Chapter 17

MICROSTRUCTURE AND ASSET PRICING

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Abstract

Market microstructure and asset pricing both consider the behavior and formation of prices in asset markets. Yet neither literature explicitly recognizes the importance and role of the factors so crucial to the other approach. This survey seeks to join the two literatures by surveying the work linking microstructure factors to asset price dynamics. In the short run, these dynamics involve issues such as the auto-correlation and cross-correlation structure of stocks, and our survey will examine the literature relating these correlation structures to microstructure factors such as non-synchronous trading and dealer behavior. In the longer run, issues such as liquidity and the relation of private information to asset price dynamics are important. We survey the theoretical work linking microstructure factors to long-run returns, and we consider why stock prices might be expected to reflect premia related to liquidity or informational asymmetries. We also survey the empirical literature testing these relationships. We then discuss what issues remain contentious, and we provide some guidance for future research. We hope to show in this survey that asset-pricing dynamics may be better understood by recognizing the role played by microstructure factors, and that microstructure research can be enhanced by a greater understanding of its linkages with fundamental economic variables.

Keywords

market microstructure, non-synchronous trading, dealer behavior, bid-ask spread

JEL classification: G12, G14

1. Introduction

Market microstructure analyzes the behavior and formation of prices in asset markets. Fundamental to this approach is the belief that features of the particular trading mechanisms used in markets are important in influencing the behavior of asset prices. The asset-pricing literature also considers the behavior and formation of asset prices. This literature focuses on linking asset-price dynamics to underlying economic fundamentals. While these two literatures share a common focus, they also share a common flaw: neither literature explicitly recognizes the importance and role of the factors so crucial to the other approach. Thus, microstructure provides extensive characterizations of short-term price behavior, but fails to consider how these microstructure factors may influence asset returns. The asset-pricing literature extensively studies asset returns, but it rarely looks to see if these returns are related to underlying asset specifics such as private information or trading practices. Given the central importance of asset pricing in finance, a junction of these two very important literatures would seem beneficial.

In this article, we seek to foster this process by surveying the work linking microstructure factors to asset price dynamics. In the short run, these asset price dynamics involve issues such as the auto-correlation and cross-correlation structure of stocks, and our survey will examine the literature relating these correlation structures to microstructure factors such as non-synchronous trading and dealer behavior. In the longer run, issues such as liquidity and the relation of private information to asset price dynamics dominate the research agenda. Here our work will survey the theoretical work linking microstructure factors to long-run returns, and in particular consider why stock prices might be expected to reflect premia related to liquidity or informational asymmetries. We also survey the extensive empirical literature testing these relationships.

We note at the outset that while our focus in this survey is broad, it is not exhaustive. Market microstructure factors can exert great influence over the level of transactions costs, the way rents are split between dealers and investors (or between different classes of investors), and the interactions between markets. All of these undoubtedly affect asset returns but, while important, they will remain largely outside of the scope of our inquiry. Similarly, a wide range of factors including behavioral biases may influence asset prices, and these factors, in turn, may be affected by microstructure variables. 1 These issues, too, will generally be left to the side. Our exclusion of these factors reflects the inevitable difficulty of trying to tie together large and diffuse literatures, requiring us to focus our efforts on only a limited number of issues. There are, however, a number of excellent survey articles and other sources on market microstructure.

1 For example, the market structure may greatly influence the volatility of asset prices. If investors react to volatility in predictably biased ways, then the microstructure may be an important determinant of these effects.

What we hope to accomplish in this survey is to show that asset-pricing dynamics may be better understood by recognizing the role played by microstructure factors. We also hope to influence the direction of microstructure research towards greater analysis of the linkages of microstructure and fundamental economic variables. To do so, we will try to highlight what is known and not known about the effect of microstructure variables on short-run and long-run asset price behavior. The paper's final section will then summarize what issues remain contentious, and provide some guidance for future research in this area.

2. Equilibrium asset pricing

A useful starting point for our analysis is the standard explanation for asset-price behavior [see, for example, Cochrane (2001)]. The basic result is that the price of an asset at date $t$ is the expectation at $t$ of the return on the asset at $t+1$ times a stochastic discount factor. In the consumption-based capital asset-pricing approach (in which rational individuals choose asset holdings to maximize their expected utility of consumption over time) this stochastic discount factor is the discounted ratio of marginal utility of consumption at $t+1$ to marginal utility of consumption at $t$.

From this basic pricing equation follow the two principles that much of the literature examines. First, idiosyncratic risk should not be priced. The price of an asset is its expected payoff discounted by the risk-free rate plus the covariance of its payoff with the stochastic discount factor. If this covariance is zero there is no adjustment in price for the risk in the asset's payoff; or more generally, if the payoff on the asset is correlated with the market only the correlation is priced and any idiosyncratic risk is not priced.

Second, viewing the return on an asset as its dividend plus its future price, it follows from the basic equation that asset prices net of dividends follow martingales. The distribution used in computing the expectation is the original distribution of payoffs transformed by the stochastic discount factor. This is simply the risk neutral probability measure. In the case in which individuals are risk neutral, or there is no aggregate risk, and discounting is ignored, or included in a drift term, this reduces to the random walk hypothesis for prices. This has the important implication that asset prices are not predictable in the sense that simple trading strategies based on past price behavior cannot be profitable. From this standard asset-pricing point of view, regardless of how asset prices are actually attained in the economy, an asset's risk and return can be analyzed from the underlying decision problems confronting agents in the economy.

This simple story, or a variant of it, has proved a useful construct for countless economic analyses of asset prices. Unfortunately, the elegance of this story may be deceptive. Asset price dynamics are much more complex than this characterization allows. Individuals can face substantial transaction costs in buying and selling securities, and these costs can influence their demand for and supply of securities. Price adjustments may be complicated by market maker's inventory positions, by price discreteness, or even by exchange price continuity rules. The informativeness of asset prices is complicated by the existence of private information that transforms securities trading from a simple transaction into a strategic game between traders. This transformation also imparts importance to other market data such as volume, trade size, and the timing of trade, as each of these variables can be informative of future security price movements. These difficulties raise the specter that equilibrium in asset prices is best viewed not as an outcome, but as a process in which the asset price cannot be viewed independently of the mechanism by which it is attained.

How, then, to reconcile this picture of asset-pricing dynamics with the idealized one given above? One answer is to argue that these complications are second-order effects; that the idealized version of asset price dynamics is "close enough," particularly if asset prices are looked at over long time intervals. Moreover, since microstructure research focuses on the trade-by-trade determination of prices, any microstructure effects must either be very short-lived or diversifiable across securities in any case.

Yet, numerous researchers have found that asset-price movements exhibit predictable patterns both in the short-run and in the long run. These patterns raise the potential for profitable arbitrage, and at the very least imply a disequilibrium in the market inconsistent with the Olympian perspective given above. This predictability suggests that insights derived from microstructure analyses of the trading process may improve our understanding of asset-pricing dynamics, even in long run. Of particular importance here is market features such as dealer behavior, trading patterns, and the nature of intra-day and inter-day price adjustment to information. In the next section, we consider how such microstructure variables may relate to some puzzles in short-term asset pricing.

