

Information Risk and Momentum Anomalies

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Abstract

In this paper, we construct an information factor (ECINF) based on an information asymmetry measure developed by Hwang and Qian (2010). We show that ECINF is not only a priced risk factor, but often the most significant factor in the asset pricing tests. This result suggests that ignoring the risk of information asymmetry may give rise to false anomalies. As a case in point, we show that ECINF can fully explain momentum anomalies and does not require us to resort to explanations involving investor irrationality or behavioral biases. We hypothesize that momentum anomalies arise because there are fewer informed traders, and hence lower information risk, in bad news firms (past losers or low earning surprise firms) than in good news firms (past winners or high earning surprise firms.) The larger cost and risk of arbitrage in taking short positions makes bad news firms less attractive to informed traders. Consistent with our hypotheses, we find that the loading on ECINF is lower in bad news firms than in good news firms. This difference in loadings increases significantly with idiosyncratic risk, and this can explain why momentum is stronger in firms with large idiosyncratic volatility. Most importantly, regardless of the level of idiosyncratic risk, the significantly positive risk adjusted returns of zero investment momentum portfolios are no longer significant once we include ECINF as an additional factor for risk adjustment.

1. Introduction

In this paper, we combine information risk literature with momentum literature. We construct an information factor (ECINF) and show that it is not only priced, but often the most significant risk factor in the asset pricing tests conducted in this paper. We further show that by using ECINF, we can fully explain both the price momentum and earnings momentum anomalies without resorting to explanations involving investors' irrationality or behavioral biases.

In the information risk literature, information risk refers to the risk that investors face due to information asymmetry. There has been intense debate over whether information risk should be priced. Information risk plays no role in traditional asset pricing models like the CAPM, the APT and the consumption CAPM because these models assume symmetric information. The argument that information asymmetry would be totally eliminated in a fully-revealing equilibrium is often used to support the view that information asymmetry should not affect asset returns. However, Easley and O'Hara (2004) show in a multiple asset partially-revealing rational expectation model that due to information asymmetry, uninformed investors face information risk as they are unable to adjust their portfolio weights to take advantage of new information as well as informed investors do. Furthermore, this information risk is not diversifiable; therefore, uninformed investors require higher returns as compensation to hold shares in firms with higher information asymmetry. On the other hand, Hughes, Liu and Liu (2007) and Lambert, Leuz and Verrecchia (2007) argue that information risk is either fully diversifiable when the economy is large enough, or that it has been captured by existing risk measures.

On the empirical front, Easley, Hvidkjaer and O'Hara (2002) use a direct information risk measure and find evidence that information asymmetry affects asset returns. Relying on the structural microstructure model developed by Easley, Kiefer, O'Hara and Paperman (1996), Easley, Hvidkjaer and O'Hara (2002) estimate the probability of information-based trade (PIN) directly from trading data and find that stocks with higher PIN have higher expected returns. However, Duarte and Young (2009) find that PIN is priced because it captures the effect of illiquidity that is unrelated to the asymmetric information. When PIN is decomposed into two components, one related to the asymmetric information and the other related to the illiquidity, only the component related to the illiquidity is priced. More recently, Hwang and Qian (2010) construct an information asymmetry measure (ECIN) based on arguments that informed traders tend to trade in large sizes; thus stocks whose large trade prices have a greater price discovery function would have higher information risk. As the price series of large trades and small trades are co-integrated, the price discovery of trades can be easily estimated via the vector error-correction model (VECM). Intuitively, Hwang and Qian (2010) use VECM to study how a temporary gap between the large trade price and the small trade price of the same stock is to be closed. If closing the gap is mostly done through the small trade price with little movement in the large trade price, then the large trade price has been closer to the long-run equilibrium price, and hence the large trade price has a greater price discovery function for this particular stock. They show that not only is ECIN positively priced, but its price impact also subsumes that of PIN. Furthermore, unlike the pricing impact of PIN, that of ECIN survives the control of various illiquidity-related measures such as bid-ask spread, stock turnover, return volatility, and the Amihud (2002) illiquidity measure (ILLIQ).

Although Hwang and Qian (2010) show that ECIN is priced as a characteristic, it would be useful to demonstrate that it can also be priced as a factor risk. As mentioned earlier, the main debates on whether information asymmetry/risk should be priced center on whether information asymmetry faced by uninformed investors is a diversifiable risk. If information asymmetry can be shown to be a priced factor risk, it will be strong evidence for the view that the risk of information asymmetry is systematic and hence not diversifiable. Furthermore, the anomalies in the literature are often declared when returns of certain portfolios cannot be explained by the traditional Fama-French factor model. Given the strong pricing effect of ECIN found in Hwang and Qian (2010), information symmetry has great potential to resolve these anomalies. Constructing an information factor based on ECIN in addition to the Fama-French factors is a natural step in this direction.

In the first part of this paper, we construct an information factor (ECINF) based on ECIN. We then show that ECINF is a priced factor via the two-stage cross-sectional regression technique (2SCSR) that estimates factor betas in the first stage, and the factor risk premium in the second stage. In the second part of the paper, we show that ECINF is instrumental in explaining both price momentum and earnings momentum to illustrate how ignoring the risk of information asymmetry can lead to false anomalies.

In the momentum literature, price momentum and earnings momentum have received the most attention.¹ Price momentum, first formally documented by Jegadeesh and Titman (1993), refers to the phenomenon in which past winners (stocks that have outperformed in the past) continue to be winners, and past losers (stocks that have underperformed in the past) continue to be losers for up to 12 months. Thus, one can earn superior returns by holding a

¹ There are other types of momentum, e.g., the return drift after analysts' forecast revision identified by Zhang (2006).

zero-investment portfolio that takes a long position in past winners and a short position in past losers. Furthermore, this superior return cannot be explained by traditional risk factors like the MKT, SMB and HML factors of Fama and French (1993).

Earnings momentum, also known as post earnings-announcement drift (PEAD) in the literature, is equally puzzling. It describes the phenomenon in which a zero-investment portfolio, with long positions in high standardized-unexpected earning (SUE) firms and short positions in low SUE firms, earns significant risk-adjusted returns for up to 12 months after the portfolio formation. PEAD, first studied by Ball and Brown (1968), was further popularized as a research topic by Bernard and Thomas (1990). More recent studies include Mendenhall (2004), Chordia and Shivakumar (2006), Vega (2006), Francis, Lafond, Olsson and Schipper (2007), Hirshleifer, Myers, Myers and Teoh (2008), Zhang (2008), and Basu, Markov and Shivakumar (2010), among others.

Momentum anomalies have been recognized by Fama (1998) as one of the biggest challenges to rational asset pricing, and they have played a major role in promoting the acceptance of behavior finance models. For example, models based on certain types of irrationality or behavioral biases of investors (e.g. Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999)) have been often cited as dominant explanations of momentum. Thus, a major contribution of this paper is to show that momentum anomalies can be resolved by a purely risk-based model as long as we take information risk into account.

Momentum anomalies are closely related to information, as they describe the asset price's movement after an information event. In the case of earnings momentum, the event is

the earnings announcement; in the case of price momentum, it is the recognition of the extreme price performance of certain stocks. Although these events are publicly known, they are likely to be preceded by intense, private, informed trading. It is both riskier and more difficult to take short positions, and arbitragers (informed traders in our context) must often do so to take advantage of bad news. Therefore, there should be fewer informed traders in bad news firms (losers or low SUE firms) than in good news firms (winners or high SUE firms) in the periods leading up to these public information events (i.e., the portfolio formation period). As there are fixed costs in information acquisition and it takes time to become well-informed about a particular stock, we expect the degree of information asymmetry or information risk of a stock in the portfolio formation period to carry over to the portfolio holding period. In other words, good news firms would continue to have higher information risk than bad news firms in the portfolio holding period, and if information risk is priced, this will be the reason that good news firms continue to outperform bad news firms after portfolio formation. This hypothesis is consistent with the finding of Cohen, Gompers and Vuolteenaho (2002) that stocks with low institutional holdings exhibit high momentum. Short selling is more difficult in stocks with low institutional holdings, as institutional investors are major suppliers of stock loans (cf. Nagel (2005)). This difficulty in short selling would make bad news firms less attractive to informed traders, which translates to a much lower information risk and hence lower returns for bad news firms than for good news firms, and a larger momentum profit for stocks with low institutional holdings.

We further test this information risk hypothesis by examining how information risk of good news and bad news portfolios varies with idiosyncratic risk. In the real world, arbitrage activities are seldom risk-free. In addition, the risk of arbitrage increases with idiosyncratic

risk, as argued by Mendenhall (2004) and Wurgler and Zhuravskaya (2002). In their model of delegated arbitrage, Shleifer and Vishny (1997) also show that idiosyncratic volatility deters arbitrage activities. Intuitively, Shleifer and Vishny (1997) show that even if information possessed by informed traders proves to be correct in the end, an unanticipated big swing in price in the direction against the positions taken by informed traders, although temporary, can force informed traders to close their positions prematurely at a big loss. Furthermore, this type of arbitrage risk is much larger for informed traders who have sold short due to the possibility of short squeeze, which is more likely for stocks exhibiting wide swings in prices, i.e., stocks with high idiosyncratic volatility. These arguments imply that an increase in idiosyncratic volatility would reduce the intensity of informed trading for both good and bad news firms, but that the impact would be larger for bad news firms. As a result, the information risk, and hence the returns of a zero investment momentum portfolio that takes long positions in good news firms and short positions in bad news firms, would increase with idiosyncratic volatility. This prediction is consistent with Zhang (2006), who shows that price momentum increases with information uncertainty using firm size and return volatility as proxies for information uncertainty. This prediction is also consistent with Mendenhall (2004), who finds that PEAD returns are larger for firms with higher idiosyncratic volatility. It is worth noting that both Zhang (2006) and Mendenhall (2004) assume that investors are irrational and that momentum is the result of behavioral biases. In contrast, we argue in this paper that investors are rational, that momentum returns reflect the higher information risk premium that good news firms' investors demand relative to those of bad news firms, and that the differential information risk premium increases with idiosyncratic volatility.

Consistent with our information risk hypothesis, we find that bad news firms have significantly lower loadings on our information factor ECINF than good news firms. The differential in risk loadings on ECINF between good news and bad news firms fully explains the momentum anomalies. In other words, we find that zero-investment momentum portfolios, which are long in good news firms and short in bad news firms, have very significantly positive loadings on ECINF. Furthermore, the significantly positive risk adjusted returns under the Fama-French three-factor model are no longer significant once we include ECINF as an additional factor for risk adjustment.

Also consistent with our hypothesis, we find not only that the returns and ECINF loading of bad news firms decrease monotonically with arbitrage risk, but also that similar patterns exist for good news firms as well. Furthermore, we observe that the zero-investment momentum profit and the loading on ECINF are larger for portfolios constructed from firms with high idiosyncratic volatility than for those with low idiosyncratic volatility. Strikingly, regardless of the strength of the momentum portfolios, they can all be fully explained by the corresponding information risk differential between good news and bad news firms. In other words, for all levels of idiosyncratic volatility, zero investment momentum portfolios no longer generate significant positive risk-adjusted returns once we include ECINF as a risk factor along with MKT, SMB and HML.

Sadka (2006) constructs a liquidity factor, which is the unexpected change in the aggregate variable-permanent component of the price impact of trades, estimated via the Glosten and Harris (1988) model, and shows that it can explain 40% to 80% of the momentum returns of NYSE firms. As the variable and permanent component of liquidity is often associated with private information, Sadka liquidity factor captures the extent of

information asymmetry and thus can also be viewed as an information-based risk factor. Note that ECINF and Sadka liquidity factor are information based factors constructed from two very different paradigms; the fact that both factors can explain momentum anomalies suggests that our results are not a fluke and that information risk indeed plays a major role in momentum anomalies. However, some evidence suggests that ECINF captures information risk better than Sadka liquidity factor. Not only does ECINF explain momentum better than Sadka liquidity factor, but in more general asset pricing tests, we also find that the risk premium of Sadka liquidity factor is subsumed by that of ECINF.

The contribution of this paper is twofold. First, we contribute to the debate on the pricing of information risk by showing that information asymmetry is not only priced as a risk characteristic as in Hwang and Qian (2010), it is also priced as a systematic factor risk. Secondly, we resolve the momentum anomalies through information risk without resorting to explanations involving investor irrationality or behavior biases. At the same time, we highlight the importance of information risk in asset pricing. Failure to incorporate it in asset pricing tests can produce misleading anomalies that are typically interpreted as evidence against market efficiency.

