Post-Earnings-Announcement Drift: Expected Growth Risk or Limits-to-Arbitrage?

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To explain post-earnings-announcement drift (PEAD), we suggest expected growth risk, which is measured as covariance between stock returns and expected future real GDP growth rates. We find that both expected growth rates and expected growth risk monotonically increase with standardized unexpected earnings, and expected growth risk is significantly priced in the cross-section of returns. The model including expected growth risk alone explains PEAD satisfactorily. We also find that after adjustment for expected growth risk, the systematic relation of PEAD with the degree of limits-to-arbitrage disappears. This indicates that the empirical evidence supporting the mispricing hypothesis due to limits-to-arbitrage is a consequence of the failure in incorporating appropriate risk and the drift is a manifestation of expected growth risk.

Keywords: Post-earnings-announcement drift; Expected growth risk; Expected real GDP growth; Limits-to-arbitrage; Pricing errors

JEL classification: G12, G14

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Abstract

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1. Introduction

Post-earnings-announcement drift (PEAD) refers to the phenomenon in which a stock price drifts in the direction of the earnings surprise several months after the firm announces earnings. This drift is quite persistent. For example, Bernard and Thomas (1989) report that the spread in average return between stocks in the top and bottom deciles in standard unexpected earnings (SUE) is positive in 41 of the 48 quarters from 1974 to 1985 and in 11 of the 16 quarters in which returns on the NYSE index are negative.[1] PEAD is a robust phenomenon that has been documented for almost five decades since Ball and Brown (1968) who first documented this phenomenon. In his review article, Kothari (2001) argues that the drift provides a serious challenge to the efficient market hypothesis because it has survived many rigorous tests for more than 30 years and cannot be fully explained yet.

Many studies attempt to provide explanations for what causes PEAD and why it persists. These studies can be categorized into two groups: the first group provides rational explanations based on the argument of unobservable latent priced risks(s), and the second group provides mispricing explanations based on the argument of delayed price response. The first group hypothesizes that the drift is simply a manifestation of some unobservable priced risk (i.e., omitted latent risk) and argues that the returns to PEAD strategies are actually compensation for such risk. Many researchers attempt to show that the PEAD phenomenon is related to several risk factors. For example, among many others, Ball, Kothari, and Watts (1993) report that there is a statistically significant positive association between changes in equities' risks and earnings. That is, betas shift

[1] Foster, Olsen, and Shelvin (1984) also report that the drift is a persistent phenomenon over the 1974 to 1981 period with no evidence of being concentrated in a specific time period.

in the same direction as earnings surprise.[2] Kim and Kim (2003) construct a risk factor related to unexpected earnings surprises and find that a four-factor model, including the new factor, reduces a substantial portion of PEAD. Chordia and Shivakumar (2005) argue that the drift is a consequence of a failure in incorporating inflation in forecasting future earnings growth, and this causes firms whose earnings growth is positively (negatively) related to inflation to be undervalued (overvalued).[3] Chordia and Shivakumar (2006) report that returns to the earnings-based zero-investment portfolio are significantly related to future macroeconomic activity. Sadka (2006) argue that a substantial portion of PEAD returns can be viewed as compensation for the variable (informational) component of liquidity risk. Garfinkel and Sokobin (2007) suggest that the drift is positively related to unexpected trading volume around earnings announcements, which is a measure of divergence in investor opinion that is treated as an additional risk, following Varian (1985).

The second group suggests a mispricing hypothesis; that is, this group hypothesizes that a price response to earnings news is delayed due to some reasons. More specifically, the drift is a consequence of a delayed price response or investor under-reaction to earnings surprise. One reason for a delayed price response is limits-to-arbitrage. Studies supporting the limits-to-arbitrage explanation (e.g., Shleifer and Vishny, 1997) argue that arbitrage is risky, costly, and limited; thus, the drift persists to the extent that the costs of the required trades to eliminate it (i.e., arbitrage costs) prevent arbitrageurs from eliminating the inefficiency in pricing. In other words, the drift is

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[2] These authors report, however, that only a small proportion of changes in earnings are attributable to the shift in beta risk.

[3] These authors also find that the firm's exposure of earnings growth to inflation varies monotonically across portfolios sorted on standardized unexpected earnings (SUE), and that lagged inflation predicts future earnings growth and abnormal returns of SUE-sorted stocks.

a consequence of systematic mispricing due to limits-to-arbitrage. Several researchers use several aspects of limits-to-arbitrage to examine their effect on the magnitude of the drift. These aspects of limits-to-arbitrage include transaction costs measured by bid–ask spreads (Bernard and Thomas, 1989, 1990), costs of trading proxied by share price and trading volume (Bhushan, 1994), degree of investor sophistication proxied by the proportion of institutional investors (Bartov et al., 2000) and experienced analysts (Mikhail et al., 2003), and arbitrage risk proxied by idiosyncratic volatility (Mendenhall, 2004). These authors present empirical evidence that is consistent with the limits-to-arbitrage explanation of PEAD.

Johnson (2002) argues in his theoretical model that the log price-dividend ratio is a convex function of expected growth in dividends, which means that changes in log price-dividend ratio or stock returns are more sensitive to changes in expected growth when expected growth is high. That is, expected growth risk rises with growth rates, and expected returns then rise. This author attempts to explain the momentum anomaly based on the convexity property in the relation between stock returns and stochastic growth rates. Since the Johnson (2002) argument is relevant in explaining the anomalies linked to under–reaction, this theoretical model has direct implication for the PEAD anomaly as well. However, there is no paper yet in the literature that attempt to explain the PEAD anomaly using expected growth risk.

The purpose of this paper is two-fold. First, we suggest a new measure of risk to explain PEAD, *expected* growth risk in the context of the Johnson (2002) model, which is never examined in the literature. We examine whether this expected growth risk explains the PEAD anomaly, that is, whether expected growth risk is a latent priced risk for PEAD. To explain PEAD using the expected growth risk defined by Johnson (2002), we need to show that three necessary conditions are satisfied: (i) expected growth rates should increase across SUE-sorted portfolios; (ii) expected growth risk should increase with expected growth rates; and (iii) expected growth risk should be priced in the cross-section of returns. We measure expected growth risk of a stock as covariance between its returns and *expected* future aggregate growth rates. Since GDP is a more suitable representative for growth at the aggregate level than any other macroeconomic variable, we use expected real GDP growth as a measure of expected aggregate growth; these data are obtained from the Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia. Expected real GDP growth is the cross-sectional median of forecasts for future real GDP growth rate made by professional forecasters. The reason we use *expected* growth rather than realized growth is that the use of expected growth is consistent with the Johnson (2002) context and, more importantly, it is more appropriate to analyze pricing issues by investigating the effect of *expected* business conditions on expected stock returns. The use of expected growth is a distinctive feature of this paper.

The second central feature of this paper is to examine whether the mispricing hypothesis for PEAD remains valid even after adjustment for expected growth risk. Among the two aforementioned reasons for a delayed price response, limits-to-arbitrage and systematic bias in expectations for future earnings, we focus on mispricing due to limits-to-arbitrage to compare with the omitted latent risk hypothesis. It is important to examine this issue, because, depending upon the results, we may be able to provide a clearer picture for the issue of whether PEAD is better explained by the omitted latent risk hypothesis or the mispricing hypothesis due to limits-to-arbitrage. As proxies for limits-to-arbitrage, we consider four aspects of limits-to-arbitrage: arbitrage risk (measured by idiosyncratic volatility); transaction costs (measured by bid–ask spread, dollar trading volume, the Amihud (2002) illiquidity, and recent stock price); short sale constraints (measured by institutional ownership and stock borrowing costs); and information uncertainty (measured by analyst forecast dispersion, analyst coverage, and cash flow volatility). To our knowledge, this is the first paper to investigate the impact of limits-to-arbitrage on PEAD with this various aspects of limits-to-arbitrage.

We find that the necessary conditions for expected growth risk defined by Johnson (2002) are satisfied; that is, both expected growth rates and expected risk monotonically increase across SUE-sorted portfolios, and expected growth risk is significantly priced in cross-sectional regression tests. The pricing ability of expected growth risk for PEAD is remarkable. That is, the expected real GDP growth factor alone explains PEAD satisfactorily, and it is superior in terms of pricing errors, defined as the difference between realized return and expected return, to the existing well-known models, such as CAPM, the Fama and French (1993) three-factor model (FF3), and the Hou, Xue, Zhang (2015) q-factor model (HXZ). Even after the expected real GDP factor is augmented to these existing models, the expected real GDP growth factor alone performs better in explaining PEAD than these augmented models.

We confirm that PEAD is more profound as the limits-to-arbitrage become more severe, consistent with the mispricing hypothesis due to limits-to-arbitrage. This systematic relation of PEAD with the degree of limits-to-arbitrage remains unchanged even after FF3 and HXZ are adjusted. When the expected real GDP factor is augmented to these models, this systematic relation is no longer observed, but PEAD remains unexplained, although substantially improved. However, remarkable results are obtained when the expected real GDP factor alone is adjusted. That is, after adjustment for expected growth risk by the expected real GDP factor alone, the systematic relation of PEAD with the degree of limits-to-arbitrage disappears and, more importantly, PEAD is completely explained. Specifically, the pricing errors from the expected real GDP factor alone do not exhibit any particular pattern across SUE portfolios for any given level of limits-to-arbitrage and even for using all stocks. These results support the omitted latent risk hypothesis rather than the mispricing hypothesis due to limits-to-arbitrage. We thus argue that the empirical evidence reported in the literature supporting the mispricing hypothesis due to limits-to-arbitrage is a consequence of the failure in incorporating appropriate risk, expected growth risk, which is never used in the literature, and the drift is a manifestation of expected growth risk.

The rest of this paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes the data. Section 4 reports empirical results for the relation among SUE and expected growth rates, and expected growth risk and for the pricing ability of expected growth risk for PEAD. Section 4 reports empirical results for the effects of expected growth risk on the systematic relation of PEAD to the degree of limits-to-arbitrage. Section 5 sets forth our conclusion.

2. Motivation and Hypothesis Development

Johnson (2002) establishes a theoretical link between expected growth rates and growth risk. In his model, the log price-dividend ratio is convex with respect to expected growth rates. This convexity implies that stocks returns (changes in the log price-dividend ratio) are more sensitively affected by changes in expected growth when expected growth is higher. As such, expected growth risk rises with expected growth rates. To see this, consider the Gordon growth model: $P = D/(k-g)$, where P is stock price, D is dividend, k is the market discount rate, g is the constant growth rate of dividends, and $k > g$. Let $Y = \log(P/D)$ be the log price to dividend ratio. Simple algebra yields $\partial Y/\partial g = 1/(k-g) > 0$ and $\partial^2 Y/\partial g^2 = 1/(k-g)^2 > 0$, indicating that the curvature of the log price-dividend ratio is convex with respect to growth rate of dividends. Figure 1 illustrates the relation between the log price-dividend ratio and growth rate of dividends. There is no source of uncertainty in the Gordon growth model, since market discount rate and growth rate of dividends are both constant. Johnson (2002) extends this intuition to a general framework with stochastic expected growth rates. Johnson (2002) studies the price momentum effect based on the convexity property in the relation between stock returns and stochastic growth rates. In fact, the Johnson (2002) argument is relevant in explaining the anomalies linked to under–reaction. Therefore, Johnson's theoretical model has direct implication for the PEAD anomaly as well.

Earnings surprise may signal a perspective of future growth of earnings (and dividends). For example, Bernard and Thomas (1990) show that unexpected changes in earnings tend to be positively autocorrelated and persistent; that is, these changes exhibit an autocorrelation of about 0.34 at a lag of one quarter. Jegadeesh and Livnat (2006a, 2006b) find that earnings surprises have more persistent effects on future earnings growth when they are the result of revenue surprises. Ceteris paribus, therefore, firms with recent large positive (small positive or negative) earnings surprises are likely to have higher (lower) expected growth rates. Consequently, the convexity of the log price-dividend ratio with respect to expected growth rates predicts that firms included in high-SUE portfolios are likely to have higher growth risk and then earn higher expected returns than firms included in low-SUE portfolios. Based on the above discussion, we propose the following testable hypotheses.

Hypothesis 1: *Firms included in high-SUE portfolios have higher expected growth rates than those included in low-SUE portfolios. SUE is a strong positive predictor of future growth rates.*

Hypothesis 2: *High-SUE portfolios have a greater exposure to expected growth risk than low-SUE portfolios. The spread in average return between high and low SUE portfolios is accounted for by their spread in the loadings on economic factors that measure growth rate risk across these portfolios.*

The limits-to-arbitrage arguments for PEAD posit that if the drift is a consequence of mispricing due to limits-to-arbitrage, PEAD should be more pronounced for stocks that are difficult to arbitrage than for stocks that are easy to arbitrage. Several researchers examine the effect of limits-to-arbitrage on PEAD. Among many others, by showing that the drift appears to be constrained by transaction costs, Bernard and Thomas (1989, 1990) argue that the drift is attributable to transaction costs (measured by bid–ask spreads). Ke and Ramalingegowda (2005) report that transient institutional investors trade less aggressively to exploit PEAD in firms with high transaction costs. Bhushan (1994) finds that the magnitude of the drift is positively correlated with the direct and indirect costs of trading, which are proxied by share price and trading volume. Bartov et al. (2000) show that the magnitude of the drift is negatively correlated with the proportion of institutional investors,[4] and Mikhail et al. (2003) show that the drift is smaller for firms that are followed by experienced analysts, perhaps because institutional investors and experienced analysts tend to be more sophisticated. Mendenhall (2004) finds that the drift is positively related to

[4] However, these authors obtain mixed evidence on using institutional ownership as a proxy for investor sophistication.

arbitrage risk, measured by idiosyncratic volatility, which is the risk faced by arbitrageurs who take positions to eliminate inefficiency in pricing. Transaction costs, degree of investor sophistication, and arbitrage risk are usually regarded as aspects of limits-to-arbitrage in the literature.

PEAD has survived for almost half a century after it was discovered by Ball and Brown (1968). It is difficult to believe that investors *systematically* underreact to earnings-related news simply due to limits-to-arbitrage for such a long period. In fact, some aspects of limits-to-arbitrage are unable to explain the drift. For example, Bernard and Thomas (1989, 1990) suggest a transaction-costs-based explanation for PEAD. However, these authors raise several questions about their own explanation, which undermine the viability of their transaction-costs-based explanation. One of the questions is: why does trading continue throughout the post-announcement period? If a price response is delayed because of transaction costs, then no trading should occur. If a trade does occur, it should occur at a price that fully reflects the available information. The other questions raised are: i) why is the drift not eliminated by traders who face no commissions and can bypass the specialist's bid–ask spread?; and ii) why would transaction costs necessarily cause under–reaction to new information? These authors agree that a transaction-costs-based explanation is unable to answer these questions.