3. Asset pricing in the short-run

Consider the following empirical findings:


(2) Short horizon returns on individual securities are negatively autocorrelated [Fama (1965), French and Roll (1986), Lo and MacKinley (1990b), Conrad, Kaul and Nimalendran (1991)].

(3) Stock returns on large firms lead stock returns on small firms [Lo and MacKinley (1990b), Boudoukh, Richardson and Whitelaw (1994)].

These costs may even influence the type of securities we see being issued. Specifically, some securities may have such high trading costs that we never observe them in actual markets.
changes would be expected to follow a random walk, so that the microstructure related
price movements captured by \( s_t \) would be unimportant. Looking over shorter intervals,
however, the change in prices can have predictable patterns unrelated to changes in the
underlying efficient price. As Hasbrouck (1996) notes: “At the level of transactions
prices, . . ., the random walk conjecture is a straw man, a hypothesis that is very easy
to reject in most markets even in small data samples. In microstructure, the question is
not ‘whether’ transactions prices diverge from a random walk, but rather ‘how much?’
and ‘why?’

To see this, let us look more closely at price changes:

\[ R_t = \Phi_t + s_{t-1} - s_{t-1} = \Phi_t + \frac{1}{2} s_t (x_t - x_{t-1}) \, , \]

where \( \Phi_t = \mathbb{E} \{ V \mid I_{t-1} \} - \mathbb{E} \{ V \mid I_{t-1} \} \), or the change in conditional expectations. In the
absence of new information, \( s_t \) should be zero. The change in the market friction
term, however, need not be zero, and in particular, may introduce different patterns into
security prices.

Suppose we assume that this market friction is a given bid/ask spread which
arises due to exogenous factors such as order processing costs. Then \( \frac{1}{2} s_t \) is half
the effective spread and the \( v_t \) term in the pricing equation can be proxied by the spread
midpoint. Roll (1984) was the first to point out that market frictions such as the
bid/ask spread could lead to divergences in price behavior from the simple random
walk story. In particular, Roll demonstrated that in the statistical framework given
above \( \text{Cov} (R_t, R_{t-1}) = -\frac{1}{4} \sigma^2 \). The intuition for this is that in the absence of any new
information, observed trade prices move between the bid and the ask price. If the price
is already at the bid, for example, the following trade at the bid results in a zero price
change while a trade at the ask results in a mean reverting process. Thus, observable
price movements become negatively serially correlated.

The market friction term may include more complex effects. For example, suppose
that dealers try to manage their inventories by adjusting prices. If a dealer has a
preferred inventory position \( Q^* \), then the pricing equation can be modified as

\[ p_t = v_t - b (Q_t - Q^*) + \frac{1}{2} s_t x_t \, . \]

Now, the observed spreads will include both the order processing component and an
inventory related factor. Because the dealer is setting prices to induce movement toward
his optimum, dealer quotes (and thus prices) and inventory will be mean reverting.

\footnote{Roll argued that “an interesting feature of this spread-induced serial covariance is that it is independent of the time interval chosen for collecting successive prices.” Thus, whether we are looking at trade by trade movements or across days, this negative serial correlation will be present. See also Harris (1990) for statistical analysis of the Roll measure.}

\footnote{For the dealer’s inventory control to be effective trades must be price sensitive. See Hasbrouck (1996) for more detail.}

3 Hasbrouck (1996) provides an excellent and more detailed description of these statistical models.
Moreover, the mid-price of the observed spread need not be a good proxy for the underlying efficient price.

An extensive literature has tested for these inventory effects in prices [see, for example, Hasbrouck (1988), Madhavan and Snidt (1993), Hasbrouck and Sofianos (1993), Manaster and Mann (1996), Lyons (1998)]. In general, results from equity markets have found positive but rather small effects, while results from other markets such as futures or foreign exchange find stronger effects. Another, large literature [see Glosten and Harris (1988), Stoll (1989), George, Kauf and Nimaniad(1991)] decomposes spreads into components due to inventory, order processing, and information (an issue we will address shortly). From our perspective here, these results suggest that over a short time horizon, prices can exhibit patterns unrelated to changes in the underlying efficient price, patterns that provide at least the potential for price predictability.

An important feature of these particular frictions is that they are linked to trading. For example, trades bouncing between the bid and ask quotes result in the observed trade price process exhibiting negative serial correlation, even though the underlying true price process remains a random walk. However, an important feature of actual markets is that trades do not occur with regular periodicity, but instead depend upon order arrivals. Even the most active stocks exhibit intra-day patterns in these order arrivals, so that trades do not occur regularly throughout the day. This has the important implication that trade prices provide only a censored sample of the underlying true price [see Lo and MacKinley (1990a), Easley and O’Hara (1992)].

An immediate implication of this censoring is that comparing trade prices across stocks can result in spurious inferences. In particular, suppose that we have two stocks with identical underlying true price processes. Now, let an innovation occur to this true price. If orders do not arrive simultaneously for both stocks, then trades will occur at different times for the two stocks. Looking at the most recent trade price in the two stocks will record different prices, even though the underlying true price of the assets is in fact the same. This non-synchronous trading introduces lags into observed price adjustment, and thus cross-sectional differences in the auto-correlation patterns in returns.

Numerous authors [see for example, Lo and MacKinley (1990a), Mech (1993), Kadlec and Patterson (1999)] have shown that non-synchronous trading plays an important role in explaining the observed pattern of large firm weekly returns leading small firm weekly returns. Indeed, Boudoukh, Richardson and Whitelaw (1994) argue a “large fraction” of the observed effect may be explained by this factor, while Kadlec and Patterson (1999) estimate it to be more on the order of 25%. An important feature of these analyses is that the order arrival process, while dependent on firm type, is not assumed linked to the underlying true process per se. If new information causes trading, however, then non-trading may be correlated with the underlying true price process; suggesting a greater complexity to the observed patterns in asset price dynamics. To understand this linkage, we need to look more closely at the role of information in price adjustment.

3.2. The adjustment of prices to information

To this point, we have considered models in which the underlying value of the asset and the trade process were independent. Trades mattered only because they caused transaction prices to move between bid and ask prices that bracket the underlying value. However, much of the microstructure literature considers a more complex story, see Kyle (1985), Glosten and Milgrom (1988), Easley and O’Hara (1987) or O’Hara (1995) for an overview. In this story, some traders, the informed, know more about the underlying value of the asset than do other traders, the uninformed, or the market maker. The market maker cannot distinguish between informed traders and uninformed traders who are trading for non-informational reasons such as liquidity shocks. He loses to the informed traders, so to have zero expected profits he must make profits from the uninformed traders. He does this by setting a bid-ask spread. The actual spread may, of course, include compensation for the fixed cost of doing business and an inventory component, as well as this asymmetric information component. We focus first on this asymmetric information component.