This paper is organized as follows. Section 2 introduces the data and the estimation of ECIN. Section 3 constructs the ECIN factor and conducts the two-stage cross-sectional regressions to show that it is a priced factor. Section 4 presents and tests the informational risk hypotheses of momentum anomalies. Section 5 conducts further tests of the information risk hypotheses that involve idiosyncratic volatility. Section 6 compares ECINF and Sadka liquidity factor, and Section 7 studies the relationship among ECINF, liquidity factors and macroeconomic variables. Section 8 concludes.

2. Estimation of ECIN and Data

2.1 Estimation of ECIN

Hwang and Qian (2010) construct an information risk measure (ECIN) based on the price discovery of large trades. They motivate the construction of ECIN as follows. First, private information is revealed in a sequence of trade prices (cf. Glosten and Milgrom (1985) and Kyle (1985)). Second, informed traders prefer large trades. Easley and O'Hara (1987) illustrate in their model that informed traders prefer to trade in large sizes in order to minimize their transaction costs and maximize their profits from their information. Third, the prices of large trades and small trades are co-integrated, so that the price discovery of trades can be estimated via the error-correction model (VECM). The VECM allows one to examine the short-run dynamics in which each of the co-integrated series moves from disequilibrium toward a long-run equilibrium, where the large trade price equals the small trade price, as they are the prices of the same stock. Intuitively, Hwang and Qian (2010) use VECM to study how a temporary gap between the large trade price and small trade price of the same stock (a disequilibrium caused by information or liquidity reason) is closed. If most of the gap is closed through adjustment in the small trade price with little movement in the large trade price, this indicates that the large trade price has been closer to the long-run equilibrium price, and hence the large trade price has a greater price discovery function for the stock in question. Because large trade is potentially privately informed trade as argued above, the error-correction coefficient of the large trade price, which measures its price discovery function, naturally becomes a good measure of the likelihood and the magnitude of private information-based trade, which is the ECIN devised by Hwang and Qian (2010).

According to the Granger representation theorem proposed by Engle and Granger (1987), if $P_{i,t}^L$ and $P_{i,t}^S$, which represent the price series of the large trade and small trade respectively, are co-integrated and $P_{i,t} = (P_{i,t}^L \ P_{i,t}^S)'$ can be represented by a q th-order vector autoregressive process VAR(q), then there is a VECM representation as follows.

$$\begin{aligned}\Delta P_{i,t}^L &= c_i^L + \alpha_i^L Z_{i,t-1} + \sum_{h=1}^{q-1} \phi_{i,h} \Delta P_{i,t-h}^L + \sum_{h=1}^{q-1} \delta_{i,h} \Delta P_{i,t-h}^S + \eta_{i,t}^L \\ \Delta P_{i,t}^S &= c_i^S + \alpha_i^S Z_{i,t-1} + \sum_{k=1}^{q-1} \lambda_{i,k} \Delta P_{i,t-k}^L + \sum_{k=1}^{q-1} \gamma_{i,k} \Delta P_{i,t-k}^S + \eta_{i,t}^S\end{aligned}\quad (1)$$

where Δ denotes the first-order time difference (i.e., $\Delta P_{i,t}^L = P_{i,t}^L - P_{i,t-1}^L$ and $\Delta P_{i,t}^S = P_{i,t}^S - P_{i,t-1}^S$); $\phi_{i,h}$, $\delta_{i,h}$, $\lambda_{i,k}$ and $\gamma_{i,k}$ are functions of the parameters in VAR(q); $\eta_{i,t}^L$ and $\eta_{i,t}^S$ are zero mean white noise processes. The subscript t represents a 20-minute time interval; c_i^L and c_i^S are constants; $Z_{i,t-1} = P_{i,t-1}^L + \theta_i P_{i,t-1}^S$ is the equilibrium error term, a stationary process with mean zero; and $(1, \theta_i)'$ is called the cointegration vector. As prices for the same stock, $P_{i,t}^L$ and $P_{i,t}^S$ should be equal in equilibrium. This suggests that the cointegration factor should be $(1, -1)'$, and hence the equilibrium error $Z_{i,t-1}$ becomes $(Z_{i,t-1} = P_{i,t-1}^L - P_{i,t-1}^S)$. α_i^L and α_i^S are the error-correcting coefficients that indicate the extent to which the price series of large trades and small trades respond to the disequilibrium (or equilibrium error) during the process of moving toward the long-run equilibrium relationship $P_{i,t}^L = P_{i,t}^S$. For example, if the disequilibrium is positive (i.e., $P_{i,t-1}^L > P_{i,t-1}^S$), the large trade price was above the small trade price in the previous period. To maintain long-run equilibrium, this gap has to be reduced by lowering the large trade price by the amount of α_i^L times the level of disequilibrium $(P_{i,t-1}^L - P_{i,t-1}^S)$ and raising the small trade price by the amount of α_i^S times the level of disequilibrium $(P_{i,t-1}^L - P_{i,t-1}^S)$. This implies that α_i^L is zero or negative, while α_i^S

is zero or positive. This means that firms with a larger (i.e., a less negative) α_i^L and hence a larger *ECIN* have higher information risk and greater information asymmetry. In this paper, we strictly follow the procedures of Hwang and Qian (2010), including data screening, trade size classification, the matching of the large trade and small trade, and the model specification of VECM in the estimation of *ECIN*.

2.2 Data

We estimate *ECIN* using ISSM/TAQ data from January 1983 through December 2006. Each firm year, *ECIN* is measured for stocks listed in the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). We exclude ISSM/TAQ intraday data with non-positive prices for trades outside regular trading hours, or with irregular terms.² The price momentum analyses are performed on NYSE/AMEX firms that contain valid monthly return data in CRSP. The construction of the SUE portfolios for earning momentum analyses also requires valid earning announcement dates and earnings per share data in Compustat; the construction of the SUE portfolios based on analysts' forecasts further requires valid I/B/E/S data. We exclude stocks with less than six months of records in CRSP and stocks with negative or zero shares outstanding. We also exclude REIT, stocks of companies incorporated outside the U.S. and closed-end funds. Finally, to avoid the biases associated with penny stocks, we exclude stocks with prices smaller than \$5 at the end of the portfolio formation month.

² We delete trades conducted outside regular trading hours of 9:30-16:00. For ISSM data, we include only trades for which the condition code is blank or “*”. For TAQ data, we include only trades for which the correction indicator is 0 or 1 and the condition code is blank or “*”. We also exclude the opening trade by deleting the first trade on or after 9:30.

3. ECIN Portfolios and the ECIN Factor

In this section, we first test whether portfolios sorted by ECIN earn diverse returns. We form portfolios as in Easley, Hvidkjaer and O'Hara (2010). At the beginning of each year, we sort all NYSE and AMEX stocks with non-missing ECIN data into size deciles according to their previous year-end market capitalizations. Within each size decile, stocks are further sorted into terciles based on their ECIN estimated over the previous year. The portfolios in the highest, medium and lowest ECIN terciles are denoted as HECIN, MECIN and LECIN, respectively. The first three columns in Panel A of Table 1 report the average ECIN for the stocks in each portfolio and show that the average ECIN within each ECIN classification decreases monotonically with firm size. The first three columns in Panel B of Table 1 report the average size of stocks in each portfolio and show that the average size declines monotonically with ECIN within each size classification, except for those within the largest size decile. The negative correlation between firm size and ECIN that we observe in Panels A and B of Table 1 is intuitive, since large firms have more informational intermediary coverage and therefore smaller information asymmetry than small firms have. However, this negative correlation also indicates that the dependent sort by ECIN is almost a second (reversed) sort by size. To correct this problem, we adopt a method similar to that of Mohanram and Rajgopal (2009): we sort three portfolios based on firm size within each size decile, where this second sort by size is independent of the sort by ECIN in the first step. We denote the largest, medium and smallest size terciles in the second sort as LSIZE, MSIZE and SSIZE, respectively. The characteristics of these portfolios are reported in the same panels in Table 1 where the characteristics of ECIN-based portfolios were reported in the first step. The ECIN portfolio net of size effect is defined as (High ECIN- Small Size)-(Low ECIN-

Large Size)³ for each size decile, and the characteristics are reported in the last column of Table 1. If high ECIN tends to pick up small firms and low ECIN tends to pick up large firms, the zero-investment portfolios defined in this way will capture the hedge return related to ECIN while neutralizing the effect of firm size. Panel C reports the time-series mean of the value-weighted average returns for each portfolio. The average return of the hedge portfolios across all size deciles is 0.704% (t -statistic=5.13). This is consistent with Hwang and Qian's (2010) finding that portfolios with higher ECIN earn higher returns after controlling for the effects of size, book-to-market and various measures of liquidity.

Table 2 reports the correlations in returns across the ten ECIN portfolios. There are significant positive correlations between each pair of ECIN portfolios, except for some correlations involving the largest size decile. The positive correlations between these portfolios suggest a common variation of returns within both high ECIN and low ECIN stocks, indicating that ECIN might capture some underlying systematic risk. To test this effect, we construct the ECIN factor, which is the average return of the ten ECIN-based zero-investment portfolios in Table 1.

Table 3 Panel A provides the summary statistics of the ECIN factor (ECINF) and the traditional factors: the market, size and book-to-market factors of Fama and French (1993) and the momentum factor of Carhart (1997). ECINF has a mean of 0.704% and a median of 0.971%. Panel B reports the correlation between factors. ECINF is negatively correlated with market and size factors and positively correlated with book-to-market and momentum

³ The results are robust when we construct the ECIN portfolios and factor as (High ECIN- Low ECIN) and when we use equal-weighted portfolio returns.

factors.⁴ The strong correlations between ECINF and other factors raise the question of whether the returns of ECINF can be captured by other risk factors. We run time-series regressions with ECINF as the dependent variable and the other factors as explanatory variables. The coefficients are reported in Panel C. The risk adjusted returns of ECINF are 0.891% (t -statistic=7.57) in the three-factor regression and 0.651% (t -statistic=6.36) in the four-factor regression. We conclude that the market, size, book-to-market and momentum factors cannot explain the return variation captured by ECINF.

We use the popular two-stage cross-sectional regression (2SCSR) at the portfolio level (cf. Fama and French (1993), Pástor and Stambaugh (2003), Sadka (2006) and Core, Guay and Verdi (2008)) to test whether ECINF is a priced factor after we control for the three Fama-French (1993) factors (MKT, SMB and HML) with or without the Carhart (1997) momentum factor (UMD).

In the first stage of the 2SCSR, following Core, Guay and Verdi (2008), we estimate multivariate factor loadings from a time-series regression of the excess return ($R_p - R_F$) for each test portfolio on the contemporaneous returns on Fama-French factors and the ECINF using the whole period data. For example, when we add ECINF to the Fama-French three-factor model, the factor loadings (β 's) for portfolio p are estimated from the following time-series regression:

$$R_{p,t} - R_{F,t} = \beta_0 + \beta_{p,MKT} MKT_t + \beta_{p,SMB} SMB_t + \beta_{p,HML} HML_t + \beta_{p,ECINF} ECINF_t + \varepsilon_{p,t} \quad (2)$$

⁴ The correlations between ECINF and market, size, book-to-market, and momentum factors are -0.462, -0.368, 0.258, and 0.477, respectively, if we use the hedge return of (High ECIN-Low ECIN).

In the second stage, we estimate risk premiums, γ_j where $j= 1$ to 4, in the following equation using the Fama-MacBeth (1973) procedure.

$$E(R_{p,t} - R_{F,t}) = \gamma_0 + \gamma_1\beta_{P,MKL} + \gamma_2\beta_{P,SMB} + \gamma_3\beta_{P,HML} + \gamma_4\beta_{P,ECINF} \quad (3)$$

If ECINF is a priced factor, the risk premium γ_4 should be significantly positive. Since the factor betas in the second-stage regression are estimates rather than true values, the estimation of equation (3) is subject to the “errors-in-variable” problem. We mitigate this concern by estimating the 2SCSR at the portfolio level (Fama and MacBeth, 1973). In addition, because the Fama-MacBeth standard errors may be understated due to this error-in-variables problem, we make the Shanken (1992) correction. The adjusted R^2 reported is the time series average of the adjusted R^2 of the cross-sectional regressions.

We perform the 2SCSR on three sets of portfolios. The first set consists of 25 portfolios formed by sorting all of the NYSE/AMEX stocks that have market equity and ECIN data independently by firm size and ECIN. Five size portfolios are formed at the end of each December. The size breakpoint is the NYSE market equity quintile at the end of the year. Stocks are also independently sorted into quintiles at the end of each December by the ECIN estimated through the year. The 25 portfolios are the intersection of the five size portfolios and five ECIN portfolios. The value-weighted monthly returns during the next 12 months are linked across years to form a single return series for each portfolio.

