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AN EMPIRICAL EXAMINATION OF NYSE LIQUIDITY COMMONALITY, DECIMALIZATION, AND MARKET MICROSTRUCTURE EFFECTS WITHIN A CONDITIONAL PRICE DURATION FRAMEWORK

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AN EMPIRICAL EXAMINATION OF NYSE LIQUIDITY COMMONALITY, DECIMALIZATION, AND MARKET MICROSTRUCTURE EFFECTS WITHIN A CONDITIONAL PRICE DURATION FRAMEWORK

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1. Introduction

The study of capital markets at the level of the transaction, commonly referred to as the study of market microstructure, is generally concerned with (Madhavan, 2000): a) price formation and price discovery, b) market structure and design, and c) the implications of information and disclosure for trading and the price process.[i] Price volatility and liquidity often surface as central themes in empirical as well as theoretical research in the area[1] because these characteristics impact directly or indirectly all aspects of financial science and financial decision-making, including models of asset prices, and thus the cost of capital. As such, understanding how the microstructure of markets empirically influences volatility and liquidity is an important line of inquiry. This study is an empirical examination of the determinants and behavior of price volatility and liquidity utilizing a unique measurement process that preserves the information inherent in transaction prices.

A thorough understanding of the determinants and behavior of volatility and liquidity and how they are interconnected, requires that empirical analysis be carried out at the level of the transaction. Most studies of these characteristics of security prices however have traditionally relied on data measured over arbitrarily chosen fixed time intervals not at the transaction level[2]. Fixed interval data by its nature

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[1] For example, Roll (1984), Hasbrouck (1991), Stoll (1989), Kyle (1985), Glosten and Milgrom (1985), Easley, Keifer, O'Hara, and Paperman (1996), Foster and Viswanathan (1995), Lee, Mucklow, and Ready (1993), Goldstein and Kavajecz (2000) Jones and Lipson (2001), Chordia, Roll, and Subrahmanyam (2002), and Kaul, and Lipson (1994).

[2] For example, Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Harford and kaul (2004), Foster and Viswanathan (1990), Harris (1986), Wood, McInish and Ord (1985), Lee, Mucklow, and Ready (1993), Bessembinder (2003) Goldstein and Kavajecz (2000), Hasbrouck and Sofianos (1993), and Jones and Lipson (2001).

masks critical aspects of the true underlying irregularly spaced transaction series. Further, fixed interval data also tends to create artificial behavior that may not be reflective of the underlying dynamics of transaction price series, such as unknown heteroskedasticity and artificial autocorrelation[3]. Finally, extant theory is in fact a theory of transactions. Drawing inferences about theories based upon transactions from tests based on fixed interval data may lead to unknown biases in conclusions. This study circumvents the problem by working with a metric that preserves the information inherent in the actual irregularly spaced transaction series. The metric is commonly referred to as 'Price Duration'[4].

This study is divided into three parts, each addressing a particular question involving price volatility and liquidity. I first focus on the determinants of volatility and liquidity. I then investigate how a change in market design, the shift by the NYSE to a decimalization pricing protocol, influenced the relation between the determinants of volatility and liquidity and those measures. I finish with an analysis of the recently conjectured hypothesis that there are common factors which influence the liquidity of financial securities. That analysis focuses on whether such common influences can be said to exist once one controls for the theoretical determinants of liquidity. The common thread tying these three parts together is the use of intra-day price duration as a reflection of the transaction process.

Price durations are defined as the time between successive price changes. They can be interpreted as the time it takes for the price to move up or down by a

[3] Engle and Lange (2001), Lo and MacKinlay (1988).
[4] As used by Engle and Lange (2001).

fixed increment. Durations are an appealing alternative to modeling price dynamics using a fixed-interval time series because they preserve the fundamental characteristics of irregularly spaced transaction data. Further, as shown later, a unique feature of a price duration is that it also provides a measure of the inverse of realized price volatility. Price durations therefore allow direct tests of the determinants of volatility that preserve the inherent informational richness of the data. In addition models of the dynamics of price duration allow the computation of a measure of expected volatility, a predicted determinant of liquidity. By approaching the price formation process from the direction of price duration I am able to preserve information about the underlying transaction process that is lost using time series price data that is based upon a fixed interval.

I formulate and test microstructure hypotheses about volatility and liquidity utilizing a general model of the dynamics of price duration that accounts for conditional autocorrelation effects, namely an Autoregressive Conditional Duration (ACD) model[5]. The first part of this study involves an investigation of the dynamics of price duration for a sample of NYSE stocks. Because a price duration can be shown to measure the inverse of volatility, the models and tests constitute an analysis of the determinants and behavior of volatility. Thus, the first part of this study initially focuses on the microstructure of price formation and specifically on volatility. I also investigate the determinants and behavior of liquidity. Expected

[5] Engle and Russell (1998), Engle and Lange (2001), Bauwens and Giot (2000).

volatility is predicted to influence liquidity by numerous extant theories[6]. The dynamic model of price duration allows me to compute expected volatility thus also allowing me to estimate its relation to liquidity. Another unique feature of this study is the definition and analysis of a direct measure of liquidity, the signed order imbalance, in contrast to measures such as volume which only indirectly measure liquidity and by their nature mask the true underlying fundamental. The second part of the study deals with market structure and design issues. The specific focus is on the impact of the recent NYSE decimalization upon the dynamics of volatility and liquidity. I examine in detail how the dynamic models of volatility and liquidity were influenced by this shift in market design (protocol). The third part of the study deals again with price formation but focuses on the recent conjecture that liquidity of securities is influenced by a set of common factors. I investigate whether common influences are present in the raw data, but more importantly whether common influences are present once controls for variables predicted to influence liquidity.

This is the first study to present a thorough set of tests of the determinants of volatility and liquidity using price duration as the underlying metric. In addition it is the first study to utilize such models to investigate the effects of a market protocol change, in this case the switch to a decimalization pricing system by the NYSE. Finally, this is the first study to examine the issue of commonality in liquidity using both an informational rich measure of liquidity, signed order imbalances, but also a measure of liquidity that controls for its underlying determinants. One such

[6] Virtually all information asymmetry microstructure works like Kyle (1985), Easley and O;Hara (1987), as well as Escribano, Pascual, and Tapia (2002), and Chordia, Roll, and Subrahmanyan (2001).

determinant being expected volatility, which itself is computed from a price duration model that also preserves the informational richness of the transaction price series. The study presents an alternative empirical estimation framework to the works of Hasbrouck and Seppi (2001) and Chordia, Roll, and Subrahmanyam (2000) which are both rooted in fixed-interval data and which do not directly control for other determinants at the microstructure level.

This study uses intra-day transaction data for a sample of NYSE stocks to construct realized price durations, defined as the lengths of time between successive price changes of at least a pre-defined threshold size. The data are for the period October 2, 2000 till May 31, 2001, and are drawn from the NYSE TAQ data set. Associated with each such duration, I isolate relevant concurrent or cumulated transaction characteristics such as the bid-ask spread, quoted depth, etc., called duration marks. These data are also drawn from the TAQ data set. Price durations have the unique feature that they are always non-negative. The dynamics of price duration are modeled using a modified Autoregressive Conditional Duration (ACD) specification[7] which directly accounts for the non-negative characteristic. The model is extremely well suited for analyzing high frequency data exhibiting volatility clusters, autoregressive effects, and occurring at irregularly spaced intervals because it circumvents the price discreteness bias and bid-ask bounce problems of fixed-period time series models. Rather, it is a dynamic model of the event time segregation

[7] The ACD model was first developed and presented in Engle & Russell, (1998).

of real price/information events between successive price deteriorations[8]. The approach also helps avoid the well-documented problem of spurious serial cross-autocorrelation associated with fixed-interval returns arising from non-trading period time-deformations (Lo and MacKinlay 1988). In addition, the duration construct processes the irregularly-spaced time series data without introducing the inevitable heteroskedasticity problems associated with a standard fixed-interval time series approach (Engle and Russell, 1998).

