accounts for just 13.2%.

Table IA.5 in the Internet Appendix explores the pricing power of the linear-weighted CAR_3-factors from Section 5 for a linear-weighted momentum factor constructed in a similar way. We find very similar results that, if anything, indicate an even stronger role for the orthogonal component, $\text{CAR}_3^{\perp}$.

7. Conclusions

We set up a stylized equilibrium model of heterogeneous beliefs to understand two key facts about stock return predictability around announcement dates: There is an *announcement day premium*, i.e., stock prices increase on average on announcement days, and there is a *price drift* following the announcement day. Our model jointly rationalizes both findings and suggests that the announcement premium is due to a *discount rate* effect akin to Savor and Wilson (2016), whereas the price drift after the announcement is driven by the gradual diffusion of private information about fundamentals.

Our results have a number of implications. First, equity investors that build strategies around earnings announcement should pay close attention to CARs orthogonalized with respect to SUE. We show in sorts and double sorts that CAR-based strategies are very profitable, much stronger than SUE-based strategies alone and that CAR and SUE can be combined to further increase the profitability of these strategies. Another attractive feature of CAR-based strategies, which is in line with our model, is that standard risk factors do not account for the returns to CAR-based strategies. Second, for empirical researchers, our findings suggest that the part of CAR unrelated to SUE *across firms* in a given quarter can be thought of as a measure of fundamental uncertainty. Conversely, the part of CAR unrelated to SUE for *an individual firm* in a given quarter can be thought of as a proxy for the private information of informed investors. Since CARs orthogonalized with respect to SUE are easy to compute and available for long periods of time, these measures should be useful in future empirical work. Third, for empirical factor models, our results suggest that CAR-based factors should be included in the set of common factors as CAR-based factors subsume momentum returns but are not subsumed by any of the other standard factors (cf., Fama and French, 2015; Huo, Xue, and Zhang, 2015, 2017).

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Appendix

A. Linear-weighted factors

This appendix gives a mathematical description of linear-weighted factors. Let X_{it} be firm i's month-t value for a sorting characteristic to be decomposed (i.e., CAR_3 in our paper) and suppose that we have the decomposition $X_{it} = \sum_{j=1}^{K} x_{it}^{j}$ into K components (i.e., $\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^{*}$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}$ in our paper). Firm i's month-t weight in the linear X-factor is then

$$w_{it}^{X} = c_t(X_{it} - \overline{X}_t), \tag{A.1}$$

where $c_t = 2/\sum_{i=1}^{N_t} |w_{it}^{X}|$ is a normalizing constant that ensures that the linear X-factor is one dollar long and one dollar short, $\overline{X}_t$ is the cross-sectional average of the X_{it}s for month t, and N_t is the number of firms in the cross-section in month t. By construction, the linear X-factor is long firm i in month t if $X_{it} > \overline{X}_t$, while it is short firm i in month t if $X_{it} < \overline{X}_t$. The linear X-factor's return for month $t+1$ is then given by

$$r_{t+1}^{X} = \sum_{i=1}^{N_t} w_{it}^{X} r_{i,t+1}, \tag{A.2}$$

where $r_{i,t+1}$ is firm i's return for month $t+1$. Similarly, firm i's month-t weight in the jth linear factor-component is given by

$$w_{it}^{j} = c_t(x_{it}^{j} - \overline{x}_t^{j}), \qquad j = 1, \ldots, K, \tag{A.3}$$

where c_t is the same normalizing constant as in Eq. (A.1) and $\overline{x}_t^{j}$ is the cross-sectional average of the x_{it}^{j}s for month t. The jth linear factor-component's return for month $t+1$ is then

$$r_{t+1}^{j} = \sum_{i=1}^{N_t} w_{it}^{j} r_{i,t+1}. \tag{A.4}$$

By construction, we have that the linear X-factor's return for month $t+1$ is the sum of the linear factor-components' returns for month $t+1$:

$$r_{t+1}^{X} = \sum_{j=1}^{K} r_{t+1}^{j}. \tag{A.5}$$

B. Proofs

This appendix provides the proofs omitted from the main text.

2.1. *Proof of Proposition 1.*

Parts 1 and 2 follows by direct computation. First, we have $r_0 > 0$ if and only

$$\lambda_a A > -\kappa\lambda_b B - \gamma Z \left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right] \equiv \underline{L}, \tag{B.1}$$

and it holds that

$$\mathbb{E}[\underline{L}] = -\gamma Z \left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right]. \tag{B.2}$$

Second, we have by definition of $r_0^{\perp}$ that

$$\mathbb{E}[r_0^{\perp}] = \frac{\gamma Z}{R_f} \left[\sigma_A^2 + \sigma_B^2 - H(\sigma_A^2, \sigma_B^2)\right]. \tag{B.3}$$

Since $H(\sigma_A^2, \sigma_B^2) < \sigma_A^2 + \sigma_B^2$ when each of ι, λ_a, and λ_b is in $(0,1)$, it follows that $\mathbb{E}[\underline{L}] < 0$ and $\mathbb{E}[r_0^{\perp}] > 0$. For part 3, note that since $\mathbb{V}[F_1] = \sigma_A^2 + \sigma_B^2$, we have

$$\frac{\partial \mathbb{E}[r_0^{\perp}]}{\partial \mathbb{V}[F_1]} = \frac{\gamma Z}{R_f} \left[1 - \frac{\partial H(\sigma_A^2, \sigma_B^2)}{\partial(\sigma_A^2 + \sigma_B^2)}\right]. \tag{B.4}$$

The term in square brackets is strictly positive since $\frac{\partial H(\sigma_A^2, \sigma_B^2)}{\partial(\sigma_A^2+\sigma_B^2)} < 1$ by the properties of the weighted harmonic mean when each of ι, λ_a, and λ_b is in $(0,1)$. This completes the proof of Proposition 1.