It would be more reasonable to believe, therefore, that there is a missing risk component in explaining this long-period-survived anomaly, PEAD. That is, a risk-based rational hypothesis would be more convincing in explaining PEAD rather than a hypothesis of mispricing due to limits-to-arbitrage. We argue that PEAD is a consequence of the failure in incorporating appropriate risk; thus, it can be explained by appropriately adjusting for risk. As such risk, we suggest expected growth risk in the context of the Johnson (2002) model. Based on the above discussion, we propose the following third testable hypothesis.

Hypothesis 3: *After adjustment for expected growth risk, PEAD becomes insignificant, regardless of the degree of limits-to-arbitrage.*

3. Data and Variable Description

Our measure of expected real GDP growth is based on the reports made by professional forecasters who are participating in the Survey of Professional Forecasters (SPF). The Survey began in 1968 and was conducted quarterly by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990. Near the beginning of every quarter, survey economists report their forecasts of expected nominal GDP levels for the current quarter (t) and the next four quarters (t+1, t+4). Each quarter, we calculate expected real GDP growth rate (EGDP) made at quarter t for one-quarter-ahead quarter t+1 as follows:

$$EGDP_{t,t+1} = ln\left(\frac{RGDP_{t,t+1}}{RGDP_{t,t}}\right) \tag{1}$$

where $RGDP_{t,t}$ and $RGDP_{t,t+1}$ are the forecasts made at quarter t for the level of real GDP for quarter t and quarter t+1, respectively, which are the CPI-adjusted values of the median forecasts for the level of nominal GDP.[5] Since the forecasts for the CPI level are available from 1981:Q3, we obtain expected real GDP growth data over the period 1981:Q3 to 2015:Q4.

[5] For example, the timing of the survey of professional forecasters for 2005:Q1 is as follows.

Accounting variables are obtained from the Compustat annual file. Capital expenditure from the cash flow statement is used for investment, common stock dividends are used for dividends, and net sales are used for sales. Quarterly earnings are obtained from the Compustat quarterly file, and earnings forecasts by analysts and number of analysts are obtained from I/B/E/S. Stock prices, returns, and trading volume data for all New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) firms are obtained from the Center for Research in Security Prices (CRSP). We also use institutional ownership and stock loan fee as proxy variables for short sale constraints. Institutional ownership data are obtained from Thomson Reuters Institutional (13f) Holdings, and stock loan fee data are obtained from the Markit database. Stock loan fee data cover the period January 2004 to December 2015.

4. Empirical Results

4.1. SUE and Expected Future Growth Rates

To explain PEAD using the expected growth risk defined by Johnson (2002), three necessary conditions must hold: (i) expected growth rates should increase monotonically across SUE portfolios; (ii) the expected growth risk should increase with expected growth rates; and (iii)

Questionnaires are sent to panelists at the end of January when the real-time quarterly historical value of GDP for the previous quarter (i.e., 2004:Q4, which is the quarter before the quarter when the survey is conducted) is available. The deadline for submission is the middle of February, and the survey results are released to the public in the middle of February. For 2005:Q1, GDP data available in the middle of the quarter (i.e., February) to investors are the actual GDP for 2004:Q4 and the forecast levels of nominal GDP for the next four quarters; 2005:Q1 (t; current), 2005:Q2 (t+1), 2005:Q3 (t+2), 2005:Q4 (t+3), and 2006:Q1 (t+4). Thus, one-quarter-ahead expected real GDP growth rate in the current quarter 2005:Q1 is calculated using the median forecasts for the level of nominal GDP for 2005:Q1, 2005:Q2 and the forecasts for the CPI level for 2005:Q1, 2005:Q2, which are made at 2005:Q1.

expected growth risk should be priced in the cross-section of returns. In the next three subsections (4.1 to 4.3), we examine whether these three conditions hold.

To examine whether SUE is related to growth rates of a firm's characteristics, such as investment, dividends, and sales, which Liu and Zhang (2008) used, we first construct SUE portfolios by sorting each month all stocks into one of ten decile portfolios based on their SUE from the most recent earnings announcement. The portfolios are held for the next one month with equal weight. SUE is calculated as the difference between the earnings for the current quarter and those for the preceding four quarters, standardized by the standard deviation of the earnings changes in the prior eight quarters. We then calculate each month portfolio-level growth rates by averaging the growth rates of the stocks in the portfolio. Following Liu and Zhang (2008), we obtain monthly measures of the growth rates of individual firms by dividing their current year growth rates by 12.

Table 1 presents time-series averages of growth rates (in percent) of investment, dividends, and sales across ten decile SUE portfolios on the portfolio formation month. Average growth rates in each portfolio are mostly statistically significant at conventional significance levels.[6] Average growth rates of these variables monotonically increase across the ten SUE portfolios, which means that firms with higher SUE tend to have greater growth in investment, dividends, and sales.

To examine how growth rates of investment, dividends, and sales evolve before and after portfolio formation, we calculate average growth rates before and after portfolio formation. Figure 2 shows the average growth rates of the lowest (P1), medium (P5), and highest (P10) SUE decile

[6] All *t*-statistics reported in this paper are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent (HAC) estimator with lag of 4.

portfolios over the period $(-36, +36)$ around the portfolio formation month ($t = 0$). It is evident that the highest SUE portfolio has positive growth rates, while the lowest SUE portfolio has negative growth rates around the portfolio formation month. The spread in average growth rates between the highest and lowest SUE portfolios is most magnified at the portfolio formation month. The widened spread persists for a period after portfolio formation and then converges to zero in 20 months, 36 months, and 9 months after the portfolio formation month in the cases of investment, dividends, and sales, respectively. This evidence that high (low) SUE portfolios maintain positive (negative) growth rates for a significant period even after portfolio formation indicates that SUE may contain information regarding expected future growth and, thus, PEAD may be a consequence of reflecting expected future growth.

To examine in a multivariate framework how SUE is related to *future* expected growth, we estimate firm-level panel regressions of growth rates (investment, dividends, and sales, respectively) on lagged SUE and several control variables at a quarterly frequency. We obtain quarterly measures of the growth rates of individual firms by dividing their current year growth rates by four, and we use the most recently available SUE up to the quarter as lagged SUE. As control variables, we use one-year-lagged growth rates, past returns during the months t-12 to t-2, and inflation rate during the months t-12 to t-2, where t is the last month of the quarter. Table 2 presents estimation results of the firm-level panel regressions. The slope coefficient estimates on lagged SUE are positive and strongly statistically significant at the 1 percent level in all cases after adjusting for the control variables. These results are consistent with the results of the previous portfolio tests that SUE is positively related to future expected growth rates of investment, dividends, and sales. Overall, the results of Tables 1 and 2 and Figure 2 support Hypothesis 1.

4.2. SUE and Expected Growth Risk

In Subsection 4.1, we present empirical evidence that SUE is strongly positively related to expected future growth. If expected future growth creates common variation in stock prices, although possibly varying across stocks, this common variation in stock prices must be attributable to common variation in expected future growth. Thus, an investor holding long and/or short positions in stocks whose prices covary with common variation in expected future growth takes on a common source of risk, expected growth risk. In this subsection, we examine how SUE is related to expected growth risk; that is, we examine whether Hypothesis 2 is supported. *Expected growth risk* of a stock is defined as covariance between its returns (i.e., variation in stock price) and expected aggregate growth rates (i.e., variation in expected aggregate growth). Since GDP is a more suitable representative for growth on the aggregate level than any other macroeconomic variable, we use EGDP as a measure of expected aggregate growth rate.

Specifically, we measure expected growth risk of a stock as covariance between its return observed at quarter t and expected real GDP growth rate made at quarter t for quarter t+1, $EGDP_{t,t+1}$. Asset returns reflect news about future GDP growth. It is known in the literature that stock market cycles tend to lead macroeconomic conditions by one or two quarters. It would be reasonable, therefore, to assume that most of the news refers to the near future, that is, next quarter GDP growth. We thus match stock returns with one-quarter-ahead expected real GDP growth rates in measuring expected growth risk. Note that returns and one-quarter-ahead expected real GDP growth rates are observed at the same quarter and, thus, there is no forward–looking bias. This matching scheme is also consistent with the context of the Intertemporal CAPM (ICAPM) since, according to the ICAPM, the return covariance should be measured with respect to the contemporaneous state variable(s) that describe the future investment opportunity set.[7]

Table 3 presents average quarterly excess returns of ten SUE portfolios and factor loading estimates obtained from regressing returns of each SUE portfolio, $R_{p,t}$, on the EGDP factor, $\mathrm{EGDP}_{t,t+1}$, and factor portfolio returns of our baseline models, such as CAPM, FF3, and HXZ. Note that we select HXZ as one of our baseline models over the other well-known existing models, such as the Carhart (1994) four-factor model and the Fama and French (2015) five-factor model (FF5), since Hou, Xue, and Zhang (2014) report that HXZ outperforms the Carhart model and FF5 in explaining the time-series behavior of PEAD.[8] Further, HXZ capture satisfactorily the factors included in FF5 and the Carhart model, while these models fail to capture the factors included in HXZ.[9] Since expected real GDP growth rates are available at quarterly frequency, we use quarterly portfolio returns in the regressions. Quarterly portfolio returns are obtained by compounding monthly portfolio returns.

Note in Table 3 that average quarterly excess returns monotonically increases across SUE portfolios from 1.19 percent (the lowest SUE; P1) to 4.60 percent (the highest SUE; P10). The difference in average return between P10 and P1 is 3.41 percent (t-statistic of 5.93). The factor

[7] See also Vassalou (2003).
[8] These authors report that the (Jensen) alpha from HXZ for the high-minus-low SUE decile portfolio (i.e., SUE10−SUE1) is insignificant, while the alphas from FF5 and the Carhart are strongly significant (see Table 6).
[9] When RMW and CMA (related to profitability and investment in FF5, respectively) and the momentum factor (in the Carhart model) are regressed on the four factors in HXZ, the intercept estimates (i.e., alphas) are all insignificant. Meanwhile, when IA and ROE (related to investment and profitability in HXZ, respectively) are regressed on the five factors in FF5 or the four factors in the Carhart model, the intercept estimates are all strongly significant. HXZ also report that IA and ROE are highly correlated with CMA and RMW, respectively; the correlations between IA and CMA and between ROE and RMW are 0.92 and 0.67, respectively.

loading estimate on EGDP, $\hat{\beta}_{\mathrm{EGDP}}$, which is the estimate of expected growth risk, also monotonically increases across SUE portfolios, no matter which baseline model is used to augment EGDP. For example, when EGDP is alone in the model, $\hat{\beta}_{\mathrm{EGDP}}$ is positive for all ten SUE portfolios and monotonically increases with SUE. The spread in $\hat{\beta}_{\mathrm{EGDP}}$ between the highest and lowest SUE portfolios is also positive and statistically significant. These results imply that a stock's returns with greater (smaller) current earnings surprise are more (less) sensitive to expected future growth rates. In other words, a stock with greater (smaller) current earnings surprise has greater (smaller) expected growth risk. Even when the other factors of the baseline model are controlled, this pattern of $\hat{\beta}_{\mathrm{EGDP}}$ remains unchanged. The spread in $\hat{\beta}_{\mathrm{EGDP}}$ between the highest and lowest SUE portfolios is positive, quite large in magnitude and statistically significant, compared to the spread in factor loading estimates on the other factors. For example, when FF3 is used as a baseline model, the spreads in factor loading estimate between P10 and P1 are 6.18 (t-statistic of 2.08) for EGDP, -0.15 (t-statistic of -1.64) for the market factor (MKT), -0.26 (t-statistic of -1.96) for SMB, and -0.29 (t-statistic of -2.79) for HML. Therefore, the above results support the first part of Hypothesis 2 that high-SUE portfolios have a greater exposure to expected growth risk than low-SUE portfolios. Note that all t-statistics reported in this paper are based on adjustment by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4.

4.3. Pricing Ability of Expected Growth Risk

Given that stocks with higher SUE have greater expected growth risk, we examine in this subsection how much of the cross-sectional spread in average return across SUE can be explained by the spread in factor loadings on the EGDP factor. We first estimate the risk premium for the EGDP factor, then compute expected returns of SUE portfolios by using these risk premium estimates and test whether these estimated returns differ significantly from observed realized returns.

To estimate risk premia, we conduct the Fama and MacBeth (1973) two-pass methodology for the period 1981:Q3 to 2015:Q4. In the first-pass time-series regression, factor loadings are estimated from multivariate regressions of quarterly returns of test assets on the factors using the full sample. In the second-pass, quarterly excess returns of test assets are quarter-by-quarter cross-sectionally regressed on their factor loading estimates. Risk premium estimates are time-series averages of the quarter-by-quarter cross-sectional regression (CSR) estimates. As test assets, we use 30 portfolios, including 10 book-to-market portfolios, 10 momentum portfolios, and 10 SUE portfolios.[10] Since we examine what drives PEAD, we include SUE portfolios as part of the test assets. We select the CAPM, FF3, and HXZ as baseline models to augment the EGDP factor. According to Savov (2011), estimation with an intercept term can lead to poorly estimated risk premia when there is little variation in factor loadings, which is a common occurrence, and omitting an intercept term and thus imposing a restriction of the model produces more power. We thus estimate CSR with no intercept.[11] In fact, even when the CSR models are estimated with an

[10] The book-to-market and momentum portfolios are taken from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), whereas the ten SUE portfolios are obtained from our measure of SUE. Although size portfolios are often used as a part of test assets in the literature, we do not include them due to a weak spread in average returns across size.

[11] There are also many studies that estimate risk premia with no intercept (e.g., Bennan, Wang, and Xie, 2004; Campbell and Vuolteenaho, 2004; Khan, 2008; and Balvers and Huang, 2009).

intercept term, the overall results for the pricing ability of expected growth risk remain qualitatively unchanged (not reported).[12]

Table 4 presents risk premium estimation results for the baseline models without the EGDP factor (Panel A), and for the model including EGDP alone and the baseline models augmenting the EGDP factor (Panel B). The results show that the risk premium estimates of the EGDP factor are positive and statistically significant in all cases considered. Specifically, when EGDP beta is alone in the CSR, the risk premium estimate on the EGDP factor, $\hat{\gamma}_{\mathrm{EGDP}}$, is 0.59 percent per quarter (t-statistic of 3.30). When the factors in the CAPM, FF3, and HXZ are controlled, $\hat{\gamma}_{\mathrm{EGDP}}$ is 0.36 percent (t-statistic of 5.69), 0.41 percent (t-statistic of 5.28), and 0.19 percent (t-statistic of 3.16), respectively.[13] We also report t-statistics in the table, adjusted by the Shanken (1992) errors-in-variables correction.