My results can be summarized as follows. I find that conditional volatility is largely determined by the interaction of past volatility, lagged (change in) nominal spread, and the lags of transaction intensity, quoted depth and absolute price change. The finding is consistent with the predictions of information asymmetry microstructure theories of Roll (1984), Kyle (1985), Glosten and Milgrom (1985), Bagehot (1971), Easley and O'Hara (1987)[9]. I find that liquidity, measured as signed order imbalances is determined by conditional volatility and other information asymmetry proxies like lagged spread, volume, number of transactions, and absolute price change, consistent with the predictions of Kyle (1985), Glosten and Milgrom (1985), Chordia, Roll, and Subrahmanyam (2001), and Lee, Mucklow and Ready (1993). The results indicate that the change in market design, the shift by the NYSE to a decimalization pricing scheme, affected the dynamics of mid-quote price formation and price revision. There is evidence conditional volatility fell following

[8] Similar to the constructs initially proposed in Cho and Frees (1998).
[9] Also Hasbrouck (1991), Stoll (1989), Blume, Easley, and O'Hara (1994)., Easley, Keifer, O'Hara, and Paperman (1996), Hasbrouck (1988), Foster and Viswanathan (1995), Easley and O'Hara (1992), and Jones, Kaul, and Lipson (1994).

the switch to decimalization, consistent with the findings of Bessembinder (2003) and in agreement with the argument made by decimalization proponents that a refinement in the pricing grid would lead to more continuous, correct and less volatile pricing. In addition, decimalization exerted a negative impact on liquidity, as measured by the dynamics of the realized market depth formation process, consistent with the conclusions in Harris (1991, 1994), Grossman and Miller (1998), and Seppi (1997). Finally, the results on tests for commonality confirm the findings in Hasbrouck and Seppi (2001) and Chordia, Roll and Subrahmanyam (2000) of a single latent factor explaining about 15% of liquidity co-variation. The commonality evidence disappears however after controlling for the effects of conditional volatility and microstructure variables. I conclude from these tests, that the documented commonality in liquidity is generated by the underlying fundamental process of liquidity formation, including the subsumed microstructural co-formation of volatility and price.

The study begins with a review of the relevant literature. A description of ACD methodology, models, and variations pertinent to each of the three issues is then presented. The data are then described, as well as filters and algorithms for handling intraday transactions. I then formulate and test different microstructure hypotheses for each of the three issues addressed, and describe the results. The final section provides concluding remarks.

2. Relevant Literature and Research Outline

Until recently, empirical studies were limited by the scarcity and limitations of transactions data. New and much more detailed transaction databases have, however become available in recent years. Researchers now have the opportunity to access the whole universe of transactions data, as databases exist which record every transaction and its related characteristics. With the advent of intra-day transaction datasets, testing theoretical models of the workings of capital markets and the price formation process have become feasible. Extant literature has focused largely on the cost of immediacy and transaction services, and the impact of that cost on the short run behavior of security prices[10]. That particular area of research constitutes the field of "market microstructure".

Market microstructure is primarily concerned with the market for transaction services, and the implications for prices. Whereas asset pricing models usually assume frictionless capital markets, market microstructure deals with the trading costs and frictions characterizing actual financial markets. In addition, microstructure theory is closely linked to the economic implications of information, since trading costs are very closely related to the information in traders' possession. In particular, microstructure models focus on the structural and informational frictions causing an asset's price to diverge from its full-information expectation.

[10] Stoll, (2002). For an excellent review, see O'Hara (1995), and Harris (2003).

2.1. Market Microstructure

Liquidity (defined as the ability to 'trade large size quickly, at low cost, when you want to trade'[11]) is determined by the interaction of two primary fundamentals, the bid-ask spread and market depth.

2.1.1 Models of the Bid-Ask Spread

The formation and components of the bid-ask spread, as well as how and why it differs across securities has been in the focus of considerable research[12]. Accounting for the bulk of trading costs and measuring one major dimension of liquidity, the bid-ask spread is defined as the difference between what buyers must pay and what sellers receive if they post active, market orders and trade through a centralized system or a market maker. The literature has identified several components of the bid-ask spread, the most important of which are: order handling costs[13], non competitive pricing[14], inventory risk[15], the option effect[16], and asymmetric information[17]. As Stoll (2002) explains, these factors are not independent. Inventory risk, the option effect, and asymmetric information are all related to uncertainty. Inventory risk arises from the release of unanticipated public information after inventory is acquired; the option effect arises from public information releases

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[11] Harris, (2003).
[12] For an excellent review of market microstructure literature, see O'hara (1995), Stoll (2002), and Harris (2003).
[13] Demsetz (1968), etc..
[14] Garman (1976) and Amihud and Mendelson (1980), atc.
[15] Smidt (1971), Stoll (1978).
[16] The option effect was developed by Copeland and Galai (1983).
[17] Originated by Bagehot (1971), Black (1986.)

before the trade; the adverse selection component results from private information held by informed traders before the trade. The order handling component of the spread is basically compensation for the services and resources market makers expend. I now turn to a brief review of how the bid-ask spread is influenced by the inventory and information effects.

2.1.1.1. Inventory Models

The study of market microstructure arose as an alternative to classical frictionless Walrasian models of trading behavior. Frictionless models work fine under perfect competition and free entry assumptions. Central to the study of market microstructure however, is the functioning of market makers as agents that provide liquidity and price continuity, and promote price stability.

Early research modeled the market maker's behavior as a supplier of "predictive immediacy," the bid-ask spread being his return[18]. Early work explained the bid-ask spread through trading volume, the stock's risk level, price, and firm size. For instance Garman (1976) and Amihud and Mendelson (1980) consider a single monopolistic market maker, with the bid-ask spread arising as compensation for the likelihood of bankruptcy or failure to provide liquidity.

These static models have limited ability to "explain variation in bid-ask spread as a part of intraday price dynamics" (Madhavan, 2000, page 9.) Since dealers must maintain an inventory in order to ensure a smooth trading process and price

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[18] Demsetz (1968).

continuity, their holdings will be affected by past transactions and expectations about future order flow. Order flow and hence inventory level is uncertain however, so a component of the bid-ask spread dealers charge will likely be compensation for assumed inventory risk (for risk-averse dealers.) Smidt (1971) introduced the first model that explained a dealer's spread dynamics as a function of his inventory position. Considering inventory carrying costs and constrained dealer capital, the dealer's situation can be described using the Gambler's Ruin Problem. Basically, the dealer adjusts both spreads and prices to avoid ruin. In a more contemporary model, Madhavan and Smidt (1993), dealers set bid and ask prices to maximize the present expected value of trading revenue minus inventory storage costs as time goes to infinity. In their model, order imbalances lead to quote revisions, and market makers quote prices that induce mean reversion in inventories.