2.2. *Proof of Proposition 2.*

To prove part 1, note first that since A, B, ϵ_A, and ϵ_B are independent and normally distributed, they are also jointly normally distributed. Since F_1 is a linear function of A and B, and r_0 is a linear function of A, B, ϵ_A, and ϵ_B, it holds that F_1 and r_0 are also jointly normally distributed. We therefore have

$$\mathbb{E}[F_1 \,|\, r_0] \;=\; \mathbb{E}[F_1] + \frac{\mathbb{COV}[F_1, r_0]}{\mathbb{V}[r_0]}\Big(r_0 - \mathbb{E}[r_0]\Big), \tag{B.5}$$

which implies that $\mathbb{E}[F_1 \,|\, r_0]$ is increasing in r_0 when $\mathbb{COV}[F_1, r_0] > 0$. To show this, note that

$$
\begin{aligned}
\mathbb{COV}[F_1, r_0] &= \mathbb{COV}\left[A + B\,,\, \tfrac{1}{Rf}\left(\lambda_a A + \kappa\lambda_b B\right)\right] \\
&= \tfrac{1}{R_f}\left(\lambda_a \sigma_A^2 + \kappa\lambda_b \sigma_B^2\right), \qquad \text{(B.6)}
\end{aligned}
$$

which is positive since λ_a, λ_b, and κ are all in $(0, 1)$. This proves part 1.

To prove part 2, note that by a similar argument to part 1, we have that F_1, $r_0^\perp$, and $\widehat{r}_0$, are jointly normally distributed. Hence, it suffices to show that F_1 has a positive covariance with each of $r_0^\perp$ and $\widehat{r}_0$. To show this, note that

$$
\mathbb{COV}[F_1, r_0^\perp] = \tfrac{1}{R_f}\kappa\lambda_b\sigma_B^2 \qquad \text{(B.7)}
$$

and

$$
\mathbb{COV}[F_1, \widehat{r}_0] = \tfrac{1}{R_f}\lambda_a\sigma_A^2 \qquad \text{(B.8)}
$$

which can be seen by direct computation or by noting that $r_0 = r_0^\perp + \widehat{r}_0$ and using Eq. (B.6) with the independence of $r_0^\perp$ and $\widehat{r}_0$. Since both covariances are positive, this proves part 2.

Finally, to prove part 3, note that the joint normality of F_1, $r_0^\perp$, and $\widehat{r}_0$ implies that the statement $\frac{\partial \mathbb{E}[F_1 \,|\, r_0^\perp]}{\partial r_0^\perp} > \frac{\partial \mathbb{E}[F_1 \,|\, \widehat{r}_0]}{\partial \widehat{r}_0}$ is equivalent to

$$
\frac{\mathbb{COV}[F_1, r_0^\perp]}{\mathbb{V}[r_0^\perp]} > \frac{\mathbb{COV}[F_1, \widehat{r}_0]}{\mathbb{V}[\widehat{r}_0]}. \qquad \text{(B.9)}
$$

Since

$$
\mathbb{V}[r_0^\perp] = \tfrac{1}{R_f^2}\kappa^2\lambda_b^2\sigma_B^2 \qquad \text{and} \qquad \mathbb{V}[\widehat{r}_0] = \tfrac{1}{R_f^2}\lambda_a^2\sigma_A^2, \qquad \text{(B.10)}
$$

it follows by using Eqs. (B.7)-(B.8) that the condition in Eq. (B.9) is satisfied when $\lambda_a > \kappa\lambda_b$. This completes the proof of Proposition 2.

2.3. Proof of Proposition 3.

For part 1, note that $r_{0,1}$ and r_0 are jointly normally distributed because they are linear functions of the independent and normally distributed A, B, ϵ_A, and ϵ_B. It thus follows that

$$\mathbb{E}[r_{0,1} \,|\, r_0] \quad = \quad \mathbb{E}[r_{0,1}] + \frac{\mathbb{COV}[r_{0,1}\,,\, r_0]}{\mathbb{V}[r_0]}\Big(r_0 - \mathbb{E}[r_0]\Big), \tag{B.11}$$

which implies that $\mathbb{E}[r_{0,1} \,|\, r_0]$ is increasing in r_0 when $\mathbb{COV}[r_{0,1}\,,\, r_0] > 0$. To show this, note that

$$\begin{aligned} \mathbb{COV}[r_{0,1}\,,\, r_0] \quad &= \quad \mathbb{COV}\left[\tfrac{1}{Rf}\left((R_f - \lambda_a)A + (R_f - \kappa\lambda_b)B\right)\,,\, \tfrac{1}{Rf}\left(\lambda_a A + \kappa\lambda_b B\right)\right] \\ &= \quad \tfrac{1}{R_f^2}\left((R_f - \lambda_a)\lambda_a\sigma_A^2 + (R_f - \kappa\lambda_b)\kappa\lambda_b\sigma_B^2\right). \end{aligned} \tag{B.12}$$

Since $R_f > 1$ while λ_a, λ_b and κ are in $(0, 1)$, both terms in the last line are positive. This proves part 1.