In this setting, buy and sell orders convey information so they affect the expected value of the asset. Let \( V_t = \mathbb{E}[V_t | I_t] \) be the prior expected value of the asset, where \( I_t \) is the public information prior to the trade at time \( t \). The trade indicator is again \( x_t = 1 \) if the trade at \( t \) is a buy and \(-1\) if the trade at \( t \) is a sell. The ask price, the price a trader has to pay for a unit of the asset, is \( p_a^t = \mathbb{E}[V_t | I_t, x_t = -1] \) and the bid price, the price a trader will receive if he sells a unit of the asset, is \( p_b^t = \mathbb{E}[V_t | I_t, x_t = 1] \).

This pricing strategy induces a spread, \( s_t = p_a^t - p_b^t \), but only if the order type affects the expected value of the asset. This occurs in markets in which some orders come from informed traders. When an order to buy arrives at the market, the expected value of the asset rises because this order is a signal of good news about the value of the asset. Similarly, the arrival of an order to sell is bad news, the expected value of the asset falls and the transaction price is lower.

The observable price of the asset at time \( t, p_t \), is thus

\[
    p_t = \begin{cases} 
    p_a^t & \text{if } x_t = +1, \\
    p_b^t & \text{if } x_t = -1.
    \end{cases}
\]

Here again trade causes prices to bounce between a bid price and an ask price. In the previous section (ignoring active inventory control for now), this bounce was purely transitory; there was no effect of a trade at time \( t \) on the price at time \( t+1 \). Now there is also a permanent component. An order to buy at time \( t \) causes a transaction at the time \( t \) ask price, \( p_a^t \), and it changes the expected value of the asset to \( p_a^t \). Bid and ask prices at time \( t+1 \) bracket this new expected value of the asset.

Orders at time \( t+1 \) also cause prices to adjust, and this adjustment process can be complex. In particular, if prices have not adjusted to true values, then informed traders can be expected to continue trading all on the same side of the market, buying when there is good news and selling when there is bad. In a simple world where information events are known to have occurred, this repeated trading is incorporated by
explain the ex-dividend behavior of stock prices in Hong Kong (a country without capital gains taxes). A natural conclusion from this work is that microstructure effects may be large enough to explain a variety of short-run asset price movements.

3.3. Statistical and structural models of microstructure data

In the previous two sections we considered simple reduced-form models of microstructure data that were designed to allow estimation of parametric effects of microstructure features on asset prices. An alternative approach is to form data and employ a purely statistical time series model of high frequency microstructure data. This data consists of trade characteristics such as price and quantity as well as the time of the trade, or the elapsed time since the last trade. Much of the literature in this area attempts to use time series models to forecast prices, price changes or volatility and to infer the information content of particular variables.7

We first consider time-series models in which time is taken to be trade-time rather than clock-time. Here, the data is treated as if observations of trades and price changes occurred at equally spaced intervals in real time. The statistical models in the previous section are examples of this approach. In their reduced-form, these models are bivariate vector autoregressions with structure imposed by the underlying economic model. Hasbrouck (1991) takes this approach to estimate the information content of trades, which in this setting is given by the persistent price impact of the unexpected component of trades. Numerous authors have used this permanent and temporary price effects approach to estimate various asset price regularities such as the informativeness of small trades [see Hasbrouck (1991)] or the impact of block trades [see Saar (2001)]. An alternative approach is to consider trades in real time and ask if there is information content in the time between trades. Two papers here are particularly relevant. Diamond and Verrecchia (DV) (1987) develop a model in which short sale constraints impart information content to the time between trades. In their model, traders learning bad news may be unable to short the stock, so longer times between trades may signal bad news. Easley and O’Hara (EOH) (1992) show that if the existence of new information is uncertain, then the time between trades carries information. Their idea is that when there has been an information event, orders arrive from both uninformed and informed traders, resulting in more trades per time interval. So when trades occur fast they have more information content, and produce greater price impacts than when trades occur slowly. This implies that the volume of trade now signals information. We discuss the literature on volume later in this section. A direct implication of both the DV and EOH models is that time itself may be predictive of future price movements.

This functional role for time is investigated empirically by Engle and Russell (ER) (1998) and by Hasbrouck (1999). Engle and Russell develop a new approach to

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6 Huang and Stoll (1994) note, however, that this need not imply the existence of arbitrage profits since the transactions costs of implementing trades may preclude such profits.

7 For a review of some of the issues in modeling high frequency data see Goodhart and O’Hara (1997).
modeling irregularly spaced data called the autoregressive conditional duration model. The ACD model focuses on the inter-temporal correlations of the time interval between events. In this setting, the events can be trades, or quote updates, or even depth changes. The ACD model "treats the arrival times of the data as a point process with an intensity defined conditional on past activity". The ACD model essentially estimates how long it will be until prices or quotes change given this past activity.

With its focus on price changes, the ACD model is related to models of volatility. Indeed, Engle (2000) finds that, as suggested by the asymmetric information model, longer time between trades and longer expected times between trades are associated with lower price volatility. Engle and Russell (1997) apply this technique to foreign exchange data and they find that changes in the bid-ask spread are predictive of future price changes. These future price changes are defined over a short horizon, but these analyses show how patterns in trade and quote data can result in predictable price variation.

Treating volatility in this way allows for the explicit inclusion of microstructure features such as intra-day seasonality. While the asset-pricing literature is replete with models of volatility [for an excellent survey see Bollerslev, Chou and Kroner (1992)], typically these models require a high degree of stationarity in the data. Thus, analyses using ARCH-type models (i.e. GARCH, P-GARCH, E-GARCH, etc.) typically remove seasonality or other microstructure factors from the data. Hashbrouck (1999) makes the important point that such real-time stationarity is refuted by the clustering of trades, price and quote changes that characterize microstructure data. Thus, he notes "a fast market is not merely a normal market that is speeded up, but one in which the relationships between component events differ". This characterization is consistent with the Easley–O’Hara (1992) argument that the information structure differs between fast and slow markets.

Investigating the linkage of microstructure variables to price volatility may also provide insights into more basic questions regarding the evolution of prices. In an intriguing paper, French and Roll (1986) showed that return volatility is significantly higher when measured during the trading day than it is during non-trading hours. They attribute this result to noise generated by the trading process. But how exactly is this occurring? Is it the case that trading creates volatility, in effect inducing traders to transact simply because the market is open? Or, if trading in fact reveals information, then might not prices be volatile because of learning?

These issues are important in microstructure because, at least over short horizons, most microstructure time-series are non-linear. Thus, while French and Roll noted the distinction between market-open volatility and market-closed volatility, other authors have shown distinct volatility patterns during the day. In particular, numerous authors have shown that price volatility overall tends to be U-shaped, while the volatility of ask-price changes actually declines over the day [see Madhavan, Richardson and Roomans (1997)].