The second set consists of 27 portfolios formed by sorting all NYSE/AMEX stocks with valid market equity, book equity and ECIN data independently by firm size, book-to-market (BM) ratio, and ECIN. The size breakpoints are the NYSE market equity 0.7 and 0.3 fractiles at the end of each June. BM for each June is the book equity at the end of the last

fiscal year divided by the market equity at the end of the last calendar year. The BM breakpoints are the 0.7 and 0.3 fractiles of the NYSE book-to-market ratio. The ECIN breakpoints for each June are the ECIN terciles estimated in the last calendar year. As the ECIN data are available from the year 1983, the portfolio is formed from the end of June 1984. The value-weighted monthly returns from July of each year through June of the next year are linked across years to form a single return series for each portfolio.

The third set consists of the 25 Fama-French portfolios formed by firm size and book-to-market (BM) quintiles. The return data comes from Kenneth French's web site at Dartmouth. The portfolios, including all NYSE/AMEX/NASDAQ stocks, are formed at the end of each June. The size breakpoints are the NYSE market equity quintiles at the end of each June. BM is the book equity at the end of the last fiscal year divided by the market equity at the end of the last calendar year. The BM breakpoints are NYSE quintiles. The value-weighted monthly returns from July of each year through June of the next year are linked across years to form a single return series for each portfolio.

Table 4 reports the coefficients of the second stage cross-sectional regressions. We first focus on Panel A and Panel B. LMKT3, LSMB3, and LHML3 in Panel A represent the factor loadings for the Fama-French three-factor model. LMKT4, LSMB4, and LHML4 and LECINF4 in Panel B represent the factor loadings for the four-factor model, where the Fama-French three-factor model is augmented by ECINF. The figures under each column represent the estimated risk premiums and t -statistics associated with each column's respective factor loading. For example, the entries in the first row of Panel B correspond to the estimated $\gamma_1, \gamma_2, \gamma_3$ and γ_4 in equation (3) using the 25 Size and ECIN portfolios. It is clear that the loadings on ECINF have significant explanatory power for the cross-sectional variation of the

expected return of all three sets of portfolios.⁵ The coefficients on the loading of ECINF for the three sets of portfolios are significant and positive at 1.235 (t -statistic =5.85), 0.776 (t -statistic =2.86), and 0.863 (t -statistic =2.83), respectively. Note that these t -statistics are much higher than those of other factors. Furthermore, comparing Panel A and Panel B, we can see that including ECINF as a risk factor significantly improves the adjusted R -square of the cross-sectional regression of expected returns. These results are consistent with Easley and O'Hara (2004) that information risk is a systematic risk and that investors require positive premiums for holding this risk. To further test whether the significance of the risk premium of ECINF is due to the omission of the momentum factor, we add the Carhart (1997) momentum factor UMD into the test and report the results in Panel C and Panel D. Adopting the same convention we use in labeling factor loadings in Panel A and Panel B, we label the factor loadings for the Fama-French four-factor model as LMKT4, LSMB4, LHML4 and LUMD4 in Panel C. The factor loadings for the five-factor model, where the Fama-French three-factor model is augmented by both UMD and ECINF, are labeled as LMKT5, LSMB5, LHML5, LUMD5 and LECINF5 in Panel D. Note that the risk premiums of ECINF remain strongly significant and positive in the five-factor model at 1.110, 0.601, and 0.893 (t -statistics are 4.36, 2.18, and 2.97, respectively). Overall, the two-stage cross-sectional regression tests provide evidence that ECINF is a priced risk factor. It is also worth noting that in all tests, whether we use the four-factor pricing model (Panel B) or the five-factor pricing model (Panel D), ECINF is always the most significant (in some cases the only significant) pricing factor. In addition, we observe that the very significant risk premium of

⁵ The insignificant (or negative) coefficients on the market and size factors loadings in Panel A may be due to the fact that beta and size effects are disappearing in the asset pricing around the recent sample period. Mohanram and Rajgopal (2009) and Core, Guay and Verdi (2008) find similar negative or insignificant coefficients for the market and size factor loadings in the comparable sample periods.

the momentum factor in Panel C has been greatly reduced by the presence of ECINF, as shown in Panel D. This result raises the possibility that the momentum factor UMD may be explained by the information risk factor ECINF. To investigate this possibility, we run time-series regressions similar to those reported in Panel C of Table 3, except that we now use UMD as the dependent variable and ECINF as an independent variable. The results are reported in Table 5. Strikingly, we find that the large and highly significant Fama-French three-factor risk-adjusted return of the Carhart (1997) momentum factor, which stands at 0.984% per month (t -statistic = 3.83), falls to an insignificant -0.05% per month (t -statistic = -0.21) after we include ECINF as an additional risk factor in the Fama-French three-factor model. The loading of ECINF for the momentum factor is positive and highly significant (t -statistic = 10.57).

In sum, we have shown that ECINF is not only a priced factor, but also the most significant factor in Table 4 and Table 5, raising the possibility that many of the anomalies in the literature may arise due to failure to take information risk into account. We investigate this possibility with momentum anomalies as an example because (1) momentum anomalies have been recognized by Fama (1998) as one of the biggest challenges to rational asset pricing, and (2) we are encouraged by comparing the result in Panel C of Table 3 with that of Table 5, which indicates that information risk is likely the root cause of momentum anomalies.

4. Information Risk Hypotheses and Momentum Anomalies

As discussed in the introduction, it is riskier and more difficult to take short positions than long positions, due to short sell constraints and the asymmetrically large impact on arbitrage risk of taking short positions. Thus we expect bad news firms to be less attractive to informed traders and to have a lower information risk than good news firms in the portfolio formation period. As there are fixed costs in information acquisition and it takes time to become well-informed about a particular stock, we expect the degree of information asymmetry or information risk of a stock in the portfolio formation period to carry over to the portfolio holding period. In other words, we expect good news firms to continue to have higher information risk than bad news firms in the portfolio holding period. We have shown in Table 4 that information risk is priced, so we expect the information risk differential between good news and bad news firms to play a major role in explaining the momentum anomalies. This discussion leads to the following hypotheses.

H1: The information risk is smaller in bad news firms than in good news firms.

H2: The profit from the zero-investment momentum portfolios that take long positions in good news and short positions in bad news firms will be greatly reduced or become insignificant after adjustment for information risk.

The risk of arbitrage increases with idiosyncratic risk, as argued by Mendenhall (2004) and Wurgler and Zhuravskaya (2002). In their model of delegated arbitrage, Shleifer and Vishny (1997) also show that idiosyncratic volatility deters arbitrage activities. Consequently, we expect that information risk decreases with idiosyncratic volatility for both good news firms and bad news firms. Furthermore, the possibility of short squeeze greatly increases the arbitrage risk of short positions relative to that of long positions. As short

squeeze is more likely in stocks with greater idiosyncratic volatility, we expect the asymmetry describing the larger arbitrage risk of short positions relative to that of long positions to further increase with idiosyncratic volatility. This may explain the stronger momentum anomalies in stocks with high idiosyncratic volatilities reported by Zhang (2006) and Mendenhall (2004), among others. These discussions lead to three more information risk hypotheses.

H3: The information risk decreases with idiosyncratic volatility for both good news and bad news firms.

H4: Due to a greater reduction of information risk in bad news firms when idiosyncratic volatility increases, the information risk differential between good news and bad news firms, and hence the momentum anomalies, are stronger when idiosyncratic volatility is high than when it is low.

H5: Irrespective of the level of idiosyncratic volatility, momentum anomalies become weaker or disappear after information risk adjustment.

4.1 Price Momentum

In this subsection, we test *H1* and *H2* in the context of price momentum. Our (J , K) momentum strategies are similar to those defined in Jegadeesh and Titman (1993). At the beginning of each month, stocks are sorted into quintiles based on the past J months' returns that skip the last month. Firms in the top (bottom) quintile are called "winners" ("losers"). The portfolio return is the value-weighted average of the component stocks' returns. Each portfolio is held for K months and liquidated after that. Therefore, in a given month t , the

momentum portfolio return of this (J, K) momentum strategy $R_{p,t}$ is the equally-weighted average of K portfolios that are formed in the current month as well as in each of the previous $K-1$ months. To obtain the risk adjusted return of the momentum portfolios, we run time-series regressions similar to those reported of Table 5.

In Table 6, the column labeled Alpha FF3 reports the intercepts of the time series regressions of the excess returns of momentum portfolios on Fama-French three-factor (MKT, SMB, HML) model. The column labeled Alpha ECINF reports the intercepts of the time series regressions of the excess returns of momentum portfolios on Fama-French three-factor model augmented by ECINF; and the column labeled ECINF Loading reports the factor loadings (i.e., coefficients) of ECINF in these regressions. Momentum portfolios are formed on NYSE/AMEX firms with different trading strategies ($J=6, 12$ and $K=6, 12$). The last row reports the regression results for the zero-investment portfolios that take long positions in the winner portfolios and short positions in the loser portfolios. We observe, for all combinations of (J, K) (for brevity, we report only for $(6, 6)$ and $(12, 12)$), that ECINF loadings increase from losers to winners, which is consistent with $H1$ that losers have lower information risk than winners have. In addition, we find that the significant positive (negative) Fama-French three-factor risk-adjusted returns of winner (loser) portfolios as well as Winner-Loser portfolios, reported in the column (Alpha FF3), become insignificant in the second column (Alpha ECINF) when ECINF is included as an additional risk factor. This latter result is even stronger than predicted by $H2$, in the sense that price momentum anomalies are not only weakened but can be fully explained by the information risk factor. For example, the zero-investment Winner-Loser portfolio of the $(6, 6)$ strategy has a positive Fama-French three-factor risk-adjusted return of 0.669% per month (t -statistic =3.03), but it

falls to an insignificant -0.083% per month (t -statistic = -0.38) in the four-factor model that also includes ECINF. The loading on ECINF is significantly positive at 0.844 (t -statistic = 8.50).

These results strongly support the information risk hypothesis. In particular, they indicate that one doesn't have to invoke the behavioral biases of irrational investors to explain price momentum, as price momentum can be fully explained with a rational risk-based model. Additional and perhaps stronger tests of $H1$ and $H2$ can be conducted by repeating the same analyses on the holding period returns in the second year after portfolio formation, at which point price momentum no longer exists (cf. Fama and French (1996) and Chan, Jegadeesh and Lakonishok (1996)). If the momentum of the holding period returns in the first year is indeed caused by the information risk differential between winner and loser portfolios, then we should expect an insignificant information risk differential in the holding period in the second year after portfolio formation when momentum ceases to exist. The second year holding period return in month t of the (J, K) momentum strategy is calculated in the same way that the first year returns have been calculated, except that the second year holding period return in month t is the equally-weighted return of the twelve portfolios that are formed between month $t - 13$ and $t - 24$. The test results are reported in Panel B of Table 6. Consistent with findings in the literature, there is no momentum profit in the second year after portfolio formation. The Fama-French three-factor risk adjusted return (Alpha FF3) of the zero-investment momentum portfolio is an insignificant 0.05% per month when the past six-month return ($J=6$) is used to form winner and loser portfolios. It is 0.036% per month and insignificant when $J=12$. This is consistent with the information risk hypothesis

that the information risk differential between the winner and loser portfolios (reported in the last column, “ECINF Loading”) is also insignificant for both $J=6$ and $J=12$.

4.2 Post-Earnings-Announcement Drift (PEAD)

In this section, we test $H1$ and $H2$ in the context of PEAD, where the good news firms and the bad news firms have large and small standardized unexpected earnings (SUE) respectively. We measure SUE with two specifications. The first is the traditional method based on the seasonal random walk (SRW) model adopted by Chan, Jegadeesh and Lakonishok (1996) and Chordia and Shivakumar (2006). It is estimated as

$$SUE_{i,q} = \frac{(E_{i,q} - E_{i,q-4})}{\sigma_{i,q}} \quad (6)$$

where $E_{i,q}$ is primary Earnings Per Share (EPS) before extraordinary items in quarter q for stock i , and $\sigma_{i,q}$ is the standard deviation of earnings changes in the prior eight quarters. $E_{i,q}$ is unadjusted for stock splits, but $E_{i,q-4}$ is adjusted for any stock splits and stock dividends during the period $(t - 4, t)$. To avoid introducing biases into the tests, we follow Chordia and Shivakumar (2006) and Sadka (2006) in scaling the earnings surprise by the standard deviation rather than by the stock price, total asset, or sales, since these variables may proxy for size or expected returns. Note that in the SRW model, the expected earnings are the actual earnings four quarters ago. To check for robustness, we also use analysts’ expected earnings as a proxy of investors’ expected earnings in our second SUE measure, which is in line with Livnat and Mendenhall (2006). In other words, in the second measure we replace the SRW forecast ($E_{i,q-4}$) in equation (6) with a measure of analysts’ expectations, which is

the median of all analysts' forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement.