Table 5 presents realized excess returns ($\bar{R}$), expected returns (E[R]), and pricing error (α) of ten SUE portfolios for each of the baseline models without and with augmented EGDP factor, respectively. All returns are of quarterly frequency. Expected return of portfolio p is computed as $\mathrm{E}(R_p) = \sum_{k=1}^{K} \hat{\gamma}_k \hat{\beta}_{pk}$, where $\hat{\gamma}_k$ is the risk premium estimate of the k^{th} factor obtained from the Fama and MacBeth (1973) quarter-by-quarter CSR (as in Table 4), and $\hat{\beta}_{pk}$ is the full-sample factor loading estimate of portfolio p on the k^{th} factor. The pricing error is

12 The results are available upon request.

13 t-statistics for risk premium estimates reported in Table 4 are computed using the typical Fama and MacBeth (1973) procedure to be comparable to t-statistics adjusted by the Shanken (1992) errors-in-variables correction. Different from the t-statistics reported in the other tables in this paper, t-statistics reported in Table 4 are not adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4.

defined as the difference between realized and expected returns ($\alpha = \bar{R} - E[R]$). As another pricing error measure, we present the ratio of expected return to realized return for each portfolio, $E[R]/\bar{R}$.

Expected returns implied from the CAPM and FF3 are almost flat across SUE portfolios. The differences in expected return between the highest (P10) and lowest (P1) SUE portfolios, $E(R_{10}) - E(R_1)$, are even negative for the cases of the CAPM and FF3; these values are -0.31 percent for the CAPM and -0.27 percent for FF3. In other words, expected PEAD premiums implied from the CAPM and FF3 are negative. Expected returns implied from HXZ tend to slightly increase across SUE portfolios. Thus, expected PEAD premium implied from HXZ is positive; $E(R_{10}) - E(R_1)$ is 1.49 percent. However, this implied expected PEAD premium is still far smaller than realized PEAD premium, $\bar{R}_{10} - \bar{R}_1$, which is 3.41 percent, although HXZ is better than the CAPM and FF3 in reproducing expected returns of SUE portfolios. These results indicate that the baseline models considered do not reproduce expected returns of SUE portfolios that are consistent with their realized returns. This poor performance of the baseline models in reproducing expected returns results in sizable and statistically significant pricing errors. The difference in pricing error between P10 and P1 (i.e., $\hat{\alpha}_{10} - \hat{\alpha}_1$), which is a measure of the extent of PEAD, is almost similar in magnitude to the difference in average realized return between P10 and P1 (i.e., $\bar{R}_{10} - \bar{R}_1$) for the cases of all three baseline models. Specifically, $\hat{\alpha}_{10} - \hat{\alpha}_1$ is 3.72 percent (t-statistic of 6.75) for CAPM, 3.67 percent (t-statistic of 7.23) for FF3, and 1.93 percent (t-statistic of 4.63) for HXZ. These pricing errors (after adjustment for risk) are roughly similar in magnitude to the difference in (unadjusted) average raw return, $\bar{R}_{10} - \bar{R}_1$. Further, the ratios of expected return to realized return ($E[R]/\bar{R}$) for most of the ten SUE portfolios are far from 1 in all three baseline models. In particular, these ratios for the zero-investment portfolio, P10-P1, for the CAPM, FF3, and HXZ are far from 1, even close to zero for CAPM and FF3; they are -0.09, -0.08, and 0.44 for these three baseline models, respectively.[14] Overall, these results indicate that the factors included in the baseline models play little role in explaining PEAD.

However, when EGDP is augmented to the baseline models and even when EGDP is alone in the model, the performance of the model in reproducing expected returns is remarkably improved with respect to pricing error and the pattern in average return across SUE. All three baseline models augmenting the EGDP factor reproduce expected returns, showing a monotonically increasing pattern across SUE portfolios, consistent with the pattern in realized returns. The differences in expected return between P10 and P1, $E(R_{10}) - E(R_1)$, for CAPM+EGDP, FF3+EGDP, and HXZ+EGDP are 1.47 percent, 1.88 percent, and 2.05 percent, respectively. However, the pricing errors $(\hat{\alpha}_p)$ still show a monotonic increasing pattern across SUE portfolios for all EGDP-augmenting models. The differences in pricing error between P10 and P1, $\hat{\alpha}_{10} - \hat{\alpha}_1$, are 1.96 percent ($t$-statistic of 2.79), 1.54 percent (t-statistic of 2.66), and 1.37 percent (t-statistic of 3.17) for these three EGDP-augmenting models, respectively. These pricing errors are much smaller than in the case of the three baseline models without augmenting the EGDP factor. However, these pricing errors are still statistically significant at the one percent level.

Remarkably, the most impressive results are obtained when the EGDP factor is alone in the model. The pricing errors obtained from using the EGDP factor alone are all statistically insignificant for all ten SUE portfolios, and they have no systematic pattern across SUE portfolios.

[14] Cooper and Priestley (2011) also use the ratio of expected return to realized return, $E[R]/\bar{R}$, as a key measure of pricing ability of the model.

Furthermore, the difference in pricing error between P10 and P1 ($\hat{\alpha}_{10} - \hat{\alpha}_1$) is statistically insignificant at the 10 percent significance level; it is only 0.76 percent (t-statistic of 0.29). Expected PEAD premium implied from the EGDP factor alone is 2.66 percent, which is the closest to the realized PEAD premium among all cases considered. Further, the ratio, $E[R]/\bar{R}$, of P10−P1 of the EGDP factor alone is 0.78, which is the closest to 1 among the models considered. Even when the EGDP factor is augmented to the baseline models, the ratios of the EGDP-augmenting models are farther from 1 than is the ratio of the EGDP factor alone. For example, these ratios for CAPM+EGDP, FF3+EGDP, and HXZ+EGDP are 0.43, 0.55, and 0.60, respectively. Note that the EGDP factor alone also shows no particular systematic pattern in the ratio across SUE portfolios, while the EGPD-augmenting models show a decreasing pattern in the ratio.

Overall, the above results indicate that the EGDP factor alone explains PEAD satisfactorily and its explanatory power for PEAD is the strongest among all models considered. The results discussed in the previous three subsections (4.1, 4.2, and 4.3) indicate that the three necessary conditions hold for Johnson (2002). We thus argue that a substantial portion of the anomalous pattern across SUE is a consequence of reflecting expected growth risk.

4.4. Limits-to-Arbitrage and Post-Earnings-Announcement Drift

The preceding subsections present the results indicating that expected growth risk explains PEAD well. That is, we show that expected growth rates and expected growth risk monotonically increase with SUE, and that expected growth risk is priced in the cross-section of returns. As a first step in addressing the second purpose of this paper, which is to examine whether the mispricing hypothesis due to limits-to-arbitrage remains valid even after adjustment for expected growth risk, we investigate how the magnitude of the drift systematically changes according to the degree of limits-to-arbitrage.

4.4.1. Proxy Variables for Limits-to-Arbitrage

We consider four aspects of limits-to-arbitrage: arbitrage risk, transaction costs, information uncertainty, and short sale constraints. These aspects of limits-to-arbitrage are known to deter arbitrage activities by investors and make stock price respond delayed to information. Firms with higher arbitrage risk, higher transaction costs, more information uncertainty, and more short-sale constraints are more difficult to arbitrage. Thus, such firms tend to be more mispriced.

A. Arbitrage risk

Arbitrage risk, which is the idiosyncratic component of a stock's risk that cannot be hedged, impedes arbitrageurs to take arbitrage activities, and thus can make the drift persist for a while. As a measure of such arbitrage risk, following Pontiff (1996), Wurgler and Zhuravskaya (2002), Ali, Hwang, and Trombley (2003), Mendenhall (2004), Mashruwala, Rajgopal, and Shevlin (2006), Doukas, Kim, and Pantzalis (2010), and Lam and Wei (2011), we use *idiosyncratic volatility*, which is the standard deviation of the residuals obtained from regressing monthly returns of individual stocks on the Fama and French (1993) three factors using past 36 monthly observations available up to each month.[15,16]

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[15] Many researchers (e.g., Wurgler andZhuravskaya, 2002; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2006; Lam and Wei, 2011, among others) use the single-factor market model to compute idiosyncratic volatility. However, we obtain qualitatively similar results, when the single-factor market model is used.

[16] Duan, Hu, and McLean (2010) use idiosyncratic volatility as a proxy for holding costs of an arbitrage

B. Transaction costs

As a measure of transaction costs, we use four variables: effective bid–ask spread, dollar trading volume, illiquidity, and recent stock price. As direct transaction costs, we use the *effective bid–ask spread*, measured as the time-series average of $2 \times |\mathrm{Price} - (\mathrm{Ask} + \mathrm{Bid})/2| \,/\mathrm{Price}$ at the end of each month over the past 12 months, where Price is the closing stock price, and Ask (Bid) is the ask (bid) quote. Chordia et al. (2009) report that transaction costs account for 70 to 100 percent of the profits from a long-short strategy designed to exploit the earnings momentum anomaly. Ng et al. (2008) find that PEAD is most pronounced when transaction costs (including the effective bid–ask spread) are high. In addition to the direct costs of trading, the indirect costs of trading are also related to limits-to-arbitrage. According to Bhushan (1994), the indirect costs of trading indicate the adverse price impact of the trade and the delay in processing the transaction. As a measure of such indirect costs of trading, this author suggests dollar trading volume, which is inversely related to these transaction costs.[17] We measure *dollar trading volume* for the month as share trading volume multiplied by the closing price in the previous month. As the third measure of transaction costs, we use the Amihud (2002) *illiquidity* measure, defined as the time series average of the ratios of absolute daily returns to daily dollar trading volume over the past one year. Bhardwaj and Brooks (1992) and Bhushan (1994) suggest that stock price is inversely related to costs of trading, such as bid–ask spread and brokerage commissions. Pontiff (1996) also uses the inverse of the stock price level as a proxy for transaction costs. Stoll (2000) shows that both recent stock price

position that occur in every period when the position is kept open.

[17] Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990) also argue that dollar-trading volume is an important determinant of these indirect trading costs.

and recent dollar trading volume are inversely related to bid–ask spread. As a fourth measure of transaction costs, we therefore use *recent stock price*, which is measured as closing stock price (the average of bid-and-ask prices if the closing price is not available) at the end of the previous month.

C. Information uncertainty

Zhang (2006) finds that firms with greater information uncertainty have relatively lower future stock returns following bad news and relatively higher future returns following good news, suggesting that information uncertainty delays the flow of information into stock prices. As a measure of information uncertainty, we use three variables: analyst coverage, dispersion in analysts' earnings forecasts, and cash flow volatility. *Analyst coverage* is measured as the number of analysts following the firm in the previous year. Greater analyst coverage is likely to analyze more sophisticatedly information about the firm, which implies less information uncertainty. Lang and Lundholm (1996) find that firms with greater analyst coverage have more informative disclosure policies. Hong, Lim, and Stein (2000) report that in firms with lower analyst coverage, firm-specific information moves more slowly to the investing public. These authors thus suggest greater analyst coverage as an indicator of less information uncertainty. Zhang (2006) and Lam and Wei (2011) also use analyst coverage as a proxy for information uncertainty. As our second measure of information uncertainty, we use *dispersion in analysts' earnings forecasts* (or forecast dispersion), which is measured as the cross-sectional standard deviation of analysts' earnings forecasts, scaled by the closing price at the end of the previous quarter. Diether, Malloy, and Scherbina (2002) interpret forecast dispersion as a measure of uncertainty about future earnings or the degree of consensus among analysts or market participants.[18] The third measure of information uncertainty is *cash flow volatility*, measured as standard deviation of cash flows from operations over the previous five years (requires a minimum of three years).[19] Minton and Schrand (1999) find that higher cash flow volatility is associated with worse S&P bond ratings, higher yield-to-maturity, lower analyst coverage, lower dividend payout ratios, higher bid–ask spreads, and higher weighted average costs of capital. In fact, these characteristics are related to information uncertainty asymmetry (i.e., information uncertainty). Zhang (2006) and Lam and Wei (2011) also use cash flow volatility as a proxy for information uncertainty.

D. Short sale constraints

Stocks with short sale constraints become overpriced when some investors are optimistic about their value, since impediments to short-selling these stocks limit the ability of arbitrageurs to exploit overpricing. Unlike the previous three aspects of limits-to-arbitrage, which have a bi-directional effect on both long-leg and short-leg sides of the PEAD-based arbitrage portfolio, short sale constraints have a unilateral effect only on the short-leg side of the PEAD-based arbitrage portfolio. Short sellers must borrow shares from an investor willing to lend. Stocks are short-sale constrained when there is a strong demand to sell short and a limited supply of shares to borrow. Using a proprietary database from a single lender, D'Avolio (2002) shows that the main suppliers

[18] Lang and Lundholm (1996), Zhang (2006), and Lam and Wei (2011), among many others, also use forecast dispersion as a proxy for information uncertainty.

[19] Cash flow is earnings before extraordinary items (item IB) minus total accruals, divided by average total book assets (item AT) over a fiscal year. Total accruals is change in current assets (item ACT) less change in cash (item CHE), the change in current liabilities (item LCT), and depreciation (item DP) plus change in short-term debt (item DLC).

of stock loans are institutional investors, such as passive index funds, insurance companies, and pension funds. This author documents that institutional ownership explains about 55 percent of the variation in loan supply across stocks and that stocks with low institutional ownership are more short sale constrained. As a measure of short sale constraints, we thus use *institutional ownership* (a proxy for loan supply) as a first measure of short sale constraints. Institutional ownership is measured as the ratio of shares owned by institutions to the total number of shares outstanding.[20] As a second measure, we use *stock loan fee* (a proxy for loan demand), which is the most direct measure of short sale constraints. As the loan fee, we use "IndicativeFee" observed on the last trading day of each month from the Markit data set, which is an indicative fee paid by the borrower for a new stock loan, based on both borrowing costs between agent lenders and prime brokers as well as rates from hedge funds to produce an indication of the current market rate.[21] This is the indicative fee data in the buy-side for a new loan and, thus, is paid by stock borrowers. On the other hand, the fee data in the sell-side are the average fees on currently outstanding loans and, thus, are received by stock lenders. The difference between the fees on the buy-side and on the sell-side is the spread charged by brokers. We use the fee data on the buy-side rather than the fee data on the sell-side, since the former is *a priori* a better measure of short sale constraints than the latter. Note that the fee data on the buy-side reflect the fees for new stock loans, while the fee data

[20] Hand (1990) shows that the probability that the marginal investor is sophisticated may be approximated by the fraction of shares held by institutions. Thus, this author, Bartov et al. (2000), and Chen, Hong, and Stein (2002) suggest institutional ownership as a proxy for investor sophistication or information uncertainty.

[21] Based on the Markit (2015) data description, this is Markit's estimate of expected borrow cost, in fee terms, for a hedge fund on a given day. This is a derived rate using the Markit Securities Finance proprietary analytics and data set.

on the sell-side do not. Due to the availability of the data, the analysis with the loan fee data starts from January 2004.