From our earlier discussion, it seems natural to attribute these volatility patterns to factors relating to information flows and to factors related to market frictions. Hashbrouck (1993) uses a VAR approach to decompose volatility into these components, while Madhavan, Richardson and Roomans (MRR) (1997) develop a structural model to do so. This latter approach uses a simple model in which the intra-day variance arises from four components: price discreteness, asymmetric information, trading costs, and an interaction term. Estimating the model using intra-day NYSE data reveals a number of interesting findings. In particular, MRR find that the public information component of volatility declines by one-third over the day, consistent with the revelation of information through trading. Conversely, the market frictions component of volatility increases over the day, accounting for 65% of the price variance by the close of trading. Of these market frictions, the bid-ask spread plays an important role, explaining more than a third of total volatility by the close of trading.

3.4. Volume and price movements

Because the time between trades is inversely related to the number of transactions, the findings discussed above imply that there may be information content in the number of trades and in volume. A widely-cited aphorism is that "it takes volume to move prices", or simply that volume and volatility are positively correlated. Such an empirical finding has been demonstrated by numerous authors, see for example Karpoff (1987), Galant, Rossi and Tauchen (1992), or Campbell, Grossman and Wang (1993). Whether this volatility linkage is due to the volume of trades or to the number of transactions is contentious. Jones, Kaul and Lipson (1994) argue that it is the number of trades that matters; they present empirical evidence that there is no additional information in volume beyond that conveyed in the number of trades. Other researchers (particularly research on liquidity which we address in the next section) argue the opposite.

It is well known that volume is also serially correlated. There is a recent theoretical literature showing how the serial correlation in volume and the correlation between volume and volatility can arise in a competitive market. He and Wang (1995) show that even when information is uncorrelated over time volume will be serially correlated in a partially revealing rational expectations equilibrium, and that volume and volatility will be contemporaneously correlated. This model relies on private information affecting trade in both the current period and possibly in future periods as traders learn from current and past prices.

Blume, Easley and O’Hara (1994) provide a model in which volume and volatility are positively correlated and in which volume has predictive content for future price

8 Stoll and Whaley (1990) present evidence that the structural procedure for opening stocks on the New York Stock Exchange appears to affect price volatility.
9 In effect, traders here can profit from using technical trading rules based on prices. Such technical trading strategies have also been analyzed by Brown and Jennings (1989) and Grundy and McNichols (1989).
changes. In this model, volume itself is informative because it provides data on the quality or precision of information in past price movements. Thus, traders watching volume can learn information regarding the future movement of prices. BEO argue that this informative effect of volume is likely to be particularly important for small, less widely held firms, a result confirmed empirically by Conrad, Hameed and Niden (1994) in their analysis of the relation of volume and weekly returns.

Campbell, Grossman and Wang (1993) develop a model in which volume can help distinguish between price changes due to public information and those that reflect changes in expected return. In their model, variation in the aggregate demands of liquidity traders can generate high volume, as can days in which there is new information. Their model predicts “price changes accompanied by high volume tend to be reversed while this is less true of price changes on days with low volume.”

Empirical evidence in Llorente, Michaeli, Saar and Wang (2002) using daily data on volume and first-order autocorrelations for individual stocks listed on the NYSE and AMEX confirms these results.

That volume may be predictive of short-run movements in prices is consistent with microstructure effects arising from the adjustment of prices to public and private information. What is more difficult to understand is the apparent role of volume in predicting longer-term price movements. In particular, a number of researchers have found that conditioning on past volume is useful in predicting asset returns for months in advance. Gervais, Kaniel and Mingelgrin (1999) find that stocks experiencing unusually high trading volume over a period of one day to a week tend to appreciate over the next month and continue to generate significant returns for horizons as long as 20 weeks. Brennan, Chordia and Subrahmanyam (1998), looking at normal as opposed to abnormal volume, find that high volume stocks tend to be accompanied by lower expected returns, a result they attribute to liquidity effects. We consider these liquidity issues more fully in the next section.

What is more perplexing are results of Lee and Swaminathan (2000). These authors find that price momentum is stronger among high volume stocks, and that past trading volume predicts the magnitude and timing of price momentum reversals. Jegadeesh and Titman (1993) demonstrated that portfolios of “winner” stocks tend to experience higher returns and “loser” stocks experience lower returns over the next three-year period. These momentum effects are puzzling because they suggest the market somehow “under-reacts” to good and bad news. Lee and Swaminathan confirm these effects, but they also show that over years 3 to 5 the return pattern reverses, with winners now under-performing, and conversely. Of particular importance is their finding that high volume winners and losers experience faster momentum reversals. Thus, volume predicts both the level and turning points of returns.

Momentum effects pose serious challenges to virtually all asset-pricing theories. Various explanations have been proposed, but momentum appears robust to obvious causes such as measurement errors and transactions costs [see, for example, Grundy and Martin (2001), Conrad and Kaul (1998), Jegadeesh and Titman (2002)]. Could microstructure effects provide part of the solution? Possibly, but the link is not obvious.

It is hard to envision how dealer inventory management or price discreteness, or bid-ask spread changes or intra-day volatility patterns could produce such long-run effects. And more puzzling still is seeing how these factors could explain the non-linearity in momentum effects.

The linkage of volume and momentum suggests that the answer might lie in the complex role played by information. Microstructure analyses highlight the important role of private information in affecting price behavior. Indeed, Hvidkjaer (2000) finds that buy-sell imbalances in momentum portfolios are consistent with traders acting on the basis of such information. What is needed is an understanding of why microstructure could influence asset returns in the long run, and it is this issue we address in the next section.

4. Asset pricing in the long-run

The previous section examined the effects of microstructure variables on short-run asset-pricing dynamics. While the specific influences discussed differ from one another, a feature common to these variables is their relation to the mechanics of trading and the subsequent adjustment of prices to equilibrium levels. Thus, the negative serial correlation found in transactions prices induced by bid-ask bounce or by market maker inventory behavior can be viewed as an artifact of the market clearing process. Similarly, the informative role of volume or the time between trades arises because of the price discovery role of markets. Over short horizons, it should not be surprising that the mechanics of trading can affect prices in predictable ways.

What may be more perplexing is why microstructure variables should have any effect on long-term asset returns. There are two issues to consider here. First, and foremost, is the economic origin of such effects. Certainly, apart from short time intervals, the problems of non-synchronous trading or bid-ask bounce will not influence asset returns. And the excessive volume on any given day will quickly dissipate once prices have adjusted to new equilibrium levels. But other, more fundamental factors can arise in the long-term that affect the risk and return faced by traders. In particular, liquidity and the underlying information risk of the asset may influence the utility of investors, an issue we address further shortly.