At the beginning of each month t , the SUE portfolios are formed based on the most recent earnings announcement, which occurs neither in the current month t , nor in the four months preceding the formation month date. We sort firms into quintiles based on the SUE in each month. Stock returns are value-weighted in each portfolio. The positions are held for K months starting from the formation month. Therefore, the portfolio return in a given month t from such a strategy R_{pt} is the equally-weighted average of K portfolios that are formed in the current month as well as in the previous $K-1$ months. The factor risk adjusted return and the loadings of the information risk factor of the PEAD momentum portfolios are estimated the same way as they are for the price momentum portfolios. The results are reported in Table 7, which follows the same format as Table 6. Panel A is for the holding period that captures the first three months after portfolio formation (i.e., $K=3$). Consistent with *HI*, the loading on ECINF increases nearly monotonically from low SUE quintiles to high SUE quintiles. The difference in information risk between high and low SUE portfolios is very significant, with a much smaller and significantly negative ECINF loading for low SUE portfolios. This is true for both SUE measures that are based either on the Seasonal Random Walk model (SRW) or on Analysts' Forecast (AF). The monthly three-factor risk-adjusted return of the zero-investment PEAD portfolios is positive and significant at 0.43% for SUE based on SRW and 0.37% for SUE based on analysts' forecast. However, after we add ECINF as an additional risk factor to account for information risk, the PEAD anomaly of both SUE measures disappears, as shown by the highly significant value of ECINF Loading and the insignificant values of Alpha ECINF in the last row in Panel A. This result is

consistent with *H2* and demonstrates that, like price momentum, PEAD can be fully explained by the information risk factor. As with price momentum, we also provide an additional test of *H1* and *H2* by testing whether the information risk differential between high SUE and low SUE portfolios is weak or insignificant in the holding period where PEAD is weaker or insignificant. As with price momentum, we also choose the second year after the portfolio formation as the holding period for such tests. The results are reported in Panel B. Consistent with the information risk hypothesis, in the second year after portfolio formation there is an insignificant PEAD, accompanied by an insignificant difference in information risk between high SUE and low SUE portfolios when the SUE is constructed based on analysts' forecasts. Also consistent with the hypothesis, PEAD profit is weak in the second year after portfolio formation with a SRW based SUE, and it can be fully explained by the correspondingly weak information risk differential of the high and low SUE portfolios.

5. Momentum Anomalies and Idiosyncratic Volatility

In this section, we test *H3*, *H4* and *H5*, which hypothesize how idiosyncratic volatility affects information risk and momentum anomalies. Arbitragers face risks daily (even one day or a few days of large stock price movements may force arbitragers to prematurely close their positions at big losses). We follow Ang, Hordrick, Xing and Zhang (2006) and measure idiosyncratic volatility (IVOL) as the standard deviation of residuals estimated from the following time series regression that regresses one month of daily returns (with at least 20 observation) for stock *i* on the contemporary Fama-French (1993) factors:

$$R_{i,d} = \alpha_i + \beta_{i,MKT}MKT_d + \beta_{i,SMB}SMB_d + \beta_{i,HML}HML_d + \varepsilon_{i,d} \quad (7)$$

where $R_{i,d}$ is the stock return on day d , MKT_d is the daily excess return on the market, SMB_d is the daily return to size factor-mimicking portfolio, and HML_d is the daily return to book-to-market factor-mimicking portfolio. We will test the hypotheses on price momentum in section 5.1 and the hypotheses on PEAD in section 5.2

5.1 Price Momentum

At the end of each month t , sample firms are sorted into quintiles based on IVOL estimated in the current month. Then within each IVOL quintile, stocks are further sorted into quintiles based on the past J -month return cumulated from month $t-J$ to $t-1$. A value-weighted momentum portfolio is formed for each past return quintile; the top quintile portfolio is referred to as Winner, and the bottom quintile portfolio is referred to as Loser. Each momentum portfolio is held for the next K months (i.e., from $t+1$ through $t+K$). In other words, we adopt a (J, K) momentum strategy for each IVOL quintile. Note that we have maintained a one-month gap between the holding period and the formation period so that our estimation of IVOL is not affected by the formation period returns.

Test results are reported in Table 8, which has a similar format to that of Table 6, except that the results are now conditioned on IVOL. As in Table 6, we report only the results of the (6, 6) and (12, 12) strategies for brevity. Furthermore, since the results of the (6, 6) and (12, 12) momentum strategies are very similar, we focus our discussion mainly on the (12, 12) strategy. Consistent with $H3$, loadings of ECINF decrease monotonically with IVOL for both Winner and Loser portfolios. Furthermore, the impact on ECINF loading of increasing IVOL is larger for losers. ECINF loading of losers decreases by 0.743 (from -0.033 to -0.776) when IVOL moves from the low quintile to the high quintile, which is larger

than the corresponding decrease of 0.438 (from 0.223 to -0.215) for winner portfolios. Consequently, consistent with *H4*, the information risk loading of the zero investment momentum portfolio *increases* from 0.257 to 0.562 when IVOL increases from the lowest to the highest quintile. We also observe that the risk-adjusted return from the Fama-French three-factor model (Alpha FF3) increases from 0.32% to 0.87% per month when IVOL increases from the low to high quintile. This result is consistent with the results of Zhang (2006), who shows that momentum increases with return volatility. He offers a behavioral explanation for this result: momentum is a result of investors' behavioral biases, which increase with information uncertainty for which return volatility is a proxy. In contrast, we show that the information risk of the zero investment momentum portfolio increases with IVOL, mostly through the larger decrease of the information risk of the loser portfolio. As we hypothesize in *H4*, this is exactly why momentum becomes stronger when IVOL is higher. Consistent with *H5*, we find that the previously significant Fama-French risk-adjusted momentum returns not only become smaller, but also become insignificant from zero after we adjust for information risk. This is also true even for the strongest momentum found in the highest IVOL quintile: Alpha FF3 is 0.87% (t -statistic =3.02) and 1.51% (t -statistic =4.61), and Alpha ECINF is now 0.37% and 0.61% for the (12, 12) and (6, 6) strategy, respectively. Neither is statistically different from zero at the 5% level.

In sum, we show that *H3*, *H4* and *H5* are all supported by the data in the case of price momentum. Note that these results constitute even stronger support for the information risk hypothesis than those in Table 6. We not only show that momentum can be explained by information risk in general, but we demonstrate that this is the case in *every* IVOL quintile, including the highest IVOL quintile where the strongest momentum is found.

5.2 Post-Earnings-Announcement Drift (PEAD)

Table 9 is similar to Table 8, except that it reports the test results of *H3*, *H4* and *H5* on PEAD, and that the Winner and Loser portfolios of Table 8 are replaced by high SUE and low SUE portfolios, respectively. Consistent with *H3*, for SRW based SUE, we observe that information risk decreases monotonically with IVOL in both low and high SUE portfolios. We observe a similar pattern for AF based SUE portfolios, except for a minor exception for the SUE portfolios in the second IVOL quintile. Although the differential impact of increasing IVOL on the information risk between low and high SUE portfolios is not as dramatic as that between loser and winner portfolios reported in Table 8, we still observe a somewhat larger information risk reduction in the low SUE portfolios than in the high SUE portfolios when IVOL increases from low to high quintile. As a result, the information risk of the zero investment PEAD portfolios that take long positions in the high SUE portfolios and short positions in the low SUE portfolios is also higher in the high IVOL quintile than in the low IVOL quintile. The information risk is 0.683 vs. 0.459 for SRW based SUE, and 0.353 vs. 0.134 for AF based SUE. These results are consistent with *H4*. Also consistent with *H4*, Table 9 reveals that PEAD is stronger when IVOL is higher. Under SRW (AF) based SUE, Alpha FF3 of the zero-investment PEAD portfolios that buy high SUE and sell low SUE portfolios is 0.362 (0.349) in the low IVOL quintile, while it is 0.651 (0.452) in the high IVOL quintile. However, consistent with *H5*, after we adjust for information risk, the PEAD becomes insignificant irrespective of the level of IVOL.

6. Comparing ECINF and Sadka Liquidity Factor

Sadka (2006) constructs a liquidity factor, which is the unexpected change in the aggregate value of the variable and permanent component of liquidity. This component of liquidity at firm level is estimated using the model of Glosten and Harris (1988). Sadka (2006) shows that his factor explains between 40% and 80% of the price momentum, as well as the PEAD portfolio returns of NYSE-listed firms, making it one of the most successful risk factors of this kind. As the variable and permanent component of the liquidity is often associated with private information, Sadka liquidity factor captures the extent of information asymmetry and thus is also an information-based risk factor. Although both ECINF and Sadka liquidity factor are information based factors, they are constructed from very different paradigms. The fact that both succeed in explaining momentum and PEAD portfolio returns suggests that information risk is indeed a very important determinant of price momentum and PEAD. At the same time, it becomes important and interesting to compare the explanatory powers of the two factors not only in momentum anomalies but also in asset pricing in general.

6.1 Using Momentum portfolios and SUE portfolios

We have assessed the explanatory power of ECINF in momentum and PEAD returns by comparing the risk-adjusted returns before and after including ECINF as an additional risk factor in the factor model. For example, in Table 6, we find that the previously significant values of Alpha FF3 become insignificant in Alpha ECINF and conclude that momentum anomalies can be fully explained by ECINF. Unfortunately, we cannot do the same tests with Sadka's factor, as it is not a traded portfolio. As a result, to compare the explanatory powers of ECINF and Sadka's factor in the same setting, we have to rely on the 2SCSR technique used in Table 4.

In Table 10, we run the 2SCSR using price momentum and SUE portfolios. We follow Sadka (2006) closely in this test, except that we use a longer time period (1984-2005) and include AMEX-listed firms. Specifically, we create two sets of portfolios: 25 momentum (MOM) portfolios sorted by the past 12-month cumulative returns and 25 SUE portfolios sorted by standardized unexpected earnings, defined as SRW based on SUE in the previous tables. The stocks are equally weighted in each portfolio, and the portfolios are rebalanced monthly.⁶ Liquidity factor SDK_PV is the non-traded permanent-variable liquidity factor in Sadka (2006) that we obtain from Wharton Research Data Services (WRDS). As in Table 4, in the first stage of the 2SCSR, the factor loadings are computed through a time-series multiple regression of portfolio excess returns on the contemporaneous factor returns over the entire sample period. In the second stage, risk premiums are estimated with the Fama and MacBeth (1973) methodology. The reported *t*-statistics (in parentheses) have been corrected for the sampling errors in the estimated factor loadings (Shanken, 1992).

Panel A of Table 10 reports results for price momentum portfolios. We can see that in regressions (2) and (6), the risk premiums of Sadka liquidity factor (in the column labeled LSDK_PV) are positive and highly significant (*t*-statistics are 3.19 and 3.97, respectively) when it is the only information factor included in the model. These results are consistent with findings in Sadka (2006). From regressions (3) and (7), we observe that the same results hold for the risk premium of ECINF (in the column labeled LECINF), which is consistent with our earlier results in Table 5 and Table 6 where we show that ECINF fully explains momentum portfolio returns. However, when the loadings of both Sadka's factor and ECINF

⁶ We use equally-weighted portfolios to allow for direct comparison with Sadka (2006). Results of value-weighted portfolios are similar.

are included in the model, as in regressions (1) and (5), we find that the risk premium of Sadka's factor becomes insignificant, while that of ECINF remains highly significant. These results suggest that both Sadka liquidity factor and ECINF can explain momentum returns as an information risk premium, but ECINF seems to capture information risk better than Sadka liquidity factor.

We run the same tests using 25 SUE portfolios and report the results in Panel B. The pattern and results in Panel B are very similar to those in Panel A, which allows us to conclude that ECINF captures information risk better than Sadka liquidity factor does in explaining PEAD portfolio returns.

6.2 Using General Portfolios

Although we have just shown that ECINF is more effective than the Sadka liquidity factor in explaining price momentum and PEAD portfolios returns, it doesn't necessarily follow that ECINF is also more effective in explaining the returns of more general portfolios. We investigate this issue in this section.