Another set of inventory models are based on the risks associated with holding inventory, namely potential price deterioration. For example, a market maker who buys at the bid price is prone to inventory risk if there is a chance the price will drop before the inventory has been moved[19]. Stoll (1978) shows the optimal bid-ask spread depends positively on the dealer's risk aversion, the stock return's variance and quoted depth, and negatively on the dealer's wealth. Stoll's model also predicts that after a sale at the bid, the dealer lowers both the bid and ask quote, and after a purchase at the ask, both the bid and the ask quotes are raised[20].

[19] Theoretical models of inventory risk include Garman (1976), Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1981, 1983), and Spiegel and Subrahmanyam (1995.)

[20] The model was subsequently extended to a multi-period framework and improved by Ho and Stoll (1981), however the predictions are basically the same.

2.1.1.2. Asymmetric Information Models

Jack Treynor (1971), (publishing under the pseudonym Walter Bagehot) suggested a distinction between traders based on the information they possess. One group of traders had no private information and traded only for liquidity purposes, and to execute portfolio rebalancing. Treynor labels these liquidity, or “noise” traders[21]. The other group of investors is comprised of traders possessing some private information; these informed investors sell at the bid if they have information justifying a lower price, and buy at the ask if the full information price level is above the current price. In Treynor’s model, the market maker and individuals who place limit orders lose in transactions with informed traders, because the informed traders can not be identified. Similarly, market makers gain from trades with liquidity traders, generally ensuring they survive and ensuring a structure in which continuous limit order posts are possible. Uninformed traders always lose to informed traders, regardless of whether they use market or limit orders. Uninformed traders end up regretting their trading or not-trading if they submit limit orders, and will lose half the spread to informed investors if they submit market orders (Harris, 2003). They can only avoid the losses by choosing not to trade. The important result of the model is that the bid-ask spread the market maker sets will contain an information component because of the possibility the market maker will be exploited by informed traders.

Kyle (1985) models the informational content of order flow in the presence of a single monopolistic informed trader and many uninformed traders. The informed

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[21] See also Black (1986.)

investor knows the distribution of the exogenous uninformed order flow and considers the price impact of her trading. The auctioneer determines the clearing price based on aggregate order flow. The model is initially a one-shot auction similar to the NYSE opening, and is subsequently extended to the limiting case of a continuous auction. In the one-shot auction setting, the market clearing price is:

$$\tilde{p} = p_0 + \lambda(\tilde{x} + \tilde{u}), \qquad [\,2.1]$$

where p_0 is the price before the auction, and $\tilde{x}$ and $\tilde{u}$ are the order flow of the informed and uninformed traders respectively. Lambda is the price impact coefficient of total order flow, generally referred to as Kyle's Lambda,

$$Lambda = 2\left[\frac{\sigma_p^2}{\sigma_u^2}\right]^{\frac{1}{2}}, \qquad [2.2]$$

where σ_p^2 is the variance of the asset price, and σ_u^2 is the variance of the exogenous uninformed order flow. The market clearing price is positively related to the variance of the asset price, and negatively related to the variance of the uninformed order flow because the informed investor finds it harder to camouflage her trade in a uniform, low variance, uninformed trading environment.

In the continuous auction setting, assuming only market orders, Kyle models the market maker's price setting behavior as a function of the net order flow. The resulting security price is set at its expected value, given the particular order flow, and net order imbalance. In the resulting rational expectations equilibrium, prices end up gradually incorporating all private information, and the market maker sets prices to clear the market. If the market maker tries to behave strategically and infers the probability of being faced with an informed trader (say he expects large trades to come from informed traders,) then equilibrium might not be reached. Market depth, defined as the size of a trade that can be arranged at a given cost[22], is proportional to the amount of noise trading, and inversely proportional to the amount of private information. In a continuous auction setting, the depth of the market and the volatility of prices are constant.

To summarize, Kyle presents a model which quantifies the intuition of Bagehot, and shows that price innovations can be modeled as functions of quantities traded, consistent with modeling price changes as consequences of new information.

As Harris (2003) points out, the adverse selection component of the bid-ask spread in this type of model arises as compensation for market maker losses to informed investors. Alternatively, Glosten and Milgrom (1985) derive the adverse selection component of the bid-ask spread from the market maker learning about the true value of the security conditional on the direction of the next trade and the probability of facing an informed trader. As Harris (2003) proves, using the so-called Glosten-Milgrom Theorem, these two perspectives lead to identical conclusions about the size of the adverse selection spread component[23].

[22] Harris, (2003).
[23] See Easley and O'Hara (1987) for a related development.

2.1.1.3. Time between Trades and Information

Easley and O'Hara (1992), in an important extension of the above models, study the role of time in price adjustment[24]. The authors relax the assumption that time is exogenous in the model. Instead, they argue the time (duration) between trades will convey information. A long duration, i.e. a prolonged period without a trade is interpreted as a lack of new information arrival. The probability of being faced with an informed trader is thus small, and therefore the market maker will adjust the bid-ask spread downward. Furthermore, the authors argue that any empirical investigation of transaction data ignoring the timing of transactions will be biased, because it will ignore the information content of the non-trading intervals. More importantly, the sequences of price changes and volumes are major factors in the market maker's information set. Market makers' quotes as hypothesized by the model will converge to their strong form efficient market values, because quotes will be revised at a rate increasing in the fraction of informed trades, approximated by trading intensity. The quantification of price durations will permit a direct test of Easley and O'Hara's predictions.

Such refined asymmetric information models predict that information is conveyed through trading, and therefore, trading affects prices and returns, because this is how information is impounded into prices. In the model, absence of trading would mean no news. Diamond and Verrechia (1987) in contrast, conclude an

[24] Easley and O'Hara (1991, 1992) and Easley, Keifer, and O'Hara (1997) all present extended models dealing with dynamic informational efficiency, and the effect of sequential information arrival upon the model described above.

absence of trades indicates bad news which informed investors can not capitalize on, due to short sale constraints.

Admati and Pfleiderer (1988) allow for two types of liquidity traders: discretionary and non-discretionary. The former trade a number of shares at a particular time, while the latter can strategically choose an optimal trading period. They show that discretionary traders will choose to trade when there is no information event, and trading activity will be unrelated to information. Absence of trades would then be characteristic of informed trading and long durations.

Holden and Subrahmanyam (1992) incorporate competition among informed traders into Kyle's model. They allow for multiple informed investors, each trying to profit from a fleeting informational advantage. The model predicts higher trading volume, faster private information revelation, short times between trades, and faster convergence to the security's true market value. In other words, markets become more efficient when competition is allowed, even in the presence of informed traders.

2.1.1.4. Empirical Evidence

Numerous empirical studies have provided at least limited support for the importance of heterogeneous information and trading activity on the bid-ask spread. Chordia, Roll, and Subrahmanyam (2001) find that spreads sharply increase in down markets and weakly decrease in up markets, constituting an asymmetric response of spread to market movements. Easley, Keifer, O'Hara, and Paperman (1996) find that large spreads are usually attributed to asymmetric private information, and pertain to less active stocks which face a greater risk of informed trading. The authors use trading volume as a proxy for adverse selection. McInish and Wood (1992) also find that spread tends to widen following large volume orders. Studies using alternative proxies for adverse selection risk feature insider ownership (Glosten and Harris 1988), market value of shares outstanding (Harris 1994), turnover (Stoll 1978), and the number of securities a dealer makes a market in (Branch and Freed 1977.) These studies find similar results. Harris (1994) finds that market tick size affects the composition of the bid-ask spread. Bollen, Smith, and Whaley (2002) conclude the spread is a function of the minimum tick size, the inverse of trading volume, dealer competition, and inventory-holding premium. The last component appears to be the major one, and is a non-linear function of share price and return volatility.