But even if these effects exist, there is a second problem, namely the ability to find them empirically. There is an overarching problem of econometric power when looking for microstructure effects in long-run data. One immediate difficulty is that expected returns may be small relative to return variation (in effect, a low signal-to-noise ratio). A second difficulty is multi-collinearity, both with respect to economic factors and with the components of trading cost. Thus, microstructure effects may be correlated with other economic features such as firm size. Similarly, high variance firms may

10 We thank Joel Hasbrouck for bringing this point to our attention.
have more asymmetric information, so that higher returns attributed to volatility may actually reflect compensation due to more complex informational risks. These econometric concerns dictate both caution in interpreting extant findings, and support for the need to develop better, more sensitive econometric techniques. Abstracting from these empirical difficulties, we now turn to the basic question of how, or why, microstructure variables could affect long-run asset returns.

4.1. Liquidity

Virtually all would agree that the liquidity of an asset is an important feature; exactly what this liquidity is would elicit more debate. In its simplest form, liquidity relates to trading costs, with more liquid markets having lower costs. Indeed, this view of liquidity is put forth by Amihud and Mendelson (1986) who note “illiquidity can be measured by the cost of immediate execution”. Abstracting from the definitional battles of what is meant by cost (or immediate, for that matter), this view of liquidity leads to the simple axiom that liquidity is a desirable property for an asset; that other things equal, traders would prefer assets in which execution costs are lower.

Whether liquidity is valued enough to affect asset returns is more controversial. Over a short period of time, higher levels of transactions costs must lower the return available to investors, and ceterus paribus, lower the price they are willing to pay for the asset. But given a long enough time horizon, are such effects large enough to actually affect returns?

The traditional view in asset pricing is no. For example, Constantinides (1986) shows theoretically that transactions costs can only have a second-order effect on the liquidiy premium implied by the equilibrium asset returns in an inter-temporal portfolio selection model. A similar conclusion is reached by Aiyagari and Gertler (1991), Heaton and Lucas (1996), Vayanos (1998) and Vayanos and Vila (1999). In effect, these authors all argue that the transactions costs are just too small relative to the equilibrium risk premium to make any real difference. Huang (2001) agrees that in general this is true, but that it need not be the case if traders are constrained from borrowing against their future income stream.13 Holmstrom and Tirole (2001) develop a model in which firms demand liquidity to meet future cash flow needs. In this model, assets’ expected returns are affected by the covariance of their returns with market liquidity.

The counter-argument is put forth by Amihud and Mendelson (AM) (1986, 1988), who argue that liquidity can more generally affect required returns. In the AM model, traders seek to maximize the present value of expected cash flows. The model allows traders to diversify and to have different time horizons. Traders buy and sell assets as part of their portfolio problem and they face execution costs in doing so. AM proxy illiquidity by the bid/ask spread, and so higher spreads result in lower overall returns for traders. AM show that a clientele develops in the market for assets with different liquidity. In particular, only traders with long horizons will hold illiquid assets, and they will demand compensation for doing so. Thus, their model predicts that in equilibrium an asset’s return will be an increasing and concave function of its bid/ask spread.

The simplicity of the AM argument is quite appealing. In this setting, illiquidity functions as a type of exogenous tax, and while some traders avoid it altogether by eschewing such assets in their portfolio, others bear the tax but demand compensation in the form of higher returns. Because bid/ask spreads measure this liquidity, the question becomes are spreads linked in an economically meaningful way to returns?

There is an extensive body of empirical research investigating this question.12 AM (1986, 1988) find a significant positive effect of bid–ask spreads on stock returns, and their results are supported by Eleswarapu (1997) and by Chalmers and Kadlec (1998) who link amortized spreads to returns. However, Chen, Grundy and Stambaugh (1990), Chen and Kan (1996) and Eleswarapu and Reinganum (1993) conclude the opposite, as does recent research by Easley, Hirukjaer and O’Hara (2002) who find no direct link between spreads and returns for the period 1982–1998.13 Indeed, Chen and Kan argue that the positive findings of AM and others are due to mis-specification of risk; that, “when returns are not “properly” adjusted for risk, variables that are functions of the most recently observed price of a stock, such as size, dividend yield, and the relative bid–ask spread, are often found to possess explanatory power on the cross-sectional difference in the risk-adjusted return”. Their argument captures Berk’s (1995) observation that any price-related variable will be related to returns under improper risk adjustment.14

But are spreads necessarily the correct measure of liquidity? Certainly, as a proxy for trading costs, spreads are only a part of the story; factors such as trading commissions, the overall volume in the market, the price impact of trades or even the trading mechanism itself also are important (see Keim and Madhavan (1995) for empirical analysis of the trading costs facing institutional traders). Indeed, the recent dramatic declines in spreads due to structural changes in tick sizes and regulatory changes

11 Huang (2001) looks at how liquidity shocks affect traders in a continuous time setting. His model uses uncertain holding periods and liquidity shocks to show how borrowing constraints may result in substantial return premia for less liquid securities.

12 We limit our discussion here to studies involving the equity markets, but this linkage of liquidity and asset returns has been investigated in other settings as well. See for example, Amihud and Mendelson (1991) and Kamara (1994).

13 We find that the association between bid/ask spreads and stock returns is mainly confined to the month of January, a result hard to reconcile with the underlying AM arguments. EHO find that spreads are insignificant when added to a Fama–French (1992) regression. However, they do find that spreads may have an effect when added to a return regression that also includes the standard deviation of returns, volume, and the volatility of turnover. This spread effect appears to arise because of the high correlation between spreads and standard deviations.

14 Essentially, the argument here is that spreads are derived from prices, and as Miller and Scholes (1982) pointed out prices may be correlated with a security’s beta, so any finding of a link between spreads and returns could simply be a measurement error of beta.
highlight the limitations of this measure. A natural direction for research, therefore, is to investigate how returns are affected by alternative measures of liquidity.

Datar, Naik and Radcliffe (1998) propose share turnover (i.e. the number of shares traded over the number of shares outstanding) as such a proxy for liquidity, arguing that liquidity should be correlated with trading frequency. They find that stock returns are a decreasing function of turnover rates. Brennan, Chordia and Subrahmanyam (1998) demonstrate a negative relation between average returns and dollar volume. Anusluhan, Chordia, and Subrahmanyam (ACS) (2001) also find negative relationships between returns and measures of turnover and dollar trading volume. More puzzling is their finding that returns are negatively related to the volatility of these measures. ACS argue that traders prefer volatility as it enhances their ability to implement trading strategies, but this explanation is contentious given the negative impact on utility usually associated with volatility.

That volume-related measures appear related to returns is intriguing, but is this effect due to liquidity? In the previous section we saw that volume plays a complex role in markets, in part because of its relationship with information on the stock's underlying true value. Indeed, Lee and Swaminathan (2000) argue that turnover may be a less than perfect proxy for liquidity because the relation between turnover and expected returns depends on how stocks have performed in the past. As we discussed in the last section, these authors argue that volume may be most useful in understanding the mysteries of momentum.