In Table 4, we show that ECINF is a priced factor, as its risk premium is always positive and significant when it is tested using three sets of portfolios that include the popular 25 Size and BM portfolios (Fama and French, 1993). Thus, we will first test whether the Sadka liquidity factor (SDK_PV) is also priced in the same sets of portfolios. As Panel A of Table 11 shows, among the three set of portfolios, the risk of SDK_PV is priced significantly at the 5% level only in 25 Size and ECIN 25 portfolios. Furthermore, even this significant risk premium of SDK_PV becomes insignificant once we include ECINF in the pricing model, as shown in Panel B. On the other hand, the significant risk premium of ECINF in the

three set of portfolios we observe in Panel B of Table 4 remains highly significant even after SDK_PV is added in the pricing model. We are mindful of the criticism that the low power of detecting the risk premium of SDK_PV may be due to a lack of variation in LSDK_PV, the loading on SDK_PV in the second stage of 2SCSR, in these three sets of portfolios. Consequently, we construct two sets of portfolios (25 Size and SDK_Beta portfolios, 27 Size, BM and SDK_Beta portfolios) with a wide variation in LSDK_PV. We first run a rolling regression every month for each stock using stock returns and the contemporaneous factors (MKT, SMB, HML and SDK_PV) during the past 60 months (we require at least 24 months of returns). SDK_Beta is the estimated coefficient of SDK_PV from such regressions. The 25 Size and SDK_Beta and 27 Size, BM and SDK_Beta are then formed in the same way as the 25 Size and ECIN portfolios and the 27 Size, BM and ECIN portfolios, respectively, except that ECIN is replaced by the SDK_Beta estimated in the previous month and the portfolio is formed and rebalanced monthly. However, we are surprised to find in Panel A that the risk premium of SDK_PV is not significant in either of the two sets of portfolios. In contrast, the risk premium of ECINF (i.e., the coefficient of LECINF5) is significantly positive in both test portfolios, as shown in Panel B. Taken together, these results suggest that ECINF is more effective than the Sadka liquidity factor in capturing information risk and is a better choice for controlling for information risk in future research.

The result that ECINF is more effective than the Sadka liquidity factor in explaining the cross section of asset returns may not come as a surprise, for two reasons. First, ECINF, as the returns of a traded portfolio, may include some stocks whose returns it is trying to explain. However, we show that this is not the case. Note that ECINF is constructed from stocks listed on NYSE /AMEX; it does not contain stocks listed on NASDAQ. However, from the result

reported in Panel B of Table 11, we continue to find that ECINF dominates SDK_PV in explaining the returns of NASDAQ 25 Size and BM portfolios that contain only NASDAQ stocks. NASDAQ 25 Size and BM portfolios are formed from the intersections of independently sorted Size and BM quintiles of NASDAQ stocks. The second and more likely explanation is that ECINF is a portfolio based on ECIN, an information asymmetry risk characteristic shown by Hwang and Qian (2010) to have a positive risk premium λ . In a factor model setting, if ECIN is assumed to be a factor loading on an unobservable factor related to aggregate information asymmetry, then we know this factor also has a risk premium of λ , and we can construct a mimicking portfolio of this factor based on its factor loading, just as we construct ECINF based on ECIN. In other words, if we are approximately correct in our assumption that ECIN measures a stock's loading on the unobservable factor, then we already know ECINF will be a priced factor. However, this advantage comes at a price: we don't know the identity or the exact specification of this unobservable information factor, except that it is related to aggregate information asymmetry. In contrast, Sadka (2006) directly specifies the unobservable information factor as the unexpected variation in the aggregate measure of the permanent-variable component of the price impact of trades, and thus the economic meaning of his information-based liquidity factor is clear. On the other hand, its power as an information-based risk factor for asset pricing may suffer if the form of asymmetry information is misspecified.

7. The Relationship among ECINF, Liquidity Factors and Macroeconomic Variables.

Although we don't know the identity of the underlying information asymmetry factor that ECINF mimics, we can learn how it is related to macroeconomic fundamental variables and other liquidity factors through the correlations of ECINF with these variables. The macroeconomic variables we focus on are the market factor in the Fama-French three factors model (MKT), and the macroeconomic variables used in Liu and Zhang (2008), which include MP (the growth rate of industrial production), UI (the unexpected inflation), DEI (the change of expected inflation), UTS (the yield spread between long-term and one-year Treasury bonds) and UPR (the default premium measured as the yield spread between Moody's Baa and Aaa corporate bonds). In addition to the Sadka liquidity factor (SDK_PV) we have analyzed in earlier tests, other liquidity factors we consider are the Pástor-Stambaugh value-weighted traded liquidity factor (PS_VWF) and non-traded liquidity factor (PS_INV) developed in Pástor and Stambaugh (2003); both factors are obtained from WRDS.

Table 12 reports the correlations among these variables. We can see that among the macroeconomic variables, ECINF is most correlated with MKT, with a correlation of -0.397, followed by those with UTS (-0.141) and MP (0.117). The highly significant negative correlation between ECINF and MKT indicates that the level of aggregate information asymmetry is lower in up markets. This is consistent with the intuition that more noise traders than informed traders are attracted into stock markets when the markets offer high returns. The positive correlation between ECINF and MP also indicates that the level of information asymmetry in the market is higher when the growth rate of the industrial output is higher, perhaps because the edge in analyzing data between traders grows wider in such a situation. Turning to liquidity factors, we see that SDK_PV is significantly correlated with DEI (0.179), UPR (-0.126), and with MKT (0.085), but we find low correlations between macroeconomic

variables and PS_VWF. The correlations between PS_INV and the macroeconomic variables are also low except for a large correlation with MKT (correlation is 0.30). It is interesting to note that there is little correlation among ECINF, PS_VWF and SDK_PV, but ECINF is negatively correlated with PS_INV (correlation is -0.16). The latter result is likely due to the fact that both ECINF and PS_INV are significantly correlated with MKT but of opposite signs.

MP is also of special interest to us in this paper because Liu and Zhang (2008) show that this macroeconomic risk factor explains more than half of the momentum profit. Since ECINF is positively correlated with MP, it would be interesting to see whether MP's explanatory power of momentum profit is independent from ECINF's. To this end, we repeat the analysis we performed in Section 6.1 in which we compare the power of ECINF and SDK_PV to explain momentum returns, except that SDK_PV is now replaced by MP. These results are reported as regressions (8) and (9) in Panel A of Table 10. Consistent with Liu and Zhang (2008), we find that winner portfolios have higher loadings on MP and that the risk premium is positive and significant (t -statistic = 2.70) as shown in regression (8). However, regression (9) reveals that once we include ECINF in the pricing model, the risk premium of MP is no longer significant. These results mirror those reported in regression (1) and regression (2), and suggest that the risk difference in information risk between winners and losers explains momentum returns better than the risk difference in liquidity and industrial output do.

8. Conclusion

In this paper, we create an information factor, ECINF, based on the information asymmetry measure ECIN developed by Hwang and Qian (2010). The two-stage cross-sectional asset

pricing tests on different sets of portfolios all reveal a significantly positive risk premium for ECINF, which can be viewed as evidence supportive of Easley and O'Hara's (2004) conclusion that the risk of information asymmetry faced by uninformed investors is not diversifiable. The significant risk premiums of ECINF contrast sharply with the findings in Mohanram and Rajgopal (2009) that the loadings of the PIN factor are insignificantly related to the cross-sectional returns, suggesting that ECINF captures the underlying information risk more efficiently than the PIN factor does.

We hypothesize that momentum anomalies (price momentum and PEAD) can be explained by information risk. Momentum anomalies arise because there are fewer informed traders, and hence lower information risk, in bad news firms (past losers or low earning surprise firms) than in good news firms (past winners or high earning surprise firms). The larger cost and risk of arbitrage in taking short positions make bad news firms less attractive to informed traders. Consistent with our hypotheses, using both price momentum and PEAD, we find that the loading on ECINF is lower in bad news firms than in good news firms. The difference in loadings on ECINF between good news and bad news firms increases significantly with idiosyncratic volatility, but mostly through the reduction of information risk in bad news firms. This finding also explains the results of Zhang (2006) and Mendenhall (2004) that momentum increases with proxy of information uncertainty such as idiosyncratic volatility. More importantly, irrespective of the level of idiosyncratic risk, the significantly positive risk adjusted returns of zero investment momentum portfolios are no longer significant once we include ECINF as an additional factor for risk adjustment. This finding suggests that the price momentum and PEAD anomalies can be fully explained by ECINF.

This paper shows that ECINF is not only a priced factor risk, but often the strongest risk factor and sometimes the only significant risk factor in the asset pricing tests we conduct. Consequently, ignoring the risk of information asymmetry may lead to false anomalies and false evidence against market efficiency and rational asset pricing. Furthermore, researchers commonly include the Carhart (1997) momentum factor to control for the momentum effect. Our result that the Carhart (1997) momentum factor can be fully explained by ECINF but not vice versa suggests that it is better and makes more economic sense to control for information risk directly by including ECINF in the factor model in future studies.

In this paper, we have explored only the role of ECINF in explaining momentum anomalies, although we also have preliminary evidence showing that ECINF can fully explain the long-term underperformance of SEO and equity issuance. We have found that firms having undertaken SEO and equity issuance activities have experienced reductions in information risk, possibly due to the greater disclosure requirement associated with these activities. We also expect ECINF to play a major role in explaining other anomalies explored in Avramov, Chordia, Jostova and Philipov (2010), who find a commonality across asset pricing anomalies: the profitability of anomaly based trading strategies is basically derived from taking a short position in high credit risk firms that experience deteriorating credit conditions. We conjecture that these firms have lower returns because they have lower information risk; they have lower information risk because conducting arbitrage activity in these firms is often difficult and risky, and hence fewer informed traders are present in these firms. We will investigate the validity of this conjecture in future works.

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Table 1 Characteristics and Returns of ECIN Portfolios

At the beginning of each year, we sort all stocks in NYSE and AMEX with non-missing ECIN data into size deciles according to their previous year-end market capitalizations. Within each size decile, stocks are further sorted into terciles based on their ECIN, estimated over the previous year following Hwang and Qian (2010). The portfolios in the highest, medium and lowest ECIN terciles are denoted as HECIN, MECIN and LECIN, respectively. Within each decile, stocks are also further sorted into terciles based on their previous year-end market capitalizations (size). The portfolios in the highest, medium and lowest size terciles are denoted as LSIZE, MSZIE and SSIZE, respectively. The two sorts within each size decile are independent. The table presents the time-series average of mean ECIN (Panel A), mean market capitalization in millions (Panel B) and value-weighted monthly return (Panel C) for each portfolio. The last column, ECIN Portfolio, is formed as (HECIN- SSIZE)-(LECIN- LSIZE). The equally-weighted mean across the size decile is reported in the Average row. In particular, the equally-weighted mean across the size decile of the ECIN portfolio return in Panel C is the ECINF, the information risk factor. The sample period is from January 1983 through December 2006 for *ECIN* and size, and from January 1984 through December 2007 for stock returns.

Panel A: ECIN

Size Deciles	LECIN	MECIN	HECIN	SSIZE	MSIZE	LSIZE	ECIN Portfolio
Small	-0.141	-0.073	-0.021	-0.075	-0.080	-0.080	0.115
2	-0.164	-0.084	-0.029	-0.085	-0.092	-0.098	0.123
3	-0.201	-0.111	-0.050	-0.109	-0.123	-0.130	0.130
4	-0.254	-0.148	-0.075	-0.149	-0.160	-0.167	0.161
5	-0.290	-0.178	-0.097	-0.180	-0.189	-0.195	0.179
6	-0.340	-0.208	-0.112	-0.206	-0.217	-0.236	0.198
7	-0.385	-0.243	-0.133	-0.240	-0.249	-0.272	0.219
8	-0.435	-0.284	-0.158	-0.274	-0.291	-0.311	0.240
9	-0.485	-0.329	-0.179	-0.319	-0.335	-0.339	0.287
Large	-0.550	-0.362	-0.171	-0.358	-0.377	-0.346	0.392
Average	-0.324	-0.202	-0.102	-0.200	-0.211	-0.217	0.204

Panel B: Market Capitalization

Size Deciles	LECIN	MECIN	HECIN	SSIZE	MSIZE	LSIZE	ECIN Portfolio
Small	17.0	17.1	16.5	6.8	13.3	21.8	14.5
2	51.4	50.1	48.7	32.1	45.4	62.6	27.8
3	121.0	116.6	111.9	83.2	108.4	142.3	50.0
4	235.2	231.8	227.5	180.3	224.2	271.5	83.5
5	396.1	391.6	385.1	323.3	380.8	448.1	113.8
6	656.1	643.2	627.1	527.7	623.2	739.9	183.1
7	1,089.9	1,065.3	1,033.6	871.1	1,028.6	1,228.1	300.7
8	1,939.4	1,874.5	1,835.4	1,479.4	1,799.4	2,222.1	638.7
9	4,265.2	4,208.0	4,144.0	2,865.1	3,834.4	5,221.3	2,235.0
Large	46,902.2	49,909.3	58,188.9	7,407.5	12,415.4	74,443.0	78,322.3
Average	5,567.4	5,850.7	6,661.9	1,377.7	2,047.3	8,480.1	8,196.9

