The Post-Earnings-Announcement Drift and Liquidity: Level, Risk, and Profitability of Trading*

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Abstract

This paper investigates the relation between the post-earnings-announcement drift anomaly and different aspects of liquidity. First, we find that, on average, bad-news firms (low standardized unexpected earnings (SUE)) are less liquid than good-news firms (high SUE), reflecting more information asymmetry and/or uncertainty among bad-news firms. Second, we argue that good-news firms are more sensitive to market-wide liquidity variations than bad-news firms. Finally, we find that when considering transaction costs, the risk-adjusted returns of the standard SUE-based trading strategy disappear after an investment amount of $200 million. Our results highlight the fundamental relation between the post-earnings-announcement drift and liquidity.

JEL classification: G12; G14

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1 Introduction

Beginning with the early work of Ball and Brown (1968), the accounting literature has argued that investors tend to underreact to earnings information; other subsequent works include Jones and Litzenberger (1970), Joy, Litzenberger, and McEnally (1977), Rendleman, Jones, and Latané (1982), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989, 1990), and Ball and Bartov (1996). These studies are traditionally based on the use of a benchmark asset-pricing model to calculate risk-adjusted expected returns. They use the capital asset pricing model (CAPM) or the market model to test the hypotheses. Some more recent works, such as Chordia and Shivakumar (2005) and Collins and Hribar (2000), use the Fama and French (1993) three-factor model. The results all indicate that investors underreact to the information content of earnings, generating return continuation, otherwise known as the post-earnings-announcement drift anomaly.

Recent studies have explored some possible explanations for the post-earnings-announcement drift anomaly. Abarbanell and Bernard (1992) suggest that analysts' underreaction could provide a partial explanation for the anomaly.[1] Others, such as Francis, Lafond, Olsson and Schipper (2004)[2] and Vega (2004), find that the post-earnings-announcement drift is related to information uncertainty. Kim and Kim (2003) construct a fourth risk factor related to unexpected earnings surprises and find that a four-factor model reduces the anomalous returns. Note, however, that these studies are fundamentally different in their approaches. Abarbanell and Bernard (1992) assume that the pricing model is correct and attempt to interpret the resulting underreaction. In contrast, Kim and Kim (2003) use the multifactor approach to find a more suitable asset-pricing model.[3] While the evidence presented in these studies suggests that the anomaly is associated with a risk factor and/or risk characteristic, it is not yet clear what this risk factor and/or characteristic might be and why the anomaly is associated with it.

This paper argues that liquidity is important for understanding the post-earnings announcement

[1] In contrast to the results reported in Abarbanell and Bernard (1992), Keane and Runkle (1998) find that analysts are unbiased and rational, after adjusting for the correlation structure in the data and earnings' skewness.

[2] They use two proxies for information uncertainty: the standard deviation of residuals from a Dechow and Dichev (2002) model, and performance adjusted abnormal accruals from a modified Jones (1991) model. These two proxies are then used in a characteristics-based test. The results suggest that returns increase with the level of information uncertainty. In contrast, the tests performed in this paper are covariation-based tests that use innovations in market-wide liquidity as a risk factor.

[3] Mendenhall (2002) finds that the post-earnings-announcement drift is related to the risk faced by arbitragers (i.e., the arbitrage-risk measure developed by Wurgler and Zhuravskaya (2002)).

drift. In this context, it is important to distinguish between liquidity *level* and liquidity *risk*. The liquidity level of a stock simply measures the amount of liquidity pertaining to that stock, i.e. the average transaction cost that would be required to trade that stock. In contrast, the liquidity risk of a stock measures the sensitivity of the stock's returns to market-wide variations in liquidity (over time). In this paper we study both types of liquidity considerations (level and risk) of the post-earnings-announcement drift anomaly, and we find that both types of considerations are fundamentally associated with it. First, we hypothesize that bad-news firms (low-SUE firms) have more information asymmetry than good-news firms (high-SUE firms). This is because bad-news firms are more likely to abandon projects and engage in restructuring, which creates an uncertain environment. To the extent that information asymmetry is fundamentally associated with liquidity or transaction-cost levels (see, e.g., Kyle (1985)), we expect that good-news firms are more liquid than bad-news firms (liquidity level). Second, we hypothesize that the same firm characteristics that cause more less uncertainty about the firm's value generate a higher sensitivity of the firm's returns to market-wide variations in liquidity (that is liquidity risk). This is because when the market experiences a negative shock to its information environment, investors cannot rely on previous assessments, especially for good-news firms. This hypothesis can explain some of the empirical findings in Sadka (2005), who shows that the performance of SUE portfolios depends on market-wide liquidity insofar as the performance of high-SUE firms is increased during periods of liquid markets, while the opposite holds true for the low-SUE firms. Additionally, we further study the relation of liquidity and other effects that have been shown important for the post-earnings-announcement drift. Bernard and Thomas (1989, 1990) show that the anomaly is stronger for small firms, while Chan, Jegadeesh, and Lakonishok (1996) show that the momentum and post-earnings-announcement drift anomalies are related. Thus, it is important to test whether liquidity risk can also explain part of SUE/size- and SUE/momentum-sorted portfolio returns.

Our empirical results confirm our hypotheses. First, we find that good-news firms are more liquid than bad-news firms, suggesting the latter have more information uncertainty. Second, we find that the sensitivity of SUE-portfolio returns to the risk entailed in market-wide liquidity can account for roughly half of the cross-sectional variation of expected returns on earnings-announcement-based portfolios and for roughly half of the abnormal returns (relative to Fama-French (1993) three factors). We also find that liquidity risk is priced in the conditional sorts, SUE/size and SUE/momentum. This suggests that part of the abnormal returns can be viewed as compensation for liquidity risk. Next, we find that the liquidity risk of SUE-sorted portfolios rather than their level of liquidity is important for explaining the cross-sectional variation of SUE-portfolio returns. From this analysis we conclude that the previously reported anomalous returns could be associated with model misspecification or with hidden transaction costs rather than, or in addition to, investors' underreaction.

Although liquidity level is not priced in the cross-section of SUE portfolios, it may still have implications for this anomaly, because it could determine the profitability of trading the anomaly after considering transaction costs. We follow the methodology of Korajczyk and Sadka (2004) to calculate the amount of investment that would drive profitability to zero. We find that when transaction costs are considered, it is difficult to obtain abnormal profits from the post-earnings-announcement drift. The risk-adjusted returns of the SUE strategy disappear after an investment amount of $200 million[4] is engaged (by a single fund). The liquidity risk of the SUE-trading strategy drops by half as the fund size increases from 0 to 200 million, and remains flat at that rate thereafter. This result suggests that roughly half the liquidity risk of an SUE-trading strategy originates from the time variation of transaction costs required for trading the SUE strategy. The other half could be viewed as the fundamental systematic liquidity risk, or informational risk, of SUE portfolios.

The rest of this paper is organized as follows. In Section 2, we develop the testable hypotheses. Section 3 describes the data used for this study as well as the methodology for forming portfolios and measures of liquidity. The average transaction costs and the information environment of SUE portfolios are discussed in Section 4. Liquidity risk is shown to explain the cross-section of expected returns of SUE portfolios in Section 5. Section 6 study the effects of transaction costs on the profitability of the post-earnings-announcement drift trading strategy. Finally, Section 7 provides the conclusion.

[4] The dollar amounts reported throughout the paper are expressed relative to market capitalization at the end of December 1999. That is, we report the dollar amount at the end of 1999 that constitutes the same fraction of total market capitalization as the initial investment in March 1983.

2 Hypothesis Development

This paper investigates both the liquidity level and the liquidity risk of the post-earnings-announcement drift anomaly. Although these two considerations, liquidity level and liquidity risk, could be studied as separate questions, we believe that they are related, as explained below.

2.1 Liquidity Level

We hypothesize that SUE portfolios differ in their information environment, i.e., their liquidity levels are different. Specifically, we argue that bad-news firms (low SUE) are subject to more information asymmetry than good-news firms (high SUE), which makes the latter more liquid.

The intuition for this argument is borrowed from accounting literature. First we mention Hayn (1995), who suggests that losing firms require investors to gather more information for their valuation analysis than profitable firms. This stems from the higher probability of bankruptcy and liquidation for losing firms. Therefore, when assessing the value of a firm, investors must also collect and interpret information regarding the probability of default and the firm's default and/or liquidation value.[5] Ertimur (2003) provides additional evidence about the information environment of loss firms: loss firms have higher bid-ask spreads than do profitable firms.

We argue that the analysis in Hayn (1995) can be expanded from loss versus profit firms to bad-news versus good-news firms (as suggested by Hayn). Underperforming firms are more likely to either abandon a project or sell some of their assets. Moreover, poor-performance firms are more likely to change/replace their management, governance structure, and business strategy and to engage in restructuring, than are successful firms. These actions would generate more uncertainty and therefore increase the likelihood of information asymmetry trading among the bad-news firms.

In addition to Hayn's argument, the accounting conservatism principle (see, e.g., Basu (1997), Ball (2001), and Ball, Kothari, and Robin (2000)) also relates to bad-news firms' information environment. Accounting rules imply that declines in profitability, losses, and write-offs would be more transitory and larger, on average, than gains. An economic loss should be fully and immediately incorporated in the earnings of the current period (resulting in a skewed earnings distribution). Moreover, Francis, Hanna, and Vincent (1996) show that firms that had previously

[5] For more on the abandonment option, see Berger, Ofek, and Swary (1996).

reported a write-off are more likely to do so in the future. On the other hand, gains are more stationary since they are a result of economic expansions of previous and current periods. Thus, it should be easier to predict earnings for good-news firms. In fact, for good-news firms, unlike for low-SUE firms, simple time-series models are good predictors of earnings. The analysis above suggests that the information environment of bad-news firms, including profitable ones, would be associated with high information costs and high information uncertainty environments.

In addition to conservatism and Hayn's argument, Lang and Lundholm (1993) show that successful firms provide more information than unsuccessful firms.[6] Their analysis also indicates that the information environment of successful firms would be more stable (less information asymmetry and less uncertainty) than that of bad-news firms.

From the above arguments we conclude that high-SUE firms are more likely to have less information uncertainty, on average, than low-SUE firms.

2.2 Liquidity Risk

In addition to the liquidity level discussed above, this paper studies the relation between the post-earnings-announcement drift and liquidity risk—the sensitivity of SUE-portfolio returns to market-wide shocks in liquidity (over time). To the extent that liquidity has the interpretation of the ratio of informed trading to noise trading in market transactions (see Kyle (1985)), we shall interpret fluctuations in market liquidity as shocks to the information environment. The risk generated by the fluctuations in aggregate uncertainty could lead to a premium on liquidity risk.

We hypothesize that sorting portfolios based on firm performance (as measured by SUE) generates portfolios with different information environments in terms of both the level of uncertainty and the sensitivity to market-wide liquidity (informational) shocks. This is because the same firm characteristics that generate high liquidity generate high sensitivity to market-wide shocks in liquidity. In the case of good-news firms, investors can rely on the information provided by these firms and can use a simple time-series model to predict earnings. The stationarity of the earnings process of good-news firms and the success of their business strategy suggest that the historical information provided in the financial statements are very important for predictions. In times of uncertainty,

[6] More specifically, Lang and Lundholm (1993) show a positive relation between analysts' rating of disclosure and firm performance.

however, these time-series predictors of earnings might not be appropriate, forcing investors to re-evaluate their earnings expectations and their expected volatilities. In contrast, investors rely less on the historical information regarding low-SUE firms. The poor performing firms are more likely to engage in restructuring, and they are more likely to change their management and their business strategy. Therefore, investors assign less weight on the available historical information of the poor performers. Since investors rely more heavily on available information for the high-SUE firms, the high-SUE firms are likely to be more sensitive to fluctuations in the market's information environment.