To prove part 2, note that by a similar argument to part 1, we have that $r_{0,1}$, $\widehat{r}_0$, and $r_0^{\perp}$ are jointly normally distributed. Furthermore, we have

$$\mathbb{COV}[r_{0,1}\,,\, r_0^{\perp}] = \tfrac{1}{R_f^2}(R_f - \kappa\lambda_b)\kappa\lambda_b\sigma_B^2 \tag{B.13}$$

and

$$\mathbb{COV}[r_{0,1}\,,\, \widehat{r}_0] = \tfrac{1}{R_f^2}(R_f - \lambda_a)\lambda_a\sigma_A^2 \tag{B.14}$$

which follows by direct computation or by noting that $r_0 = r_0^{\perp} + \widehat{r}_0$ and using Eq. (B.12) along with the independence of $r_0^{\perp}$ and $\widehat{r}_0$. Since both covariances are positive, this proves part 2.

Finally, to prove part 3, note that the joint normality of $r_{0,1}$, $r_0^{\perp}$, and $\widehat{r}_0$ implies that the statement $\frac{\partial \mathbb{E}[r_{0,1} \,|\, r_0^{\perp}]}{\partial r_0^{\perp}} > \frac{\partial \mathbb{E}[r_{0,1} \,|\, \widehat{r}_0]}{\partial \widehat{r}_0}$ is equivalent to

$$\frac{\mathbb{COV}[r_{0,1}\,,\, r_0^{\perp}]}{\mathbb{V}[r_0^{\perp}]} > \frac{\mathbb{COV}[r_{0,1}\,,\, \widehat{r}_0]}{\mathbb{V}[\widehat{r}_0]}. \tag{B.15}$$

Using the expressions for $\mathbb{V}[r_0^{\perp}]$ and $\mathbb{V}[\widehat{r}_0]$ in Eq. (B.10) along with Eqs. (B.13)-(B.14), the condition in Eq. (B.15) is satisfied when $\lambda_a > \kappa\lambda_b$. This completes the proof of Proposition 3.

Internet Appendix for

Dissecting Announcement Returns

(not for publication)

IA.1. Additional results and robustness

This appendix provides additional results and robustness omitted from the main text.

IA.1.1. The role of the trend in earnings surprises

Table IA.1 shows results from pooled regressions of firms' announcement returns (CAR_3, in %) on de-trended earnings surprises (SUE^*), raw earnings surprises (SUE), and the trend in earnings surprises ($\overline{\mathrm{SUE}}_{8,1}$). To avoid undue influence of outliers, independent variables, excluding the factor returns, are trimmed at the 1st and 99th percentiles. Test-statistics are computed using standard errors triple-clustered at the firm, industry, and quarter levels, where the industries are the Fama and French 49.

The first three specifications show the individual effects of the three earnings surprise measures. The fourth and fifth specifications show the effects of each of SUE and SUE^* while controlling for $\overline{\mathrm{SUE}}_{8,1}$. Because of the collinearity resulting from the fact that the sum of SUE^* and $\overline{\mathrm{SUE}}_{8,1}$ equals SUE for each firm and each announcement, all three measures cannot be used in the same regression.

The sixth specification shows the effect SUE^* while controlling for $\overline{\mathrm{SUE}}_{8,1}$ as well as return-based control variables at the firm- and market-level. At the firm-level, we control for one- and four-quarter lagged CAR_3 as well as past performance 12-to-2 months ($r_{12,2}^{\mathrm{RDQ}}$) and 2-to-1 month ($r_{2,1}^{\mathrm{RDQ}}$) before the announcement. At the market level, we control for cumulative 3-day returns for the Fama and French (2015) factors including the three past-performance factors.

Table IA.1: Announcement returns, earnings surprises, and the trend in earnings surprises. This table shows results from pooled regressions of firms' cumulative 3-day abnormal returns around earnings announcement dates (CAR_3, in %) on earnings surprises, de-trended earnings surprises, the trend in earnings surprises, and return controls.

SUE* is standardized unexpected earnings de-trended by firms' moving average over the most recent 8 announcements excluding the current announcement. SUE is raw standardized unexpected earnings. $\overline{\text{SUE}}_{8,1}$ is firms' moving average standardized unexpected earnings over the most recent 8 announcements excluding the current announcement. The return controls at the firm-level are one- and four-quarter lagged CAR_3 as well as past performance 12-to-2 months ($r_{12,2}^{\text{RDQ}}$) and 2-to-1 month ($r_{2,1}^{\text{RDQ}}$) before the announcement. The return controls at the market level are cumulative 3-day returns for the Fama and French (2015) factors [i.e., the market factor (MKT), the small-minus-big size factor (SMB), the high-minus-low value factor (HML), the robust-minus-weak profitability factor (RMW), and the conservative-minus-aggressive investment factor (CMA)] as well as cumulative 3-day returns for the past performance factors [i.e., the momentum factor (MOM), the short-term reversal factor (STREV), and the long-term reversal factor (LTREV)]. Independent variables, excluding the factor returns, are trimmed at the 1st and 99th percentiles. Test-statistics (in parentheses) are computed using standard errors triple-clustered at the firm, industry, and quarter levels, where the industries are the Fama and French 49. R^2 is adjusted for degrees of freedom.