4.4.2. Basic Characteristics of Proxies for Limits-to-Arbitrage

Panel A of Table 6 presents the average, minimum, first quintile (Q1), median, third quintile (Q3), and maximum of each of the ten proxy variables for limits-to-arbitrage. Panel B presents the Spearman correlation coefficients among SUE, growth rates of sales (GROWTH), and the ten limits-to-arbitrage proxy variables. This panel shows that SUE is positively correlated with GROWTH. Also, SUE is generally negatively correlated with the degree of limits-to-arbitrage. That is, firms with greater SUE tend to have lower degree of limits-to-arbitrage; lower idiosyncratic volatility, lower transaction costs (lower bid–ask spread, larger dollar trading volume, higher stock price), less information uncertainty (smaller forecast dispersion, more analyst coverage), and less short sale constraints (greater institutional ownership, lower loan fee). Firms with higher growth rates of sales also tend to have a smaller degree of limits-to-arbitrage. Panel C of Table 6 presents time-series average values of the limits-to-arbitrage proxy variables across ten decile SUE portfolios. The pattern in these average values across SUE portfolios is consistent with the pattern of the correlation coefficients reported in Panel B.

4.4.3. SUE-Based Zero-Investment Profits According to the Degree of Limits-to-Arbitrage

As an initial procedure to investigate the effects of limits-to-arbitrage on PEAD, we first construct portfolios in a two-way independent sorting on idiosyncratic volatility (IVOL) and SUE. That is, we construct 25 (=5 × 5) portfolios based on the intersection of the five break-points of IVOL and SUE. The portfolios are held for one month with equal weight and rebalanced every month. We then compute quarterly returns of the portfolios by compounding their monthly returns. Table 7 presents average quarterly raw excess returns (in percent) $(\bar{R}_p)$ over the whole period, 1981:Q3 to 2015:Q4, of the 25 portfolios sorted on IVOL and SUE. Average quarterly excess raw returns monotonically increase across five SUE portfolios within each IVOL quintile portfolio and using all stocks. The differences in average return between the largest and smallest SUE quintile portfolios, $\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE1}}$, are all positive and statistically strongly significant. More importantly, $\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE1}}$ monotonically increases with IVOL. Further, the difference in $\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE5}}$ between the highest (P5) and lowest (P1) IVOL portfolios (i.e., difference-in-difference; DiD) is positively statistically significant; it is 3.87 percent per quarter (t-statistic of 4.51). These results indicate that the profit (before adjustment for risk) from the zero-investment strategy based on SUE increases with IVOL. In other words, PEAD seems more profound as the degree of arbitrage risk increases.

To examine the effects of the other aspects of limits-to-arbitrage on PEAD, we also construct 25 portfolios in a (5×5) two-way independent sorting on the other limits-to-arbitrage proxy variable and SUE, as done with IVOL above, except for stock loan fee. Since the indicative fee data are heavily clustered, at the end of each month we sort a firm into one of two groups. If the indicative fee of the firm is less than or equal to the median value of all indicative fees for the month, the firm is sorted into the low loan fee group and, otherwise, into the high loan fee group. Thus, we construct 10 $(= 2 \times 5)$ portfolios in the case of stock loan fee. According to the degree of limits-to-arbitrage, stocks are sorted on each limits-to-arbitrage proxy variable into one of five quintile portfolios from P1 (easy to arbitrage; least limits-to-arbitrage) to P5 (difficult to arbitrage; most limits-to-arbitrage).

Table 8 reports only $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ for the five quintile portfolios sorted on each limits-to-arbitrage proxy variable from P1 (easy to arbitrage) to P5 (difficult to arbitrage). Thus, P5−P1 indicates the difference in $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ between P5 and P1 (i.e., DiD). Note that the first column in Table 8 lists $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ for IVOL, which is copied from the last column in Table 7, and the remaining nine columns contain $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ for the other nine limits-to-arbitrage proxy variables. We observe in Table 8 an increasing pattern of $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ across the five (or two) portfolios sorted on the other limits-to-arbitrage proxy variables, which is similar to the case sorting on IVOL. That is, $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ are all positive and statistically significant and, more important, they monotonically increase with the degree of limits-to-arbitrage for all nine limits-to-arbitrage proxy variables. In particular, the differences in $\bar{R}_{\text{SUE5}} - \bar{R}_{\text{SUE1}}$ between P5 and P1 are all positive and strongly statistically significant at the one percent level for all of the cases. These results indicate that (risk-unadjusted) PEAD becomes more profound as the limits-to-arbitrage become more severe, which is consistent with the mispricing hypothesis due to limits-to-arbitrage.

4.5. Expected Growth Risk, Limits-to-Arbitrage, and PEAD

We examine in Subsection 4.4 the systematic relation of PEAD with the degree of limits-to-arbitrage without adjustment for risk. In this section, we examine the issue on whether this systematic relation is maintained after adjustment for risk, especially expected growth risk. It is important to analyze this issue, because such analysis can provide a clearer picture for the issue on whether PEAD is better explained by the omitted latent risk hypothesis or the mispricing hypothesis due to limits-to-arbitrage. If we obtain results that do not support the mispricing hypothesis after adjustment for expected growth risk, it could be argued that PEAD is a consequence of the omission of risk(s), rather than a systematic mispricing due to limits-to-arbitrage.

4.5.1. Arbitrage Risk Effect on PEAD After Adjustment for Expected Growth Risk

The results in Subsection 4.4 about $\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE1}}$ indicate the profits from the SUE-based zero-investment strategy before adjustment for risk. Here, we examine how such profits are affected after adjustment for risk. In other words, we examine whether the mispricing hypothesis due to limits-to-arbitrage for PEAD is rejected after adjustment for risk, especially for expected growth risk.

We compute pricing errors (or abnormal returns) of 25 (5×5) portfolios constructed in a two-way independent sorting on IVOL and SUE, as in Table 7. The pricing error ($\hat{\alpha}_p$) is defined, as in Table 5, as the difference between quarterly realized ($\bar{R}_p$) and expected ($\mathrm{E}(R_p)$) returns of the portfolio. The risk premium estimates are obtained in the CSR from using these 25 portfolios as test assets. Table 9 presents the pricing errors of the portfolios, which are obtained from using FF3 and FF3 augmenting EGDP (Panel A), HXZ and HXZ augmenting EGDP (Panel B), and the EGDP factor alone (Panel C). As benchmarks, we select FF3 and HXZ to examine how much pricing performance is improved when EGDP is augmented to the model.

Panels A and B of Table 9 shows that even after adjustment for FF3 or HXZ, the mispricing hypothesis due to limits-to-arbitrage for PEAD is still supported. After adjustment for FF3, the extent of PEAD across IVOL is almost unchanged. Specifically, the difference in pricing error between SUE5 and SUE1 ($\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$) across IVOL has a similar pattern to the difference in average raw return between SUE5 and SUE1 ($\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE1}}$). That is, $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$ are all positive and statistically significant at the one percent level, and more importantly, they monotonically increase across the five IVOL portfolios from 1.47 percent (t-statistic of 4.48) (P1) to 5.35 percent (t-statistic of 5.03) (P5). Thus, the difference in $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$ between the highest and lowest IVOL portfolios (i.e., DiD) is positive and strongly statistically significant; it is 3.88 percent (t-statistic of 3.58). This is similar in magnitude and statistical significance to the difference in $\bar{R}_{\mathrm{SUE5}} - \bar{R}_{\mathrm{SUE1}}$ between P5 and P1, which is 3.87 (t-statistic of 4.51) (reported in Table 7). After adjustment for HXZ (Panel B), the mispricing hypothesis due to limits-to-arbitrage is less supported than the case of adjustment for FF3. However, this mispricing hypothesis is still hardly rejected. PEAD, measured by $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$, is statistically significant for stocks that are most difficult to arbitrage; it is 3.19 percent (t-statistic of 2.60). Further, the difference in $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$ between the highest and lowest IVOL portfolios is positive and statistically significant at the 10 percent level; it is 2.59 percent (t-statistic of 1.82).

When the EGDP factor is augmented to FF3 or HXZ for the adjustment, Panels A and B show that PEAD is no longer related to the degree of arbitrage risk and, thus, the mispricing hypothesis due to limits-to-arbitrage is no longer supported. That is, the monotonic pattern of $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$ across IVOL disappears. The differences in $\hat{\alpha}_{\mathrm{SUE5}} - \hat{\alpha}_{\mathrm{SUE1}}$ between the highest and lowest IVOL portfolios become statistically insignificant; they are 0.03 percent (t-statistic of 0.04) for FF3+EGDP and 1.11 percent (t-statistic of 1.44) for HXZ+EGDP. However, these results do not necessarily mean that these augmenting models explain PEAD itself. The pricing error still tends to be increasing with SUE within some IVOL portfolios. Specifically, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$'s are still statistically significant for the two lowest and highest IVOL portfolios (at the 1 percent and 10 percent levels, respectively) in the case of adjustment for FF3+EGDP and for the lowest and highest IVOL portfolios (at the 10 percent and 1 percent levels, respectively) in the case of adjustment for HXZ+EGDP. In particular, using all stocks, the pricing error increases with SUE from -0.49 percent (t-statistic of -2.49) (SUE1) to 0.57 percent (t-statistic of 2.47) (SUE5), and thus, the difference between these two pricing errors ($\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$) is positive and strongly statistically significant in the case of adjustment for FF3+EGDP; it is 1.06 percent (t-statistic of 4.68). We also obtain the similar results in the case of adjustment for HXZ+EGDP. That is, using all stocks, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ is 0.67 percent (t-statistic of 3.41). The above results therefore indicate that when the EGDP factor is augmented to FF3 or HXZ, the effect of arbitrage risk on PEAD is well explained, but PEAD itself is still unexplained.

However, when the EGDP factor is alone in the model (Panel C), it is observed that the effect of arbitrage risk on PEAD as well as PEAD itself are well explained. Specifically, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ is statistically significant for only one IVOL quintile portfolio, and the difference in $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ between the highest and lowest IVOL portfolios is statistically insignificant; it is -1.55 percent (t-statistic of -0.35). Note that the pricing errors from the EGDP factor alone are statistically insignificant for all 25 portfolios. Even when using all stocks, the pricing errors show no particular pattern across the five SUE portfolios, and they are all statistically insignificant. Further, the difference in pricing error between SUE5 and SUE1 ($\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$) for using all stocks is statistically insignificant; it is 0.55 percent (t-statistic of 0.27). Thus, the EGDP factor alone well explains both the systematic relation of PEAD with the degree of arbitrage risk and PEAD itself.

To investigate the main reason for the strong explanatory power of expected growth risk for PEAD, we estimate factor loadings on the four factors (FF3 plus the EGDP factor) for the 25 portfolios sorted on IVOL and SUE. The factor loadings are estimated from multivariate time-series regressions of quarterly excess returns of each portfolio on the four factors using the full-period sample. Table 10 presents these factor loading estimates. It shows that the cross-sectional spread in factor loading estimate on the EGDP factor, $\hat{\beta}_{\text{EGDP}}$, is closely associated with that of average return across the portfolios. That is, only $\hat{\beta}_{\text{EGDP}}$ among the four factor loadings has a pattern consistent with average returns across the portfolios. $\hat{\beta}_{\text{EGDP}}$ increases with SUE within each IVOL quintile portfolio and it decreases with IVOL within each SUE quintile portfolio, as do average portfolio returns (see Table 7). In particular, the difference in $\hat{\beta}_{\text{EGDP}}$ between SUE5 and SUE1, $\hat{\beta}_{\text{EGDP, SUE5}} - \hat{\beta}_{\text{EGDP, SUE1}}$, monotonically increases with the degree of arbitrage risk, IVOL, from 1.30 to 10.36. The difference in $\hat{\beta}_{\text{EGDP, SUE5}} - \hat{\beta}_{\text{EGDP, SUE1}}$ between the highest and lowest IVOL portfolios is positive and statistically significant; it is 9.06 (t-statistic of 2.27). However, the factor loading estimates on the other factors (MKT, SMB, and HML) have no such pattern in the cross-section.

4.5.2. Effects of Other Limits-to-Arbitrage on PEAD after Adjustment for Expected Growth Risk

To further examine the effects of limits-to-arbitrage on PEAD after adjustment for expected growth risk, as for IVOL in Subsection 4.5.1, we conduct a similar procedure for each of the other nine limits-to-arbitrage proxy variables. Table 11 presents only the difference in pricing error between SUE5 and SUE1, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$, for the five quintile portfolios from P1 (easy to arbitrage) to P5 (difficult to arbitrage) sorted on each of the ten (including IVOL) limits-to-arbitrage proxy variables. Expected returns and pricing errors are computed using the EGDP factor alone (Panel A), FF3 and FF3+EGDP (Panel B), and HXZ and HXZ+EGDP (Panel C), respectively. Note that the first column in Table 11 contains $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ for IVOL, which is copied from the last column in Table 9, and the remaining nine columns contain $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ for the other nine limits-to-arbitrage proxy variables. For each case of the limits-to-arbitrage proxy variables, we construct a different set of 25 portfolios in a two-way independent sorting on SUE and the limits-to-arbitrage proxy variable to use as test assets in estimating risk premiums and expected returns.

Table 11 shows that the overall results obtained from using the nine limits-to-arbitrage proxy variables are qualitatively similar to those obtained from using IVOL in Subsection 4.5.1. Specifically, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ obtained from the EGDP factor alone shows no particular pattern across the degree of limits-to-arbitrage. Notably, it is statistically significant for only three among all 47 (= 5×9 + 2) cases. Moreover, the differences in $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ between P5 (difficult to arbitrage) and P1 (easy to arbitrage) are statistically insignificant at conventional significance levels for all ten limits-to-arbitrage proxy variables. The absolute t-values of these differences for all ten cases are less than 1.[22] These results are consistent with Hypothesis 3. Even when using all

[22] They are -1.55 percent (t-statistic of -0.35) for IVOL, -1.97 percent (t-statistic of -0.53) for bid-ask spread, 1.81 percent (t-statistic of 0.58) for dollar trading volume, -0.08 percent (t-statistic of -0.02) for illiquidity, -1.54 percent (t-statistic of -0.32) for stock price, -2.98 percent (t-statistic of -0.64) for analyst dispersion, 0.15 percent (t-statistic of 0.06) for analyst coverage, 1.21 percent (t-statistic of 0.55) for cash flow volatility, 0.48 percent (t-statistic of 0.14) for institutional ownership, and 1.38 percent (t-statistic of 0.57) for stock loan fee.

stocks, the differences in pricing error between SUE5 and SUE1, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$, are statistically insignificant for all of the ten limits-to-arbitrage proxy variables (in the last row of Table 11). The absolute t-values of these differences for all ten cases are also less than 1. The above results indicate that the EGDP factor alone fully explains both the systematic relation of PEAD with the degree of limits-to-arbitrage and, more importantly, PEAD itself.