There are, of course, other measures of liquidity to consider. A variety of authors propose variants on the price impact of trading. In particular, markets in which trades move prices a great deal are considered less liquid than those with smaller price effects. Breen, Hodrick and Korajczyk (2000) calculate liquidity as the relation between price changes and net turnover (defined over 5 and 30 minute periods, respectively). They find these price impacts exhibit substantial cross-sectional variation, while remaining remarkably stable when measured over their four-year sample period.

Amihud, Mendelson and Lauterbach (AML) (1997) use the liquidity ratio, defined as the daily volume divided by the absolute value of the daily return, to capture this liquidity effect [see also Cooper, Groth and Avera (1986) and Berkman and Elswarapu (1998) for studies using the liquidity ratio]. AML use a natural market experiment, the transition of trading on the Tel Aviv Stock Exchange from a call auction mechanism to more continuous trading, to investigate how trading mechanisms affect stock prices. This clever study shows that the transition between trading mechanisms resulted in both substantial liquidity gains and significant price increases for the transferred shares. Whether the enhanced liquidity caused the price increase, however, is not something this study can determine, in part, because the liquidity ratio itself is defined by daily returns.

Muscarella and Piwowar (2001) show similar effects accompanying the movement of stocks from call market trading to continuous trading on the Paris Bourse. They find that stocks moving to continuous trading experience a price gain of more than 5%. Such stocks also exhibit increases in volume and, not surprisingly, in the liquidity ratio.

Interestingly, this study also documents that inactive stocks moving from continuous trading to call trading did not fare well; prices generally fell, volume remained relatively stable, and there was a (weakly) significant decline in the liquidity ratio. These results suggest that call market trading did not enhance liquidity for inactive stocks as has been conjectured by numerous authors.

Brennan and Subrahmanyam (BS) (1996) propose linking illiquidity to the price impact of trades as captured by the Kyle λ. The λ variable is essentially the slope coefficient in a regression relating the price change to trade-by-trade signed order flow. In the Kyle (1985) model, the λ variable arises because of strategic trading by an informed investor, and so in that context it is a measure of adverse selection. BS argue that adverse selection is a primary cause of illiquidity, and they use the Kyle measure to provide a proxy for this trading cost. This is also one of the first studies to use transactions data to measure the nature of illiquidity.

BS conclude “there is a significant return premium associated with the fixed and variable costs of transacting”. They find that the relation between the premium and the variable cost of transacting is concave, but that it is convex when measured with respect to the fixed costs of transacting. This latter result is inconsistent with the clientele argument of Amihud and Mendelson, but it may, as the authors note, reflect the difficulty of measuring this cost variable using transactions data.

Amihud (2000) also investigates the idea that illiquidity is the relationship between the price change and the associated order flow. In this analysis, illiquidity is defined by the average ratio of the daily absolute return to the (dollar) trading volume on that day. In effect, this measure gives the percentage daily price change per dollar of daily volume, and conceptually it is the inverse of the liquidity ratio defined earlier. The paper finds a positive cross-sectional link between asset returns and this illiquidity measure. A puzzle with this and other measures based on daily volume-normalized price movements, however, is that the theoretical link to investors' trading problems is not straightforward. Moreover, the earlier findings that volume alone is linked to returns raise difficulties in knowing exactly how to interpret these composite variables. Of course, given the difficulty of even defining liquidity, such problems should not be unexpected.

A more controversial argument in this research is that expected market illiquidity affects expected stock returns. The notion here is that liquidity can be time-varying for the market as a whole, and investors demand compensation for bearing this market-related risk. Amihud calculates expected market liquidity by averaging the illiquidity measure defined above over all firms in the market, and then assuming that investors expect this market variable to follow an autoregressive process. The analysis hypothesizes that a rise in expected market illiquidity induces both an income and a substitution effect. For all stocks, there is a general fall in stock prices to compensate

15 In some sense, this measure is like a Kyle λ but defined over total daily price change and volume.
for the reduced liquidity. However, traders also substitute from less liquid to more liquid stocks, resulting in an increase in some stock prices.

Pastor and Stambaugh (2001) take this argument one step further by arguing that liquidity per se is a priced factor in asset returns. These authors use a variant of a volume-linked price change as their liquidity measure. Their individual liquidity measure is a complicated one, entailing “the average effect that a given volume on day d has on the return for day d + 1, when the volume is given the same sign as the return on day d”. This measure is similar to that of Amihud (2000), but its use of today’s volume and tomorrow’s return makes this essentially the same variable investigated by Llorente, Michaela, Saar and Wang (2002). Pastor and Stambaugh then calculate each stock’s sensitivity, or “liquidity beta”, by constructing a market liquidity measure, given by the equally weighted average of the liquidity measures of individual stocks on the NYSE and Amex for the years 1962–1999. Their empirical findings suggest that such liquidity betas are highly significant factors in explaining asset returns.16

Why would liquidity have a common factor or act as one in asset returns? Chordia, Roll, and Subrahmanyam (CRS) (2000), Hasbrouck and Seppi (HS) (2001) and Huberman and Halka (HH) (2001) address this issue. CRS argue that commonality in liquidity could arise for reasons related to common variation in dealer inventories. If trading volume induces co-movements in dealers’ inventories, then this in turn could cause co-movements in liquidity measures such as spreads and depths. Asymmetric information, one of the usual suspects in microstructure studies, is less likely to be the source “because few traders possess privileged information about broad market movements”. CRS calculate the time series averages of market spreads, and they provide evidence of weak commonality in several liquidity variables. Huberman and Halka (2001) provide similar empirical results, and they conjecture that a systematic component of liquidity arises “because of the presence and effect of noise traders”. They note, however, that their empirical results do not provide hard evidence of this explanation.17

Hasbrouck and Seppi (2001), however, question the importance of any commonality in liquidity. These authors use a principal components analysis to show that common factors exist in the order flows of the 30 stocks in the Dow–Jones Industrial Average. Using canonical correlation analysis, they document that the common factor in returns is highly correlated with the common factor in order flows. Their results on liquidity, however, are quite different in that variations in liquidity are found to be largely idiosyncratic. This suggests that variations in liquidity at the aggregate level could be diversified away. They conclude “any liquidity-linked differences in expected return are

most likely due to predictable changes in the level of liquidity, rather than to variability in liquidity, per se”.

Whether liquidity affects asset returns remains contentious. What does appear robust is that asset returns behave in ways not predicted by traditional asset-pricing theories. While these divergences may be due to liquidity, there is an alternative microstructure-based explanation to which we now turn.

4.2. Information

In standard consumption-based asset-pricing models, asset prices are such that the representative individual, or a collection of individuals with homogenous beliefs, chooses to hold the existing supply of assets. As the individuals’ beliefs about the value of the assets change over time, asset prices change, and this movement, along with dividends, generates returns. This basic model leads to an elegant asset-pricing theory in which the price of each asset is primarily dependent on the covariance of its returns with the returns on the entire collection of assets, or the “market”. Individuals need not hold idiosyncratic risk, and so in equilibrium they will not be compensated for holding this risk. Only market risk is priced.