The sample covers earnings announcements between fiscal 1972Q1 and fiscal 2016Q3.

	Intercepts, slopes, and test-statistics (in parentheses) from regressions of the form $CAR_{3,it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + \epsilon_{it}$					
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.28 (5.29)	0.28 (5.17)	0.29 (5.78)	0.28 (5.25)	0.28 (5.18)	0.29 (5.98)
SUE*	0.79 (13.50)				0.93 (13.22)	0.93 (11.90)
SUE		0.91 (13.34)		0.95 (13.58)		
$\overline{\text{SUE}}_{8,1}$			−0.07 (−2.32)	−0.29 (−9.27)	0.60 (11.36)	0.63 (10.56)
$r_{12,2}^{\text{RDQ}}$						0.00 (−4.86)
$r_{2,1}^{\text{RDQ}}$						−0.01 (−5.09)
$\text{lag}_1(\text{CAR}_3)$						0.02 (5.18)
$\text{lag}_4(\text{CAR}_3)$						0.01 (4.65)
MKT_3						−0.10 (−2.86)
SMB_3						0.69 (11.93)
HML_3						0.04 (0.50)
RMW_3						0.09 (1.02)
CMA_3						0.07 (1.27)
MOM_3						−0.11 (−4.42)
STRev_3						0.07 (2.61)
LTRev_3						0.09 (2.04)
R^2	1.5%	1.7%	0.0%	1.8%	1.7%	3.0%

IA.1.2. Univariate sorts on announcement returns and earning surprises

Table IA.2 shows results from univariate sorts on announcement returns (CAR_3) and, for comparison, de-trended earnings surprises (SUE^*). The portfolios are from a decile-sort, using NYSE-breakpoints, and are value-weighted and rebalanced at the end of each month. Quarterly fundamentals data is employed starting from the end of the month following the earnings announcement date (RDQ).

The table shows each portfolios' average excess return as well as its abnormal returns relative to the CAPM, the Fama and French three-factor and five-factor models, both including the momentum factor, and the q-factor model. It also shows the portfolios' value-weighted CAR_3, SUE^*, and $\overline{\text{SUE}}_{8,1}$, as well as equal-weighted market capitalization (M) and number of firms (n). Test-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags.

Table IA.2: Univariate sorts on announcement returns and earnings surprises. This table shows average excess returns to portfolios sorted on firms' abnormal returns around earnings announcement dates (CAR_3, in Panel A) and firms' de-trended earnings surprises (SUE^*, in Panel B). The portfolios are formed using a decile sort, using NYSE breakpoints, and are value-weighted and rebalanced monthly. The table also shows the portfolios' abnormal returns relative to the CAPM, the Fama and French three-factor and five-factor models, both including the momentum factor, and the q-factor model. Finally, it shows the portfolios' average value-weighted characteristics [CAR_3, SUE^*, and the trend in earnings surprises, $\overline{SUE}_{8,1}$] and average equal-weighted market capitalization (M, in $ millions) and number of firms (n). Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags.

Data are monthly and cover July 1972 to December 2016.