Panel C: Stock Returns (%)

Size Deciles	LECIN	MECIN	HECIN	SSIZE	MSIZE	LSIZE	ECIN Portfolio	<i>t</i> -value
Small	0.448	0.610	1.255	1.349	0.889	0.572	0.029	0.06
2	-0.150	0.761	1.382	0.634	0.577	0.725	1.623	5.00
3	0.100	0.960	1.343	0.688	0.743	0.893	1.449	5.32
4	0.536	1.153	1.471	1.029	1.064	1.055	0.962	3.81
5	0.366	1.311	1.457	0.847	1.233	1.026	1.270	5.21
6	0.878	1.204	1.346	1.079	1.166	1.174	0.564	2.66
7	0.906	1.281	1.396	1.173	1.209	1.185	0.502	2.55
8	1.106	1.241	1.378	1.167	1.155	1.350	0.455	3.10
9	1.048	1.276	1.250	1.169	1.127	1.244	0.277	1.53
Large	1.106	1.141	1.149	1.239	1.064	1.107	-0.088	-0.48
Average	0.634	1.094	1.343	1.037	1.023	1.033	0.704	5.13

Table 2 Return Correlations between ECIN-Based Zero-Investment Portfolios

At the beginning of each year, we sort all stocks in NYSE and AMEX with non-missing ECIN data into size deciles according to their previous year-end market capitalizations. Within each size decile, stocks are further sorted into terciles based on their ECIN estimated over the previous year. The portfolios in the highest, medium and lowest ECIN terciles are denoted as HECIN, MECIN and LECIN, respectively. Within each decile, stocks are also further sorted into terciles based on their previous year-end market capitalizations (size). The portfolios in the highest, medium and lowest size terciles are denoted as LSIZE, MSZIE and SSIZE, respectively. The two sorts within each size decile are independent. The zero-investment ECIN portfolio for each size decile is formed as (HECIN- SSIZE)-(LECIN- LSIZE). The Pearson correlations between the value-weighted monthly return of the 10 zero-investment ECIN portfolios are reported in the table, and the corresponding p -values are in parentheses. The sample period is from January 1984 to December 2007.

	2	3	4	5	6	7	8	9	Large
Small	0.324 (0.000)	0.347 (0.000)	0.284 (0.000)	0.290 (0.000)	0.180 (0.002)	0.034 (0.561)	0.099 (0.094)	0.014 (0.817)	0.053 (0.366)
2		0.374 (0.000)	0.231 (0.000)	0.352 (0.000)	0.269 (0.000)	0.128 (0.030)	0.089 (0.132)	0.186 (0.002)	-0.120 (0.042)
3			0.411 (0.000)	0.368 (0.000)	0.213 (0.000)	0.173 (0.003)	0.098 (0.096)	0.159 (0.007)	0.055 (0.356)
4				0.358 (0.000)	0.351 (0.000)	0.224 (0.000)	0.077 (0.195)	0.126 (0.033)	0.016 (0.786)
5					0.386 (0.000)	0.338 (0.000)	0.146 (0.013)	0.085 (0.149)	0.026 (0.660)
6						0.337 (0.000)	0.202 (0.001)	0.209 (0.000)	0.045 (0.443)
7							0.270 (0.000)	0.222 (0.000)	0.173 (0.003)
8								0.140 (0.018)	0.185 (0.002)
9									0.181 (0.002)

Table 3 Descriptive Statistics and Time-Series Relations of Risk Factors

This table reports the descriptive statistics and time-series relations of the three Fama and French (1993) factors (MKT, SMB and HML), the Carhart (1997) momentum factor (UMD) and the information risk factor (ECINF). MKT is the excess return on the market, the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to the size factor-mimicking portfolio. HML (High minus Low) is the return to the book-to-market factor-mimicking portfolio. UMD (Up minus Down) is the return to the momentum factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio. Panel A reports the descriptive statistics of the factors. Panel B reports the correlations. Panel C reports the time series regression of ECINF on the three/four other risk factors. The sample period is from January 1984 to December 2007.

Panel A: Descriptive Statistics

	N	Mean	STD	MIN	Median	MAX	<i>t-stat</i>
MKT	288	0.636	4.283	-23.130	1.045	12.430	2.52
SMB	288	0.004	3.299	-16.790	-0.190	21.960	0.02
HML	288	0.361	3.097	-12.400	0.315	13.850	1.98
UMD	288	0.822	4.262	-25.060	0.955	18.390	3.27
ECINF	288	0.704	2.330	-14.319	0.971	6.483	5.13

Panel B: Correlation Matrix of the Factors

	MKT	SMB	HML	UMD
SMB	0.200			
HML	-0.488	-0.414		
UMD	-0.099	0.100	-0.063	
ECINF	-0.397	-0.451	0.198	0.437

Panel C: Time-Series Regressions

Regression	Intercept	MKT	SMB	HML	UMD	Adj. R ²
(1)	0.891 (7.57)	-0.215 (-7.05)	-0.315 (-8.31)	-0.135 (-2.97)		0.315
(2)	0.651 (6.36)	-0.174 (-6.64)	-0.343 (-10.63)	-0.098 (-2.54)	0.243 (10.57)	0.507

Table 4 Monthly Cross-sectional Portfolio Regressions of Returns on Factor Loadings

This table reports the monthly cross-sectional regression of portfolio excess returns on factor loadings for three sets of portfolios. The first set (25 Size and ECIN) is constructed from the intersections of size and ECIN quintiles, which are formed by sorting all NYSE/AMEX common stocks (1984-2007) independently by size and ECIN at the end of December of each year. The second set (27 Size, BM and ECIN) is constructed from the intersections of size, BM and ECIN terciles, which are formed by sorting all NYSE/AMEX common stocks independently by size and book-to-market and ECIN at the end of June of each year. The third set (Fama-French 25 Size and BM) is constructed according to Fama and French (1993). Data for Fama-French factors (MKT, SMB, HML and UMD) and 25 Size and BM portfolio returns are obtained from Kenneth French's web site at Dartmouth. ECINF is the information risk factor-mimicking portfolio constructed in Table 1. The pricing tests are conducted with the Two-Stage Cross-Sectional Regressions. In the first stage, factor loadings are estimated through a time-series multiple regression of value-weighted portfolio excess returns on the tested factors (subsets of MKT, SMB, HML, UMD and ECINF) over the entire sample period. In the second stage, the Fama and MacBeth procedure is performed. Each month, a cross-sectional regression of portfolio excess returns is run on the estimated factor loadings estimated in the first stage. The coefficients of the cross-sectional regressions are then averaged through time, and t -statistics (in parentheses) are corrected for the sampling errors in the estimated factor loadings (Shanken, 1992). Adj. R^2 is the time-series average of adjusted R^2 from the cross-sectional regressions. Panel A reports the regressions on the factor loadings from the Fama-French three-factor model (LMKT3, LSMB3 and LHML3). Panel B reports the regressions on the factor loadings from the Fama-French three-factor model augmented by ECINF (LMKT4, LSMB4, LHML4 and LECINF4). Panel C reports the regressions on the factor loadings from the Fama-French four-factor model (LMKT4, LSMB4, LHML4 and LUMD4). Panel D reports the regression on the factor loadings from the Fama-French four-factor model augmented by ECINF (LMKT5, LSMB5, LHML5, LUMD5 and LECINF5).

Panel A: Regressions Using Loadings from the Fama-French Three-Factor Model

Portfolios	LMKT3	LSMB3	LHML3	Adj. R ²
25 Size and ECIN	-2.875 (-6.43)	-0.781 (-2.80)	0.658 (1.65)	0.245
27 Size, BM, and ECIN	-1.185 (-2.36)	-0.504 (-2.04)	0.718 (2.88)	0.286
Fama-French 25 (Size and BM)	-1.100 (-2.52)	-0.078 (-0.38)	0.377 (1.94)	0.465

Panel B: Regressions Using Loadings from the Fama-French Three-Factor Model Augmented by ECINF

Portfolios	LMKT4	LSMB4	LHML4	LECINF4	Adj. R ²
25 Size and ECIN	-0.718 (-1.14)	-0.041 (-0.13)	0.667 (1.53)	1.235 (5.85)	0.324
27 Size, BM, and ECIN	-0.178 (-0.31)	-0.242 (-0.91)	0.534 (2.04)	0.776 (2.86)	0.312
Fama-French 25 (Size and BM)	-1.013 (-2.05)	-0.001 (-0.00)	0.340 (1.61)	0.863 (2.83)	0.520

Panel C: Regressions Using Loadings from the Fama-French Three-Factor Model Augmented by UMD

Portfolios	LMKT4	LSMB4	LHML4	LUMD4	Adj. R ²
25 Size and ECIN	-0.294 (-0.51)	0.088 (0.31)	0.302 (0.73)	3.481 (5.41)	0.294
27 Size, BM, and ECIN	0.458 (0.72)	-0.291 (-1.19)	0.537 (2.23)	1.975 (2.79)	0.309
Fama-French 25 (Size and BM)	-0.064 (-0.11)	-0.037 (-0.18)	0.419 (2.10)	2.859 (3.54)	0.477

Panel D: Regressions Using Loadings from the Fama-French Three-Factor Model Augmented by UMD and ECINF

Portfolios	LMKT5	LSMB5	LHML5	LUMD5	LECIN5	Adj. R ²
25 Size and ECIN	-0.427 (-0.72)	0.066 (0.22)	0.514 (1.19)	2.254 (2.89)	1.110 (4.36)	0.358
27 Size, BM, and ECIN	0.340 (0.51)	-0.251 (-0.95)	0.517 (1.99)	1.638 (2.14)	0.601 (2.18)	0.322
Fama-French 25 (Size and BM)	-0.466 (-0.86)	-0.005 (-0.02)	0.377 (1.78)	2.166 (2.77)	0.893 (2.97)	0.523

Table 5 Time-Series Regressions of UMD on the Fama-French Three Factors and ECINF

This table reports the contemporary regressions of the momentum factor (UMD) on ECINF and the three Fama and French (1993) factors (MKT, SMB and HML). MKT, the excess return on the market, is the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to the size factor-mimicking portfolio. HML (High minus Low) is the return to the book-to-market factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio created in Table 1. Data for factors MKT, SMB, HML and UMD are from Kenneth French's web site at Dartmouth.

Regression	Intercept	MKT	SMB	HML	ECINF	Adj. R ²
(1)	0.984 (3.83)	-0.169 (-2.54)	0.115 (1.38)	-0.150 (-1.51)		0.022
(2)	-0.051 (-0.21)	0.080 (1.31)	0.481 (6.14)	0.007 (0.08)	1.162 (10.57)	0.297

Table 6 Momentum Portfolios and Information Risk

This table reports the time-series regression of the momentum portfolios. The sample includes all common stocks in NYSE/AMEX for years 1984-2007. Momentum portfolios of the (J, K) strategy are formed based on the previous J month's returns (skipping the last month) and held for K months. At the end of each month t , sample firms are sorted into quintiles based on cumulative returns from month $t-J$ to $t-1$; the Winner (Loser) is the portfolio quintile that has the highest (lowest) cumulative returns. In Panel A, the positions are held for the following K months, $t+1$ through $t+K$. In Panel B, the holding period is month $t+13$ to $t+24$. We follow Jegadeesh and Titman (1993) in calculating momentum portfolio returns from the (J, K) strategy to avoid using test statistics based on overlapping returns. The value-weighted portfolio excess returns are regressed on the three contemporaneous Fama-French risk factors (MKT, SMB, HML) and the information risk factor (ECINF). MKT, the excess return on the market, is the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to size factor-mimicking portfolio. HML (High minus Low) is the return to book-to-market factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio. The table reports the alphas from the Fama-French three-factor model (Alpha FF3), and the alphas and the ECINF factor loadings (Alpha ECINF and ECINF Loading) from the Fama-French three-factor model augmented by ECINF. The t -statistics are in parentheses.