As with the case of using IVOL, however, Panel B of Table 11 shows that $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ obtained from using FF3 are mostly statistically significant at the five percent level (42 among all 47 cases) and exhibit an increasing pattern with the degree of limits-to-arbitrage proxied by the other nine variables. The differences in $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ between P5 and P1 are statistically significant at the 5 percent level for seven of the ten limits-to-arbitrage proxy variables. However, when the EGDP factor is augmented to FF3, the performance of the model is remarkably improved with respect to pricing error, although it is not better than the case of using the EGDP factor alone. That is, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ are statistically significant at the 5 percent level for only 9 of all 47 cases, and the differences in $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ between P5 and P1 are statistically insignificant at conventional significance levels for all ten limits-to-arbitrage proxy variables. However, using all stocks, the differences in pricing error between SUE5 and SUE1, $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$, are still statistically significant at the one percent level for five cases among the ten limits-to-arbitrage proxy variables. When HXZ is used as a baseline model for the adjustment (Panel C), the results are qualitatively similar to the case of using FF3.

Overall, the above results indicate that expected growth risk explains PEAD satisfactorily and the drift is a manifestation of expected growth risk. That is, we obtain the results supporting the omitted latent risk hypothesis for PEAD rather than the mispricing hypothesis due to limits-to-arbitrage. We thus argue that the empirical evidence reported in the literature supporting the mispricing hypothesis due to limits-to-arbitrage is a consequence of the failure in incorporating appropriate risk, expected growth risk.

5. Conclusion

Two competing hypotheses (or explanations) have been suggested in the literature to explain the anomalous drift in stock price after earnings announcements, PEAD: an omitted latent risk hypothesis and a mispricing hypothesis due to limits-to-arbitrage. For the omitted latent risk explanation, this paper suggests a new measure of risk to explain PEAD: expected growth risk in the context of the Johnson (2002) model, which is never used in the literature. We examine whether this expected growth risk explains the PEAD anomaly, that is, whether expected growth risk is a latent priced risk for PEAD. Then, we examine whether the mispricing explanation due to limits-to-arbitrage for PEAD remains valid even after adjustment for expected growth risk. As a measure of expected growth risk of a stock, we use covariance between its returns and *expected* real GDP growth rates. The use of expected growth is a distinctive feature of this paper.

We find that both expected growth rates and expected risk monotonically increase across SUE-sorted portfolios, and expected growth risk is significantly priced in the cross-section of returns. These are necessary conditions that must hold for the expected growth risk defined in Johnson (2002) to explain PEAD. The EGDP factor alone explains PEAD satisfactorily, and it is superior in terms of pricing ability to the existing well-known models, such as the CAPM, FF3, and HXZ. The model including the EGDP factor alone performs even better in explaining PEAD than the existing models augmenting the EGDP factor.

We also find that the systematic relation of PEAD with the degree of limits-to-arbitrage remains unchanged even after FF3 and HXZ are adjusted. When the EGDP factor is augmented to these models for the adjustment, the systematic relation of PEAD with the degree of limits-to-arbitrage is well explained; that is, the mispricing hypothesis due to limits-to-arbitrage is no longer supported. However, PEAD remains unexplained with these augmented models. When the EGDP factor alone is adjusted, the systematic relation of PEAD with the degree of limits-to-arbitrage disappears and, more importantly, PEAD itself is completely explained. These results support the omitted latent risk hypothesis rather than the mispricing hypothesis due to limits-to-arbitrage. We thus argue that the empirical evidence reported in the literature supporting the mispricing hypothesis due to limits-to-arbitrage is a consequence of the failure in incorporating appropriate risk, expected growth risk, which is never used in the literature, and the drift is a manifestation of expected growth risk.

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Table 1. Growth Rates of Investment, Sales, and Dividend Across SUE Portfolios

This table reports time-series average growth rates (in percent) of dividend, investment, and sales for ten SUE decile portfolios. All stocks listed on NYSE and AMEX are sorted each month into one of ten deciles based on their standardized unexpected earnings (SUE) from the most recent earnings announcement. Portfolios are held for the next month. SUE is calculated as the difference between earnings for the current quarter and those for the preceding four quarters, standardized by the standard deviation of the earnings changes in the prior eight quarters. Each month after ranking all stocks based on their SUE measure, we calculate portfolio level growth rates by averaging growth rates for the stocks in the portfolio. Following Liu and Zhang (2008), we obtain monthly measures of the growth rates of individual firms by dividing their current year growth rates by 12. Numbers in parentheses indicate *t*-statistics, which are adjusted by Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors with lag of 4. The sample period ranges from January 1981 to December 2015.

	Growth rates of		
SUE portfolios	Investment	Dividends	Sales
P1 (lowest)	-0.75	0.01	0.06
	(-3.73)	(0.04)	(0.70)
P2	-0.17	0.48	0.22
	(-1.05)	(5.04)	(2.81)
P3	-0.08	0.35	0.22
	(-0.49)	(3.86)	(3.10)
P4	-0.05	0.39	0.23
	(-0.32)	(4.40)	(3.29)
P5	0.14	0.44	0.36
	(0.94)	(4.34)	(5.10)
P6	0.38	0.60	0.50
	(2.56)	(6.70)	(7.49)
P7	0.58	0.70	0.61
	(4.37)	(7.98)	(9.28)
P8	0.78	0.74	0.71
	(6.03)	(11.34)	(11.96)
P9	0.82	0.79	0.77
	(6.01)	(10.44)	(11.61)
P10 (highest)	1.15	1.04	0.97
	(8.91)	(10.62)	(14.03)
P10−P1	1.90	1.04	0.90
	(14.83)	(7.03)	(16.55)

Table 2. Predictive Regression of Future Growth Rates

This table presents estimation results from firm-level panel regressions of growth rates (investment, dividends, sales) on lagged standardized unexpected earnings (SUE) and control variables at quarterly frequency. Quarterly measures of growth rates of individual firms are obtained by dividing their current year growth rates by four, and SUE most recently available up to the quarter is used as lagged SUE. As control variables, we use one-year-lagged growth rates, past returns during the months t-12 to t-2 ($\text{Return}_{t-12,t-2}$), and inflation rate during the months t-12 to t-2 ($\text{INF}_{t-12,t-2}$), where t is the first month of the quarter. To account for heteroscedasticity and autocorrelation in the residuals, we adjust the standard errors of the estimates using two-way clustering, and report the corresponding t-statistics. The sample period ranges from 1981:Q3 to 2015:Q4.

	Dividend growth				Investment growth				Sales growth			
Intercept	1.72	0.78	0.78	0.23	0.85	0.06	-1.12	-1.07	1.64	0.93	1.02	0.43
	(8.54)	(4.43)	(1.12)	(0.62)	(2.49)	(0.24)	(-1.17)	(-1.79)	(14.12)	(7.85)	(3.19)	(1.62)
Lagged SUE	0.96	0.44	0.96	0.44	1.48	1.07	1.47	1.06	0.91	0.62	0.91	0.62
	(8.82)	(7.36)	(9.29)	(7.37)	(13.81)	(12.12)	(14.84)	(12.03)	(17.76)	(13.10)	(18.40)	(13.14)
Lagged growth	-0.31	-0.14	-0.31	-0.15	-0.54	-0.50	-0.55	-0.50	0.09	0.15	0.09	0.15
	(-4.54)	(-1.71)	(-4.62)	(-1.77)	(-20.35)	(-14.70)	(-20.70)	(-14.78)	(2.13)	(2.06)	(2.02)	(1.99)
$\text{Return}_{t-12,t-2}$			0.39	0.21			0.86	0.46			0.28	0.20
			(1.68)	(2.06)			(2.52)	(2.31)			(2.33)	(2.19)
$\text{INF}_{t-12,t-2}$		0.05		0.05		0.06		0.06		0.02		0.02
		(9.21)		(9.56)		(9.94)		(10.36)		(9.25)		(9.59)
Adj R^2	3.80%	5.83%	4.04%	5.94%	4.25%	7.71%	4.59%	7.90%	4.75%	7.23%	4.89%	7.38%
No. of obs.	158,400	86,227	158,400	86,227	284,192	126,482	284,192	126,482	332,514	139,548	332,514	139,548

Table 3. Exposure for SUE Portfolios on Expected Real GDP Growth

This table presents average quarterly excess raw returns (in percent) and factor loading estimates obtained from regressing q ($R_{p,t}$) on expected real GDP growth rate made at quarter t for quarter t+1 ($\text{EGDP}_{t,t+1}$) plus the market factor (MKT), the Fa or Hou, Xue, and Zhang (2015) q-factor model (HXZ). Quarterly returns of SUE portfolios and the Fama and French factor p monthly returns of these portfolios. Numbers in parentheses indicate t-statistics, which are adjusted by Newey-West consistent (HAC) standard errors with lag of 4. The sample period ranges from 1981:Q3 to 2015:Q4.

SUE	Excess	EGDP alone		CAPM+EGDP			FF3+EGDP					
port	raw return	const	EGDP	const	EGDP	MKT	const	EGDP	MKT	SMB	HML	const
P1	1.19	0.46	0.97	-0.02	-2.12	1.17	1.10	-5.21	1.12	0.65	0.91	0.59
(low)	(1.20)	(0.15)	(0.21)	(-0.01)	(-0.64)	(9.02)	(0.52)	(-1.53)	(11.62)	(5.87)	(9.96)	(0.34)
P2	1.58	0.45	1.66	-0.02	-1.28	1.12	0.85	-3.64	1.05	0.51	0.81	0.44
	(1.90)	(0.16)	(0.41)	(-0.01)	(-0.56)	(11.32)	(0.66)	(-1.74)	(14.01)	(6.69)	(12.43)	(0.42)
P3	1.59	-0.20	2.80	-0.66	-0.12	1.11	0.19	-2.40	1.03	0.50	0.86	-0.43
	(1.95)	(-0.08)	(0.72)	(-0.47)	(-0.06)	(12.17)	(0.21)	(-1.70)	(20.86)	(6.43)	(11.43)	(-0.53)
P4	2.20	-0.75	4.78	-1.21	1.85	1.12	-0.32	-0.57	1.05	0.520	0.84	-0.90
	(2.58)	(-0.30)	(1.27)	(-0.83)	(0.97)	(12.81)	(-0.33)	(-0.40)	(22.91)	(6.40)	(13.22)	(-1.24)
P5	2.53	-0.24	4.49	-0.70	1.58	1.11	0.41	-1.48	1.06	0.64	0.87	-0.51
	(2.89)	(-0.09)	(1.05)	(-0.51)	(0.84)	(10.23)	(0.47)	(-1.11)	(18.81)	(8.13)	(8.26)	(-0.61)
P6	3.11	0.60	4.03	0.16	1.22	1.07	1.18	-1.59	1.03	0.59	0.78	0.21
	(3.81)	(0.25)	(1.09)	(0.13)	(0.66)	(11.14)	(1.24)	(-1.03)	(22.51)	(6.13)	(11.87)	(0.25)
P7	3.56	1.27	3.65	0.81	0.73	1.11	1.59	-1.37	1.05	0.45	0.72	0.89
	(4.52)	(0.51)	(0.95)	(0.66)	(0.40)	(13.64)	(1.62)	(-0.84)	(22.13)	(5.17)	(8.74)	(1.08)
P8	3.61	0.97	4.27	0.53	1.48	1.06	1.29	-0.58	1.00	0.45	0.74	0.34
	(4.47)	(0.36)	(1.03)	(0.50)	(1.06)	(12.47)	(1.61)	(-0.49)	(27.94)	(4.08)	(9.36)	(0.41)
P9	3.89	0.38	5.77	-0.06	3.03	1.04	0.67	1.11	0.97	0.42	0.75	-0.11
	(4.89)	(0.16)	(1.54)	(-0.05)	(2.14)	(13.80)	(1.28)	(1.24)	(23.61)	(4.89)	(11.90)	(-0.21)
P10	4.60	1.26	5.47	0.84	2.78	1.02	1.51	0.97	0.97	0.39	0.62	0.60
(high)	(6.04)	(0.51)	(1.41)	(0.81)	(1.92)	(12.01)	(2.03)	(0.82)	(21.18)	(3.25)	(7.74)	(0.81)
P10-	3.41	0.80	4.50	0.86	4.90	-0.15	0.41	6.18	-0.15	-0.26	-0.29	0.01
P1	(5.93)	(0.47)	(1.95)	(0.50)	(1.90)	(-1.74)	(0.22)	(2.08)	(-1.64)	(-1.96)	(-2.79)	(0.01)

Table 4 Cross-Sectional Regression Estimates for Risk Premia

This table presents risk premium estimates obtained from the Fama and MacBeth (1973) two-pass methodology. In the first-pass time-series regression, factor loadings are estimated from multivariate regressions of quarterly returns of test assets on quarterly returns of the factors using the whole-period sample. In the second-pass, returns of test assets are cross-sectionally regressed quarter-by-quarter on factor loading estimates obtained from the first-pass regression. The risk premium estimates are time-series averages of the quarter-by-quarter cross-sectional regression estimates. The test assets consist of 30 portfolios (10 book-to-market portfolios, 10 momentum portfolios, 10 SUE portfolios). FF3 and HXZ indicate the Fama and French (1993) three-factor and the Hou, Xue, and Zhang (2015) q-factor model, respectively. MKT, SMB, and HML are the factors related to market, size, and book-to-market, respectively. IA and ROE are the factors related to investment and ROE, respectively. EGDP is expected real GDP growth rate made at quarter t for quarter t+1. Numbers in parentheses indicate t-statistics and those in brackets indicate t-statistics adjusted by the Shanken (1992) errors-in-variables correction. The sample period is 1981:Q3 to 2015:Q4.

	Model	Risk premium estimates					
		$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\hat{\gamma}_{IA}$	$\hat{\gamma}_{ROE}$	$\hat{\gamma}_{EGDP}$
(1)	CAPM	2.11					
		(2.77)					
		[2.76]					
(2)	FF3	2.07	-0.19	0.41			
		(2.84)	(-0.39)	(0.75)			
		[2.84]	[-0.38]	[0.74]			
(3)	HXZ	1.75	1.36		0.59	2.50	
		(2.39)	(2.80)		(1.35)	(4.03)	
		[2.38]	[2.60]		[1.20]	[3.55]	
(0)	EGDP only						0.59
							(3.30)
							[1.36]
$(1)'$	CAPM+EGDP	1.94					0.36
		(2.55)					(5.69)
		[2.35]					[3.52]
$(2)'$	FF3+EGDP	2.17	0.29	0.92			0.41
		(2.97)	(0.60)	(1.72)			(5.28)
		[2.92]	[0.46]	[1.52]			[2.95]
$(3)'$	HXZ+EGDP	1.86	1.22		0.35	2.19	0.19
		(2.54)	(2.53)		(0.77)	(3.72)	(3.16)
		[2.53]	[2.28]		[0.64]	[3.15]	[2.40]

Table 5. Realized Returns versus Expected Returns

This table presents quarterly excess realized returns ($\bar{R}$), expected returns (E[R]), and pricing error ($\hat{\alpha}$) (in percent) of ten SUE decile portfolios. The expected return of the portfolio is computed as $\mathrm{E}(R_p) = \sum_{k=1}^{K} \hat{\gamma}_k \hat{\beta}_{pk}$, where $\hat{\gamma}_k$ is the risk premium estimate of the k^{th} factor obtained from the Fama and MacBeth (1973) cross-sectional regressions, and $\hat{\beta}_{pk}$ is the factor loading estimate of portfolio p on the k^{th} factor. The pricing error is defined as the difference between excess realized and expected returns ($\hat{\alpha} = \bar{R} - E[R]$). EGDP is expected real GDP growth rate made at quarter t for quarter t+1. 'P10-P1' indicates the zero-investment portfolio by taking a long position in the highest SUE portfolio (P10) and a short position in the lowest SUE portfolio (P1). Numbers in parentheses indicate t-statistics adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4. The sample period is 1981:Q3 to 2015:Q4.