	Portfolio										
	Low	2	3	4	5	6	7	8	9	High	High−Low
Panel A: Sorts on CAR_3											
$\mathbb{E}[r^e]$	0.09	0.49	0.55	0.40	0.58	0.57	0.59	0.59	0.70	0.97	0.88
	(0.35)	(2.11)	(2.60)	(1.97)	(3.11)	(2.73)	(3.05)	(3.01)	(3.07)	(3.70)	(6.94)
α_{CAPM}	−0.60	−0.08	0.05	−0.11	0.10	0.08	0.10	0.08	0.16	0.31	0.91
	(−7.33)	(−1.10)	(0.63)	(−1.58)	(1.89)	(1.39)	(2.03)	(1.25)	(2.68)	(2.80)	(7.35)
$\alpha_{FF3+MOM}$	−0.46	−0.03	0.05	−0.13	0.00	0.05	0.06	0.04	0.13	0.38	0.84
	(−4.88)	(−0.42)	(0.70)	(−1.96)	(0.07)	(0.90)	(1.19)	(0.59)	(2.24)	(3.87)	(6.14)
$\alpha_{FF5+MOM}$	−0.36	−0.07	−0.03	−0.15	−0.04	0.04	0.02	0.00	0.10	0.51	0.87
	(−4.08)	(−0.82)	(−0.52)	(−2.12)	(−0.71)	(0.67)	(0.44)	(−0.01)	(1.70)	(5.18)	(6.39)
α_q	−0.37	−0.07	−0.03	−0.10	−0.05	0.03	0.01	−0.01	0.08	0.50	0.87
	(−4.00)	(−0.90)	(−0.43)	(−1.33)	(−0.89)	(0.55)	(0.19)	(−0.17)	(1.30)	(4.72)	(6.70)
CAR_3	−9.97	−4.67	−2.73	−1.44	−0.38	0.61	1.71	3.08	5.13	10.59	
SUE^*	−0.32	−0.23	−0.17	−0.10	−0.01	0.03	0.06	0.16	0.15	0.26	
$\overline{SUE}_{8,1}$	0.12	0.14	0.18	0.19	0.15	0.18	0.17	0.18	0.16	0.10	
Average M	717	1,612	2,063	2,324	2,342	2,451	2,518	2,297	1,879	905	
Average n	565	387	349	341	353	334	329	330	358	545	
Panel B: Sorts on SUE^*											
$\mathbb{E}[r^e]$	0.40	0.38	0.48	0.43	0.55	0.55	0.61	0.70	0.67	0.77	0.37
	(1.68)	(1.65)	(2.19)	(1.87)	(2.73)	(2.64)	(3.37)	(3.29)	(3.39)	(3.48)	(3.57)
α_{CAPM}	−0.17	−0.19	−0.06	−0.11	0.06	0.05	0.12	0.16	0.15	0.22	0.38
	(−2.36)	(−3.25)	(−0.92)	(−1.74)	(0.89)	(0.75)	(2.09)	(2.25)	(2.28)	(2.87)	(3.59)
$\alpha_{FF3+MOM}$	−0.10	−0.11	−0.03	−0.09	0.09	0.03	0.07	0.14	0.11	0.11	0.21
	(−1.28)	(−1.80)	(−0.48)	(−1.34)	(1.36)	(0.46)	(1.36)	(1.93)	(1.68)	(1.39)	(1.80)
$\alpha_{FF5+MOM}$	−0.07	−0.10	0.01	−0.05	0.10	−0.03	0.01	0.08	0.06	0.11	0.18
	(−0.94)	(−1.58)	(0.14)	(−0.57)	(1.37)	(−0.47)	(0.22)	(1.11)	(1.07)	(1.31)	(1.53)
α_q	−0.03	−0.07	0.03	0.00	0.13	−0.06	−0.01	0.05	0.04	0.07	0.10
	(−0.37)	(−1.03)	(0.50)	(0.01)	(1.72)	(−0.81)	(−0.07)	(0.67)	(0.62)	(0.74)	(0.80)
CAR_3	−0.24	−0.13	−0.18	−0.12	0.21	0.40	0.58	0.73	0.90	1.22	
SUE^*	−3.08	−1.25	−0.65	−0.30	−0.06	0.15	0.41	0.75	1.27	2.57	
$\overline{SUE}_{8,1}$	0.70	0.43	0.36	0.29	0.23	0.17	0.06	−0.09	−0.24	−0.27	
Average M	1,761	1,768	1,698	1,718	1,922	1,926	1,992	1,966	1,874	1,607	
Average n	419	407	389	370	358	356	362	383	403	444	

IA.1.3. Dissecting PEAD using linear-weighted CAR_3-factors that exclude all smallcaps

Table VIII and Figure 5 in the main text use linear-weighted CAR_3-factors to perform an exact decomposition of post-earnings announcement drift (PEAD) into the components of CAR_3. To avoid undue influence from small firms, the factors exclude microcaps, defined as firms with a market capitalization below the 20th percentile of the monthly NYSE market capitalization distribution. In this appendix, we show that we obtain very similar results even when we construct the factors in a much more conservative manner that excludes *all* smallcaps, defined as firms with a market capitalization below the 50th percentile of the monthly NYSE market capitalization distribution.

Table IA.3 shows the performance of the linear CAR_3-factor that excludes all smallcaps as well as the performance of the corresponding factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). The table shows each factor's average excess return as well as results from time-series regressions of the factor's returns on the factors from the Fama and French (2015) five-factor model, including the momentum factor, and the Huo, Xue, and Zhang (2015) q-factor model. Test-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags. Figure IA.1 shows these factors' average cumulative excess returns from 1 to 24 months after portfolio formation. See Appendix A for a mathematical description of the factor construction and portfolio weights.

Table IA.3: Linear-weighted CAR_3-factors that exclude all smallcaps. This table shows the average excess return to the linear-weighted CAR_3-factor that excludes all smallcaps. It also the average excess returns to corresponding linear-weighted factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). Finally, it shows results from time-series regressions of these factors' returns on the factors from the Fama and French (2015) five-factor model, including the momentum factor, and the Huo, Xue, and Zhang (2015) q-factor model. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags. Smallcaps are defined as firms with a market capitalization below the 50th percentile of the monthly NYSE market capitalization distribution.

The factor returns are monthly and cover July 1972 to December 2016.