Consider for example a state of uncertainty (e.g., uncertainty about the demand or the effects of new products on the market). In these states, the firms might choose to change their business strategy and actions. But this analysis applies mostly to good-news firms. Poorly performing firms are already likely to change their actions and/or strategy. Thus, we expect the returns of high-SUE firms to be more sensitive to shocks to the market's information environment.

Another possible example is large-scale accounting frauds. When a fraud is discovered, the market overall is more uncertain about the information contained in financial reports. However, the low-SUE firms are less likely to be "boosting" earnings, signaling that their reports are reliable and perhaps even generating an inverse relation between their prices and "fraud" shocks. On the other hand, the stock returns for firms showing the highest unexpected earnings during these periods are expected to be highly sensitive to market perception of the reliability of financial reporting.

If investors are reluctant to hold this type of aggregate information risk, we expect liquidity risk to carry a premium on news-sorted portfolios. In sum, we hypothesize that the better the firm's news (on average), the more sensitive are its returns to market-wide information shocks, thereby carrying more liquidity risk premium.

3 Data

The empirical analysis in this paper utilizes several different types of databases: intraday data for the estimation of liquidity (price impacts), and monthly/quarterly/annual data for the asset-pricing analysis. Our sample period is limited to 1983-2001 because of the availability of intraday data. Intraday data is obtained from two databases. First, the Institute for the Study of Securities

Markets (ISSM) database includes tick-by-tick data for trades and quotes of NYSE- and AMEX-listed firms for the period January 1983 through December 1992 (it also includes NASDAQ-listed stocks for part of the sample). Second, the New York Stock Exchange Trades and Automated Quotes (TAQ) database includes data for NYSE, AMEX, and NASDAQ for the period January 1993 through August 2001. We also use the CRSP monthly stock return database as well as COMPUSTAT annual and quarterly files.

Our universe includes 807,305 observations of 11,079 firms listed on NYSE, AMEX, and NASDAQ, with available returns and earnings information to calculate SUEs as described below. For the analysis of the liquidity levels of firms, we merge this sample with the estimated measures of liquidity (see description below) using intraday data. The measures of liquidity are estimated for NYSE-listed firms alone.

3.1 Formation of Portfolios

To investigate the post-earnings-announcement drift, we sort stocks into portfolios according to their standardized unexpected earnings (SUE). This measure is based on a model of seasonal random walk with a drift. More specifically, SUE for stock i in month t is defined as

$$SUE_{i,t} = \frac{E_{i,q} - E_{i,q-4} - c_{i,t}}{\sigma_{i,t}} \tag{1}$$

where $E_{i,q}$ is the most recent quarterly earnings announced as of month t for stock i (not including announcements in month t), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. This measure has been used by Chan, Jegadeesh, and Lakonishok (1996) except that they do not include a drift term, i.e. they assume $c_{i,t} = 0$. The drift term is added here to comply with Bernard and Thomas (1989, 1990) and Ball and Bartov (1996), who use a seasonal random walk with a trend. SUE-based portfolios without a drift term are also analyzed in this paper (see section 5.3). The portfolios are rebalanced every month while holding each stock up to four months after the announcement date.

Table 1 reports the performance of 20 SUE-sorted portfolios. The results confirm the anomaly documented in previous studies insofar as returns increase with SUE. The return spread of highest minus lowest SUE group is 1.32% per month (with a t-statistic of 4.15). Risk-adjusted returns are also computed using the CAPM and Fama-French (1993) three-factor model. Consistent with previous findings, the anomalous pattern in portfolio returns remains even after adjusting for these types of risks. The risk-adjusted return spread is slightly larger: 1.74% per month for the CAPM and 1.72% using the Fama-French three factors.

3.2 The Measure of Liquidity

The measure of liquidity used in this paper relies on microstructure models of price impact of trades. The market-microstructure literature documents that actual trading induces both permanent and transitory effects on prices.[7] The permanent price impact is associated with information asymmetry and the amount of noise trading (see Kyle (1985)), and the temporary price impact is often considered driven by inventory costs of the market maker. In addition, each component may be further decomposed into fixed and variable costs as a function of the number of shares traded (corresponding to the intercept and slope of a price-impact function). For example, the bid-ask spread can be viewed as the fixed (and transitory) component of a more general price-impact function. Since we are interested in measuring information uncertainty, we focus on the permanent slope of the price-impact function, which has the economic interpretation of Lambda in the Kyle (1985) model, i.e., the ratio of informed- versus noise-trading activity.

The empirical model that decomposes price impact into its different components is shown in Glosten and Harris (1988). Sadka (2005) estimates the latter model for NYSE-listed firms over the period 1983-2001, per firm per month.[8] Since this paper focuses on the uncertainty component of liquidity, we use the variable/permanent component of price impact estimated in Sadka (2005) to proxy for the information environment of different stocks (see Appendix for further discussion and details of estimation). Henceforth, we shall simply refer to this measure as price impact. In this paper we argue that good-news firms have less information uncertainty than bad-news firms, which we test below by comparing their price impacts.

[7] Theoretical studies include Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Admati and Pfleiderer (1988), and Easley and O'Hara (1987, 1992), while empirical evidence is provided in Glosten and Harris (1988), Hasbrouck (1991a,b), Keim and Madhavan (1996), Kraus and Stoll (1972), and Madhavan and Smidt (1991), and others.

[8] For summary statistics see Table 1 in Sadka (2005).

3.3 A Liquidity Risk Factor

To proxy for shocks to the economy-wide information environment, we use the liquidity factor proposed by Sadka (2005). This factor is constructed using the measure of price impact discussed above. Market-wide liquidity in a particular month is calculated as the cross-sectional average of price impact that month. As mentioned in Sadka (2005), three additional adjustments are implemented to the time series of market liquidity. First, an ARMA model is used to proxy for shocks to aggregate liquidity. Second, since price impact measures illiquidity rather than liquidity, a minus sign is added so that positive changes to aggregate price impact could be interpreted as the market becoming more liquid. Third, for pure expositional purposes the measure is scaled by an order of 5. For the time series of this factor see Figure A1 (this figure is borrowed from Figure 4 in Sadka (2005)). The average innovation is zero, with a standard deviation of 5.75×10^{-3}; the minimum is -0.0354 and the maximum is 0.0160. This factor has low correlations with Fama-French (1993) factors: MKT_t 0.15, SMB_t 0.07, and HML_t -0.05.[9] In this paper we argue that investors' preferences of holding risk vary with market-wide uncertainty and it generates, in part, the post-earnings-announcement drift.

4 Liquidity Level and Information Environment

4.1 Empirical Evidence

In Section 2.1, we hypothesize that bad-news firms would be less liquid than good-news firms. To test this hypothesis, Figure 1 plots the time-series means of the average price impact of the stocks in each of the ten SUE-sorted portfolios. The results are consistent with the hypothesis that bad-news firms are less liquid: The informational transaction costs are higher for bad-news firms; the average cost is declining consistently as we move toward the good-news portfolios. Notice that the firms used in the sample are relatively more liquid than the average in the market. This is consistent with the firm-selection process of our sample, as firms are required to have sufficient information to form their SUE variable.

To provide additional insight, each portfolio's turnover, measured as the monthly volume scaled

[9] We thank Ken French for providing these risk factors on his Web site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

by the number of shares outstanding, is also plotted. In contrast to the price-impact results, both high- and low-SUE portfolios experience high turnover. We believe that the reason why turnover and price impact produce different results is that turnover does not take into account who initiated the trade and therefore is not a good proxy for imbalance in the order flow. The results here suggest that, on average, both high- and low-SUE firms are heavily traded, but their liquidity characteristics differ—trades of the low-SUE firms are associated with more informational trading activity, while high-SUE firms attract a higher fraction of noise traders.

Two comments are noteworthy. First, the results regarding the liquidity level of SUE portfolios do not provide a complete explanation for the *existence* of the anomaly. To the extent that liquidity level carries a premium,[10] one would expect low-liquidity firms to have higher expected returns than high-liquidity firms. However, our results indicate the opposite phenomenon: The high-SUE firms are more liquid than low-SUE firms, yet high-SUE firms outperform low-SUE firms. Second, the liquidity level of SUE portfolios can provide a partial explanation for the *persistence* of the anomaly, specifically, the low-SUE firms. The relatively low-liquidity level of low-SUE firms suggests that an attempt to arbitrage this phenomenon may be too costly.[11] Reed (2002) finds similar results while testing the model of Diamond and Verrecchia (1987), who argue that short-sales constraints reduce the adjustment speed of prices to private information, especially for bad news. Therefore, limits to arbitrage may be a partial explanation for why low-SUE firms continue to underperform even though this phenomenon has been known for many years. We re-visit this point Section 6.

5 Liquidity Risk and the Cross-Section of Expected Returns

This section tests the pricing of the cross-section of expected return of SUE-sorted portfolios using the Fama and French (1993) three-factor model and the non-traded liquidity factor defined in Section 3.3. As discussed above, we expect the post-earnings-announcement drift trading strategy to be sensitive to market liquidity. We emphasize that the liquidity factor used here is non-traded, and therefore, the hypothesis is tested using two appropriate methods: the beta-pricing approach

[10] Studies such as Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Easley, Hvidkjaer, and O'Hara (2002) argue that low-liquidity stocks outperform high-liquidity stocks.

[11] This type of argument is related to a recently emerging line of literature that studies post-transaction costs profitability of trading strategies. See, e.g., Knez and Ready (1996), Mitchell and Pulvino (2001), Chen, Stanzl, and Watanabe (2002), Korajczyk and Sadka (2004), and Lesmond, Schill, and Zhou (2004).

using cross-sectional regressions, and the stochastic discount factor approach using the General Methods of Moments. Also, since the factor is not a traded portfolio, one cannot use it directly to calculate the cumulative risk-adjusted abnormal returns (also known as CAR) as used by the previous studies (e.g., Bernard and Thomas (1989) and Ball and Bartov (1996)). Nevertheless, we will provide below some quantification of the SUE-portfolios premiums associated with liquidity risk. The test methodologies are described in Sections 5.1 and 5.2 using 20 SUE-sorted portfolios, and they are then applied to the other appropriate portfolio sorts in Section 5.3.[12]

5.1 Cross-Sectional Regressions

5.1.1 General Approach and Results

The 20 SUE-sorted portfolios described in Section 3.1 are used to test linear asset-pricing models of the form

$$E\left[R_i\right] = \gamma_0 + \gamma' \beta_i \tag{2}$$

where $E\left[R_i\right]$ denotes the expected return of portfolio i (excess of risk-free rate), β_i are factor loadings and γ is a vector of premiums. Since loadings are unobservable, they are pre-estimated through a multiple time-series regression

$$R_{i,t} = \alpha_i + \beta_i' f_t + \varepsilon_{i,t} \tag{3}$$

where f_t is a vector of factors (either traded or non-traded).

The model in Equation (2) may be consistently estimated using the cross-sectional regression method proposed by Black, Jensen, and Scholes (1972), and Fama and MacBeth (1973). First, regression (3) is estimated using the full sample. Then, the model in (2) is estimated every month resulting in a time series $\widehat{\gamma}_t$. The time-series mean and standard error are finally calculated. In addition, since (2) is estimated using sample estimates of β_i' rather than the true values, (2) is subject to the "errors-in-variables" problem. Thus, we follow Shanken (1992) to correct standard

[12] This section comprehensively extends the analysis in Sadka (2005). First, while Sadka includes only NYSE stocks, our sample includes all available stocks, including NYSE, NASDAQ, and AMEX firms. If the liquidity factor, estimated using a sample of NYSE stocks, is a risk factor, it should price the anomaly when including all stocks as well. Second, in addition to SUE-sorted portfolios, this section includes additional sorts that have been shown to be important for the post-earnings-announcement drift. Bernard and Thomas (1989, 1990) show that the anomaly is stronger for small firms. Chan, Jegadeesh, and Lakonishok (1996) show that the momentum and post-earnings-announcement drift anomalies are related. In this section, we test whether the liquidity factor is pricing SUE/size- and SUE/momentum-based portfolios.

errors for this bias. Last, the adjusted R^2 of the cross-sectional regression is calculated as an intuitive measure that expresses the fraction of the cross-sectional variation of average excess returns captured by the model.