Panel A: Holding Period ($t+1, t+K$)

	J=6, K=6			J=12, K=12		
	Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading
Loser	-0.463 (-2.98)	0.082 (0.55)	-0.612 (-8.82)	-0.359 (-2.54)	-0.032 (-0.21)	-0.368 (-5.40)
2	-0.060 (-0.70)	0.115 (1.27)	-0.196 (-4.73)	-0.166 (-1.79)	-0.060 (-0.60)	-0.119 (-2.56)
3	-0.064 (-1.07)	-0.055 (-0.84)	-0.010 (-0.33)	-0.062 (-0.86)	-0.055 (-0.69)	-0.009 (-0.23)
4	-0.001 (-0.02)	-0.158 (-2.41)	0.176 (5.82)	0.021 (0.31)	-0.031 (-0.42)	0.058 (1.71)
Winner	0.206 (2.22)	-0.001 (-0.01)	0.232 (5.19)	0.172 (1.90)	0.088 (0.89)	0.095 (2.08)
Winner-Loser	0.669 (3.03)	-0.083 (-0.38)	0.844 (8.50)	0.532 (2.60)	0.120 (0.55)	0.462 (4.64)

Panel B: Holding Period ($t+13, t+24$)

	J=6			J=12		
	Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading
Loser	-0.085 (-0.86)	-0.044 (-0.4)	-0.047 (-0.94)	-0.057 (-0.53)	0.007 (0.06)	-0.073 (-1.33)
2	-0.007 (-0.11)	-0.058 (-0.80)	0.056 (1.69)	-0.044 (-0.57)	-0.09 (-1.07)	0.052 (1.34)
3	-0.002 (-0.03)	-0.019 (-0.31)	0.020 (0.68)	-0.004 (-0.06)	-0.053 (-0.73)	0.055 (1.65)
4	-0.016 (-0.26)	-0.033 (-0.5)	0.019 (0.63)	0.051 (0.77)	0.015 (0.20)	0.041 (1.23)
Winner	-0.035 (-0.47)	0.049 (0.60)	-0.095 (-2.53)	-0.021 (-0.24)	0.046 (0.49)	-0.075 (-1.75)
Winner-Loser	0.050 (0.35)	0.093 (0.60)	-0.048 (-0.68)	0.036 (0.22)	0.038 (0.21)	-0.002 (-0.02)

Table 7 Post-Earnings-Announcement Drift and Information Risk

This table reports the time-series regression of the earnings momentum portfolios. The sample includes common stocks in the NYSE/AMEX in years 1984-2007. We estimate SUE using both a rolling seasonal random walk (SRW) model and analysts' forecasts (AF). In the SRW model, SUE for stock i in month t is defined as $(E_{i,q} - E_{i,q-4})/\sigma_{i,q}$, where $E_{i,q}$ is the quarterly earning most recently announced as of month t (not including announcements in month t) for firm i , $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,q}$ is the standard deviation of earnings changes in the prior eight quarters. With analysts' forecasts, SUE is the earnings surprise based on I/B/E/S reported analysts' forecasts and actual earnings, where $E_{i,q-4}$ in the definition of the SRW model is replaced by a measure of analysts' expectations represented by the median of analysts' forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement. At the beginning of each month t , stocks are sorted into quintiles by SUE. In Panel A, the positions are held for the following three months, t through $t+2$. In Panel B, the holding period is month $t+12$ to $t+23$. We follow Jegadeesh and Titman (1993) in calculating the portfolio return of a holding period that is longer than one month to avoid using test statistics based on overlapping returns. The value-weighted portfolio excess returns are regressed on the contemporaneous Fama-French three factors (MKT, SMB, and HML) and the information risk factor (ECINF). MKT, the excess return on the market, is the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to the size factor-mimicking portfolio. HML (High minus Low) is the return to the book-to-market factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio. The table reports the alphas from the Fama-French three-factor model (Alpha FF3), the alphas and the ECINF factor loadings (Alpha ECINF and ECINF Loading) from the Fama-French three-factor model augmented by ECINF. The t -statistics are in parentheses.

Panel A: Holding Period ($t, t+2$)

	SRW			AF		
	Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading
Low	-0.283 (-2.54)	0.075 (0.68)	-0.402 (-7.91)	-0.154 (-1.35)	0.088 (0.74)	-0.285 (-5.22)
2	-0.128 (-1.28)	0.020 (0.18)	-0.166 (-3.35)	-0.174 (-1.86)	-0.117 (-1.16)	-0.067 (-1.43)
3	-0.036 (-0.44)	-0.077 (-0.84)	0.045 (1.08)	-0.012 (-0.13)	0.028 (0.28)	-0.048 (-1.00)
4	0.001 (0.02)	-0.011 (-0.13)	0.014 (0.35)	-0.023 (-0.32)	0.044 (0.57)	-0.078 (-2.20)
High	0.146 (1.65)	0.016 (0.17)	0.146 (3.33)	0.210 (2.83)	0.171 (2.12)	0.046 (1.25)
High-Low	0.429 (2.83)	-0.060 (-0.40)	0.548 (7.91)	0.365 (2.78)	0.083 (0.61)	0.332 (5.30)

Panel B: Holding Period ($t+12, t+23$)

	SRW			AF		
	Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading
Low	-0.249 (-2.32)	-0.14 (-1.20)	-0.122 (-2.27)	-0.047 (-0.47)	0.015 (0.14)	-0.073 (-1.46)
2	-0.099 (-1.39)	0.005 (0.07)	-0.117 (-3.33)	0.004 (0.05)	0.001 (0.01)	0.004 (0.09)
3	0.003 (0.04)	0.102 (1.36)	-0.112 (-3.24)	-0.043 (-0.48)	0.086 (0.9)	-0.152 (-3.45)
4	-0.032 (-0.43)	0.122 (1.59)	-0.173 (-4.88)	-0.074 (-0.93)	0.026 (0.3)	-0.117 (-2.99)
High	0.026 (0.29)	0.032 (0.34)	-0.008 (-0.17)	0.035 (0.44)	0.119 (1.39)	-0.098 (-2.49)
High-Low	0.275 (2.53)	0.173 (1.46)	0.115 (2.11)	0.082 (0.93)	0.103 (1.08)	-0.025 (-0.57)

Table 8 Momentum Portfolios and Idiosyncratic Volatility

This table reports the time-series regressions of portfolios sorted by idiosyncratic volatility (IVOL) and then by price momentum. The sample includes all common stocks in NYSE/AMEX for years 1984-2007. The idiosyncratic volatility for each stock is the variance of the residual from a Fama-French three-factor regression using daily returns. Momentum portfolios of the (J, K) strategy are formed based on the previous J month returns (skipping the last month) and held for K months. At the end of each month t , sample firms are sorted into quintiles based on IVOL estimated in the current month. Then within each IVOL quintile, the momentum portfolios are sorted by cumulative return from month $t-J$ to $t-1$; the Winner (Loser) is the portfolio quintile that has the highest (lowest) cumulative returns. The positions are held for the following K months, $t+1$ through $t+K$. We follow Jegadeesh and Titman (1993) in calculating momentum portfolio returns for the (J, K) strategy to avoid using test statistics based on overlapping returns. The dependent variables are the value-weighted excess returns for momentum quintiles. The portfolio returns are regressed on the contemporaneous three Fama-French risk factors (MKT, SMB, and HML) and the information risk factor (ECINF). MKT, the excess return on the market, is the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to size factor-mimicking portfolio. HML (High minus Low) is the return to the book-to-market factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio. The table reports the alphas from the Fama-French three-factor model (Alpha FF3), the alphas and the ECINF factor loadings (Alpha ECINF and ECINF Loading) from the Fama-French three-factor model augmented by ECINF. The t -statistics are in parentheses.

Momentum	IVOL	J=6, K=6			J=12, K=12		
		Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading
Loser	Low	0.062 (0.57)	0.160 (1.35)	-0.110 (-2.02)	-0.094 (-0.88)	-0.064 (-0.55)	-0.033 (-0.62)
	2	-0.160 (-1.33)	0.065 (0.51)	-0.253 (-4.29)	-0.259 (-2.07)	-0.054 (-0.41)	-0.230 (-3.73)
	3	-0.404 (-2.81)	-0.007 (-0.05)	-0.446 (-6.60)	-0.356 (-2.49)	-0.098 (-0.64)	-0.290 (-4.13)
	4	-0.670 (-3.80)	-0.143 (-0.80)	-0.592 (-7.22)	-0.598 (-3.73)	-0.226 (-1.35)	-0.417 (-5.41)
	High	-1.235 (-5.02)	-0.367 (-1.53)	-0.975 (-8.87)	-0.877 (-3.87)	-0.186 (-0.82)	-0.776 (-7.41)
	Winner	Low	0.189 (1.84)	-0.068 (-0.64)	0.289 (5.88)	0.227 (2.29)	0.028 (0.27)
	2	0.273 (2.87)	0.025 (0.25)	0.279 (6.18)	0.246 (2.66)	0.063 (0.64)	0.206 (4.55)
	3	0.103 (0.95)	-0.121 (-1.05)	0.252 (4.75)	0.132 (1.28)	-0.015 (-0.14)	0.165 (3.23)
	4	0.248 (1.90)	0.060 (0.43)	0.211 (3.26)	0.090 (0.71)	0.060 (0.43)	0.034 (0.53)
	High	0.271 (1.51)	0.242 (1.23)	0.033 (0.37)	-0.008 (-0.05)	0.183 (1.01)	-0.215 (-2.57)
Winner-Loser	Low	0.127 (0.87)	-0.228 (-1.5)	0.399 (5.69)	0.321 (2.27)	0.093 (0.61)	0.257 (3.68)
	2	0.434 (2.65)	-0.040 (-0.24)	0.533 (6.97)	0.505 (2.92)	0.117 (0.65)	0.436 (5.23)
	3	0.507 (2.53)	-0.114 (-0.57)	0.697 (7.56)	0.488 (2.50)	0.082 (0.40)	0.455 (4.80)
	4	0.918 (3.68)	0.203 (0.80)	0.803 (6.89)	0.687 (2.98)	0.286 (1.16)	0.451 (3.97)
	High	1.506 (4.61)	0.608 (1.82)	1.009 (6.57)	0.870 (3.02)	0.369 (1.20)	0.562 (3.97)

Table 9 Post-Earnings-Announcement Drift and Idiosyncratic Volatility

This table reports the time-series regressions of portfolios sorted by idiosyncratic volatility (IVOL) and then by standardized unexpected earnings (SUE). The sample includes all common stocks in NYSE/AMEX for years 1984-2007. The idiosyncratic volatility for each stock is the variance of the residual from a Fama-French three-factor regression using daily returns in the month before the earnings announcement month. We estimate SUE using both a rolling seasonal random walk (SRW) model and analysts' forecasts (AF). With the SRW model, SUE for stock i in month t is defined as $(E_{i,q} - E_{i,q-4}) / \sigma_{i,q}$ where $E_{i,q}$ is the quarterly earning most recently announced as of month t (not including announcements in month t) for firm i , $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,q}$ is the standard deviation of earnings changes in the prior eight quarters. With analysts' forecasts, SUE is the earnings surprise based on I/B/E/S reported analysts' forecasts and actual earnings, where $E_{i,q-4}$ in the definition of the SRW model is replaced by a measure of analysts' expectations represented by the median of analysts' forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement. At the beginning of each month t , stocks are first sorted into quintiles by the IVOL estimated in the month before the most recent earnings announcement month, then within each IVOL quintile, stocks are further sorted into quintiles by SUE. In Panel A, the positions are held for the following three months, t through $t+2$. In Panel B, the holding period is from month $t+12$ to $t+23$. We follow Jegadeesh and Titman (1993) in calculating the portfolio return of a holding period that is longer than one month to avoid using test statistics based on overlapping returns. The value-weighted portfolio excess returns are regressed on the contemporaneous three Fama-French risk factors (MKT, SMB, and HML) and the information risk factor (ECINF). MKT, the excess return on the market, is the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. SMB (Small minus Big) is the return to the size factor-mimicking portfolio. HML (High minus Low) is the return to the book-to-market factor-mimicking portfolio. ECINF is the return to the information risk factor-mimicking portfolio. The table reports the alphas from the Fama-French three-factor model (Alpha FF3), the alphas and the ECINF factor loadings (Alpha ECINF and ECINF Loading) from the Fama-French three-factor model augmented by ECINF. The t -statistics are in parentheses.