		Component factors from CAR_3 decomposition		
	CAR_3	$\text{CAR}_3^{\perp}$	$\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$	$\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$
Panel A: Average excess returns				
$\mathbb{E}[r^e]$	0.43	0.32	0.10	0.02
	(5.73)	(4.52)	(4.54)	(2.07)
Panel B: Time-series regression results from FF5+MOM model				
$\alpha_{\text{FF5+MOM}}$	0.39	0.30	0.07	0.02
	(6.14)	(4.49)	(3.34)	(2.80)
β_{MKT}	−0.04	−0.04	0.01	−0.01
	(−2.01)	(−2.04)	(1.51)	(−2.98)
β_{SMB}	0.06	0.08	−0.03	0.01
	(1.66)	(1.97)	(−2.04)	(2.21)
β_{HML}	−0.15	−0.12	−0.02	0.00
	(−3.33)	(−2.80)	(−1.02)	(−1.02)
β_{RMW}	−0.15	−0.16	−0.01	0.02
	(−3.12)	(−2.85)	(−0.97)	(4.33)
β_{CMA}	0.09	0.05	0.07	−0.03
	(1.22)	(0.71)	(3.59)	(−3.53)
β_{MOM}	0.19	0.15	0.03	0.01
	(8.02)	(6.56)	(4.06)	(4.05)
Panel C: Time-series regression results from q-factor model				
α_q	0.39	0.34	0.04	0.01
	(3.92)	(3.44)	(2.00)	(1.80)
β_{MKT}	−0.05	−0.05	0.01	−0.01
	(−1.62)	(−1.75)	(1.46)	(−2.38)
β_{ME}	0.13	0.12	0.00	0.01
	(1.43)	(1.36)	(−0.16)	(3.39)
β_{ROE}	0.15	0.06	0.05	0.03
	(2.36)	(1.13)	(3.56)	(6.00)
$\beta_{\text{I/A}}$	−0.13	−0.15	0.05	−0.03
	(−1.49)	(−1.95)	(3.40)	(−4.45)

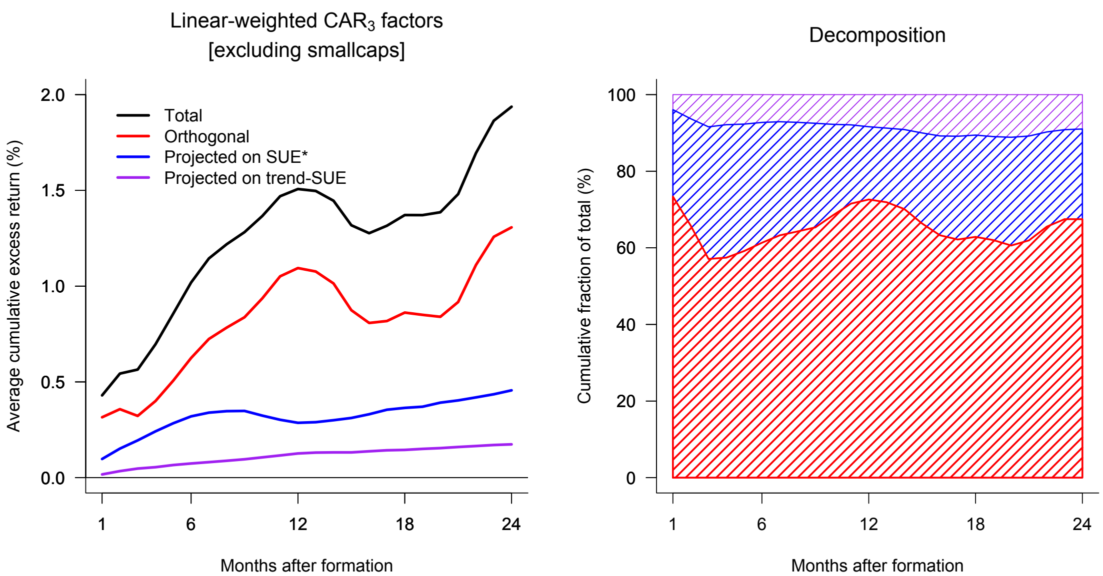

Figure IA.1: Dissecting PEAD using linear-weighted CAR_3-factors that exclude all smallcaps. The left panel shows average cumulative excess returns, from 1 to 24 months after portfolio formation, to the linear-weighted CAR_3-factor that excludes all smallcaps as well as the corresponding linear-weighted factor components ($\text{CAR}_3^{\perp}$, $\widehat{\text{CAR}}_3 \,|\, \text{SUE}^*$, and $\widehat{\text{CAR}}_3 \,|\, \overline{\text{SUE}}_{8,1}$). The right panel shows a decomposition of the linear-weighted CAR_3-factor's average cumulative excess returns from 1 to 60 months after portfolio formation into the fractions that are due to the linear-weighted factor components. Smallcaps are defined as firms with a market capitalization below the 50th percentile of the monthly NYSE market capitalization distribution. The factor returns monthly and cover January 1972 to December 2016.

IA.1.4. Value-weighted conditional announcement factors

Table IA.4 shows the performance of value-weighted conditional announcement factors constructed using the same basic procedure as the strategies from the double-sorts on SUE^* and CAR_3 in Table VII. However, we add an additional control for size to bring these factors as close as possible to their counterparts from the five-factor and q-factor models.

Specifically, the factors are constructed from independent $2 \times 3 \times 3$ triple-sorts on size, SUE^*, and CAR_3, using NYSE-breakpoints. The sorts on size use the median market capitalization as the breakpoint while the sorts on SUE^* and CAR_3 use the 30th and 70th percentiles as breakpoints. These sorts produce 12 portfolios, which are value-weighted and rebalance at the end of each month. From these portfolios, we construct a conditional CAR_3-factor, denoted by $CAR_3 \,|\, SUE^*$, as the long-short strategy that buys the 6 high-CAR_3 portfolios in equal weights and shorts the 6 low CAR_3 portfolios in equal weights. We also construct a conditional SUE^* factor, denoted by $SUE^* \,|\, CAR_3$, as the long-short strategy that buys the 6 high-SUE^* portfolios in equal weights and shorts the 6 low-SUE^* portfolios in equal weights.