We consider four different factor specifications. First, the CAPM is re-examined using MKT as a single factor. Then, the Fama and French (1993) factors, SMB and HML, are added, and finally the non-traded liquidity factor, LIQ, is added separately to both models.

Before introducing the results of the cross-sectional regressions, we provide some statistical intuition by plotting the liquidity loadings of the SUE portfolios in Figure 3. For each portfolio, this figure shows the risk-adjusted returns, α_i, of time-series regression (3) of returns (excess of risk-free rate) on the three Fama-French factors (these values are also presented in Table 1) and the liquidity loadings for SUE-sorted portfolios. The latter is computed as the coefficient of LIQ in the regression (3) with the three Fama-French factors and the non-traded liquidity factor LIQ. The figure shows that the loading on the liquidity factor is negative for the low-SUE portfolios and higher for the high-SUE portfolios. It seems that adjusted returns are increasing with liquidity loading, i.e., returns seem to be correlated with liquidity risk. The cross-sectional tests below indicate that the observed pattern in Figure 3 is statistically significant.

The results of the cross-sectional regressions are reported in Table 2 and illustrated in Figure 3. Table 2.A shows that, in both cases wherein the liquidity factor is added to CAPM and Fama-French three-factor model, liquidity risk is important in pricing SUE portfolios. The corrected t-statistics of the liquidity premiums are 2.81 and 2.01, respectively. In addition, when adding the liquidity-risk factor, the adjusted R^2 increases from 23% and 18% to 67% and 71% for the CAPM and the Fama-French three-factor model, respectively. The results are similar when restricting the sample to NYSE-listed firms alone (see Table 2.B). The corrected t-statistics of the liquidity premiums are 2.51 and 2.35, respectively. When adding the liquidity-risk factor, the adjusted R^2 increases from 23% and 45% to 68% and 71% for the CAPM and the Fama-French three-factor model, respectively. These results support our hypothesis that the liquidity factor is important in explaining expected returns to SUE-sorted portfolios. In other words, the previously anomalous reported returns to SUE-sorted portfolios can be viewed in part as a compensation for liquidity risk.

Note that many studies argue that investors fail to fully understand and incorporate the time-series properties of earnings and the information content of earnings announcements (e.g., Bernard and Thomas (1990) and Ball and Bartov (1996)). As indicated earlier in this paper, these analyses fundamentally rely on the specification of the underlying pricing model. Our results indicate a possibility of model misspecification in earlier studies since the liquidity factor yields a positive and statistically significant premium.[13] Therefore this result suggests that investors may have factored liquidity risk in their risk modeling of SUE portfolios.

5.1.2 The Estimated Premiums

The results of the cross-sectional regressions enable us to draw inferences about liquidity risk through the statistical significance of the risk premiums, without discussing the magnitude of the estimates themselves. Depending on the asset-pricing model used, the market premium estimate varies between 3.83% and 5.67% per month, while the liquidity premium estimate varies between 2.82% and 1.07% per month. It is important to note that the premiums are measured as return per unit of risk loading. Therefore, it is difficult to interpret the magnitude of the premiums, especially in the case of a non-traded factor such as LIQ. We further elaborate this issue next.

5.1.3 How Much of the SUE-Return Spread is Explained by Liquidity Risk?

The cross-sectional tests study whether liquidity risk generates, in part, the post-earnings-announcement drift. However, these tests do not provide insight on the magnitude of the risk-adjusted returns. To show the effects of liquidity risk on the SUE-return spread of 20 portfolios, we calculate for each factor model the unexplained return spread $E\left[R_{20}-R_1\right]-\gamma'\left[\beta_{20}-\beta_1\right]$, where β_i and γ are the factor loadings and risk premiums, respectively, calculated for each model (see estimation in Table 2). The results are 1.75%, 1.50%, 0.84%, and 0.82% for the asset-pricing models CAPM, Fama-French three factor model, CAPM and liquidity, and Fama-French three factors and liquidity, respectively. We therefore conclude that liquidity risk can explain roughly half of the SUE-return spread.

Last, it is important to note that, although the evidence supports the relation between the post-earnings-announcement drift anomaly and liquidity risk, the risk models tested here do not

[13] For more evidence of the pricing of liquidity risk in different contexts see Pástor and Stambaugh (2003) and Acharya and Pedersen (2005).

fully explain the expected returns. This may occur for a number of reasons. First, it is possible that the model is still misspecified. Second, the estimated liquidity measure used in this paper may not be the "true" factor, and some measurement errors affect our results. Third, it is possible that the post-earnings-announcement drift truly represents investors' underreaction to earnings information over and beyond the premium attributed to liquidity risk. Last, some of the abnormal profits may be associated with high transaction costs, which would imply possible limits to arbitrage (see Section 6).

5.2 The Stochastic Discount Factor Approach

The stochastic discount factor approach is another method used to test different asset-pricing models. This method is added to the analysis for robustness purposes. The advantage of this approach is that it provides a distribution theory for the weighted pricing errors, which enables one to test the validity of a pricing model.

It is well known that as long as the law of one price holds in the economy, there exists some random variable, a stochastic discount factor d_t, which prices all assets; i.e., for any (excess) return $R_{i,t}$, the following is satisfied

$$E\left[R_{i,t}d_t\right] = 0 \tag{4}$$

If the factor-based asset-pricing models explain returns, the stochastic discount factor can be expressed as[14]

$$d_t\left(\delta\right) = 1 - \delta' f_t \tag{5}$$

The universe contains 20 portfolios, which translates to 20 moment conditions over 222 months. The asset-pricing models tested have four factors at most. Therefore we are left with an over-identified system. The moment conditions are constructed as follows. Define R_t as the 20×1 vector of portfolio returns at time t. Define the sample analogs

$$\begin{aligned} R_T &= \frac{1}{T}\sum_{t=1}^{T} R_t \\ D_T &= \frac{1}{T}\sum_{t=1}^{T} R_t f_t' \end{aligned} \tag{6}$$

[14] Since excess returns of the portfolios are used, the constant term is normalized to a value of 1.

The sample analog of the moment conditions is given by

$$w_T = R_T - D_T\delta \tag{7}$$

For a given weighting matrix Ω the estimates of δ are those that minimize $J(\delta)$ such that

$$J(\delta) = w_T'\Omega^{-1}w_T \tag{8}$$

Since the system is linear the solution is analytically solved as

$$\delta_T = -\left(D_T'\Omega^{-1}D_T\right)^{-1} D_T'\Omega^{-1}R_T \tag{9}$$

For the empirical analysis, two empirical tests are conducted. First, following Hansen (1982), the optimal weighting matrix is used. (This is achieved by first using the identity matrix and then conducting several iterations until no improvement is achieved.) In this case, δ_T is a consistent estimator of δ, and it has an asymptotically normal distribution. Hansen (1982) shows that when Ω^{-1} is optimal, then $T \times J(\delta_T)$ is asymptotically distributed χ^2 with N-K degrees of freedom (N is the number of moment conditions, i.e., the number of portfolios, and K is the dimension of δ). This is the basis for the over-identifying restriction tests, which are used to test the different asset-pricing models here.

Second, notice that the optimal weighting matrix depends on the asset-pricing model tested. Hansen and Jagannathan (1997) develop a method that helps to evaluate the different asset-pricing models on a common scale. They propose a common weighting matrix for all models

$$\Omega = E\left[R_t R_t'\right] \tag{10}$$

They show that the resulting $J(\delta)$ has the interpretation of the least-square distance between the given estimated stochastic discount factor and the nearest point to it in the set of all discount factors that price assets correctly. However, since Ω^{-1} may not be optimal, $T \times J(\delta_T)$ will not generally converge to a χ^2 distribution. Therefore, to calculate the p-values, we follow the correction presented in Jagannathan and Wang (1996). To adjust for serial correlation of the moment conditions, a Bartlett kernel is applied, both when using the Hansen (1982) optimal matrix and the Hansen and Jagannathan (1997) sample moment matrix (henceforth referred to as the HJ matrix).

The empirical results are presented in Table 3. Both Hansen and HJ methods reject the CAPM with a p-value of about zero. The Fama-French three-factor model is rejected using both the HJ matrix (p-value of 0%) and the optimal matrix (p-value of 0%). When the liquidity factor is added to the CAPM, the model remains rejected by both methods at the 5% significance level. However, when liquidity risk is added to the Fama-French three factors, the model cannot be rejected by the HJ model. The p-values are 0% for the optimal matrix and 11.87% for the HJ matrix. In addition, it is important to note that in all cases the liquidity factor is statistically significant, which indicates that liquidity risk helps to price SUE-sorted portfolios. These results re-affirm the conclusions of the cross-sectional-regression tests regarding the significance of the liquidity factor in explaining the cross-sectional variation of returns.

5.3 Further Examinations

In this section, we examine additional SUE-based sorts and their relation to liquidity risk. For example, price momentum and market capitalization have been shown to be related to the post-earnings-announcement drift anomaly. In what follows, we test whether the above results regarding liquidity risk are robust even after controlling for different economic variables. For brevity, we only report the results of cross-sectional regressions below. The results using the stochastic discount factor approach further strengthen our conclusions.

5.3.1 SUE-Sorted Portfolios Without a Drift Term

We begin with the robustness test for the definition of the variable SUE. Different studies use different definitions of SUE to form post-earnings-announcement portfolios. For example, Chan, Jegadeesh, and Lakonishok (1996) and Chordia and Shivakumar (2005) use the seasonal random walk model (without a drift term) to form SUE portfolios. In contrast, Bernard and Thomas (1990) and Ball and Bartov (1996) form portfolios based on a seasonal random walk with a drift model, which is similar to the SUE definition used in this paper. In this subsection, we examine the sensitivity of our results to the different definitions of SUE.

Ball and Watts (1972) and others investigate the time-series properties of earnings, and they show that earnings follow a random walk with a trend. To test whether investors fully incorporate the information contained in earnings, Bernard and Thomas (1989) use SUE with a drift. We hypothesize that if (a) prices reflect the information about the time-series properties of earnings, and (b) the four-factor asset-pricing model (which includes the Fama-French three factors and the liquidity factor) is correct and prices SUE-sorted portfolios, then the four-factor model should also perform well using SUE without a drift. The results presented in Table 5.A are consistent with this hypothesis. These results are very similar to the results reported in Table 2.A. Yet, the liquidity premiums estimated using SUE with a drift seem larger (and more statistically significant) than those estimated using SUE without a drift. Our results are consistent with the hypothesis that investors fully understand the information about the time-series properties of earnings.

5.3.2 Earnings Momentum and Price Momentum

In tangent to earnings momentum (i.e., post-earnings-announcement drift), the financial literature has documented price momentum (see Jegadeesh (1990) and Jegadeesh and Titman (1993, 2001)). This anomaly generally describes the empirical observation that firms that have outperformed in the past tend to continue to outperform in the future. Momentum strategies exhibit high abnormal returns that cannot be explained by standard measures of risk to date (see, e.g., Fama and French (1996) and Grundy and Martin (2001)). Therefore, behavioral explanations based on some type of bounded rationality of investors, such as overconfidence or underreaction to information, have been developed to explain momentum continuation (see, e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)).

The fact that both price and earnings momentum are, by definition, momentum strategies, raises the question of whether they are both manifestations of the same underlying economic variable.[15] Chan, Jegadeesh, and Lakonishok (1996) show that these two anomalies are not the same since each exhibits abnormal returns, even after controlling for the other. This paper sheds light on the commonality between price and earnings momentum. Both anomalies are informational drifts. High (low) performance measures as either earnings or returns result in continuation of returns and both anomalies are associated with liquidity risk.