Ho and Macris (1984) find that the bid-ask spread is positively related to asset risk, and incorporates significant inventory effects. They find the spread to be negatively related to the level of dealer's inventory. Glosten and Harris (1988) find that the bid-ask spread contains an information component, as well as another joint component that includes dealer's risk aversion and inventories. Also, they find that the adverse selection component of the bid-ask spread increases with trade size.

Hasbrouck (1988) estimates a bivariate vector autoregressive model of volume and prices, and finds volume is related to price revisions (confirming an old Wall Street adage that "it takes volume to move prices".) Moreover, he finds information effects exceed inventory effects.

2.1.2. Price Effects Associated with Trading and Depth

Quoted bid and ask prices only apply to trades of specified size (quoted depth.) Institutional investors like pension funds and mutual funds often trade quantities much larger than the posted depth. Large orders may have an inherent price impact resulting in worse price execution[25]. Market depth, therefore provides an important complementary dimension of market liquidity, quality and trading costs. Large trades are usually executed through "block" negotiation in the upstairs market, or "worked" throughout the day to minimize their price impact[26]. Studies focusing on the effects of block trading[27] have discovered evidence of a price impact associated with large trades, although it is mild, and temporary at best. Furthermore, large trades have a pronounced asymmetric impact on price, with price increases from purchases persisting, thus possibly reflecting an adjustment to new information. Studies by Barclay and Warner (1993), Chan and Lakonishok (1995), and Keim and Madhavan (1996) fail to support the theory that informed traders and insiders execute large trades. Rather, informed traders execute medium-sized transactions, or they chop up their transactions, thus giving rise to auto-correlated order imbalances. Keim and Madhavan (1996) find that the price impact of block trades is positively related to trade size, and negatively related to market capitalization. This body of literature is

[25] Price execution is defined as the eventual actual price at which the transaction takes palce.
[26] For details on block negotiation, see Harris (2003.)
[27] See Scholes (1972), Krauss and Stoll (1972*a* and 1972b), and Holthausen, Leftwich and Mayers (1987.)

supplemented by recent works[28] on the interaction of liquidity and trading strategies of large investors.

Other studies[29] have investigated the price effects of institutional "herding." They show that such trades do in fact have a persistent effect on price, and that buying precedes future positive returns.

Consistent with these observations, Chordia and Subrahmanyam (2002) develop a model which explicitly considers how market makers accommodate autocorrelated order imbalances resulting from large traders splitting their orders. The authors show that autocorrelated net order imbalances lead to a positive relation between lagged imbalances and returns, with the relationship reversing sign after accounting for current imbalance. The model isolates signed net order imbalances rather than cumulative trading volume as the major price moving factor, and is consistent with Kyle's (1985) intuition. In other words, the old adage "it takes volume to move prices" should in fact be "it takes order imbalance to move prices." The argument is extremely pertinent to this research, because my primary liquidity measure of realized market depth (VNET) is in fact the realized signed net order imbalance transacted within a price duration. Chordia and Subrahmanyam (2002) test their model using daily data, while the duration framework takes the model one step further, thus allowing a direct test of microstructure effects – a feature that is arguably lost when using cumulated daily signed volumes.

[28] Dubil (2002), Bertsimas and Lo (1998), Jarrow (1992), Frey and Patie (2001).
[29] Lakonishok, Schleifer, and Vishny (1992), Wermers (1999), and Stoll (2000.)

French and Roll (1986) examine returns on trading vs. non-trading days and document a greater return variance on trading than on non-trading days. They offer several alternative explanations for their results. Public information might arrive with greater frequency during business hours with the result that prices are revised to reflect the newly available information. Alternatively, private information might be introduced during business hours through informed trading. Finally, the trading process itself might lead to higher volatility on trading days. French and Roll find that the private information hypothesis is supported, and that volatility in stock returns during business hours is due to informed traders entering the market at the open and prices eventually impounding the new information. French and Roll's argument is formalized in subsequent models by Admati and Pfleiderer (1989) and Foster and Viswanathan (1990). Alternative tests utilizing intraday data (Harris 1986, Madhavan, Richardson, and Roomans 1997, and Wood, McInish, and Ord 1985) have documented U-shaped patterns in the bid ask spread and volume during the day, and tend to support these price formation hypotheses. Jain and Joh (1988) find that day-of-week and time-of-day dummies are significant in explaining trading volume, and are correlated with returns.

In summary, extant research supports the existence of both inventory and information effects on liquidity, and finds evidence that trading affects the time series pattern of spreads and volatility. Thus, controlling for the alternative hypothesized components of the bid-ask spread[30], the evidence suggests that cross-sectional variation in spreads can be explained by economic variables.

2.1.2.1. Net Order Imbalances and Price Changes

Several authors have argued that it is net order flow, or order imbalances, and not volume that moves prices[31]. The idea is intuitively appealing since total volume will inevitably aggregate transactions on both sides of the market, thus rendering impossible any test of the respective price effects of buy versus sell orders. Madhavan and Smidt (1991) disentangle order flow's signal of future value from inventory effects and find a significant information effect, and a weak inventory effect. Their findings support the hypothesis that order imbalances lead to quote revisions. The relation is also confirmed by Hasbrouck and Sofianos (1993) and Chordia, Roll, and Subrahmanyam (2002) who find that signed order imbalances reduce market liquidity, and that returns are correlated with previous imbalances. Dennis and Weston (2001) argue that economies of scale exist in the acquisition of information, and that institutions and insiders are more informed than individual investors. They find evidence that market makers move prices in response to institutional trades, supporting the information asymmetry hypothesis. The idea is that trade size or order flow reflects the underlying disagreement amongst traders about a security's true value. On the other hand, Jones, Kaul, and Lipson (1994) argue that trade sizes, and

[30] George, Kaul, and Nimalendran (1991) find the adverse selection component only accounts for 8 to 13 percent of the quoted spread. Huang and Stoll (1997) find that 38 percent of the spread is due to inventory and adverse selection costs.
[31] Madhavan and Smidt (1991), Hasbrouck and Sofianos (1993), Chordia, Roll, and Subrahmanyam (2002).

therefore volume contain no information beyond that contained in transaction frequency, and claim the number of transactions is more important than size. Their finding is consistent with the Mixture of Distributions Hypothesis (MDH)[32]. MDH implies a positive relation between volume and volatility because they are jointly determined by the number of information events which serves as a mixing variable and explains their positive correlation.

2.1.3. Plan of Study

The literature abounds with alternative explanatory variables and empirical proxies that could readily be used as independent variables representing order processing, inventory, and information effects impacting spreads and overall liquidity, market quality and trading costs. Intraday models of price formation provide insights about how to identify the influence of asymmetric information and inventories on prices. These models predict the inventory effect will be transitory, and the asymmetric information effect will lead to a permanent change in prices, since the (net) order flow acts as a signal about future security value and leads to a permanent belief revision.