Panel A: EGDP alone

SUE portfolio	Excess raw return ($\bar{R}$)	EGDP			
		E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]/$\bar{R}$
1	1.19	0.57	0.45	(0.20)	0.56
2	1.58	0.98	0.43	(0.26)	0.69
3	1.60	1.66	-0.23	(-0.19)	1.16
4	2.19	2.82	-0.79	(-1.26)	1.39
5	2.54	2.65	-0.28	(-0.37)	1.12
6	3.11	2.38	0.57	(0.81)	0.81
7	3.57	2.16	1.24	(1.58)	0.63
8	3.61	2.52	0.93	(1.54)	0.73
9	3.88	3.41	0.33	(0.48)	0.91
10	4.60	3.23	1.22	(1.84)	0.73
P10-P1	3.41	2.66	0.76	(0.29)	0.78

Panel B: CAPM

SUE portfolio	Excess raw return ($\bar{R}$)	MKT				MKT+EGDP			
		E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]/$\bar{R}$	E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]/$\bar{R}$
1	1.19	2.61	-1.42	(-3.04)	2.19	1.52	-0.50	(-0.73)	1.49
2	1.58	2.49	-0.91	(-2.95)	1.57	1.72	-0.30	(-0.63)	1.21
3	1.60	2.49	-0.90	(-3.00)	1.56	2.12	-0.69	(-1.52)	1.48
4	2.19	2.50	-0.30	(-0.86)	1.14	2.83	-0.80	(-1.85)	1.39
5	2.54	2.48	0.05	(0.16)	0.98	2.72	-0.34	(-0.70)	1.15
6	3.11	2.40	0.71	(2.30)	0.77	2.52	0.44	(1.03)	0.85
7	3.57	2.48	1.08	(4.11)	0.70	2.42	0.98	(2.53)	0.71
8	3.61	2.38	1.23	(4.13)	0.66	2.59	0.86	(2.14)	0.75
9	3.88	2.35	1.54	(5.38)	0.60	3.11	0.62	(1.75)	0.83
10	4.60	2.30	2.30	(7.28)	0.50	2.99	1.46	(3.85)	0.67
P10-P1	3.41	-0.31	3.72	(6.75)	-0.09	1.47	1.96	(2.79)	0.43

SUE portfolio	Excess raw return ($\bar{R}$)	Panel C: Fama and French three-factor model (FF3)							
		FF3				FF3+EGDP			
		E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]$/\bar{R}$	E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]$/\bar{R}$
1	1.19	2.47	-1.28	(-4.42)	2.07	1.16	-0.14	(-0.30)	1.13
2	1.58	2.31	-0.73	(-4.64)	1.46	1.50	-0.08	(-0.23)	1.06
3	1.60	2.27	-0.68	(-3.56)	1.43	1.96	-0.53	(-1.47)	1.37
4	2.19	2.35	-0.15	(-0.68)	1.07	2.75	-0.72	(-2.24)	1.36
5	2.54	2.41	0.12	(0.73)	0.95	2.53	-0.16	(-0.54)	1.07
6	3.11	2.33	0.77	(4.58)	0.75	2.35	0.60	(1.89)	0.80
7	3.57	2.34	1.22	(6.38)	0.66	2.34	1.06	(3.23)	0.69
8	3.61	2.23	1.38	(5.03)	0.62	2.54	0.91	(2.48)	0.74
9	3.88	2.19	1.70	(6.84)	0.56	3.15	0.58	(2.03)	0.84
10	4.60	2.20	2.40	(8.34)	0.48	3.04	1.41	(3.86)	0.68
P10-P1	3.41	-0.27	3.67	(7.23)	-0.08	1.88	1.54	(2.66)	0.55

SUE portfolio	Excess raw return ($\bar{R}$)	Panel D: Hou, Xue, Zhang (2015) q-factor model (HXZ)							
		HXZ				HXZ+EGDP			
		E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]$/\bar{R}$	E[R]	$\hat{\alpha}$	$t(\hat{\alpha})$	E[R]$/\bar{R}$
1	1.19	1.80	-0.78	(-2.31)	1.76	1.41	-0.38	(-1.22)	1.37
2	1.58	1.93	-0.52	(-2.07)	1.37	1.68	-0.27	(-1.07)	1.19
3	1.60	2.49	-1.06	(-4.91)	1.74	2.33	-0.90	(-3.90)	1.63
4	2.19	2.34	-0.31	(-1.32)	1.15	2.53	-0.50	(-2.05)	1.25
5	2.54	2.71	-0.34	(-1.63)	1.14	2.72	-0.35	(-1.56)	1.15
6	3.11	2.89	0.07	(0.34)	0.98	2.79	0.16	(0.76)	0.94
7	3.57	2.76	0.64	(3.15)	0.81	2.69	0.70	(3.14)	0.79
8	3.61	3.30	0.15	(0.75)	0.96	3.24	0.22	(0.95)	0.94
9	3.88	2.98	0.76	(3.92)	0.80	3.26	0.47	(2.24)	0.87
10	4.60	3.30	1.15	(4.92)	0.74	3.46	0.98	(3.62)	0.78
P10-P1	3.41	1.49	1.93	(4.63)	0.44	2.05	1.37	(3.17)	0.60

Table 6 Summary Statistics of Limits-to-Arbitrage Proxy Variables

Panel A of this table presents the average, minimum, first quintile (Q1), median, third quintile (Q3), and maximum of each of the limits-to-arbitrage proxy variables in the pooled sample. Panel B presents the Spearman correlation coefficients among standardized unexpected earnings (SUE), growth rates of sales (GROWTH), and the limits-to-arbitrage proxy variables. Panel C presents time-series averages of the limits-to-arbitrage proxy variables across ten decile SUE portfolios.

Limits-to-arbitrage proxy variables	Abbrev.	Mean	Min	1%	Q1	Median	Q3	99%	Max
					Panel A: Basic statistics				
Arbitrage risk:									
Idiosyncratic volatility	IVOL	0.086	0.000	0.002	0.012	0.026	0.062	0.938	785.048
Transaction costs:									
Bid–ask spread (%)	BidAsk	0.151	0.000	0.025	0.073	0.113	0.176	0.750	45.115
Dollar trading volume ($M)	VOLUME	5,099	0	0.337	31	339	2,548	79,498	1,260,428
Illiquidity	ILLIQ	2.20	0.00	0.00	0.00	0.02	0.24	36.61	7245.07
Recent stock price ($)	PRICE	65.19	0.02	0.50	10.00	21.63	36.63	118.75	226,000
Short sale constraints:									
Institutional ownership ratio	IOR	0.461	0.000	0.000	0.215	0.467	0.689	1.000	1.000
Stock borrowing costs (%)	FEE	1.00	0.25	0.25	0.38	0.38	0.50	14.00	115.00
Information uncertainty:									
Forecast dispersion	DISP	0.20	0.00	0.00	0.02	0.04	0.10	2.53	207.00
Analyst coverage	ACOV	11.35	2.00	2.00	5.00	9.00	16.00	35.00	52.00
Cash flow volatility	CVOL	0.087	0.001	0.007	0.033	0.057	0.098	0.480	37.403

	SUE	GROWTH	IVOL	BidAsk	VOLUME	ILLIQ	PRICE	IOR	FEE	DISP	ACOV	CVOL
						Panel B: Correlation coefficients						
SUE	1											
GROWTH	0.13	1										
IVOL	-0.01	-0.02	1									
BidAsk	-0.05	-0.05	0.21	1								
VOLUME	0.04	0.00	-0.01	-0.02	1							
PRICE	-0.01	-0.04	0.13	0.11	-0.02	1						
ILLIQ	0.00	0.01	0.00	-0.01	0.01	0.00	1					
IOR	0.07	0.04	-0.05	-0.09	0.20	-0.10	-0.01	1				
FEE	-0.04	-0.04	0.11	0.16	-0.03	0.02	-0.01	-0.20	1			
DISP	-0.05	-0.03	0.04	0.04	-0.02	0.02	0.00	-0.04	0.04	1		
ACOV	0.04	0.00	-0.09	-0.08	0.29	-0.08	-0.01	0.16	-0.05	-0.03	1	
CVOL	0.00	0.02	0.02	0.08	-0.03	0.02	-0.07	-0.10	0.13	0.02	-0.08	1

SUE portfolio	IVOL	BidAsk	VOLUME($)	ILLIQ	PRICE	IOR	FEE	DISP	ACOV	CVOL
				Panel C: Time-series averages						
1 (smallest)	0.0811	0.160	4,372,357	1.41	23.17	46.9%	1.07%	0.23	11.19	0.076
2	0.0672	0.148	4,501,431	1.44	25.37	46.8%	0.90%	0.16	11.13	0.077
3	0.0710	0.149	4,192,936	1.56	24.36	46.0%	0.92%	0.16	10.98	0.081
4	0.0735	0.149	4,128,273	1.76	23.66	45.9%	0.88%	0.16	10.97	0.086
5	0.0764	0.149	3,998,297	1.88	23.47	45.7%	0.92%	0.14	11.04	0.090
6	0.0682	0.143	4,559,341	1.59	26.29	47.4%	0.76%	0.12	11.40	0.083
7	0.0647	0.141	4,906,132	1.51	28.09	47.4%	0.83%	0.11	11.56	0.079
8	0.0617	0.140	5,075,564	1.43	29.17	47.4%	0.82%	0.10	11.51	0.077
9	0.0626	0.142	5,017,316	1.39	30.04	47.6%	0.80%	0.10	11.34	0.076
10 (largest)	0.0545	0.139	5,951,059	0.94	36.04	50.7%	0.71%	0.08	12.05	0.071
P10-P1	-0.0266	-0.021	1,578,702	-0.47	12.88	3.9%	-0.36%	-0.15	0.86	-0.004

Table 7 Average Returns of Portfolios Sorted on Idiosyncratic Volatility and SUE

This table presents average quarterly excess returns (in percent) for portfolios constructed in a (5×5) two-way independent sorting on idiosyncratic volatility (IVOL) and standardized unexpected earnings (SUE). The portfolios are held for one month with equal weight and rebalanced every month. Quarterly returns are obtained by compounding monthly returns. Idiosyncratic volatility is measured as the standard deviation of the residuals from regressing individual stock excess returns on the Fama-French three factors using past 35 monthly observations available up to the portfolio formation month (i.e., t-36 to t-1). SUE is calculated as the difference between earnings for the current quarter and those for the preceding four quarters, standardized by the standard deviation of the earnings changes in the prior eight quarters. P5−P1 indicates the zero-investment return by selling short the highest IVOL portfolio and buying long the lowest IVOL portfolio. Numbers in parentheses indicate t-statistics, which are adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4. The sample period is 1981:Q3 to 2015:Q4.

IVOL portfolio	SUE portfolio 1(small)	2	3	4	5(large)	SUE5−SUE1
1(low)	1.67	1.72	2.27	2.77	3.38	1.70
	(2.54)	(3.00)	(3.73)	(4.75)	(5.77)	(4.50)
2	1.68	2.35	2.61	3.05	3.52	1.83
	(2.11)	(3.13)	(3.75)	(4.03)	(5.20)	(5.80)
3	1.66	2.34	2.89	3.27	3.93	2.27
	(2.03)	(2.92)	(3.53)	(4.13)	(4.92)	(5.06)
4	1.14	2.22	2.78	4.10	4.52	3.39
	(1.13)	(2.08)	(2.72)	(4.49)	(4.67)	(6.38)
5(high)	0.02	0.28	2.88	3.97	5.59	5.57
	(0.02)	(0.22)	(1.89)	(2.86)	(3.89)	(6.53)
P5−P1	-1.65	-1.44	0.60	1.20	2.22	**3.87**
	(-1.40)	(-1.51)	(0.47)	(1.03)	(1.84)	**(4.51)**
All Stocks	1.24	1.78	2.69	3.43	4.19	2.95
	(1.41)	(2.13)	(3.15)	(4.20)	(5.14)	(7.86)

Table 8 Differences in Average Raw Return Between the Largest and Smallest SUE Portfolios Across Portfolios Sorted on Limits-to-Arbitrage

This table presents the differences in average excess raw returns between the largest and smallest SUE quintile portfolios (SUE5−SUE1) within each quintile portfolio sorted on the limits-to-arbitrage proxy variable in a (5×5) two-way independent sorting (except for sorting on stock loan fee). When stock loan fee is used in the (2×5) two-way sorting, stocks are assigned every month into one of two (low- and high-fee) portfolios based on the indicative fee. According to the difficulty of limits-to-arbitrage, stocks are sorted on each proxy variable for limits-to-arbitrage into one of five quintile portfolios from P1 (easy to arbitrage) to P5 (difficult to arbitrage). 'P5−P1' indicates the difference in SUE5−SUE1 between the difficult-to-arbitrage and the easy-to-arbitrage portfolios. Numbers in parentheses indicate t-statistis, which are adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4.