The table shows each factor's average excess return as well as results from time-series regressions of the factor's returns on the factors from the Fama and French (2015) five-factor model, including the momentum factor, and the Huo, Xue, and Zhang (2015) q-factor model. Test-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags.

Table IA.4: Value-weighted conditional announcement factors. This table shows the performance of conditional announcement factors relative to the Fama and French (2015) five-factor model, including the momentum factor, and the Huo, Xue, and Zhang (2015) q-factor model. The conditional announcement factors are from independent $2 \times 3 \times 3$ on size, SUE*, and CAR_3 using NYSE-breakpoints. The sorts on size use the median market capitalization as the breakpoint while the sorts on SUE* and CAR_3 use the 30th and 70th percentiles as breakpoints. The $CAR_3 \,|\, SUE^*$ factor is the long-short strategy that buys the 6 high-CAR_3 portfolios in equal weights and shorts the 6 low CAR_3 portfolios in equal weights. The $SUE^* \,|\, CAR_3$ is the long-short strategy that buys the 6 high-SUE* portfolios in equal weights and shorts the 6 low-SUE* portfolios in equal weights. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags. R^2 is adjusted for degrees of freedom.

The factor returns are monthly and cover July 1972 to December 2016.

	Dependent variable							
	$CAR_3 \,\|\, SUE^*$				$SUE^* \,\|\, CAR_3$			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Spanning tests relative to FF5+MOM model								
Intercept	0.41	0.35	0.37	0.37	0.44	0.38	0.31	0.30
	(8.25)	(5.88)	(7.67)	(7.25)	(7.68)	(6.01)	(5.48)	(5.71)
MKT			−0.02	−0.02			0.05	0.05
			(−1.50)	(−1.46)			(2.57)	(2.59)
SMB			−0.01	−0.01			−0.07	−0.07
			(−0.88)	(−0.83)			(−2.11)	(−2.12)
HML			−0.06	−0.06			−0.05	−0.05
			(−2.50)	(−2.39)			(−0.97)	(−0.96)
RMW			−0.03	−0.03			0.00	0.00
			(−1.12)	(−1.12)			(0.00)	(0.01)
CMA			0.05	0.05			0.24	0.24
			(1.20)	(1.13)			(3.34)	(3.35)
MOM			0.11	0.11			0.09	0.09
			(6.49)	(5.99)			(3.17)	(2.96)
$CAR_3 \,\|\, SUE^*$						0.15		0.01
						(1.94)		(0.16)
$SUE^* \,\|\, CAR_3$		0.12		0.01				
		(2.06)		(0.16)				
R^2		1.6%	18.2%	18.0%		1.6%	16.7%	16.6%
Panel B: Spanning tests relative to q-factor model								
Intercept	0.41	0.35	0.36	0.34	0.44	0.38	0.25	0.22
	(8.25)	(5.88)	(6.25)	(5.67)	(7.68)	(6.01)	(4.14)	(3.55)
MKT			−0.03	−0.04			0.04	0.05
			(−1.81)	(−1.96)			(2.01)	(2.16)
ME			0.04	0.04			−0.01	−0.01
			(1.01)	(1.03)			(−0.30)	(−0.40)
ROE			0.13	0.12			0.17	0.16
			(4.19)	(3.88)			(3.38)	(3.21)
IA			−0.04	−0.05			0.19	0.20
			(−0.86)	(−1.15)			(3.72)	(3.89)
$CAR_3 \,\|\, SUE^*$						0.15		0.08
						(1.94)		(1.45)
$SUE^* \,\|\, CAR_3$		0.12		0.08				
		(2.06)		(1.51)				
Adj. R^2		1.6%	8.0%	8.5%		1.6%	15.9%	16.3%

IA.2. Dissecting momentum with linear-weighted announcement return factors

Table IA.5 shows factor spanning tests that explore the pricing power of linear-weighted CAR_3 factors for the momentum anomaly. The dependent factor is in all specifications a linear-weighted momentum-factor (MOM^{LW}) constructed using the same procedure as the linear-weighted CAR_3 factors in Section 5. As in the main text, we exclude microcaps.

In Panel A, the independent factors are the linear-weighted CAR_3-factors and the factors from Fama and French's (2015) five-factor model. The first specification shows that MOM^{LW} earns an average excess return of 0.70% per month with a t-statistic of 2.52. The second specification shows that the correpsonding five-factor abnormal return is 1.01% per month with a t-statistic of 2.70 because of the negative and significant loading on HML. The specification's total R^2 is 17.1%, of which 63.5% of is due to HML. The third specification shows that the CAR_3-factor subsumes MOM^{LW} by itself (abnormal return of -0.45% per month with a t-statistic of -1.83) with an R^2 of 23.0%. The fourth specification shows that controlling for the Fama and French factors has no effect on this result, and that the CAR_3-factor accounts for 58.4% of the specification's total R^2. The fifth specification shows that when the CAR_3-factor is replaced by its factor-components, 54.4% of the total R^2 is due to the orthogonal component. The sixth specification shows that with controls for the Fama and French factors, the marginal contribution of orthogonal component is 32.8%, but that it is still has the highest marginal contribution.