A central focus of this study is the modeling of the time between successive price changes. I assume there is a latent information arrival stochastic directing process which drives trades and thus price changes. The Autoregressive Conditional Duration (ACD) models applied will allow direct modeling of the evolution of the

[32] Clark (1973), Harris (1987), Andersen (1996).

time between price changes. The time between price changes provides a measure of price volatility that does not impose an arbitrary, fixed interval framework on the analysis. The model's treatment of time is better suited for analyzing irregularly spaced, ultra-high frequency transaction data, while circumventing the heteroskedasticity inherent in fixed-interval data. Furthermore, the duration construct helps avoid problems like bid-ask bounce, and the spurious autocorrelation of returns arising from working with discrete prices and non-trading periods.

Microstructure theories can then be tested by examining the impact of variables hypothesized to affect the price and spread formation process upon the expectation of the conditional price duration. In addition, as outlined in Section 6, the price duration framework allows me to estimate a model of realized market depths and thus test the influence of different hypothesized determinants of liquidity.[33] The setting will also allow direct tests of the above mentioned liquidity effects in the presence of large traders, as well as provide insights about optimal liquidation strategies for large portfolios.

2.2. Market Protocol Change: Decimalization at the NYSE

2.2.1. Market Protocols

The NYSE started as a call auction market, in which trading took place at pre-specified times according to prescribed rules. This mechanism is now a remnant of

[33] The empirical setting also enables construction of market reaction curves (Engle and Lange 2001) that can be examined in trying to pinpoint the key driving factors of market depth and liquidity dynamics.

the past[34], even though it still characterizes the exchange's opening procedures where a single clearing price is set to clear the market and maximize trading volume. During the rest of the day, the NYSE operates as a continuous auction in which investors "trade against resting orders placed earlier by other investors and against the 'crowd' of floor brokers" (Stoll, 2002 page 3.) In addition, the NYSE is a hybrid auction/dealer market because specialists are allowed to trade for their own accounts in order to maintain liquidity and price continuity in their assigned stocks.

Investors submit two types of orders. Market orders require immediate execution at the best available price, limit buy orders set a maximum price to buy and sell orders a minimum price to sell. The highest limit order to buy and the lowest limit order to sell establish the market and the quantities at those prices determine the depth of the market. Market orders then trade with the best limit orders. Priority rules are typically used to determine how market and limit orders are fulfilled. First priority is given to orders with the best price and secondary priority to orders posted first at a given price. Until recently, the NYSE had stipulated minimum increments by which stock prices could change. These are known as tick size. Tick sizes affect the way priority rules operate. As Harris (1991) notes, the secondary priority is meaningless if the tick size is very small. If the tick size is small, investors and/or dealers can "step in front of" limit orders to buy by quoting a slightly higher price and incurring a relatively small cost[35]. On the other hand, when tick size is small, investors placing

[34] For a detailed description of the trading environment, see Harris (2003.)
[35] A *Business Week* (October 27, 2003) article "Under the Gun at the Big Board" refers to the increased specialist use of 'penny-jumping', lack of transparency, and unclear trade-through rules. A WSJ article (February 18, 2004 C1) "Five Specialists Agree to Pay Big Board Fines" also documents the rising

limit orders and thus supplying liquidity to the market run an increased chance of their buy limit orders being "picked off" if new information warrants a lower price. Too low a tick size could therefore discourage investors from placing limit orders and hence reduce market depth and liquidity. Thus, an optimal minimum tick size may be consistent with the operational efficiency of capital markets.

2.2.2. Decimalization and the Tick Size

Decimalization refers to the practice of quoting security prices in one-cent increments, rather than a fraction of a dollar. Up until June 1997, the NYSE tick size was 1/8th of a dollar. The 1/8th tick size dates back to October 13, 1915, when the NYSE switched from quoting prices as percentage of par to quoting them in dollars. Angel, (1997) provides some history behind the seemingly arbitrary 1/8th rule. Before 1915, the minimum tick size was 1/8th of a percent, dating back as far as 1817. Street lore suggests the 1/8th rule arose form the Spanish "pieces of eight' coins that were chopped into eight pieces for use in the colonies, but no historical evidence supports the argument, especially since the first NYSE prices were quoted in British pre-decimal currency units. After June, 1997, the NYSE switched to a 1/16th of a dollar minimum tick size. The New York Stock Exchange completed the switch to decimal pricing in January 2001. By the end of April 2001, all major exchanges in the USA had switched to decimal pricing, replacing the 1/8 or 1/16 increment quotes.

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incidence of the specialist practice of stepping-in-front of orders. Both provide anecdotal evidence of hindered liquidity, partly due to the decimalization switch.

Proponents of decimalization claimed that refining the pricing grid and the associated bid-ask spread would lead to a decrease in transaction costs, enable more smaller-sized trades, and increase market participants' welfare by reducing the opportunities for market makers to extract excessive profits. The NYSE approved decimalization with the stated intent of making prices easier to understand, reducing spreads, and making the NYSE conformable to international markets. However, arguments favoring an optimal fractional tick size also exist.

2.2.3. Literature on the Effects of Decimalization

Harris (1991, 1994) states that reducing the tick size decreases liquidity by decreasing the cost of getting inside someone else's quote, thus decreasing the incentive to post limit orders. Posting a limit order also reveals the investor's information set which can move the price in an unfavorable direction. A larger tick size will then increase investor compensation for the vulnerability of exposing their positions through limit order postings. Angel (1997) provides empirical evidence that a larger relative tick size increases willingness to post limit orders.

Brown, Laux, and Schachter (1991) also claim that an optimal, non-decimal tick size might exist that minimizes the costs of negotiating and bargaining. In addition, a wider relative tick size leads to fewer possible prices and correspondingly less information to track, thus making the contents of the order book much easier for market makers to track.[36] Furthermore, a wider minimum tick size reduces the probability of trading errors (Brown, Laux, and Schachter, 1991) and encourages dealers to make a market in a stock by effectively setting a minimum bid-ask spread[37] and encouraging market makers to conduct more research and promote the stock better if they are also brokers. The latter argument pertains to the NYSE since some specialist firms are owned by large brokerage firms.

In an early version of Chakravarty, Wood, and Van Ness (2004), the authors provide an overview of the theoretical literature focusing on tick size, splitting it into five streams:

1) Research claiming optimal minimum tick size arises due to market frictions from Bertrand competition among liquidity providers (Anshuman and Kalay (1998), Bernhardt and Hughson (1996), Kandel and Marx (1997).)

2) Research claiming minimum tick size helps coordinate negotiation (Brown, Laux, and Schachter (1991), and Cordella and Foucault (1999).)

3) Research relating tick size and payment for order flow, claiming that a reduction in tick size might diminish the practice of paying for order flow and increase transparency and trading volume. (Chordia and Subrahmanyam (1995), and Battalio and Holden (1996))

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[36] The existence of an optimal number of pieces of information held in short term memory is supported by cognitive research by Miller (1956) and Simon (1974).

[37] See Harris (1991, 1994), Ball and Chordia (2001), Grossman and Miller (1988), and Niemeyer and Sandås (1993)

4) Research claiming smaller tick size will reduce bid-ask spreads thus enhancing liquidity (Hart (1993), Peake (1995), O'Connell (1997).)

5) Research claiming a lower tick size will lower spreads and depth due to a decline in profitability of supplying liquidity (Harris (1994, 1998), Grossman and Miller (1998), and Seppi (1997).)