To test how important is liquidity risk in explaining the SUE and momentum investment strategies, we conduct a simple dependent double sort of SUE and momentum as follows. Every month, stocks are sorted into five groups according to SUE. Then, the stocks within each group are again sorted into four groups according to their past 12-month cumulative returns, excluding the last month. The last month is excluded because of short-horizon microstructure effects, such as bid-ask

[15] Jackson and Johnson (2004) also find that momentum and post-event drift anomalies are manifestations of the same underlying mechanism. However, they do not examine earnings announcements.

bounce (see Jegadeesh and Titman (1993), Fama and French (1996), and Carhart (1997)). The stocks in each of the 20 groups are combined to form an equal-weighted portfolio, and the portfolios are rebalanced every month. This procedure results in 5x4 SUE/momentum portfolios.

Table 4.A reports summary statistics for the SUE/momentum-sorted portfolios. The table reports the equal-weighted average returns, the time-series mean of the average market capitalization of firms in a portfolio (relative to the market average), SUE, and momentum. Notice that, consistent with past studies, both the SUE spread and price momentum spread are exhibited in the data. Although the 5x4 sort illustrates that these anomalies are related and that their returns are highly correlated, the anomalies are not exactly the same phenomenon. The SUE/momentum sort shows that in each momentum sort, there is a significant dispersion in SUE, and the distributions of SUE conditional on momentum overlap each other. These results are consistent with the above-mentioned study of Chan, Jegadeesh, and Lakonishok (1996).

With respect to liquidity risk, Table 5.B shows that liquidity risk remains an important determinant of SUE portfolios. The liquidity premiums appear smaller than those reported in Table 2.A using 20 SUE-sorted portfolios, yet they remain statistically significant. Notice that HML receives a negative premium when the liquidity factor is excluded, which is consistent with the negative correlation of value and momentum (see Asness (1997)). Also, the regression adjusted R^2 increases consistently when adding the liquidity risk factor to CAPM and to the Fama-French three-factor model.

5.3.3 The Post-Earnings-Announcement Drift and Size

Rendleman, Jones, and Latané (1987) and Bernard and Thomas (1989) document that the post-earnings-announcement drift is more pronounced within SUE deciles among relatively small market-capitalization firms. Similar to the analysis above for price and earnings momentum, we investigate the relation between size and earnings momentum using dependent double sorts of size and SUE. This procedure results in 5x4 SUE/size portfolios, with the interpretation of different size portfolios controlling for SUE (e.g., Bernard and Thomas (1989)). Summary statistics are reported in Table 4.B. They confirm the previously reported results in the literature: The SUE-return spread among the small-size group is larger than the large-size group. Notice that the distribution of the variable SUE is similar among different size groups, which indicates that size and SUE are not highly correlated. The results of the cross-sectional regressions are reported in Table 5.C. Liquidity risk seems to be priced.

5.4 The Drift Around Subsequent Earnings Announcements

Bernard and Thomas (1989, 1990) show that the post-earnings-announcement drift is most pronounced in the short period prior to subsequent earnings announcements. To test the implications and the relation between these findings and liquidity, estimates of liquidity are needed for these trading days.[16] In this paper, only monthly liquidity measures are available to us, which prevents the extension of the analysis to explore the "short-window" anomaly. This issue should be the subject of future research.

6 Liquidity Level, Liquidity Risk, and the Profitability of Trading

6.1 Why Liquidity Risk and Not Liquidity Level?

As noted in Section 4.1, the liquidity level is less likely to explain the anomaly. In fact, the liquidity level explanation would predict return reversals after earnings announcements because low-SUE portfolios are less liquid and should therefore earn higher expected returns. But we observe the opposite in that low-SUE firms exhibit lower average returns. This section provides evidence of the hypothesis that liquidity risk, rather than liquidity level, prices the post-earnings-announcement drift anomaly.

In Table 6 we include both liquidity level and liquidity loadings (calculated using (3)) in the Fama-MacBeth regressions. The sample is now restricted to NYSE-listed firms with available liquidity measures. The results are consistent with the hypothesis that systematic risk is priced, while liquidity level is not. Liquidity level has a negative premium in all model specifications, but the premium is statistically significant only when liquidity loadings and the Fama-French factors loadings are excluded. In contrast, the liquidity premium is positive and statistically significant in all models, i.e., liquidity risk is priced and liquidity level is not, in the context of SUE portfolios. The t-statistic for the liquidity premium varies from 3.45 to 5.03.

Figure 4 provides additional insight for this result. Stocks in the cross-section are sorted every

[16] See, e.g., Lee, Mucklow, and Ready (1993), and Affleck-Graves, Callahan, and Chipalkatti (2002).

month into ten liquidity categories using the measure of price impact (1–highest liquidity ranking, 10–lowest liquidity ranking). The average liquidity ranking of a portfolio is calculated as the average ranking of its constituent assets. Figure 4 plots the time-series average liquidity ranking of ten portfolios sorted based on SUE. This figure is similar to Figure 1, except that it highlights the relative position of the liquidity level of each SUE portfolio among the entire distribution of liquidity in the cross section. The results indicate that the spread in liquidity among the SUE portfolios is much lower than the market-wide cross-sectional spread in liquidity. There is a clear downward trend in liquidity as we move from the low-SUE portfolio to the high-SUE portfolio. Moreover, the difference between the liquidity levels of the high- and the low-SUE portfolios is statistically significant (shown by the 95% confidence intervals on the graph). Yet, the average liquidity ranking of the ten SUE portfolios varies between 4.43 and 4.20. In other words, the liquidity-level aspect of the anomaly is not particularly strong; it seems statistically yet not economically significant. Thus, even if liquidity level carries a premium (e.g., Easley, Hvidjaker, and O'Hara (2002), and Amihud and Mendelson (1986)), we do not expect it to significantly affect the post-earnings-announcement drift. The results suggest that the firm characteristics that generate a spread in both liquidity level and liquidity risk, generate an economically significant spread only for the latter.

Although we conclude that liquidity level does not price SUE portfolios, liquidity level might still be important in understanding the post-earnings-announcement drift anomaly. This is because in addition to proxying for information asymmetry, liquidity level is also a measure of transaction costs.

6.2 Is the SUE-Return Spread Robust to Transaction Costs?

In this section we investigate the effect of trading costs on the profitability of the SUE trading strategy using the framework developed in Korajczyk and Sadka (2004). In general, transaction costs occur because each month the SUE portfolio is rebalanced. Rebalancing happens because some firms are added and some firms are dropped. Furthermore, the weight of each firm in the portfolio changes every month and one needs to adjust the portfolio weights back to equal-weights (in the case of equally weighted strategies such as the SUE strategy investigated in the post-earnings-announcement drift literature). Korajczyk and Sadka (2004) incorporate transaction costs into a trading strategy as follows. For a particular initial investment amount in the beginning of the sample, they calculate the net returns of a strategy assuming it is maintained as a self-financing strategy, that is, the fund does not experience additional external investment throughout the sample period. Under the assumption that transaction costs are perfectly forecastable through an empirical characteristics model (the one presented in Breen, Hodrick, and Korajczyk (2002)), and under the portfolio weights defined by the strategy, they calculate the number of shares to be bought or sold in the beginning of each month, so that the total cost (including transaction costs) would be equal to the value of the fund at the end of the previous month. This ensures a self-financing investment strategy, and returns net of transactions costs could be easily calculated. Since the transaction costs used here are proportional costs, i.e. the costs increase with the amount of investment, the net profitability of a trading strategy decreases with the initial size of the fund. Our goal is to estimate the size of a SUE fund that could be implemented before abnormal returns are driven to zero.

Using the above-described framework, we simulate the profitability of buying good-news firms and selling bad-news firms (Portfolio 20 minus Portfolio 1). For the analysis, we use the sample of firms and their estimated transactions costs, which is used in Korajczyk and Sadka (2004). Therefore, the sample includes NYSE-listed firms with available transaction costs data as measured in Breen, Hodrick, and Korajczyk (2002). The results are presented in Figure 5. Without considering transactions costs (0 investment amount) the strategy earns a Fama-French risk-adjusted return of 1.12 percent per month with a t-statistic of 5.7 (notice, these returns are similar to those we report for our NYSE sample earlier). However, when transaction costs are considered, we find that the risk-adjusted returns of the SUE trading strategy disappear after an investment amount of $200 million[17] is engaged (by a single fund). This result highlights the difficulty in obtaining abnormal profitability using SUE trading strategies.

Nevertheless, it is important to note that the break-even fund size represent marginal investments over and above those already implemented by traders in this market. Thus, as in all anomaly-based trading strategies, we are unable to assess infra-marginal profits earned by existing traders. Moreover, the portfolio weights that we use (equal weights) are those dictated by the SUE portfolio analyzed throughout the paper and they are also the ones commonly used in this literature.

[17] The dollar amounts reported throughout the paper are expressed relative to market capitalization at the end of December 1999. That is, we report the dollar amount at the end of 1999 that constitutes the same fraction of total market capitalization as the initial investment in March 1983.

However, these weights are not necessarily optimal when transactions costs are considered.

In addition to the net risk-adjusted returns, we calculate the liquidity loading of the SUE trading strategy as a function of the initial investment amount. The liquidity loading is calculated through a regression of the monthly net returns of the strategy on the three Fama and French (1993) factors and the liquidity factor. Interestingly, the liquidity loading of the SUE trading strategy drops from 0.28 to 0.13 as the fund size increases from 0 to 200 million, and remains flat at 0.13 thereafter. This result suggests that roughly half the liquidity risk of an SUE trading strategy originates from the time variation of transaction costs required to trade the SUE strategy. The other half could be viewed as the fundamental systematic liquidity risk, or informational risk, of SUE portfolios.

7 Conclusion

This paper tests the relation between the post-earnings-announcement drift and liquidity. First, we find that bad-news firms are less liquid, which suggests that they are subject to a more uncertain and costly information environment. Second, we provide further evidence that the post-earnings-announcement drift can be partially interpreted as compensation for liquidity risk (as distinct from liquidity level). In other words, the returns of trading strategies designed to capture the drift are sensitive to market-wide liquidity—good-news firms are more sensitive to market-wide liquidity than bad-news firms. Good-news firms earn less when markets become less liquid, while bad-news firms earn more. Thus, we argue that good-news firms earn higher expected returns than bad-news firms. In other words, systematic liquidity risk rather than liquidity level is priced in the cross-section of post-earnings-announcement drift portfolios.

This paper illustrates the importance of using an appropriate benchmark model in assessing anomalies. Bernard and Thomas (1989, 1990), Ball and Bartov (1996), and others have found, using the CAPM benchmark, that investors fail to fully incorporate the information content of earnings. However, our results suggest that the extent to which investors are naive with respect to earnings' expectations is likely to be overstated by previous studies because of a misspecified benchmark pricing model. When a liquidity risk factor is introduced, and a suitable factor model is tested, investors' behavior could be better explained in a rational fashion.

In sum, this paper alludes to two important considerations that must be taken into account when testing anomalies. First, one must consider transaction and information-gathering costs associated with anomaly-based trading strategies (as suggested by Korajczyk and Sadka (2004) and Carhart (1997), respectively). Second, our analysis suggests that a liquidity risk factor should be included in benchmark pricing models. The evidence presented in the paper suggests that liquidity risk can account for roughly half the SUE-return spread. Furthermore, half of the liquidity risk of a SUE trading strategy originates from the time variation of transaction costs required to trade the SUE strategy, while the other half represents fundamental systematic liquidity risk.