Panel B replaces the Fama and French factors with those from Huo, Xue, and Zhang's (2015) q-factor model. The second specification shows that MOM^{LW} is subsumed by the q-factor model (abnormal return of 0.33% per month with a t-statistic of 0.75) because of its large and positive loadings on ME and especially ROE. The specification's total R^2 is 16.9%, of which 49.8% is due to ROE and 35.2% is due to ME. The fourth specification shows that when the CAR_3 factor is included alongside the q-factors, the abnormal return of MOM^{LW} becomes significantly negative. The specification's total R^2 is 32.8%, of which 59.7% is due to the CAR_3-factor, whereas only 18.1% is due to ROE and 14.4% is due to ME. The sixth specification shows that when we replace the CAR_3-factor with its factor-components, the orthogonal component has the highest marginal contribution (38.6%) to the total R^2.

Table IA.5: Dissecting momentum with linear-weighted CAR_3 factors. This table shows time-series regressions of a linear-weighted momentum factor (MOM^{LW}) on the linear-weighted CAR_3-factor or the linear-weighted CAR_3-factor components ($CAR_3^{\perp}$, $\widehat{CAR}_3 \,|\, SUE^*$, and $\widehat{CAR}_3 \,|\, \overline{SUE}_{8,1}$). Additional regressors are the factors from the Fama and French (2015) five-factor model and the Huo, Xue, and Zhang (2015) q-factor model. The linear-weighted momentum and CAR_3 factors exclude microcaps, defined as firms with a market capitalization below the 20th percentile of the monthly NYSE market capitalization distribution. Test statistics (in parentheses) are computed using Newey and West's (1987) heteroscedasticity and autocorrelation corrected standard errors with 12 lags. R^2 is adjusted for degrees of freedom. $\%R^2$ is based on a Shapley-value decomposition of the total R^2.

The factor returns are monthly and cover July 1972 to December 2016.

Estimates, test-statistics (in parentheses), and R^2 decomposition from time-series regressions of the form $MOM_t^{LW} = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$

Independent variable	(1)	(2) Estimate	(2) $\%R^2$	(3)	(4) Estimate	(4) $\%R^2$	(5) Estimate	(5) $\%R^2$	(6) Estimate	(6) $\%R^2$
Panel A: Additional regressors are from the FF5 model										
Intercept	0.70	1.01		−0.45	−0.05		−0.79		−0.42	
	(2.52)	(2.70)		(−1.83)	(−0.19)		(−3.11)		(−1.33)	
CAR_3				1.67	1.45	58.4%				
				(5.52)	(9.02)					
$CAR_3^{\perp}$							1.37	54.4%	1.15	32.8%
							(3.29)		(6.17)	
$\widehat{CAR}_3 \,\|\, SUE^*$							4.63	31.3%	4.87	23.5%
							(4.18)		(5.10)	
$\widehat{CAR}_3 \,\|\, \overline{SUE}_{8,1}$							7.11	14.4%	6.13	8.5%
							(5.27)		(3.43)	
MKT		−0.12	2.5%		−0.05	0.7%			−0.07	0.7%
		(−1.36)			(−0.71)				(−1.08)	
SMB		0.28	13.7%		0.23	6.2%			0.31	6.7%
		(1.58)			(1.72)				(2.23)	
HML		−0.89	63.5%		−0.62	25.6%			−0.49	19.0%
		(−3.40)			(−3.00)				(−2.29)	
RMW		−0.24	11.0%		−0.20	5.0%			−0.28	5.4%
		(−0.59)			(−0.58)				(−0.78)	
CMA		0.37	9.4%		0.11	4.2%			−0.01	3.4%
		(0.82)			(0.30)				(−0.04)	
Total R^2		17.1%	100%	23.0%	33.2%	100%	28.2%	100%	38.6%	100%
Panel B: Additional regressors are from the q-factor model										
Intercept	0.70	0.33		−0.45	−0.53		−0.79		−0.71	
	(2.52)	(0.75)		(−1.83)	(−2.21)		(−3.11)		(−2.74)	
CAR3				1.67	1.44	59.7%				
				(5.52)	(4.48)					
$CAR_3^{\perp}$							1.37	54.4%	1.26%	38.6%
							(3.29)		(4.01)	
$\widehat{CAR}_3 \,\|\, SUE^*$							4.63	31.3%	4.67	22.6%
							(4.18)		(4.33)	
$\widehat{CAR}_3 \,\|\, \overline{SUE}_{8,1}$							7.11	14.4%	3.52	6.6%
							(5.27)		(1.38)	
MKT		−0.03	1.0%		0.02	0.7%			−0.02	0.6%
		(−0.44)			(0.39)				(−0.40)	
ME		0.58	35.2%		0.45	14.4%			0.45	13.6%
		(2.15)			(2.70)				(2.68)	
ROE		0.80	49.8%		0.56	18.1%			0.33	10.6%
		(2.90)			(1.94)				(0.92)	
I/A		−0.51	14.0%		−0.48	7.1%			−0.58	7.4%
		(−1.32)			(−1.54)				(−1.95)	
Total R^2		16.9%	100%	23.0%	32.8%	100%	28.2%	100%	35.8%	100%