The empirical effect of decimalization on market liquidity, price volatility, and welfare do not suggest any overall benefit was gained. Bacidore (1997) finds that a reduction in tick size from 1/16th of a dollar to 5 cents on The Toronto Stock Exchange decreased spreads, but left depth and trading volume unaffected. A reduction from 5 cents to a penny, however, lead to almost no discernible changes in any market quality variables. Other research[38] has confirmed decimalization led to decreased spreads and depth on The Toronto Stock Exchange. Ball and Chordia (2001) and Goldstein and Kavajecz (2000) find that reducing NYSE ticks from 1/8th to 1/16th decreased quoted spreads, corresponding depths, and limit order book depth.[39] Studies on the NYSE change to sixteenths[40], and the AMEX switch to sixteenths (Ronen and Weaver, 2001) also find that tick size reduction reduces spreads and depths, thus making it costlier to execute large trades.

Gibson, Singh, and Yeramilli (2003) conclude that the adverse selection and inventory components of the spread remained relatively unaffected by the switch to

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[38] Huson, Kim, and Mehrorta (1997), Porter and Weaver (1997), Ahn, Cao, and Choe (1998), and Weaver (2003.)

[39] Ball and Chordia (2001) support the move to decimalization, claiming it will lead to more efficient spreads closer to the "true" spreads for large, liquid stocks.

[40] Bollen and Whaley (2001), Ricker (1998), Goldstein and Kavajecz (2000), Jones and Lipson (2001), and Alexander and Peterson (2003).

decimal prices, and the reduction in spreads after NYSE decimalization was due mainly to a diminished order-processing component. Chung and Chuwonganant (2001) investigate the frequency of quote revisions, using it as a proxy for market quality, efficiency, price discovery, and competitiveness. They find that the frequency of quote revisions has increased with decimalization, thus reducing price rigidity. They also find that minimum price variation rather than minimum tick size is the binding constraint on absolute spread quote behavior. Bessembinder (2003) reports that intraday volatility declined following decimalization but the quote revision process remained relatively unaffected. Dyl, White, and Gorman (2002) argue that decimalization will likely have no impact on dollar trading volume, because lower spreads will induce more information gathering and market making efforts that compensate for higher trading costs. The only change as the market reaches its new equilibrium, they hypothesize, will be lower stock prices, as firms split their stocks, striving to achieve an "optimal preferred price range" for their shares that decreases with spreads and tick size.

2.2.4. Plan of Study

All studies investigating the impact of decimalization have shown that even though bid-ask spreads have generally decreased after decimalization[41], thus improving liquidity by reducing trading costs, another component of liquidity, namely market depth has deteriorated. Contrary to what regulators hoped for, the net result

[41] Preliminary results by NYSE Senate Subcommittee on Securities and Investment, May 24 2001, state the average bid-ask spread has narrowed by 37 percent.

seems to be increased trading costs for institutional investors, and the impact is unclear for smaller sized trades. The welfare implications of the switch are ambiguous.[42]

By analyzing intraday transactions (TAQ) data from the NYSE, this study will empirically test for changes in the liquidity and realized market volatility processes brought about by decimalization, within the framework of price durations. In addition, I will test the validity of existing market microstructure theories in the presence of decimal prices, and examine the effect of decimalization on price formation dynamics in light of alternative microstructure hypotheses.

2.3. Liquidity and Commonality in Liquidity

2.3.1. Overview and Literature on Liquidity

Liquidity in financial markets is commonly defined as the ability to 'trade large size quickly, at low cost, when you want to trade'[43]. Liquidity (trading) costs may exert a significant influence on required returns[44] and thus influence corporate costs of capital.

The two major components of trading costs are costs of immediacy and market depth. In the most general case, immediacy is represented by market maker bid and ask quotes, and depth by the quantity of shares that can be transacted at those quotes. Liquidity is thus a bi-dimensional concept, influenced by the interaction of

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[42] Bessembinder (2003) finds no deterioration in selected market quality measures after decimalization.
[43] Harris, (2003).
[44] Amihud and Mendelson (1986), Jacoby, Fowler, and Gottesman (2000), Jones (2001), and Butler, Grullon, and Weston (2002).

immediacy and depth. Early microstructure research, for the most part overlooked this bi-dimensional aspect, concentrating only on one of the two measures, namely immediacy costs[45]. These models assume constant trade size. On the other hand, early studies dealing with market depth instead assume a single liquidation price, thus assuming away the second dimension of liquidity[46].

Recent empirical studies have investigated the relation between the two liquidity components. Lee, Mucklow, and Ready (1993) find evidence that NYSE specialists manage adverse selection risks by dynamically setting both immediacy costs and depths. The authors detect a negative contemporaneous relation between depth and spread size. Goldstein and Kavajecz (2000), and Jones and Lipson (2001) also emphasize the relation between spreads and market depths, within the context of new market reforms like decimalization, and changes in rules and policies. Escribano, Pascual, and Tapia (2002) is among one of the few studies to propose alternative, bi-dimensional proxies measuring liquidity. They find that heterogeneous expectations about future volatility usually give rise to unambiguous liquidity changes, and that volatility is a major factor in the contemporaneous evolution of spreads and depths. Chung and Zhao (2003) find that spreads and depths are strategically adjusted mostly in the early and late hours of the day, consistent with the higher volatility characterizing those times. The authors also find that depth revisions are much more common than spread revisions. A theoretical model of the exact inter-temporal

[45] Ho and Stoll (1981), Glosten and Milgrom (1985), others.
[46] Other models of depth (Charoenwong and Chung, 1998, Kavajecz, 1999) are mainly just extensions of the asymmetric information models of the spread.

relation between spreads and depths changes resulting from market maker adjustment to concurrent shocks is, however still lacking.

Chordia, Roll, and Subrahmanyam (2002) examine the empirical relation between trading activity, liquidity and market returns using signed order imbalances to approximate trading activity pressures[47]. Similar to the Chordia and Subrahmanyam (2002) order imbalance treatment, the authors claim order imbalances could proxy for asymmetric information and therefore reduce market liquidity and bring about a permanent price revision, just as in Kyle (1985.) In addition, random order imbalances could lead to temporary price and depth quotation changes, as market makers try to smooth their inventory positions. The authors find that lagged values of liquidity and market returns can predict liquidity, consistent with the hypothesis that price fluctuations decrease liquidity because they increase inventory risk. In a related paper, Chordia, Roll, and Subrahmanyam (2001) detect negative serial autocorrelation in daily liquidity measures and an asymmetric response of spreads to up and down markets. Spreads seem to decrease and depth increases in up markets, while the opposite is true for down markets. In addition, spreads and depth respond to market volatility, and day-of-week effects. Contrary to general intuition, recent market volatility is found to reduce spreads, a finding difficult to fit into existing theoretical models.

[47] An extensive line of research (Gallant, Rossi, and Tauchen (1992), Lo and Wang (2000)) has documented the relation between trading volume and market return. For an excellent summary, see Karpoff (1986).