SUE	IVOL	SRW			AF			
		Alpha FF3	Alpha ECINF	ECINF Loading	Alpha FF3	Alpha ECINF	ECINF Loading	
Low	Low	-0.004 (-0.03)	0.121 (0.89)	-0.140 (-2.25)	-0.027 (-0.20)	-0.039 (-0.26)	0.014 (0.21)	
	2	-0.228 (-1.67)	-0.225 (-1.50)	-0.003 (-0.05)	0.079 (0.52)	0.152 (0.92)	-0.086 (-1.13)	
	3	-0.27 (-1.72)	-0.078 (-0.46)	-0.215 (-2.75)	-0.372 (-2.13)	-0.157 (-0.84)	-0.253 (-2.94)	
	4	-0.545 (-2.76)	-0.046 (-0.23)	-0.560 (-5.97)	-0.472 (-2.46)	-0.069 (-0.35)	-0.474 (-5.16)	
	High	-1.106 (-3.84)	-0.136 (-0.48)	-1.089 (-8.36)	-0.671 (-2.11)	0.160 (0.50)	-0.978 (-6.60)	
	High	Low	0.358 (2.66)	0.074 (0.52)	0.319 (4.88)	0.322 (2.63)	0.196 (1.48)	0.148 (2.44)
	2	0.222 (1.72)	-0.025 (-0.18)	0.277 (4.39)	0.218 (1.81)	0.017 (0.13)	0.237 (4.04)	
3	0.060 (0.44)	-0.002 (-0.01)	0.069 (1.00)	0.161 (1.11)	0.109 (0.69)	0.061 (0.84)		
4	0.007 (0.04)	-0.033 (-0.18)	0.045 (0.52)	-0.177 (-1.12)	-0.25 (-1.45)	0.086 (1.09)		
High	-0.455 (-2.17)	-0.093 (-0.41)	-0.406 (-3.95)	-0.219 (-0.97)	0.312 (1.34)	-0.625 (-5.83)		
High-Low	Low	0.362 (2.02)	-0.047 (-0.25)	0.459 (5.31)	0.349 (2.07)	0.235 (1.29)	0.134 (1.59)	
	2	0.450 (2.45)	0.200 (1.01)	0.281 (3.08)	0.139 (0.71)	-0.136 (-0.65)	0.324 (3.38)	
	3	0.329 (1.68)	0.076 (0.36)	0.284 (2.91)	0.534 (2.52)	0.266 (1.17)	0.315 (3.00)	
	4	0.552 (2.15)	0.013 (0.05)	0.605 (4.86)	0.295 (1.24)	-0.181 (-0.73)	0.560 (4.88)	
	High	0.651 (2.02)	0.043 (0.13)	0.683 (4.33)	0.452 (1.37)	0.152 (0.43)	0.353 (2.16)	
	High	Low	0.362 (2.02)	-0.047 (-0.25)	0.459 (5.31)	0.349 (2.07)	0.235 (1.29)	0.134 (1.59)

Table 10 Pricing Information Risk and Liquidity Risk with Cross-Sectional Regressions

In this table, two different sets of portfolios are analyzed: 25 momentum (MOM) portfolios and 25 portfolios sorted by standardized unexpected earnings (SUE). Momentum is calculated as the past 12-month cumulative returns (skipping the last month). SUE for stock i in month t is defined as $(E_{i,q} - E_{i,q-4})/\sigma_{i,q}$, where $E_{i,q}$ is the quarterly earning most recently announced as of month t (not including announcements in month t), $E_{i,q-4}$ is earnings four quarters ago and $\sigma_{i,q}$ is the standard deviation of earnings changes in the prior eight quarters. The stocks are equally weighted in each portfolio, and the portfolios are rebalanced monthly. Liquidity factor SDK_PV is the non-traded permanent-variable liquidity factor in Sadka (2006) is obtained from WRDS. The returns (excess of risk-free rate) of the two sets of 25 portfolios are used separately to estimate the cross-sectional regression models of the form $E(R_{p,t}) = \gamma_0 + \gamma' \beta_p$, where $R_{p,t}$ are the returns of portfolio p in month t , and β_p 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 are the Fama and French three factors (MKT, SMB, and HML), the non-traded Sadka's liquidity factor (SDK_PV), and the information risk factor $ECINF$. MP is the macroeconomic risk factor as in Liu and Zhang (2008), denoting the growth rate of industrial production. The regression models are estimated using the Fama and MacBeth procedure. Risk premium estimates are reported in percentages. T-statistics (in parentheses) are corrected for the sampling errors in the estimated β_p (Shanken, 1992). Adjusted R^2 is computed as the time-series average of the adjusted R^2 from the cross-sectional regressions. The analysis includes NYSE and AMEX stocks for the period January 1984-December 2005.

Panel A: MOM Portfolios

	LMKT	LSMB	LHML	LSDK_PV	LECINF	MP	Adjusted R^2
(1)	0.505 (0.56)	0.523 (0.73)	-0.511 (-0.93)	-0.143 (-0.50)	0.744 (2.91)		0.592
(2)	0.865 (1.00)	-0.692 (-0.92)	-0.584 (-1.16)	0.442 (3.19)			0.560
(3)	0.497 (0.56)	0.262 (0.33)	-0.376 (-0.68)		0.655 (2.96)		0.580
(4)	3.245 (3.18)	-2.578 (-2.98)	-3.940 (-3.71)				0.474
(5)	1.121 (1.40)			0.077 (0.28)	0.649 (2.74)		0.529
(6)	-0.490 (-1.00)			0.579 (3.97)			0.493
(7)	1.226 (2.15)				0.666 (3.14)		0.518
(8)	-2.790 (-2.76)	0.300 (0.62)	-2.778 (-3.52)			0.339 (2.37)	0.495
(9)	-0.660 (-0.64)	0.996 (1.86)	-0.709 (-1.27)		0.709 (3.30)	-0.021 (-0.14)	0.573

Panel B: SUE Portfolios

	LMKT	LSMB	LHML	LSDK_PV	LECINF	Adjusted R ²
(1)	-0.922 (-1.12)	-1.186 (-1.59)	0.235 (0.34)	0.090 (0.70)	1.380 (4.98)	0.198
(2)	-1.646 (-2.21)	-2.623 (-4.06)	0.995 (1.64)	0.217 (1.84)		0.180
(3)	-1.086 (-1.40)	-1.180 (-1.59)	0.243 (0.35)		1.421 (5.20)	0.193
(4)	-2.661 (-3.68)	-3.197 (-4.65)	1.347 (2.18)			0.166
(5)	-0.509 (-0.67)			0.069 (0.57)	1.384 (5.29)	0.185
(6)	0.695 (0.92)			0.753 (4.79)		0.095
(7)	-0.617 (-0.87)				1.403 (5.39)	0.182

Table 11 Pricing Information Risk and Liquidity Risk Using General Portfolios

This table reports the monthly cross-sectional regression of portfolio excess returns on factor loadings. The first three sets of portfolios (25 Size and ECIN, 27 Size, BM and ECIN, Fama-French 25 Size and BM) are the same sets of portfolios used in Table 4. The fourth set (25 Size and SDK_Beta) and the fifth set (27 Size, BM, and SDK_Beta) of portfolios are constructed in the same ways as 25 Size and ECIN and 27 Size, BM and ECIN are constructed except that ECIN is replaced by SDK_Beta. The sixth set (NASDAQ 25 Size and BM) of portfolios are formed from the intersections of independently sorted Size and BM quintiles of NSADAQ stocks. For each stock, a rolling regression, using the monthly return in past 60 months (with at least 24 valid observations), is run against Fama-French three factors (MKT, SMB, HML) and Sadka's liquidity factor (SDK_PV). SDK_Beta is estimated as the coefficient of SDK_PV. Thus, unlike the other sets of portfolio which are rebalanced yearly, 25 Size, SDK_Beta and 27 Size, BM and SDK_Beta are rebalanced monthly. The pricing tests are conducted with two-stage cross-section regressions. In the first stage, factor loadings are estimated through a time-series multiple regression of value-weighted portfolios excess returns on the tested factors (subsets of MKT, SMB, HML, UMD, SDK_PV and ECINF) over the entire sample period. In the second stage, the Fama and MacBeth procedure is performed. Each month, a cross-sectional regression of portfolio excess return is run on the estimated factor loading estimated in the first stage. The coefficients of cross-sectional regressions are then averaged through time, and *t*-statistics (in the parentheses) are corrected for the sampling errors in the estimated factor loadings (Shanken, 1992). Adjusted R² is computed as the time-series average of the adjusted R² from the cross-sectional regressions. Panel A reports the regressions on the factor loadings from the Fama-French three-factor model augmented by SDK_PV (LMKT4, LSMB4, LHML4, and LSDK_PV4). Panel B reports the regressions on the factor loadings from the Fama-French three-factor model augmented by SDK_PV and ECINF (LMKT5, LSMB5, LHML5, LUMD5 and LECINF5). Data for Fama-French factors (MKT, SMB, HML and UMD) and 25 Size and BM portfolio returns are obtained from Kenneth French's web site at Dartmouth. SDK_PV (1983-December 2005) is obtained from WRDS. ECINF is the information risk factor constructed in Table 1.

Panel A: Regressions Using Loadings from the Fama-French Three-Factor Model Augmented by SDK_PV

Portfolios	LMKT4	LSMB4	LHML4	LSDK_PV 4	Adj. R ²
(1) 25 Size and ECIN	-1.245 (-1.93)	-0.523 (-1.78)	0.387 (0.87)	0.817 (3.16)	0.366
(2) 27 Size, BM, and ECIN	-1.168 (-2.00)	-0.545 (-2.01)	0.793 (3.04)	0.059 (0.36)	0.320
(3) Fama-French 25 (Size and BM)	-0.995 (-2.10)	-0.025 (-0.11)	0.377 (1.82)	0.309 (1.88)	0.513
(4) 25 Size and SDK_Beta	-0.029 (-0.05)	-0.660 (-2.10)	0.786 (1.85)	0.255 (1.55)	0.367
(5) 27 Size, BM, and SDK_Beta	-0.453 (-0.80)	-0.364 (-1.44)	0.581 (2.31)	0.084 (0.60)	0.312
(6) NASDAQ 25 Size and BM	-1.421 (-2.74)	-0.728 (-2.37)	0.495 (1.94)	0.465 (2.38)	0.327

Panel B: Regressions Using Loadings from the Fama-French Three-Factor Model Augmented by SDK_PV and ECINF

Portfolios	LMKT5	LSMB5	LHML5	LSDK PV 5	LECIN5	Adj. R2
(1) 25 Size and ECIN	-0.919 (-1.29)	-0.135 (-0.41)	0.609 (1.20)	0.256 (0.72)	1.259 (5.89)	0.405
(2) 27 Size, BM, and ECIN	-0.148 (-0.24)	-0.266 (-0.88)	0.593 (2.12)	0.111 (0.63)	0.848 (2.91)	0.349
(3) Fama-French 25 Size and BM	-1.051 (-2.07)	0.029 (0.12)	0.365 (1.59)	0.204 (1.22)	0.875 (2.64)	0.558
(4) 25 Size and SDK_Beta	-0.109 (-0.18)	-0.176 (-0.56)	0.220 (0.53)	0.010 (0.06)	0.738 (2.43)	0.413
(5) 27 Size, BM, and SDK_Beta	-0.253 (-0.40)	-0.158 (-0.56)	0.498 (1.81)	-0.049 (-0.31)	0.745 (2.16)	0.370
(6) NASDAQ 25 Size and BM	-1.891 (-3.49)	-0.353 (-1.04)	0.168 (0.58)	0.387 (1.82)	1.415 (3.63)	0.419

Table 12 The Correlations Among ECINF, Liquidity Factors and Macroeconomic Variables

This table reports the correlations among ECINF, liquidity factors and macroeconomic variables. ECINF is the return to the information risk factor-mimicking portfolio constructed in Table 1. MKT is the excess return on the market, the value-weighted return on all NYSE/AMEX/NASDAQ stocks minus the one-month Treasury bill rate. The macroeconomic variables as in Liu and Zhang (2008) include MP (the growth rate of industrial production), UI (the unexpected inflation), DEI (the change of expected inflation), UTS (the yield spread between long-term and one-year Treasury bonds) and UPR (the default premium measured as the yield spread between Moody's Baa and Aaa corporate bonds). Liquidity factors are Sadka liquidity factor (SDK_PV), Pastor-Stambaugh value-weighted traded liquidity factor (PS_VWF) and non-traded liquidity factor (PS_INV).

	MKT	MP	UI	DEI	UTS	UPR	SDK_PV	PS_INV	PS_VWF
ECIN	-0.397	0.117	-0.058	-0.059	-0.141	-0.034	0.078	-0.161	0.011
MKT		-0.175	-0.074	0.002	-0.027	-0.004	0.085	0.300	-0.016
MP			0.023	0.106	0.022	-0.112	-0.035	-0.043	-0.050
UI				0.662	0.135	0.050	-0.019	0.012	0.003
DEI					0.065	-0.023	0.179	0.054	0.009
UTS						0.241	0.004	0.007	0.005
UPR							-0.126	-0.012	-0.016
SDK_PV								0.202	-0.043
PS_INV									0.134