Portfolios sorted on the variable	Sorting variable: Limits-to-arbitrage proxy									
	Idiosyn volatil	Bid-ask spread	Dollar trading volume	Illiquid -ity	Recent stock price	Analy disper-sion	Analyst cover-age	Cash flow volatil	Instit owner-ship	Stock loan fee
1	1.70	2.29	0.89	1.17	1.66	0.61	0.95	1.28	1.41	1.04
(easy)	(4.50)	(5.70)	(2.13)	(2.68)	(6.03)	(2.02)	(2.29)	(2.64)	(2.76)	(1.06)
2	1.83	2.23	1.24	1.14	1.69	1.03	0.99	1.46	1.76	
	(5.80)	(5.98)	(2.53)	(2.55)	(5.01)	(2.92)	(1.54)	(2.64)	(3.94)	
3	2.27	2.00	2.93	2.35	2.45	1.11	1.90	2.80	1.83	
	(5.06)	(4.63)	(5.17)	(4.37)	(5.09)	(2.56)	(3.55)	(5.42)	(2.66)	
5	3.39	3.32	3.97	4.05	3.81	2.24	1.59	3.14	3.92	
	(6.38)	(8.11)	(6.56)	(6.90)	(6.63)	(4.28)	(2.27)	(4.21)	(7.04)	
5	5.57	4.95	5.96	5.82	5.75	2.71	3.50	3.98	5.57	4.27
(difficult)	(6.53)	(6.45)	(8.22)	(8.25)	(5.79)	(3.78)	(6.90)	(6.49)	(7.80)	(3.15)
P5−P1	3.87	2.66	5.06	4.65	4.09	2.10	2.56	2.69	4.16	3.23
	(4.51)	(3.49)	(6.45)	(6.08)	(4.29)	(2.84)	(4.61)	(4.37)	(5.02)	(3.26)
All stocks	2.95	2.96	3.00	2.90	3.07	2.90	1.54	1.79	2.53	2.66
	(7.86)	(8.70)	(7.18)	(7.14)	(7.74)	(6.38)	(4.51)	(3.81)	(5.65)	(2.47)

Table 9. Pricing Errors: Realized Returns Versus Expected Returns

This table presents the pricing error ($\hat{\alpha}_p$) (in percent) of 25 (5×5) portfolios constructed in a two-way independent sorting on idiosyncratic volatility (IVOL) and standardized unexpected earnings (SUE). Pricing error ($\hat{\alpha}_p = \bar{R}_p - \mathrm{E}(R_p)$) is defined as the difference between quarterly excess realized ($\bar{R}_p$) and expected ($\mathrm{E}(R_p)$) returns of the portfolio. The expected return of the portfolio is computed as $\mathrm{E}(R_p) = \sum_{k=1}^{K} \hat{\gamma}_k \hat{\beta}_{pk}$, where $\hat{\gamma}_k$ is the risk premium estimate of the k^{th} factor obtained from the Fama and MacBeth (1973) cross-sectional regressions, and $\hat{\beta}_{pk}$ is the factor loading estimate of portfolio p on the k^{th} factor. Numbers in parentheses indicate t-statistics adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4. The sample period is 1981:Q3 to 2015:Q4.

IVOL portfolio	SUE portfolios					SUE5−SUE1
	1(small)	2	3	4	5(large)	
Panel A: Baseline model = Fama and French three-factor model (FF3)						
Using FF3						
1	-0.19	-0.22	0.14	0.38	1.28	1.47
(low)	(-0.79)	(-1.06)	(0.70)	(1.69)	(5.41)	(4.48)
2	-0.99	-0.17	0.07	0.15	0.63	1.62
	(-3.91)	(-0.73)	(0.31)	(0.69)	(3.25)	(5.16)
3	-1.13	-0.69	0.30	-0.08	1.03	2.16
	(-3.72)	(-2.29)	(0.95)	(-0.30)	(3.48)	(4.34)
4	-1.91	-0.89	-0.13	0.80	1.14	3.05
	(-4.37)	(-2.43)	(-0.34)	(2.50)	(3.24)	(4.75)
5	-2.51	-2.18	1.46	1.37	2.84	5.35
(high)	(-3.41)	(-4.50)	(4.12)	(2.98)	(4.82)	(5.03)
P5-P1	-2.31	-1.96	1.32	1.00	1.56	**3.88**
	(-2.94)	(-3.99)	(3.22)	(1.99)	(2.70)	**(3.58)**
All stocks	-1.35	-0.83	0.37	0.52	1.38	2.73
	(-5.00)	(-5.52)	(2.98)	(3.30)	(6.88)	(6.70)
Using FF3 + EGDP factor						
1	-0.41	-0.11	0.03	0.34	0.78	1.18
(low)	(-1.08)	(-0.35)	(0.11)	(1.03)	(2.26)	(2.44)
2	-0.86	-0.04	-0.19	0.05	0.72	1.58
	(-2.33)	(-0.11)	(-0.56)	(0.15)	(2.44)	(3.37)
3	-0.32	-0.02	0.66	-0.02	0.14	0.46
	(-0.85)	(-0.06)	(1.32)	(-0.05)	(0.32)	(0.72)
4	-0.88	-0.65	-0.80	1.36	-0.04	0.84
	(-1.79)	(-1.19)	(-1.49)	(2.47)	(-0.08)	(1.33)
5	0.03	-3.06	0.90	1.33	1.25	1.22
(high)	(0.06)	(-4.65)	(1.98)	(1.92)	(1.66)	(1.88)
P5-P1	0.44	-2.95	0.86	0.99	0.47	**0.03**
	(0.69)	(-4.25)	(1.51)	(1.31)	(0.60)	**(0.04)**
All stocks	-0.49	-0.78	0.12	0.61	0.57	1.06
	(-2.49)	(-3.41)	(0.80)	(2.46)	(2.47)	(4.68)

IVOL portfolio	SUE portfolios 1(small)	2	3	4	5(large)	SUE5−SUE1
Panel B: Baseline model = Hou, Xue, and Zhang (2015) q-factor model (HXZ)						
Using HXZ						
1	-0.36	0.62	0.07	0.55	0.25	0.60
(low)	(-0.99)	(1.69)	(0.23)	(1.66)	(0.68)	(1.26)
2	0.07	-0.42	-0.09	-0.14	0.10	0.03
	(0.20)	(-1.20)	(-0.27)	(-0.44)	(0.35)	(0.07)
3	-0.42	-0.12	-0.47	-0.04	-0.63	-0.21
	(-1.14)	(-0.31)	(-1.05)	(-0.10)	(-1.43)	(-0.36)
4	-0.53	-0.22	0.05	-0.01	0.59	1.12
	(-1.19)	(-0.41)	(0.09)	(-0.03)	(1.28)	(1.73)
5	-0.35	-2.31	-0.14	0.92	2.85	3.19
(high)	(-0.52)	(-3.33)	(-0.39)	(1.37)	(3.29)	(2.60)
P5-P1	0.01	-2.94	-0.21	0.37	2.60	**2.59**
	(0.02)	(-4.38)	(-0.41)	(0.51)	(2.81)	**(1.82)**
All stocks	-0.32	-0.49	-0.11	0.25	0.63	0.95
	(-1.79)	(-2.14)	(-0.91)	(1.18)	(2.52)	(3.36)
Using HXZ + EGDP factor						
1	-0.45	0.41	0.04	0.50	0.29	0.74
(low)	(-1.30)	(1.47)	(0.15)	(1.63)	(0.86)	(1.65)
2	-0.20	-0.29	-0.21	-0.10	0.29	0.49
	(-0.61)	(-0.91)	(-0.66)	(-0.32)	(1.05)	(1.14)
3	-0.27	0.03	-0.08	0.02	-0.60	-0.33
	(-0.78)	(0.08)	(-0.20)	(0.06)	(-1.46)	(-0.59)
4	-0.40	-0.27	-0.33	0.53	0.20	0.61
	(-0.98)	(-0.53)	(-0.65)	(1.27)	(0.48)	(1.07)
5	0.25	-2.69	-0.05	1.08	2.10	1.84
(high)	(0.56)	(-4.49)	(-0.15)	(1.76)	(3.57)	(3.23)
P5-P1	0.70	-3.10	-0.09	0.58	1.81	**1.11**
	(1.21)	(-4.89)	(-0.20)	(0.89)	(2.97)	**(1.44)**
All stocks	-0.21	-0.56	-0.13	0.41	0.46	0.67
	(-1.53)	(-2.71)	(-1.05)	(2.00)	(2.03)	(3.41)

IVOL portfolio	SUE portfolios 1(small)	2	3	4	5(large)	SUE5−SUE1
	Panel C: EGDP alone					
1	-0.90	-0.54	-0.32	0.02	0.37	1.27
(low)	(-1.10)	(-0.82)	(-0.43)	(0.02)	(0.37)	(1.59)
2	-1.19	-0.13	-0.48	-0.14	0.72	1.91
	(-1.82)	(-0.20)	(-0.76)	(-0.19)	(1.17)	(2.62)
3	0.11	0.41	0.79	0.27	0.01	-0.10
	(0.08)	(0.36)	(0.79)	(0.49)	(0.01)	(-0.05)
4	0.12	-0.07	-1.07	2.22	0.08	-0.04
	(0.06)	(-0.05)	(-1.56)	(1.54)	(0.08)	(-0.01)
5	1.94	-2.14	1.13	2.72	1.67	-0.27
(high)	(0.36)	(-0.91)	(0.38)	(0.86)	(0.86)	(-0.06)
P5-P1	2.84	-1.60	1.45	2.70	1.29	**-1.55**
	(0.48)	(-0.57)	(0.41)	(0.69)	(0.49)	**(-0.35)**
All stocks	0.02	-0.49	0.01	1.02	0.57	0.55
	(0.01)	(-0.61)	(0.02)	(1.56)	(1.14)	(0.27)

Table 10. Factor Loading Estimates for Portfolios Sorted on SUE and Idiosyncratic Volatility

This table presents the factor loading estimates on the four factors for 25 (5×5) portfolios formed each month in a two-way independent sorting on idiosyncratic volatility (IVOL) and standardized unexpected earnings (SUE). The factor loadings are estimated from multivariate time-series regressions of quarterly excess returns of each portfolio on the four factors using the full-period sample. The four factors are the Fama and French (1993) factor portfolios (MKT, SMB, and HML), and the expected real GDP growth rate (EGDP). Numbers in parentheses indicate t-statistics, which are adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4. The sample period is 1981:Q3 to 2015:Q4.

IVOL portfolio	SUE portfolios 1(small)	2	3	4	5(large)	SUE5−SUE1
			β_{MKT}			
1 (low)	0.76	0.77	0.77	0.78	0.72	-0.04 (-0.76)
2	1.03	0.99	0.95	0.98	0.92	-0.12 (-2.19)
3	1.05	1.08	1.08	1.03	0.96	-0.08 (-0.95)
4	1.15	1.19	1.23	1.13	1.11	-0.04 (-0.53)
5 (high)	1.33	1.16	1.20	1.21	1.25	-0.08 (-0.77)
P5-P1	0.57	0.39	0.43	0.44	0.53	-0.04
	(3.41)	(2.87)	(2.43)	(2.56)	(3.21)	(-0.38)
All stocks	1.06	1.04	1.05	1.03	0.99	-0.07
	(15.98)	(24.47)	(20.72)	(26.61)	(22.31)	(-1.24)
			β_{SMB}			
1 (low)	0.26	0.20	0.22	0.12	0.23	-0.03 (-0.44)
2	0.39	0.54	0.43	0.35	0.32	-0.07 (-1.01)
3	0.66	0.66	0.74	0.52	0.57	-0.09 (-0.96)
4	1.03	1.03	0.88	0.93	0.85	-0.18 (-1.80)
5 (high)	1.73	1.76	1.76	1.86	1.67	-0.06 (-0.31)
P5-P1	1.47	1.56	1.54	1.75	1.44	-0.03
	(4.05)	(5.55)	(4.35)	(5.44)	(5.42)	(-0.16)
All stocks	0.81	0.84	0.81	0.75	0.73	-0.08
	(12.64)	(14.04)	(11.37)	(9.33)	(10.13)	(-1.17)
			β_{HML}			
1 (low)	0.44	0.44	0.39	0.33	0.33	-0.11 (-1.54)
2	0.56	0.52	0.47	0.42	0.36	-0.19 (-2.28)
3	0.51	0.49	0.59	0.36	0.37	-0.14 (-1.06)
4	0.52	0.56	0.67	0.44	0.38	-0.14 (-1.31)
5 (high)	0.82	0.58	0.92	0.60	0.62	-0.19 (-1.12)
P5-P1	0.38	0.14	0.53	0.27	0.29	-0.08
	(1.53)	(0.73)	(1.80)	(0.99)	(1.29)	(-0.58)
All stocks	0.57	0.52	0.61	0.43	0.41	-0.16
	(7.01)	(6.82)	(7.38)	(4.91)	(4.06)	(-1.66)

			β_{EGDP}			
1 (low)	-0.06	-0.58	0.19	0.70	1.24	1.30 (0.67)
2	-0.88	-1.27	0.07	0.40	0.23	1.11 (1.06)
3	-2.82	-2.23	-2.45	0.23	1.83	4.64 (2.29)
4	-4.05	-2.33	-0.46	-2.26	2.14	6.19 (2.00)
5 (high)	-10.68	-2.26	-5.04	-4.38	-0.32	10.36 (2.86)
P5-P1	-10.62	-1.69	-5.23	-5.08	-1.56	9.06
	(-1.88)	(-0.53)	(-0.96)	(-1.13)	(-0.32)	(2.27)
All stocks	-3.70	-1.73	-1.54	-1.06	1.02	4.72
	(-1.67)	(-1.25)	(-1.10)	(-0.85)	(0.98)	(2.47)

Table 11. Difference in Pricing Error Between the Largest and Smallest SUE Portfolios Across Portfolios Sorted on Limits-to-Arbitrage

This table presents differences in pricing error (in percent) between the largest and smallest SUE quintile portfolios (i.e., $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$) within each quintile portfolio sorted by the proxy variable for limits-to-arbitrage in a (5×5) two-way independent sorting (except for sorting on stock loan fee). When stock loan fee is used in the (2×5) two-way sorting, stocks are assigned every month into one of two (low- and high-fee) portfolios based on the indicative fee. According to the difficulty of limits-to-arbitrage, stocks are sorted on each limits-to-arbitrage proxy variable into one of five quintile portfolios from P1 (easy to arbitrage) to P5 (difficult to arbitrage). The pricing error in each portfolio ($\hat{\alpha}_p = \bar{R}_p - \text{E}(R_p)$) is defined as the difference between the quarterly realized ($\bar{R}_p$) and expected ($\text{E}(R_p)$) returns of the portfolio. The expected return of the portfolio is computed as $\text{E}[R_p] = \sum_{k=1}^{K} \hat{\gamma}_k \hat{\beta}_{pk}$, where $\hat{\gamma}_k$ is the risk premium estimate of the k^{th} factor obtained from the Fama and MacBeth (1973) cross-sectional regressions, and $\hat{\beta}_{pk}$ is the factor loading estimate of portfolio p on the k^{th} factor. The models used to estimate the expected return are the model including the EGDP factor alone (Panel A), the Fama and French (1993) three-factor model (FF3) and FF3 augmenting the EGDP factor (expected real GDP growth rate) (Panel B), and the Hou, Xue, and Zhang (2015) q-factor model (HXZ) and HXZ augmenting the EGDP factor (Panel C). P5−P1 indicates the difference in $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ between P5 and P1. Ave $|\alpha|$ indicates the average of the absolute values of $\hat{\alpha}_{\text{SUE5}} - \hat{\alpha}_{\text{SUE1}}$ of five quintile portfolios sorted on the limits-to-arbitrage proxy variable. Numbers in parentheses indicate t-statistics, which are adjusted by Newey-West heteroscedasticity and autocorrelation consistent standard errors with lag of 4. The sample period is 1981:Q3 to 2015:Q4.