Appendix: Price Impact Model

This appendix contains a short summary of the estimation procedure developed in Sadka (2005). Let m_t denote the market maker's expected value of the security, conditional on the information set available at time t (t represents event time of a trade)

$$m_t = E_t\left[\widetilde{m}_{t+1}|D_t, V_t, y_t\right] \tag{A1}$$

where V_t is the order flow, D_t is an indicator variable that receives a value of (+1) for a buyer-initiated trade and (-1) for seller-initiated, and y_t is a public information signal. To determine the sign of a trade, we follow the classification scheme proposed by Lee and Ready (1991), which classifies a trade whose price is above the midpoint of the quoted bid and ask as buyer-initiated and below the midpoint—seller-initiated. (Trades whose price equals the midpoint are discarded from the estimation.)

The literature distinguishes between two main effects, permanent and transitory, that trades may have on prices. The permanent effects are attributed to the possibility of insiders trading on private information, and transitory effects are associated with the costs of making a market, such as inventory and order processing. Sadka (2005) assumes price impacts have linear functional forms, and therefore, distinguishes between fixed costs per total trade, which are independent of the order flow, and variable costs per share traded, which depend on the order flow. Therefore, there are four components of price impacts, which are denoted as follows. The fixed costs are Ψ and $\overline{\Psi}$ (permanent and transitory, respectively), and the variable costs are λ and $\overline{\lambda}$ (permanent and transitory, respectively).

To estimate the permanent price effects, we follow the formulation proposed by Glosten and Harris (1988) and assume that m_t takes a linear form such that

$$m_t = m_{t-1} + D_t\left[\Psi + \lambda V_t\right] + y_t \tag{A2}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (A2) describes the innovation in the conditional expectation of the security value through new information, both private (D_t, V_t) and public (y_t). Notice that information induces a permanent impact on expected value.

Assuming competitive risk-neutral market makers, the (observed) transaction price, p_t, can be written as

$$p_t = m_t + D_t \left[\overline{\Psi} + \overline{\lambda} V_t\right] \quad \text{(A3)}$$

Notice that $\overline{\Psi}$ and $\overline{\lambda}$ are temporary effects because they only affect p_t, and are not carried on to p_{t+1}. Taking first differences of p_t (Eq. (A3)) and substituting Δm_t from Eq. (A2) we have

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \overline{\Psi} \Delta D_t + \overline{\lambda} \Delta D_t V_t + y_t \quad \text{(A4)}$$

where y_t is the unobservable pricing error.

The formulation in Eq. (A4) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature has documented predictability in the order flow (see, e.g., Hasbrouck (1991a,b) and Foster and Viswanathan (1993)). For example, to reduce price impact costs, traders may decide to break up large trades into smaller trades, which would create an autocorrelation in the order flow. Thus, following Brennan and Subrahmanyam (1996), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997), Eq. (A4) is adjusted to account for the predictability in the order flow. In particular, the market maker is assumed to revise the conditional expectation of the security value only according to the *unanticipated* order flow rather than the entire order flow at time t. The unanticipated order flow, denoted by $\varepsilon_{\lambda,t}$, is calculated as the fitted error term from a five-lag autocorrelation regression of the order flow $D_t V_t$. (After computing $\varepsilon_{\lambda,t}$, the unanticipated sign of the order flow, $\varepsilon_{\Psi,t}$, is calculated while imposing normality of the error $\varepsilon_{\lambda,t}$—see Sadka (2005) for more details.) Therefore, Eq. (A4) translates to

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \overline{\Psi} \Delta D_t + \overline{\lambda} \Delta D_t V_t + y_t \quad \text{(A5)}$$

Last, the literature documents different price effects induced by block trades (see, e.g., Madhavan and Smidt (1991), Keim and Madhavan (1996), Nelling (1996), and Huang and Stoll (1997)). In light of this, large/block trades, generally considered as trades above 10,000 shares, are separated from smaller trades in the estimation using dummy variables. The model in Eq. (A5) is estimated separately for each stock every month using OLS (including an intercept) with corrections for serial correlation in the error term.

References

Abarbanell Jeffery, S. and Victor L. Bernard, 1992, Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior, *Journal of Finance* 47, 1181-1207.

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics*, forthcoming.

Admati, Anat, and Paul Pfleiderer, 1988, Theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Affleck-Graves, John, Carolyn M. Callahan, and Niranjan Chipalkatti, 2002, Earnings predictability, information asymmetry, and market liquidity, *Journal of Accounting Research* 40, 561-583.

Amihud, Yakov, and H. Mendelson, 1986, Asset pricing and bid-ask spread, *Journal of Financial Economics* 17, 223-250.

Asness, Clifford S., 1997, The interaction of value and momentum strategies, *Financial Analysts Journal* (March/April), 29-36.

Ball, Ray, 2001, Infrastructure requirements for an economically efficient system of public financial reporting and disclosure. Brookings - Wharton Papers on Financial Services.

Ball, Ray and Eli Bartov, 1996, How naive is the stock market's use of earning information, *Journal of Accounting and Economics* 21, 319-337.

Ball, Ray and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Ball, Ray, S. P. Kothari, and Ashok Robin, 2000, The effect of international institutional factors on properties of accounting earnings, *Journal of Accounting and Economics* 29, 1-51.

Ball, Ray, and Ross Watts, 1972, Some time series properties of accounting income, *Journal of Finance*, 27, 663-681.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Basu, Sudipta, 1997, The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics*, 24, 3-37.

Berger, Philip G., Eli Ofek, and Itzhak Swary, 1996, Investor valuation of abandonment option, *Journal of Financial Economics* 42, 257-287.

Bernard, Victor L. and Jacob K. Thomas, 1989, Post-Earnings announcement drift and: Delayed price response or risk premium? *Journal of Accounting Research*, 27, 1-36.

Bernard, Victor L. and Jacob K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics*, 13, 305-340.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: some empirical tests, in Michael Jensen, Ed.: Studies in the theory of capital markets (Praeger, New York), pp. 79-121.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Chen, Zhiwu, Werner Stanzl, and Masahiro Watanabe, 2004, Price impact costs and the limit of arbitrage, Working paper, Yale School of Management.

Chordia, Tarun, and Lakshmanan Shivakumar, 2005, Inflation illusion and post-earnings-announcement drift, *Journal of Accounting Research*, forthcoming.

Collins Daniel W., and Paul Hribar, 2000, Earnings based and accrual based market anomalies: one effect or two? *Journal of Accounting and Economics,* 29, 101-123.

Copeland, Thomas E., and Dan Galai, 1983, Information effects on the bid-ask spread, *Journal of Finance* 38, 1457-1469.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under and overreactions, *Journal of Finance* 53, 1839-1886.

Dechow, Patricia, and Ilia Dichev, 2002, Quality of accruals and earnings: the role of accrual estimation errors, *The Accounting Review* 77, 35-59.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277-311.

Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 577-606.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is information risk a determinant of asset returns? *The Journal of Finance* 58, 2185-2210.

Ertimur, Yonca, 2003, Financial information environment of loss firms, working paper, New York University.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

Foster, George, Chris Olsen, and Terry Shevlin, 1984, Earnings releases, anomalies, and the behavior of security returns, *The Accounting Review*, 59, 574-603.

Foster, F. Douglas, and S. Viswanathan, 1993, Variation in trading volume, return volatility, and trading costs: evidence on recent price formation models, *Journal of Finance* 48, 187-211.

Francis, Jennifer, J. Douglas Hanna, and Linda Vincent, 1996, Causes and effects of discretionary asset write-offs, *Journal of Accounting Research* 34, 117-134.

Francis, Jennifer, Ryan Lafond, Per Olsson, and Katherine Schipper, 2004, Financial anomalies and information uncertainty, working paper, Duke University.

Glosten, Lawrence R., and P. R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.

Glosten, Lawrence R., and L. E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21, 123-142.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the sources of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.

Hansen, Lars Peter, 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029-1054.

Hansen, Lars Peter, and Ravi Jagannathan, 1997, Assessing specification errors in stochastic discount factor models, *Journal of Finance* 62, 557-590.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.

Hasbrouck, Joel, 1991b, The summary informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571-595.

Hasbrouck, Joel, and Duane J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* 59, 383-411.

Hayn, Carla, 1995, The information content of losses, *Journal of Accounting and Economics* 20, 125-154.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Huang, Roger D., and Hans R. Stoll, 1997, The components of the bid-ask spread: a general approach, *Review of Financial Studies* 10, 995-1034.

Jackson, Andrew, and Timothy Johnson, 2004, Unifying underreaction anomalies, *Journal of Business*, forthcoming.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3-53.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: an evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

Jones, Charles P., and Robert H. Litzenberger, 1970, Quarterly earnings reports and intermediate stock price trends. *Journal of Finance*, Vol. 25, No. 1. (Mar., 1970), pp. 143-148.

Jones, Jennifer J., 1991, Earnings management during import relief investigations, *Journal of Accounting Research* 29, 193-228.

Joy, O. Maurice, Robert H. Litzenberger, and Richard W. McEnally, 1977, The adjustment of stock prices to announcements of unanticipated changes in quarterly earnings, *Journal of Accounting Research* Vol. 15, No. 2. (Autumn, 1977), pp. 207-225.

Keane, Michael P. and David E. Runkle, 1998, Are financial analysts' forecasts of corporate profits rational, *Journal of Political Economy* 106, 768-805.

Keim, Donald B., Ananth Madhavan, 1996, The upstairs market for large-block transactions: analysis and measurement of price effects, *Review of Financial Studies* 9, 1-36.

Kim, Dongcheol, and Myung-Sun, Kim, 2003, A multifactor explanation of post-earnings-announcement drift, *Journal of Financial and Quantitative Analysis*, 38, 383-398.

Knez, Peter J., and Mark J. Ready, 1996, Estimating the profits from trading strategies, *Review of Financial Studies* 9, 1121-1163.

Korajczyk, Robert A., and Ronnie Sadka, 2004, Are momentum profits robust to trading costs? *Journal of Finance*, 59, 1039-1082.

Kraus, Alan, and Hans R. Stoll, 1972, Price impact of block trading on the New York Stock Exchange, *Journal of Finance* 27, 569-588.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lang Mark and Russell Lundholm, 1993, Cross-sectional determinants of analyst ratings of corporate disclosure, *Journal of Accounting Research* 31, 246-271.

Lee, Charles M. C., Blinda Mucklow, and Mark J. Ready, 1993, Spreads, depths, and the impact of earnings information: an intraday analysis, *Review of Financial Studies* 6, 345-374.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance*, 2017-2069.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics*, 71, 349-380.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035-1064.

Madhavan, Ananth, and Seymour Smidt, 1991, A Bayesian model of intraday specialist pricing, *Journal of Financial Economics* 30, 99-134.

Mendenhall, Richard, 2005, Arbitrage risk and post-earnings-announcement drift, *Journal of Business*, forthcoming.

Mitchell, Mark, and Todd Pulvino, 2001, Characteristics of risk and return in risk arbitrage, *Journal of Finance* 56, 2135-2175.

Nelling, Edward F., 1996, The price effects of 'shopping the block', Unpublished manuscript, Georgia Institute of Technology.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy 111*, 642-685.

Reed, Adam, 2002, Costly short-selling and stock price adjustment to earnings announcements, Working paper, University of North Carolina.

Rendleman, Richard J. Jr., Charles P. Jones, and Henry A. Latané, 1982, Empirical anomalies based on unexpected earnings and the importance of risk adjustments, *Journal of Financial Economics,* 10, 269-287.

Rendleman, Richard J. Jr., Charles P. Jones, and Henry A. Latané, 1987, Further insight into the standardized unexpected earnings anomaly: size and serial correlation effects, *The Financial Review* 22, 131-144.

Sadka, Ronnie, 2005, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics*, forthcoming.

Shanken, Jay, 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1-33.

Vega, Clara, 2004, Are investors overconfident? Working paper, University of Rochester.

Wurgler, Jeffrey, and Katia Zhuravskaya, 2002, Does arbitrage flatten demand curve for stocks? *Journal of Business*, 75, 583-608.