Much of the market microstructure literature, on the other hand, focuses on differences in information between individuals, and on how the flows of differential information generate trade, spreads and price changes. Typically in this literature one asset is priced at a time. 18 There is no mention of market versus idiosyncratic risk; everything seems to be idiosyncratic risk as it is asset-specific. For this reason, it is natural to suspect that the issues microstructure examines cannot affect long-run asset prices.

Verifying this conjecture requires integrating these two paradigms of asset prices and their evolution. At one level this is simple. If everything else is held constant (endowments and preferences), then in the consumption-based asset-pricing approach, prices evolve because beliefs change. Beliefs change because the information available to individuals about the fundamental value of the assets changes. So, in a very important sense, these paradigms are alike: both theories analyze the pricing of assets in response to information flows.

But pushing the information story a little further reveals differences. If individuals begin with a common prior on asset values and they receive common information (such as observations of past prices and realized asset payoffs), then nothing changes in the standard asset-pricing theory: there is no role for information-based effects on returns. If individuals receive differential information, and the economy is in a revealing-rational expectations equilibrium, then individuals still have common equilibrium beliefs and, again, nothing changes. But, more realistically, if the equilibrium in the

16 Liquidity betas are calculated using volume signed by future returns to predict returns. As with all priced-linked measures, the issue of miss-specification of risk raised by Berk (1995) must be considered.

17 Sias, Starks and Tenic (2001) investigate whether such noise trader risk is priced. They find no evidence using closed-end fund data that it is.

18 Exceptions to this are work on the influence of information on basket securities, and the work on stock index futures, see Subrahmanyam (1991).
asset market is not fully revealing, then individuals receiving differential information will have differing beliefs in equilibrium. Assets may still be priced according to some “market expectation” as in Lintner (1969), but no individual’s belief will be characterized by this market expectation. Individuals will have different perceptions of market and idiosyncratic risk, and they will hold differing portfolios. Now, it is not just fundamental values that matter for asset prices; the distribution of information also matters, just as it does in the market microstructure literature.

The literature on partially revealing rational expectations, beginning with Grossman and Stiglitz (1980), shows how differential information affects asset prices. Admati’s (1983) paper generalized this analysis to multiple assets, and she showed how individuals face differing risk-return tradeoffs when differential information is not fully revealed in equilibrium. Wang (1993) showed in a two-asset, multi-period model that private information causes uninformed traders to demand compensation for the adverse selection problem they face, but that this effect is mitigated by the reduction in risk caused by partial revelation of information. Brennan and Cao (1997) use a similar idea to explain how superior information about home country assets can help explain international equity flows. Jones and Slezk (1999) use a multi-asset, multi-period partially revealing rational expectations to show that standard risk-return predictions are altered in predictable ways. Easley and O’Hara (2001) construct a multi-asset partially revealing expectations equilibrium in which the distribution of information affects the required rate of return on assets. This analysis shows that if information about an asset is private, rather than public, then uninformed investors demand a higher rate of return on the asset to compensate for the risk of trading with better informed traders.

The market microstructure literature demonstrates that the existence of differential information has a significant impact on the fine details of short run asset prices. The literature above shows that theoretically it could also have an impact on long run asset prices. But does it? A natural approach to this question is to measure the extent of differential information asset-by-asset and ask whether this measure of differential information is priced.

Since information, particularly private information, is not directly observable its presence can only be inferred from market data34 trades and prices. Fortunately, the microstructure literature provides ways to do this. Both the Kyle λ, from Kyle (1985), and the probability of information-based trade (PIN), from Easley, Kiefer and O’Hara (1997b), are measures of the importance of private information in a microstructure setting. Kyle’s λ measures the responsiveness of prices to signed order flow. It can be estimated by regressing price changes on signed order flow. PIN measures the fraction of orders that arise from informed traders. It can be estimated from data on trades. There is a substantial literature estimating each of these measures and showing that they provide insights into microstructure phenomena. See Glosten and Harris (1988), Hasbrouck (1991), Foster and Viswanathan (1993), Brennan and Subrahmanyan (1996) and Amihud (2000) on the Kyle λ; and, Easley, Kiefer and O’Hara (1996, 1997a,b), Easley, Kiefer, O’Hara and Paperman (1996) and Easley, Hvidkjaer and O’Hara (2002) on the probability of information-based trade.

Brennan and Subrahmanyan (1996) and Amihud (2000) argue that stocks with high λ's are less attractive to uninformed investors, and they find support for this argument in transactions data and daily data, respectively. Easley, Hvidkjaer and O’Hara (2002) use a structural microstructure model to estimate the probability of information-based trade in each NYSE common stock yearly for the period 1983 to 1998. They show this information variable is priced by including it in a Fama–French (1992) asset-pricing regression. Stocks with higher probabilities of information-based trade are shown to require higher rates of return. A difference of 10 percentage points in the probability of information-based trade between two stocks leads to a difference in their expected returns of 2.5% per year. These results provide evidence that asymmetric information affects long-run asset pricing.

There is another role that information may play in long-run asset pricing that does not fit into the asymmetric information approach discussed above. Merton (1987) proposes an asset-pricing model in which agents are unaware of the existence of some assets. In Merton’s model, all agents who know of an asset agree on its return distribution, but information is incomplete in that not all agents know about every asset. Merton shows that assets with incomplete information have a smaller investor base, and with limited demand, these assets command a lower price. In the standard microstructure approach, all investors know about every asset but information is asymmetric: some investors know more than others about returns. Both approaches lead to cross-sectional differences in asset prices due to information, or to the lack of information.

A related literature considers the role of participation constraints on traders [see, for example, Basak and Cuoco (1998) and Shapiro (2002)]. Here the story is that some traders are prohibited for exogenous reasons from holding certain assets. These prohibitions may be from lack of knowledge as in Merton, or they could reflect market imperfections such as suitability requirements or institutional portfolio restrictions that limit the securities available for investment. Such prohibitions result in the same structure analyzed in Merton, although potentially for a different reason. This research also shows that cross-sectional differences can arise in asset returns. Whether these constraints are actually binding in the market, or even if they are, whether they can be viewed as part of the market microstructure, is debatable. But research in this general area does suggest that the simple story expounded in traditional asset pricing may be too rudimentary; that features of trade and trading do matter for asset price behavior.

A related issue is the impact of short-sale restrictions and other market constraints on investing such as margin requirements. These features introduce heterogeneity into the investor pool, and so may also affect cross-sectional asset pricing.
5. Linking microstructure and asset pricing: puzzles for researchers

Our contention in this paper is that features of the trading process provide important insights into short-term and long-term asset price behavior. We have reviewed a wide range of literature investigating these asset-pricing effects, but the vastness of the area dictates that many other papers not mentioned here are relevant to this general question. What has emerged from this survey is cogent and compelling evidence that microstructure factors affect asset-pricing behavior. But also apparent from our review are the many puzzles and challenges that impair our understanding. In this final section, we outline those issues we think most important for future research.