2.3.2. Liquidity Commonality

A handful of recent empirical studies (the two major ones being Chordia, Roll, and Subrahmanyam (2000), and Hasbrouck and Seppi (2001)) have examined and documented commonality in trading activity and liquidity in equity markets. The issue of correlated liquidity is of particular interest, for it could help explain the driving forces behind the October 1987 stock market crash, or the documented 1998 credit sensitive bonds global liquidity crisis that gave rise to other financial crises characterized by diminishing, even disappearing liquidity[48]. These studies detect the presence of common factors in order flows, proxies for liquidity, and returns. Liquidity commonality could have important implications for asset pricing if it represents a systematic, non-diversifiable factor[49]. Acharya and Pedersen (2002) also argue that common, systematic liquidity risks could make required returns a function of expected illiquidity and the correlation between security return and illiquidity and their market counterparts. Pastor and Stambaugh (2002) find that securities having a high return or liquidity in illiquid markets command a premium.

Commonality might be due to different types of market-wide liquidity shocks[50]. Basket trading, program trading, and herding by large institutional investors

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[48] Chordia, Sarkar, and Subrahmanyam (2003) give an example of LTCM's 1998 London and Tokyo offices lack of buyers and sellers.

[49] Jones (2001), and Amihud (2002) claim that since liquidity is persistent, it could help predict future returns and will be negatively related to contemporaneous returns.

[50] Cai (2003) provides an alternative explanation for the 1998 LTCM liquidity crisis. His paper supports the claim that dealers engaged in very heavy "front running" during LTCM's financial crisis and margin calls. Because LTCM's exposures were known and easy to anticipate, dealers stepped in front of upcoming LTCM orders and benefited from the subsequent price change. Since it is illegal for dealers to step in front of their own customers, but not illegal to step in front of other dealers' customers, the situation could have easily given rise to the documented ubiquitous liquidity crisis, as well as correlated liquidity across different bonds.

could lead to correlated inventory fluctuations, giving rise to liquidity commonality. Such effects could arise from public news releases[51] about macroeconomic factors or portfolio-wide liquidity shocks. Alternatively, commonality could also arise from market-wide informational asymmetries. Friederich and Payne (2002, page 10) offer one intuitive explanation for the latter. If a given sample of stocks has "at least one common return driver and a subset of traders has access to a model that provides better than average forecasts of the driver," the activity of these traders will generate market-wide informational asymmetries. Chordia, Roll, and Subrahmanyam (2000) similarly argue that revolutionary new technologies employed with varying success by different firms might also induce an "outbreak of asymmetric information." Barberis, Schleifer, and Wurgler (2003) model correlated uninformed trading and its implications for return co-movements. Alternatively, Fernando (2003) presents a model in which the incidence of common factors in liquidity is explained by co-varying investor heterogeneity rather than common liquidity shocks, while cross-asset liquidity commonality is attributed to correlated idiosyncratic liquidity shocks and correlated fundamentals.

2.3.2.1. Empirical Evidence on Commonality in Liquidity

Hasbrouck and Seppi (2001) sample the 30 stocks in the Dow Jones Industrial Average (DJIA) and find[52] evidence of correlated common factors in order flows and

[51] Following models by Subrahmanyam (1991), Chowdhry and Nanda (1991), Kumar and Seppi (1994), and Caballe and Krishnan (1994).
[52] Their results confirm the Lo and Wang (2000) theoretically hypothesized factor structure for trading volume in the presence of portfolio rebalancing and liquidation.

returns. More importantly, using principal components analysis, they find common factors in the levels of liquidity proxies[53]. These components, as mentioned earlier, can either be the result of unsophisticated liquidity trades arising from momentum, tax-effects, portfolio rebalancing or correlated trading based on forecasts of underlying driving variables. Hasbrouck and Seppi (2001) use principal components and canonical correlation techniques to detect common cross-firm factors in liquidity and order flows. The common factors of signed and absolute order flow explain part of the variation in returns. In addition, liquidity also exhibits common factors[54], even though these factors explain only a modest portion of cross-firm variation after accounting for seasonality. The modest evidence of commonality leads the authors to the conclusion that common liquidity shocks are only eminent in short-lived, crisis-like episodes, and are not characteristic, or sustainable in periods of normal trading. The authors suggest that a part of the explanation for the modest degree of commonality might be the presence of both transitory (immediacy related) and permanent (informational) components in liquidity measures. Their approach, aggregating over a fixed-time interval (15 minutes), does not allow a clear segregation of the two effects because it potentially averages transitory and permanent episodes, and will further be confounded by the presence of unequally

[53] The research is separate from the bulk of studies (Jain and Joh (1988), Foster and Viswanathan (1990), Wood, McInish and Ord (1985)) establishing time-of-day liquidity effects, or liquidity patterns around idiosyncratic, firm-specific events (as in Lee, Mucklow and Ready (1993), Foster and Viswanathan (1995).) Also, refer to Section II – A.
[54] The identity of the factors is, as usual, unknown. Henker and Martens (2002) present some evidence that one of the factors might be a common cost component due to portfolio effects of dealers hedging their positions by varying the spreads of stocks they deal in which exhibit correlated liquidity. That common factor is largest for securities with highest trading frequencies.

spaced trades and bid-ask bounce. I suggest that employing the duration framework isolating meaningful information events (price changes) might provide a remedy to this problem because my liquidity measure is predicated upon the particular price change it brought about, as discussed in sections 2.3.3 and 6.3.

Chordia, Roll, and Subrahmanyam (2000) present an alternative method of detecting commonality in liquidity. Friedrich and Payne (2002) describe the method as a "stock-by-stock time series market model regression," of the change in a liquidity variable on the concurrent change in a cross-sectional market or industry average of the same variable. Also included as independent variables are all the traditional determinants of liquidity such as volatility, volume, price, number of transactions, etc. The linear relationship is justified by Subrahmanyam (1991). Chordia, Roll, and Subrahmanyam (2000) test whether inventory or asymmetric information sources govern commonality, and if trading cost shocks are non-diversifiable and therefore priced. With regard to inventory effects in commonality, the authors find that greater market-wide trading (most likely due to more uninformed trading) possibly decreases inventory risks and thus decreases specialist spreads. The presence of market-wide informational asymmetry evidenced by a greater number of transactions, however[55] promptly increases spreads. The authors' model does not permit them to test whether market-wide asymmetric information has common driving factors, only that it gives rise to commonality in liquidity.

[55] Consistent with Barclay and Warner (1993), and Jones, Kaul, and Lipson (1994)

Chordia, Roll, and Subrahmanyam (2000) speculate that even though their results show that most of the cross-sectional variation in liquidity is diversifiable, assets with higher sensitivity to liquidity shocks might require higher average expected returns. The claim is formalized by Acharya and Pedersen (2002) who show that time-varying common factors in liquidity influence required returns. The prediction is further confirmed by Pástor and Stambaugh (2002) who find that over a 34-year period, the average return on stocks that are highly sensitive to liquidity exceeds the average returns of stocks less sensitive to liquidity. Vayanos and Wang (2002) develop a search-based model of asset trading and show that market-wide liquidity can influence cross-sectional stock returns and that liquid assets trade at a premium relative to less liquid assets.

Chordia, Sarkar, and Subrahmanyam (2003) extend the search for commonality in liquidity by considering how stock and bond liquidity co-vary. They find significant correlations between liquidity shocks across the two markets, supporting the claim that a common factor like macro liquidity might drive liquidity measures.

Huberman and Halka (2001) also find evidence that supports the existence of a market-wide systematic component of liquidity. Using autoregressive models on a range of liquidity proxies, the authors find that the residuals from two mutually exclusive samples are positively correlated even after controlling for microstructure variables. Their econometric model is structurally very similar to the Chordia, Roll, Subrahmanyam (2000) "market regression" setting.