Table 1
Performance of SUE Portfolios

Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The table reports the equal weighted excess returns, as well as risk-adjusted returns (alpha) using the CAPM and Fama-French three factors. T-statistics are reported as two digit numbers. The analysis includes NYSE, AMEX, and NASDAQ firms for the period March 1983 through August 2001.

	Excess Returns	CAPM Alpha	FF Alpha
1 (Low)	-0.0006	-0.0075	-0.0074
	-0.16	-2.94	-3.88
2	0.0000	-0.0063	-0.0068
	0.00	-2.77	-4.06
3	0.0015	-0.0049	-0.0050
	0.40	-2.16	-3.02
4	0.0015	-0.0047	-0.0052
	0.42	-2.30	-3.53
5	0.0038	-0.0022	-0.0024
	1.09	-1.01	-1.67
6	0.0047	-0.0014	-0.0012
	1.33	-0.63	-0.85
7	0.0058	-0.0003	-0.0008
	1.69	-0.13	-0.53
8	0.0065	0.0002	-0.0003
	1.85	0.12	-0.23
9	0.0090	0.0027	0.0019
	2.53	1.27	1.37
10	0.0082	0.0021	0.0016
	2.35	0.98	1.12
11	0.0078	0.0015	0.0014
	2.17	0.69	0.97
12	0.0085	0.0021	0.0016
	2.38	1.01	1.14
13	0.0106	0.0044	0.0041
	3.01	2.08	3.10
14	0.0112	0.0047	0.0041
	3.14	2.33	3.18
15	0.0108	0.0043	0.0038
	3.00	2.09	2.73
16	0.0119	0.0055	0.0054
	3.30	2.58	3.85
17	0.0145	0.0077	0.0077
	3.85	3.59	5.74
18	0.0134	0.0065	0.0067
	3.55	3.08	4.81
19	0.0152	0.0083	0.0081
	4.16	4.37	6.16
20 (High)	0.0168	0.0099	0.0098
	4.55	5.04	7.34
(20) - (1)	0.0132	0.0174	0.0172
	4.15	10.74	10.47

Table 2

Cross-sectional regressions of SUE Portfolios

Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Equal-weighted returns (excess of risk-free rate) of the 20 portfolios are used in cross-sectional regressions to estimate asset-pricing models of the form $E(R_{i,t}) = \gamma_0 + \gamma`\beta_i$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The regression models are estimated using the Fama-MacBeth procedure. Standard errors are also corrected for the sampling errors in the estimated β_i (Shanken (1992)). The results are reported for two sets of universes: NYSE, AMEX, and NASDAQ (Panel A), and NYSE alone (Panel B). The sample period is March 1983 through August 2001.

Panel A: NYSE+AMEX+NASDAQ

	Intercept	MKT	SMB	HML	LIQ	Adjusted R2
Premium	-4.73	5.67				0.23
T-statistic	-4.92	5.99				
Premium	-4.95	5.53			2.22	0.67
T-statistic	-1.90	2.29			2.81	
Premium	-4.35	6.35	-1.29	-0.66		0.18
T-statistic	-3.08	5.52	-1.37	-0.71		
Premium	-4.00	3.84	3.62	-5.23	2.82	0.71
T-statistic	-0.87	1.10	0.97	-1.33	2.01	

Panel B: NYSE

	Intercept	MKT	SMB	HML	LIQ	Adjusted R2
Premium	-2.80	4.08				0.23
T-statistic	-3.42	4.34				
Premium	-4.17	5.13			1.33	0.68
T-statistic	-2.12	2.49			2.51	
Premium	-1.18	3.83	-3.27	-1.46		0.45
T-statistic	-1.05	3.42	-2.84	-1.68		
Premium	-3.16	4.84	-1.11	-1.57	1.07	0.71
T-statistic	-1.52	2.52	-0.66	-1.14	2.35	

Table 3
Testing Liquidity with the Stochastic Discount Factor Approach

Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Equal-weighted returns (excess of risk-free rate) of the 20 portfolios are used to estimate asset-pricing models using the moment conditions of the form $E[R_{i,t}(1 - \delta' f_t)] = 0$, where $R_{i,t}$ are the returns of portfolio *i*, and f_i is a vector of factors. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The models are estimated with the Generalized Method of Moments. Panel A uses the Hansen (1982) optimal weighted matrix, and Panel B uses the weighting matrix proposed by Hansen and Jagannathan (1997). The *J*-value is the minimized value of the GMM criterion, multiplied by the number of periods (222 months). *P*-values are also reported. The analysis includes NYSE-listed stocks for the period March 1983 to August 2001.

	MKT	SMB	HML	LIQ	J-value	P-value (%)
Panel A: Hansen (1982)						
Estimate	3.07				70.57	0.00
T-value	7.61					
Estimate	3.86			0.76	24.45	8.01
T-value	4.45			3.75		
Estimate	1.92	-1.62	-0.01		51.23	0.00
T-value	4.64	-2.11	0.15			
Estimate	2.84	-0.70	-1.27	0.65	26.31	4.98
T-value	1.84	-1.52	-1.08	3.33		
Panel B: Hansen-Jagannathan (1997)						
	MKT	SMB	HML	LIQ	J-value	P-value (%)
Estimate	0.95				0.04	0.00
T-value	1.23					
Estimate	0.49			0.98	0.02	4.77
T-value	-0.48			3.93		
Estimate	2.03	-4.24	0.48		0.02	0.00
T-value	4.16	-4.54	-0.99			
Estimate	1.80	-2.57	-0.40	0.70	0.01	11.87
T-value	0.46	-2.50	-1.21	3.25		

Table 4
Summary Statistics of Momemtum/SUE Portfolios and Size/SUE Portfolios

This table reports summary statistics for two sets of portfolios: 5x4 SUE/momentum portfolios, and 5x4 SUE/size portfolios. The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Momentum is calculated as the past 12-month cumulative returns (excluding the last month). Size is measured as market capitalization (scaled by the cross-sectional average). To form the first set of portfolios, firm are sorted every month to five groups according to SUE, and then the firms within each group are sorted again into five momentum groups. Similarly, the third set of portfolios is formed using dependent sorts of SUE and size. The table reports equal-weighted returns (excess of risk-free rate), size, momentum, and SUE of the portfolios. Each of these variables is calculated as the time-series average of the average variable of the firms in the portfolio. The analysis includes NYSE-listed firms for the period March 1983 through August 2001.

Panel A: SUE/Momentum portfolios

SUE		Low	Momentum		High
Low	Return (%)	0.20	0.43	0.48	0.62
	SUE	-1.44	-1.98	-1.10	-1.19
	Momentum	-0.36	-0.09	0.08	0.40
	Size	0.40	0.86	1.17	1.30
	Return (%)	0.33	0.69	0.78	0.94
	SUE	-0.21	-0.20	-0.20	-0.19
	Momentum	-0.26	0.00	0.17	0.54
	Size	0.47	1.00	1.21	1.14
	Return (%)	0.41	0.76	0.95	1.34
	SUE	0.01	0.01	0.01	0.01
	Momentum	-0.22	0.05	0.22	0.65
	Size	0.53	0.99	1.35	1.20
	Return (%)	0.94	0.91	1.05	1.32
	SUE	0.21	0.22	0.22	0.23
	Momentum	-0.19	0.08	0.27	0.75
	Size	0.56	1.05	1.31	1.09
High	Return (%)	1.05	1.16	1.30	1.93
	SUE	0.83	0.89	0.90	0.90
	Momentum	-0.14	0.14	0.34	0.93
	Size	0.68	1.19	1.41	1.06

Panel B: SUE/Size portfolios

SUE		Low	Size		High
Low	Return (%)	0.19	0.33	0.54	0.64
	SUE	-1.94	-1.16	-1.25	-1.37
	Momentum	-0.10	-0.01	0.04	0.10
	Size	0.04	0.13	0.42	3.17
	Return (%)	0.71	0.64	0.67	0.73
	SUE	-0.20	-0.20	-0.20	-0.20
	Momentum	0.03	0.13	0.13	0.16
	Size	0.04	0.13	0.43	3.23
	Return (%)	1.04	0.90	0.71	0.81
	SUE	0.01	0.01	0.01	0.01
	Momentum	0.10	0.20	0.19	0.22
	Size	0.04	0.14	0.46	3.44
	Return (%)	1.57	0.95	0.85	0.82
	SUE	0.22	0.22	0.22	0.22
	Momentum	0.15	0.25	0.25	0.26
	Size	0.04	0.14	0.44	3.40
High	Return (%)	1.96	1.37	1.14	0.95
	SUE	0.87	0.89	0.89	0.89
	Momentum	0.25	0.35	0.35	0.33
	Size	0.04	0.15	0.47	3.68

Table 5
Cross-sectional regressions of Additional SUE-Based Test Portfolios

This table reports the results of cross-sectional regressions using three different sets of portfolios: (1) 20 portfolios sorted on standardized unexpected earnings (SUE) without a drift term; (2) 5x4 SUE/momentum portfolios; and (3) 5x4 SUE/size portfolios. The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Momentum is calculated as the past 12-month cumulative returns (excluding the last month). Size is measured as market capitalization. To form the first set of portfolios, firms are sorted every month based SUE without a drift (i.e. assuming $c_{i,t} = 0$). For the second set of portfolios, firm are sorted every month to five groups according to SUE, and then the firms within each group are sorted again into five momentum groups. Similarly, the third set of portfolios is formed using dependent sorts of SUE and size. Equal-weighted returns (excess of risk-free rate) of the portfolios are used in cross-sectional regressions to estimate asset-pricing models of the form $E(R_{i,t}) = \gamma_0 + \gamma`\beta_i$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The regression models are estimated using the Fama-MacBeth procedure. Standard errors are also corrected for the sampling errors in the estimated β_i (Shanken (1992)). The analysis includes firms listed on NYSE for the period March 1983 through August 2001.

Panel A: SUE portfolios (without a drift)

	Intercept	MKT	SMB	HML	LIQ	Adjusted R2
Premium	-1.61	2.76				0.11
T-statistic	-2.31	3.62				
Premium	-3.23	4.06			1.39	0.64
T-statistic	-1.49	1.95			2.27	
Premium	1.54	0.01	-3.97	1.61		0.63
T-statistic	1.41	0.01	-3.47	1.92		
Premium	-0.47	1.73	-1.87	0.23	0.79	0.74
T-statistic	-0.41	1.55	-1.91	0.28	2.80	

Panel B: SUE/Momentum portfolios

	Intercept	MKT	SMB	HML	LIQ	Adjusted R2
Premium	-0.25	1.25				0.06
T-statistic	-0.65	2.44				
Premium	-0.45	1.23			0.67	0.51
T-statistic	-0.77	1.74			2.02	
Premium	-2.39	4.01	-2.29	-0.33		0.48
T-statistic	-2.82	5.47	-3.39	-0.36		
Premium	-3.35	3.78	-1.38	1.10	0.62	0.60
T-statistic	-3.59	4.47	-2.44	1.52	2.07	

Panel C: SUE/Size portfolios

	Intercept	MKT	SMB	HML	LIQ	Adjusted R2
Premium	-2.59	3.85				0.09
T-statistic	-3.01	4.12				
Premium	-2.94	3.98			0.73	0.20
T-statistic	-2.30	2.97			2.28	
Premium	-4.52	4.96	0.18	-0.10		0.13
T-statistic	-4.25	4.60	0.37	-0.14		
Premium	-4.33	4.80	0.42	-0.40	0.63	0.18
T-statistic	-3.17	3.50	0.81	-0.47	1.72	

Table 6
Liquidity Risk and Liquidity Level of SUE Portfolios

Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock i in month t is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month t for firm i (not including announcements in month t), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. Equal-weighted returns (excess of risk-free rate) of the 20 portfolios are used in cross-sectional regressions to estimate asset-pricing models of the form $E(R_{i,t}) = \gamma_0 + \gamma`\beta_i + \gamma_1 Z_i$, where $R_{i,t}$ are the returns of portfolio i, β_i is a vector of factor loadings, and Z_i is portfolio characteristic. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The characteristic (Level) in the regressions is the time-series mean of the average price impact of firms in each portfolio (each month price impacts are pre-scaled by the market average). The regression models are estimated using the Fama-MacBeth procedure. Standard errors are corrected using the Newey-West procedure. The sample includes NYSE-listed firms with available intraday data for the period March 1983 through August 2001.