At the top of the list is the role of volume. As we have seen in this survey, volume appears to play an important role both in the short-run and in the long-run. Numerous empirical papers find that statistical significance almost magically appears when volume (or a member of its extended family such as turnover) is added to a regression. But theory provides few reasons for this significance, and the range of stories advanced to explain this phenomenon is impressive, but ultimately unconvincing.

Why should volume matter? We believe it is because volume, as with other market statistics, proxies for features related to price discovery in markets. Thus, the accounting literature [see, for example, Kim and Verrecchia (1991)] has linked volume to dispersion of beliefs regarding public information. Blume, Easley and O’Hara (1994) have suggested the link is to the quality of private information. Research on dividend recapture, or portfolio insurance, or “triple witching” days, has pointed to particular trading strategies as responsible for episodic high volume. We suspect that all of these theories may be correct, as well as others not yet discovered.

A challenge for theoretical researchers is that volume is extremely difficult to work with mathematically. Unlike prices, which can, at least with some transformations, be viewed as approximately normally distributed, the distribution of volume is non-normal and often complex. In the theoretical microstructure literature, traders (and market makers) learn from watching market data, and it is this learning process that leads to market efficiency. Yet our models of learning from volume are few, and our consonant inability to understand volume may follow as a result.

Increased empirical focus on volume may lead to greater insights into its correlation with other variables, and this in turn may aid our understanding of its role theoretically. We may also need to think more deeply about the process of price formation, and recognize that our existing results are based on models that are mathematically tractable, but not necessarily economically valid. 20

The role of information in long-run asset pricing is a second puzzle for researchers. More theoretical work integrating the microstructure and asset-pricing approaches is needed. So far there is no complete analysis in which: asset prices are determined in a microstructure setting, without the fiction of a Walrasian auctioneer; traders are fully optimizing, with rational expectations but differential information and unrestricted risk preferences; and, prices are fully endogenous, the fiction of an exogenous value process common in the microstructure literature is dropped. Indeed, one way to characterize the shortcomings of both fields is to recognize that microstructure analyzes the transition to a “true” value process, while asset pricing assumes this transition has occurred (flawlessly) and then investigates what causes the value process to arise. As we noted earlier in the paper, this dichotomy is unlikely to capture the complex process of price discovery.

Addressing these shortcomings may require rethinking basic concepts such as risk and efficiency. In asset pricing, risk relates only to aggregate uncertainty. The combination of diversification with the presumed efficiency of the price discovery process negates any importance to asset-specific risk. 21 Is this view too optimistic? In microstructure models, prices are always efficient with respect to public information, but this is relatively meaningless; it is the evolution of prices to incorporate private information that is important. Why then should the same not be true for the market as a whole? Does it make sense to assume that the overall market is priced “correctly” when it is so difficult for each individual asset to achieve this state?

One response to this criticism is simply that if markets are not efficient then profitable trading opportunities will arise. Thus, asset-pricing models have been supported largely by empirical findings against such profit opportunities. Yet, recent empirical research is more troubling. Beta seems, at best, mis-priced, the explanatory power of traditional asset-pricing approaches (at least as captured by $R^2$) is now vanishingly small, and the persistence of momentum all suggest that this base of empirical support has eroded. Moreover, the limits to arbitrage literature [see Shleifer and Vishny (1997)] argues that heterogeneity may more accurately characterize markets, undermining further the story that assets can be viewed interchangeably.

Researchers have responded with the search for new and improved factors in asset pricing, but the theoretical justification for such variables is often lacking. In our view, the problem is more basic: if asset prices are not always “efficient”, then traders may face a wide variety of risks in portfolio selection. And foremost among these may be risks arising from asymmetric information, which can inhibit the ability of simple diversification strategies to remove asset-specific risks.

More empirical work is needed to determine how robust are the recent findings that measures of differential information are priced. Microstructure models provide measures of private information, but these measures are admittedly crude. Both the Kyle $\lambda$ and the PIN measure developed by Easley et al. (1997b) require an exogenous specification of the periodicity of information events (conveniently chosen to be a

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20 Thus, models of behavioral finance in which prices reflect alternative learning structures may yield insights into market statistics such as volume, and into the behavior of short-and long-run asset prices.

21 For elaboration of these issues, see O’Hara (2003).
day). The λ measure involves both prices and aggregated quantities, leading to interpretation difficulties due to a wide range of factors. The PIN measure uses imbalances of buy and sell orders to infer the population parameters of informed and uninformed traders as well as the probabilities of new information and its direction. We would be the first to agree that it is barely too simple a measure to capture all the dimensions of information; that more complex market statistics might prove more accurate and have greater predictive ability. In our own research, we are investigating whether integrating ACD-based approaches with our sequential trade structural model might lead to better specifications of information-based trading [see Easley, Engle, O'Hara and Wu (2000)]. We are also investigating the cross-sectional determinants of PIN, with a view to understanding its correlation with accounting-based measures.

Another approach that may prove fruitful in understanding how traders view risk in markets is experimental economics. Research by Bossaerts and Plott (1999) for example, shows that the CAPM does not hold when traders face limited numbers of illiquid assets. Experimental research by Bloomfield, O'Hara and Saar (2002) shows how informed and uninformed traders contribute to the production of liquidity in an electronic market. Because experimental analyses can “hold constant” other factors, such research may also suggest ways to deal with the econometric power problem in empirical long-term asset-pricing studies noted earlier.

A third puzzle for researchers is the role and importance of liquidity in asset pricing. Here, the challenges are legion, as even defining liquidity entails controversy. Nonetheless, liquidity issues seem to be important in a wide range of markets, and for assets ranging from equities to bonds to derivatives and real estate. Is liquidity best viewed as a type of tax borne by investors, or is it something more complex, and potentially more important? Is liquidity time-varying, suggesting that traders need be concerned with more than the first moment of liquidity? Is liquidity a priced factor, or are “liquidity” shocks really serving as a proxy for more fundamental disturbances in the economy?

These questions suggest revisiting the fundamental issue of whether liquidity effects, per se, are simply too small relative to aggregate shocks to be important in asset pricing. The argument advanced by Huang (2001) that liquidity matters when investors cannot borrow seems intriguing, but it seems more likely to provide insights into the liquidity of different classes of assets, rather than the cross-sectional differences within an asset class. Moreover, the liquidity spillovers between markets that prompt the infamous “flights to quality” suggest that liquidity issues may be important in a portfolio context [see Chordia, Sarkar and Subrahmanyan (2002)]. Increased empirical research on liquidity seems particularly promising in shedding light on these issues.

22 Hasbrouck (1999) argues that such a one-day specification is not supported by analyses of actual market data.

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