Portfolios sorted on the variable	Sorting variable: Limits-to-arbitrage proxy									
	Idiosyn volatil	Bid-ask spread	Dollar trading volume	Illiqui-dity	Recent stock price	Analy disper-sion	Analyst cover-age	Cash flow volatil	Instit owner-ship	Stock loan fee
	Panel A: Using EGDP alone									
1	1.27	1.84	-0.28	0.18	0.34	1.45	0.09	-0.98	-0.20	-0.88
(easy)	(1.59)	(2.26)	(-0.17)	(0.12)	(0.29)	(1.54)	(0.05)	(-0.47)	(-0.10)	(-0.32)
2	1.91	1.91	-0.66	-1.12	1.48	0.50	-1.54	-0.44	-0.58	
	(2.62)	(2.35)	(-0.31)	(-0.46)	(1.76)	(0.44)	(-0.50)	(-0.22)	(-0.25)	
3	-0.10	-0.40	-0.52	0.29	0.59	-2.06	-0.91	1.54	-0.64	
	(-0.05)	(-0.20)	(-0.16)	(0.12)	(0.35)	(-0.67)	(-0.29)	(0.90)	(-0.22)	
4	-0.04	2.29	-0.55	0.00	0.17	-0.19	-1.69	-1.71	0.50	
	(-0.01)	(1.68)	(-0.13)	(0.00)	(0.06)	(-0.08)	(-0.46)	(-0.42)	(0.15)	
5	-0.27	-0.13	1.53	0.10	-1.20	-1.54	0.24	0.23	0.27	0.50
(difficult)	(-0.06)	(-0.03)	(0.38)	(0.02)	(-0.21)	(-0.38)	(0.07)	(0.06)	(0.06)	(0.11)
P5-P1	-1.55	-1.97	1.81	-0.08	-1.54	-2.98	0.15	1.21	0.48	1.38
	(-0.35)	(-0.53)	(0.58)	(-0.02)	(-0.32)	(-0.64)	(0.06)	(0.55)	(0.14)	(0.57)
All	0.55	1.10	-0.10	-0.11	0.28	-0.13	-0.37	-0.76	-0.27	-0.44
stocks	(0.27)	(0.70)	(-0.03)	(-0.04)	(0.12)	(-0.04)	(-0.19)	(-0.27)	(-0.11)	(-0.25)

Portfolios sorted on the variable	Idiosyn volatil	Bid-ask spread	Dollar trading volume	Illiqui-dity	Recent stock price	Analy disper-sion	Analyst cover-age	Cash flow volatil	Instit owner-ship	Stock loan fee
Panel B: Baseline model = Fama-French (1993) three-factor model (FF3)										
Using FF3										
1	1.47	2.06	0.85	1.09	1.69	1.26	0.85	1.43	0.88	0.43
(easy)	(4.48)	(5.18)	(1.94)	(2.69)	(5.37)	(2.72)	(2.19)	(3.52)	(1.48)	(0.57)
2	1.62	2.56	1.43	1.35	1.72	1.63	1.66	1.26	1.13	
	(5.16)	(6.24)	(3.08)	(2.87)	(4.99)	(3.60)	(3.56)	(2.27)	(1.58)	
3	2.16	1.53	2.89	2.47	2.00	2.53	1.07	1.85	2.56	
	(4.34)	(3.43)	(5.75)	(5.09)	(4.98)	(3.73)	(1.79)	(4.01)	(3.15)	
4	3.05	3.76	4.03	4.52	3.85	3.74	1.36	1.54	2.57	
	(4.75)	(5.87)	(5.52)	(6.91)	(7.20)	(6.28)	(2.03)	(2.47)	(2.66)	
5	5.35	3.86	6.24	5.92	5.84	5.77	1.76	3.69	3.07	4.22
(difficult)	(5.03)	(4.15)	(7.83)	(7.18)	(5.35)	(6.48)	(1.91)	(6.96)	(2.67)	(2.59)
P5-P1	3.88	1.81	5.39	4.83	4.15	4.52	0.90	2.27	2.20	3.79
	(3.58)	(1.85)	(6.39)	(5.64)	(3.94)	(5.10)	(0.89)	(4.06)	(1.83)	(2.35)
All	2.73	2.75	3.09	3.07	3.02	2.99	1.34	1.95	2.04	0.92
stocks	(6.70)	(7.31)	(7.33)	(7.58)	(7.78)	(6.41)	(3.36)	(4.97)	(3.67)	(1.19)
Using FF3 + EGDP										
1	1.18	1.75	-0.27	0.15	0.20	0.97	0.80	-0.19	-0.38	-1.25
(easy)	(2.44)	(3.18)	(-0.33)	(0.20)	(0.29)	(2.28)	(1.55)	(-0.37)	(-0.52)	(-1.32)
2	1.58	1.90	-0.47	-0.60	1.20	1.53	-0.14	0.17	-0.60	
	(3.37)	(3.51)	(-0.56)	(-0.80)	(1.59)	(3.20)	(-0.28)	(0.29)	(-0.88)	
3	0.46	0.27	-0.22	0.73	0.80	0.47	0.39	1.97	0.10	
	(0.72)	(0.45)	(-0.26)	(0.93)	(0.93)	(0.90)	(0.89)	(2.62)	(0.11)	
4	0.84	2.88	-0.17	1.00	0.43	0.95	-0.13	0.15	0.66	
	(1.33)	(3.74)	(-0.19)	(1.29)	(0.46)	(1.69)	(-0.24)	(0.24)	(0.88)	
5	1.22	0.82	2.04	1.32	-0.42	0.99	1.98	1.47	1.12	0.94
(difficult)	(1.88)	(1.44)	(1.84)	(1.36)	(-0.49)	(1.58)	(3.30)	(1.62)	(1.13)	(0.64)
P5-P1	0.03	-0.93	2.31	1.17	-0.61	0.02	1.19	1.66	1.49	2.18
	(0.04)	(-1.04)	(1.45)	(0.87)	(-0.45)	(0.03)	(1.41)	(1.44)	(1.03)	(1.09)
All	1.06	1.53	0.18	0.52	0.44	0.18	0.98	0.58	0.71	-0.51
stocks	(4.68)	(5.91)	(0.63)	(1.83)	(1.25)	(0.79)	(3.98)	(3.90)	(3.29)	(-0.51)

Portfolios sorted on the variable	Idiosyn volatil	Bid-ask spread	Dollar trading volume	Illiqui-dity	Recent stock price	Analy disper-sion	Analyst cover-age	Cash flow volatil	Instit owner-ship	Stock loan fee
				Panel C: Baseline model = Hou-Xue-Zhang q-factor model (2015) (HXZ)						
				Using HXZ						
1	0.60	0.79	-1.02	-0.54	0.08	0.25	-0.03	-0.14	-1.01	-0.91
(easy)	(1.26)	(1.40)	(-2.47)	(-1.08)	(0.23)	(0.69)	(-0.10)	(-0.34)	(-1.81)	(-1.40)
2	0.03	0.36	-0.18	-0.93	0.51	0.34	-0.45	-0.12	0.11	
	(0.07)	(0.63)	(-0.38)	(-1.62)	(1.20)	(0.94)	(-1.24)	(-0.26)	(0.20)	
3	-0.21	0.22	1.41	0.15	0.48	0.62	0.53	0.69	-1.81	
	(-0.36)	(0.35)	(3.01)	(0.33)	(1.02)	(1.15)	(1.51)	(1.32)	(-3.46)	
4	1.12	1.27	1.69	2.60	1.84	0.74	-0.03	1.28	0.76	
	(1.73)	(1.88)	(2.88)	(3.26)	(3.10)	(1.32)	(-0.07)	(1.95)	(1.39)	
5	3.19	2.34	5.72	4.80	5.15	1.68	2.20	1.68	4.03	1.46
(difficult)	(2.60)	(2.08)	(5.86)	(4.30)	(3.55)	(1.99)	(5.26)	(2.17)	(3.56)	(2.35)
P5-P1	2.59	1.55	6.74	5.33	5.07	1.43	2.23	1.82	5.04	2.37
	(1.82)	(1.13)	(5.97)	(4.12)	(3.43)	(1.49)	(3.74)	(1.89)	(3.79)	(2.31)
All	0.95	1.00	1.52	1.22	1.61	0.73	0.44	0.68	0.42	0.15
stocks	(3.36)	(3.19)	(5.30)	(3.69)	(3.78)	(2.38)	(3.70)	(3.54)	(2.01)	(0.30)
				Using HXZ + EGDP						
1	0.74	0.78	-0.58	-0.37	-0.36	0.33	0.05	-0.30	-1.06	-0.76
(easy)	(1.65)	(1.38)	(-0.91)	(-0.63)	(-0.71)	(0.91)	(0.14)	(-0.71)	(-1.85)	(-0.94)
2	0.49	0.34	-0.67	-1.26	0.65	0.34	-0.59	-0.15	-0.56	
	(1.14)	(0.59)	(-0.91)	(-1.88)	(0.99)	(0.94)	(-1.63)	(-0.34)	(-0.98)	
3	-0.33	0.23	-0.29	0.05	0.11	0.42	0.30	0.94	-1.08	
	(-0.59)	(0.36)	(-0.38)	(0.10)	(0.16)	(0.91)	(0.89)	(1.93)	(-2.30)	
4	0.61	1.27	-0.31	0.87	-0.09	0.62	-0.29	0.65	0.18	
	(1.07)	(1.83)	(-0.43)	(1.23)	(-0.12)	(1.28)	(-0.80)	(1.44)	(0.32)	
5	1.84	2.42	2.25	1.72	0.13	1.40	1.92	1.42	1.96	0.59
(difficult)	(3.23)	(3.93)	(2.43)	(2.02)	(0.20)	(2.54)	(4.44)	(1.97)	(2.56)	(0.91)
P5-P1	1.11	1.64	2.83	2.09	0.49	1.07	1.87	1.72	3.01	1.36
	(1.44)	(1.87)	(2.51)	(1.88)	(0.52)	(1.73)	(3.16)	(1.85)	(2.86)	(1.13)
All	0.67	1.01	0.08	0.20	0.09	0.62	0.28	0.51	-0.11	-0.43
stocks	(3.41)	(3.65)	(0.44)	(1.19)	(0.35)	(3.17)	(3.48)	(3.79)	(-0.77)	(-0.83)

Figure 1. Growth Rates, SUE Stocks, and Price-Dividend Ratio

The figure summarizes the relation between growth rates of SUE stocks and the price-dividend ratios.

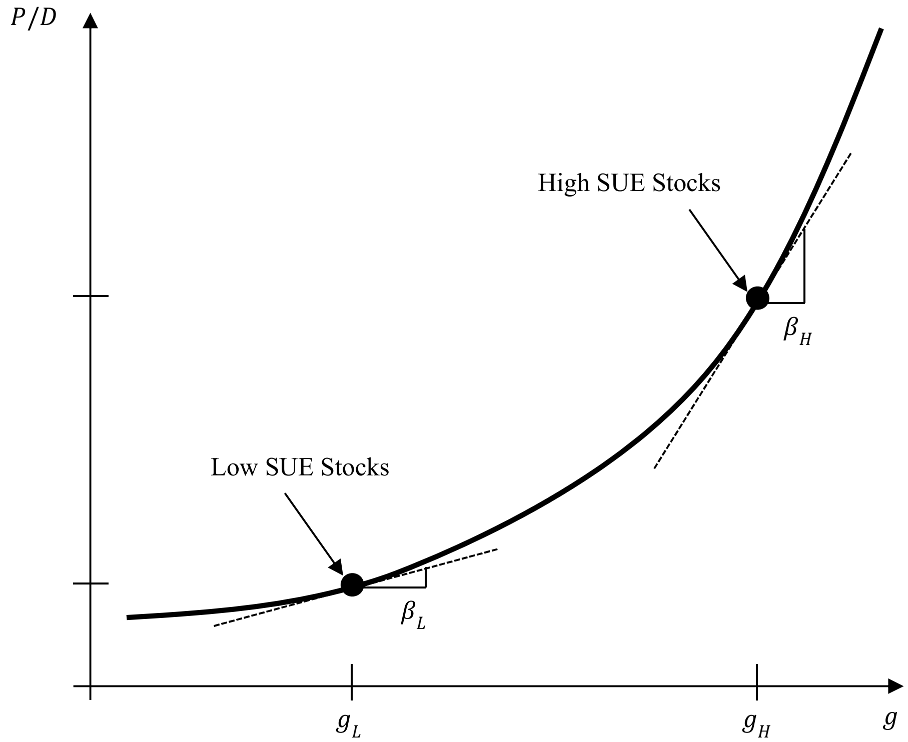
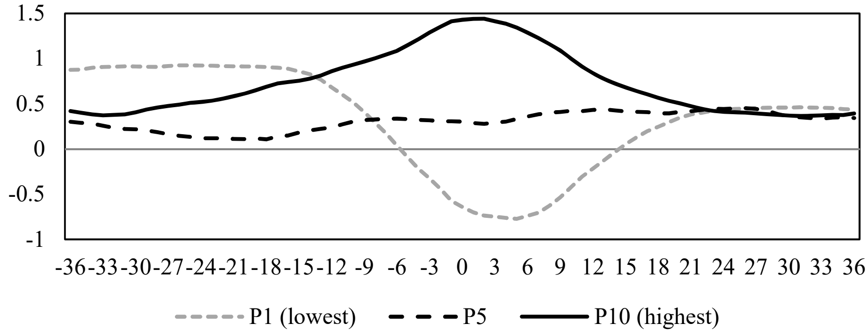


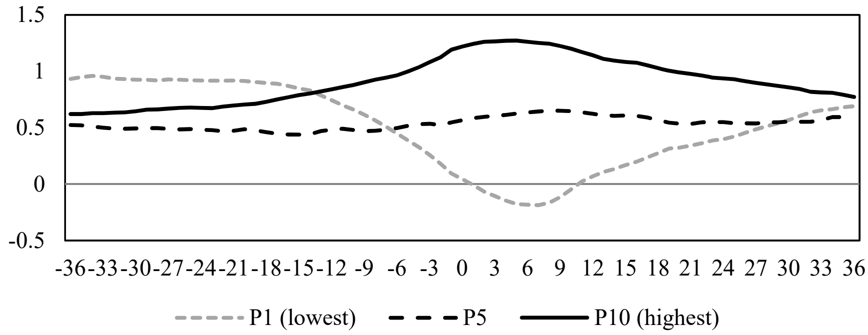
Figure 2. Average Growth Rates

This figure plots average growth rates of investment, dividends, and sales over the period $(-36, +36)$ around the portfolio formation month ($t = 0$) for the lowest (P1), medium (P5), and highest (P10) portfolios sorted on standardized unexpected earnings (SUE). Each month, we calculate portfolio-level growth rates by averaging the growth rates for the firms in the portfolio. We obtain monthly measures of the growth rates of individual firms by dividing their current year growth rates by 12.

Panel A. Investment Growth



Panel B. Dividend growth



Panel C. Sales growth