	Intercept	MKT	SMB	HML	LIQ	Level	Adjusted R2
Premium	-2.13	3.36					0.22
T-statistic	-3.10	4.44					
Premium	1.35	2.84				-3.32	0.29
T-statistic	1.36	3.91				-3.58	
Premium	-2.62	3.46			1.24		0.62
T-statistic	-3.63	4.54			5.03		
Premium	-1.36	3.27			1.16	-1.17	0.61
T-statistic	-1.24	4.41			4.55	-1.28	
Premium	-1.35	3.37	-3.02	-0.77			0.57
T-statistic	-1.78	4.28	-4.46	-1.46			
Premium	-0.60	3.25	-2.85	-0.73		-0.78	0.55
T-statistic	-0.58	4.24	-4.22	-1.39		-0.91	
Premium	-2.32	3.56	-1.62	-0.39	0.90		0.73
T-statistic	-2.74	4.45	-2.61	-0.73	3.55		
Premium	-2.30	3.55	-1.62	-0.39	0.90	-0.01	0.71
T-statistic	-1.91	4.51	-2.64	-0.73	3.45	-0.02	

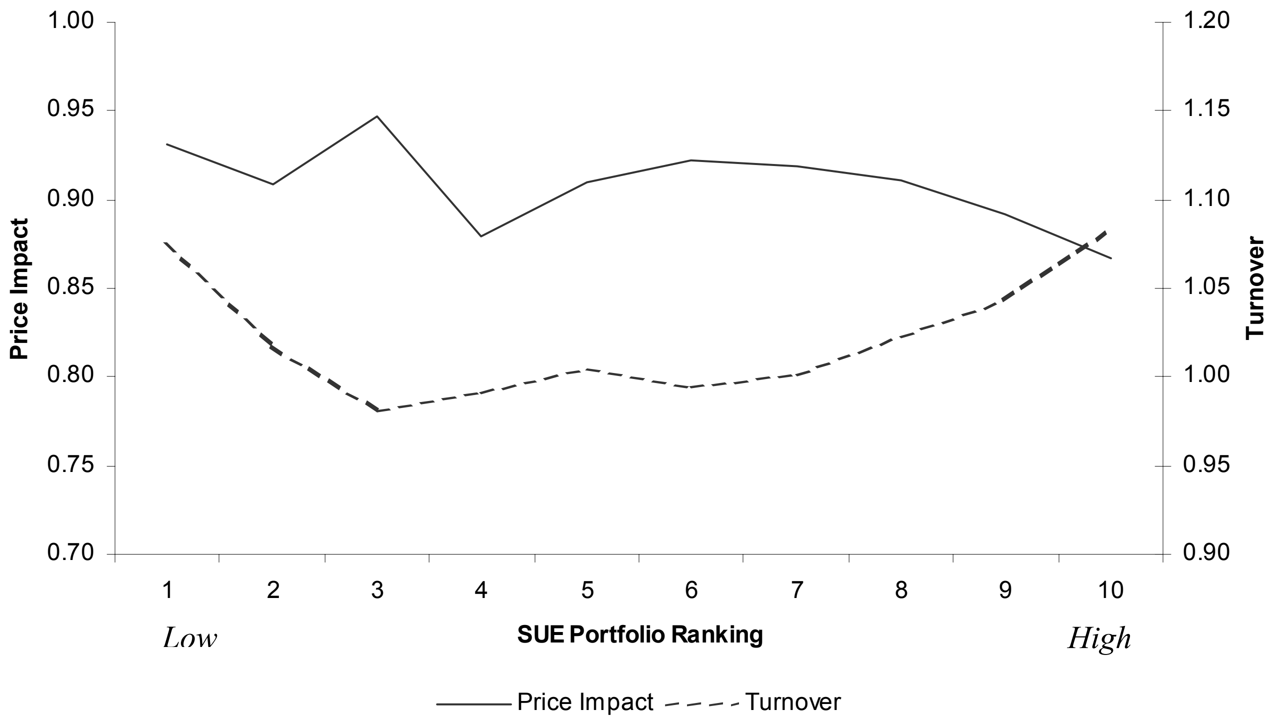


Figure 1. Uncertainty level and turnover of standardized unexpected earnings (SUE) portfolios. Every month firms are sorted into ten groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q\text{-}4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The figure reports the average price impact of the portfolios during the month following portfolio formation. Turnover is defined as volume over number of shares outstanding. Price impacts are permanent (variable) price impacts estimated using intraday data. Both turnover and price impact are scaled by their cross-sectional average every month. The analysis includes NYSE-listed stocks for the period March 1983 to August 2001.

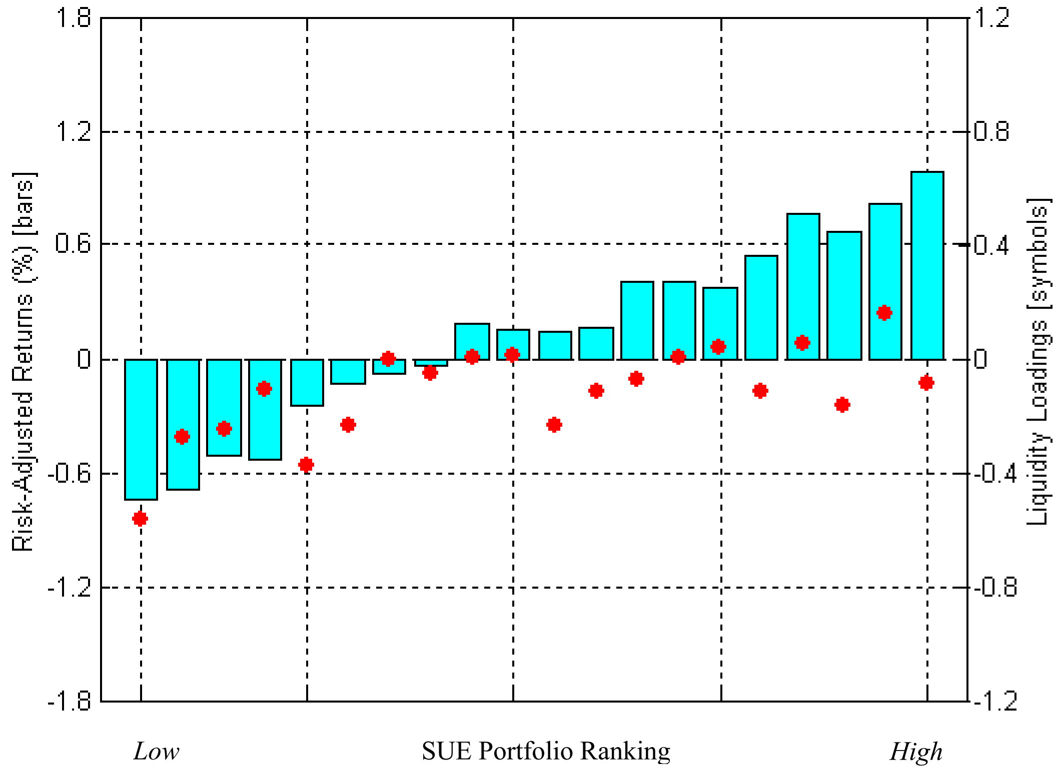
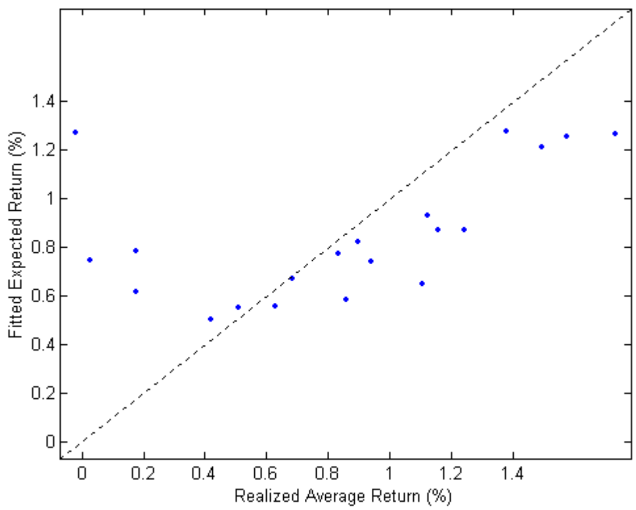
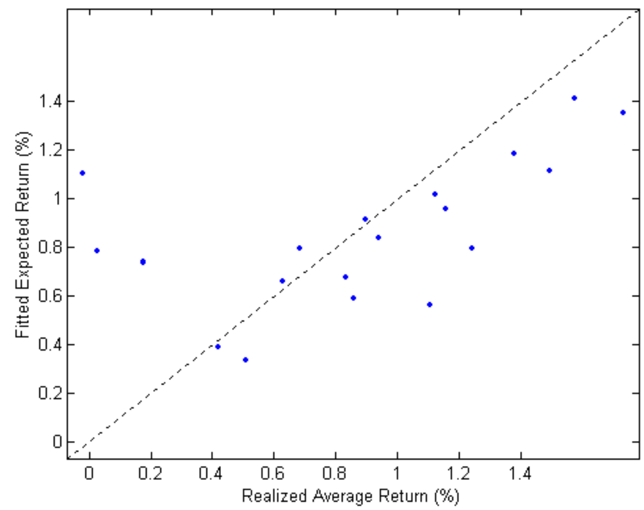


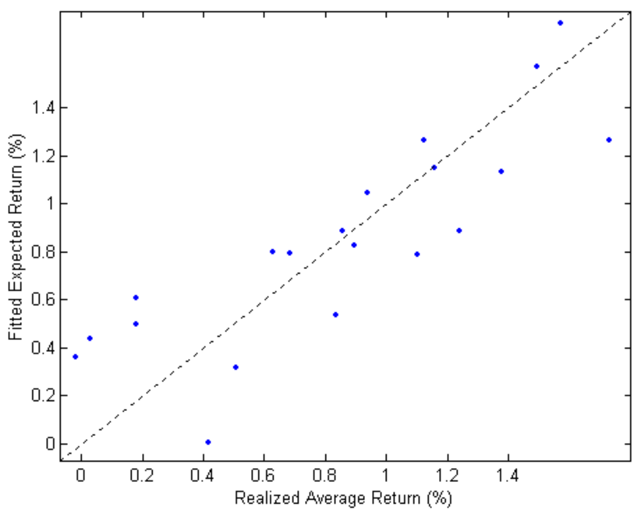
Figure 2. Risk-adjusted returns and liquidity loadings of SUE portfolios. Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q\text{-}4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The liquidity loadings (points on the graph) are calculated using time-series regressions of portfolio returns on the Fama-French three factors MKT, SMB, and HML, and the non-traded liquidity factor LIQ. Risk-adjusted returns (bars on the graph) are calculated using similar time-series regressions, but without including the non-traded factor. The analysis includes NYSE, AMEX, and NASDAQ stocks (with available information) for the period March 1983 to August 2001.



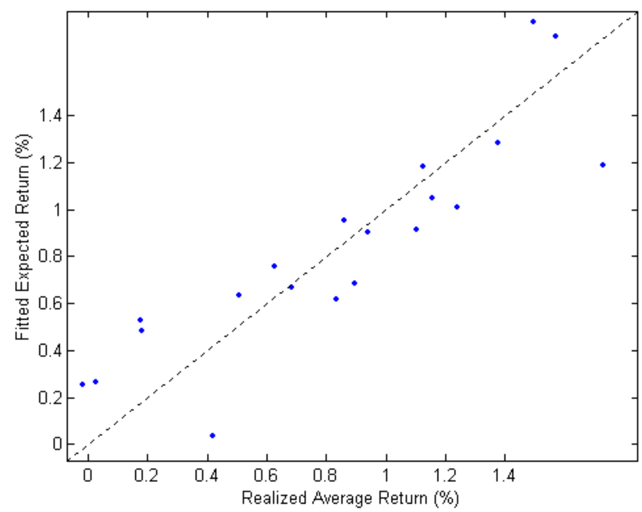
(a) CAPM



(b) FF



(c) CAPM+LIQ



(b) FF+LIQ

Figure 3. SUE portfolios and liquidity risk. Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q\text{-}4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. Each scatter point in each of the graphs represents one of the 20 portfolios, with the realized average return (excess of risk-free rate) on the horizontal axes, and the fitted expected return on the vertical axes. The realized average return is the time-series average return, and the fitted expected return is calculated as the fitted value from $E(R_{i,t}) = \gamma_0 + \gamma`\beta_{i,}$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a vector of factor loadings, and γ is a vector of the estimated risk premiums. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, and HML, and the non-traded liquidity factor, LIQ. The straight line in each graph is the 45° line from the origin. The analysis includes all listed stocks (with available information) for the period March 1983 to August 2001.

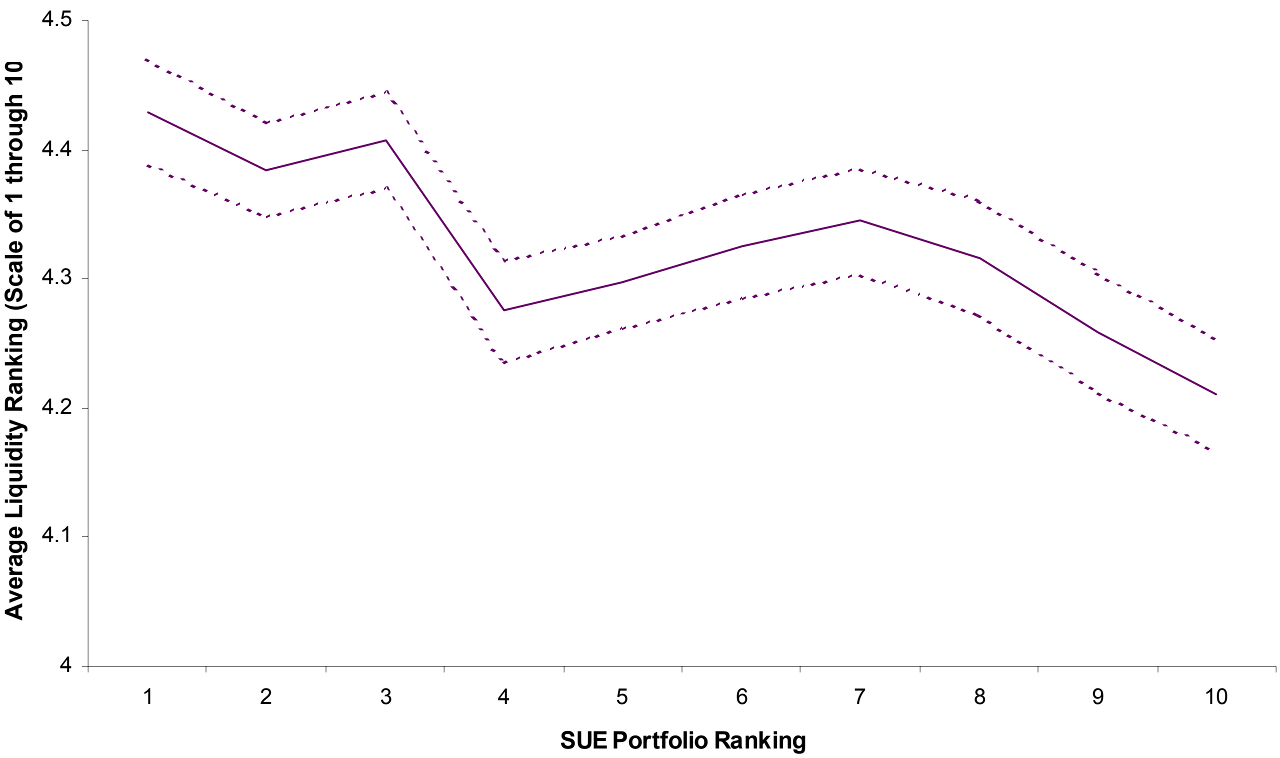
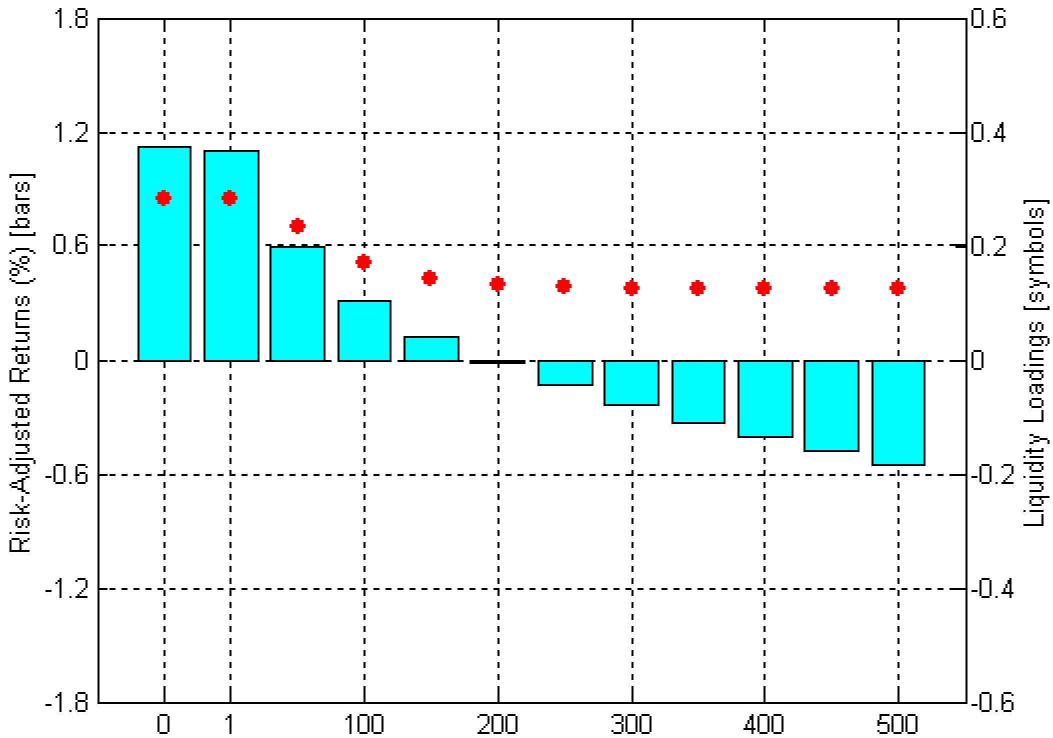


Figure 4. Liquidity ranking of standardized unexpected earnings (SUE) portfolios. Every month firms are sorted into ten groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q\text{-}4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. Independent of the SUE sorts, stocks are sorted each month into ten liquidity categories of equal number of firms (1–most liquid, 10–least liquid). The liquidity category of a portfolio is calculated as the average liquidity category of its constituent stocks. The figure reports the time-series average liquidity category of the SUE portfolios during the month following portfolio formation. The dashed lines are the 95% confidence intervals. The analysis includes NYSE-listed stocks for the period March 1983 to August 2001.



[millions of Dollars]

Figure 5. Performance evaluation of SUE trading strategies. Every month firms are sorted into 20 groups based on the standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$ where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*), $E_{i,q\text{-}4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. We evaluate the performance of a strategy buying the good-news firms (Portfolio 20) and selling the bad-news firms (Portfolio 1) using the framework and in Korajczyk and Sadka (2004). We form the portfolio spread in the beginning of February 1983 with a certain initial monetary amount of investment. We rebalance the portfolio on a monthly basis, following the trading rule of the strategy, until the end of December 1999. The execution costs of trading any stock *i* are assumed to follow the model $\Delta p_i/p_i = \lambda_i \Delta q_i$, where $\Delta p_i/p_i$ is the relative price improvement as a result of trading Δq_i (signed) shares. The price impact coefficients λ_i are those used in Korajczyk and Sadka (2004). They are calculated as the fitted values of cross-sectional regressions of measured price impacts on firm characteristics. These regressions used the Trades and Quotes data for the period January 1993 until May 1997. Assuming that the estimated price impacts are perfectly foreseeable, we rebalance the portfolio every month while keeping it self-financing, after considering the price impact of trades. For every initial investment, we calculate the time series of monthly returns, net of price impacts. We then report the intercept (Alpha) using Fama and French (1993) regressions (bars on the graph), and the liquidity loadings (points on the graph), which are calculated using time-series regressions of portfolio returns on the Fama-French three factors MKT, SMB, and HML, and the non-traded liquidity factor LIQ. The initial investment is quoted relative to market capitalization of December 1999. The analysis uses monthly returns of all NYSE stocks available on CRSP.

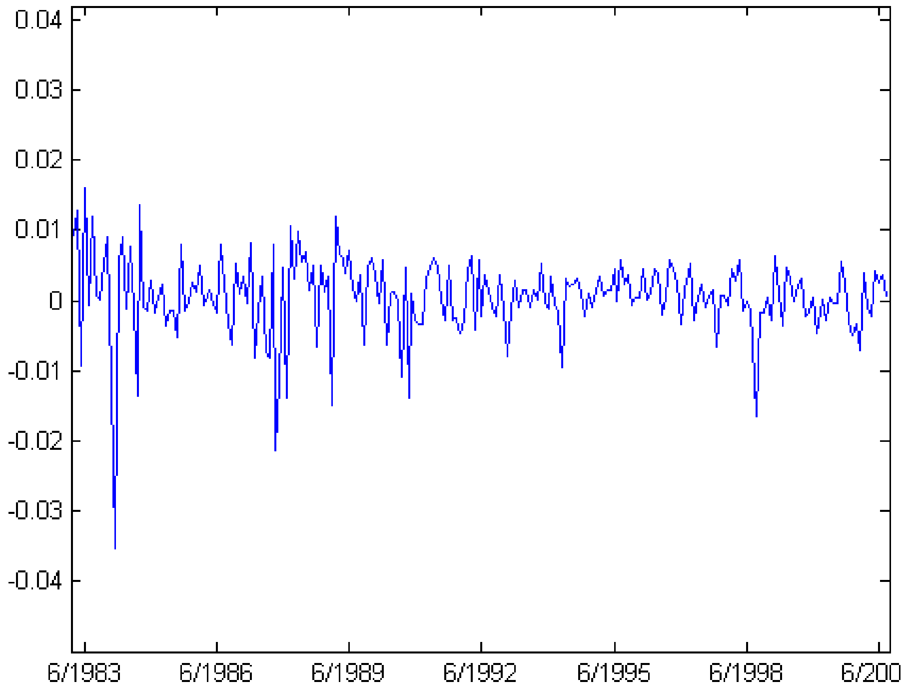


Figure A1. The time series of shocks to aggregate information uncertainty. Firm-specific price impacts are calculated each month using intraday data from ISSM and TAQ databases. The price-impact model used is the Glosten and Harris (1988) empirical model. The estimation procedure is described in Sadka (2005). Aggregate monthly price impact is measured as the cross-sectional average of the firm-specific price impacts within a month. Shocks to aggregate liquidity are proxied as residuals from an ARMA model of the time series of aggregate liquidity. The numbers on the horizontal axis correspond to the month of December of a given year. The analysis includes NYSE-listed firms (with available intraday information) for the period March 1983 to August 2001.