Harford and Kaul (2004) extend the fixed-time 15-minute interval analysis of Hasbrouck and Seppi (2001) and try to identify possible sources of the order flow commonality they detect with principal component analysis and its correlation with returns. They find that commonality is strong for the stocks included in the S&P500 index while not so pervasive for non-index stocks whose modestly co-varying order flow tends to be driven by market order flow and industry forces. They find individual stock and aggregate order flow co-movement is the driving force behind correlated returns. An interesting implication of their findings is that market makers might utilize aggregate order flow in addition to stock specific order flow to model their price, spread, and depth quoting behavior. The principal components they detect only explain a modest portion (9-16% for the first component) of the co-variation in index stocks order flow and the proportion explained is even weaker for non-index stocks. The modest explanatory power of their components confirms the results of Hasbrouck and Seppi (2001) but is in disagreement with the Chordia, et al (2000) finding of significant commonality in changes of daily measures of trading costs. The authors claim a new estimation strategy or aggregation method is needed to reconcile these findings. My duration-based analysis is one such alternative estimation method, for it provides an event time model of trading costs (price impact or realized depth measures) explicitly controlling for market microstructure and conditional volatility effects.

The major differences between the Hasbrouck and Seppi (2000) and the Chordia, Roll and Subrahmanyam (2000) liquidity commonality procedures are the statistical framework (principal components vs. market regression), time interval (15 minute vs. daily), form of variables (levels vs. changes.) Hasbrouck and Seppi claim using levels is more appropriate because differencing an otherwise stationary series like spreads or depths will induce spurious autocorrelation in residuals. Principal components (or factor) analysis, while more general, does not produce a clear definition of the underlying factors generating commonality.

2.3.3. Plan of Study

I first estimate a model of realized market depth that incorporates instantaneous volatility and microstructure effects. I then test for commonality in the raw realized market depths and the model's residuals. The approach takes direct account of price duration and will include the expected conditional durations and thus conditional volatility effects in liquidity formation. Furthermore, the effect of decimalization on liquidity commonality will also be investigated within the construct of price durations and associated realized depths.

The methodology is unique, because until now the commonality literature has investigated aggregated daily time series (Chordia, Roll, and Subrahmanyam, 2000), or arbitrary fixed, intra-day time interval spans (Hasbrouck and Seppi, 2001) without accounting for the effects of variables microstructure theory predicts might influence liquidity formation and neglecting the more realistic aspect of event time price and depth formation. The approach presented here is rooted in price durations, and is thus first estimated in discrete, event time, offering a better approximation of actual price and depth formation dynamics. The ACD model framework will thus enable individual stock liquidity measures to be explicitly adjusted for the effects of conditional expected volatility, providing an indirect way of testing whether conditional expected volatility determines commonality in liquidity. This integrated approach to liquidity modeling, starting with the estimation of expected duration dynamics, then incorporating their effect into a model of realized market depths will allow me to isolate the event time realized shocks to liquidity formation. Next, a common factor and principal component analysis is carried out on the set of realized depth shocks. Detecting a common factor behind the co-variation of liquidity shocks, having controlled for sources of cross-sectional variation and event-time isolated microstructure effects could strengthen the notion of market-wide systematic liquidity shocks, a component which financial theory and the existing literature suggest will most likely be priced.

Hasbrouck and Seppi (2001) argue that the common factors of signed and absolute order flow could in fact explain a portion of returns. My research takes a unified approach to price (return) and liquidity formation modeling, since it is set up in the discrete event time of individual price durations rather than trying to model the formation of liquidity and returns as two disjoint processes, and imposing some fixed-interval aggregation across the two in order to examine dependence. My liquidity measure and its associated residual from my market depth regression is inherently tied to the subsumed return it brought about or was associated with by the very definition of a price duration as the time between a price movement of at least a predetermined magnitude. A more refined microstructure approach can thus be implemented to model the individual price changes; all within the duration time construct predicated on real price events rather than fixed time-intervals. Hasbrouck and Seppi (2001) and Harford and Kaul (2004) assume that causation runs from trading activity to prices and their fixed interval analysis strives to connect price changes to changes in order flow. My analysis will relax that assumption by modeling the dynamics of the price and depth formation processes through their synthetic co-evolution within the event time defined price duration construct. It is thus a sensible alternative to the approach in Harford and Kaul (2004.)

The models of realized market depth should be of particular interest to portfolio managers and large traders concerned about the price impact of their trades. In addition, the results will shed further light upon the existence of liquidity commonality. Finally, the impact of decimalization will provide insights about whether changes in market design or trading regime characteristics give rise to or at least influence to some degree the strength of the commonality manifested by market liquidity characteristics.

3. Methodology – Price Duration and the ACD Framework

Transaction data usually arrives at irregular time intervals, while standard econometric techniques are based on fixed time interval analysis. Historically, such data have been aggregated over some fixed time interval day, week, month, etc. in order to apply current fixed-interval time series econometric models. The technique is known as calendar time sampling. The length of the sampling interval often changes the pattern of the empirically detected price dynamics. In addition, if a long interval is chosen, Engle and Russell (1998) claim the microstructure properties of the data are lost. If too short an interval is chosen, excess heteroskedasticity will generally be present. Further, the rate of transaction arrival varies over the course of the day, week, or year. Often times, transaction frequency might depend on news releases or other unobservable events, which can be thought of as a stochastic directing process. In such cases, a trading time sampling technique utilizing a time scale set by trade arrivals would be more appropriate if the objective is to characterize the determinants of price formation. Often times, the major driving variable to be modeled and forecast is the quantity transacted over a period of time, which is determined by the transaction arrival rates.

Models set in trading time, a type of "deformed" or "market" time are better suited for analyzing the microstructure effects present in the data, and for modeling transaction arrivals. Inter-trade duration models represent an important class of such models. These models focus on the time between transactions or other qualifying events. In addition to the time between transactions, multiple relevant contemporaneous characteristics associated with each transaction can also be analyzed. These factors are viewed as a separate vector of random variables that identify or further describe each duration event and will be called duration "marks." The terminology is borrowed from the literature on point processes[56]. When dealing

[56] Snyder and Miller (1991).

with price transaction data in deformed trading time spanned by each trade duration, the marks are usually the number of shares traded, the transaction price, and the posted bid and ask prices, but the list can be expanded to include other relevant market microstructure variables such as market design or reform indicators.

Similarly, the inter-trade duration construct can be expanded to accommodate a thinned, or weighted duration measure. The bulk of this study utilizes one such measure, called the price duration. Instead of measuring the time between every transaction, the price-weighted duration gauges the time between absolute price changes of a given magnitude. Mid-quote price changes are usually used in this approach. These price-weighted durations will therefore incorporate accumulated intertrade durations, thus allowing further insight to the price formation process. The process eliminates the problems of bid-ask bounce and price discreteness associated with trade duration modeling and by isolating only meaningful price events it proxies for the underlying information generating process driving price formation. It is thus a viable complementary alternative to fixed interval empirical research.

3.1. Duration Models

Following Chapter 14 of Gourieroux and Jesiak (2002), a short description of dynamic duration models, presented in a price duration context follows.

Denote by τ_n^m, n = 1,….N^m , m = 1, …M, the duration between the (n-1)th and the nth significant price change[57] on day m. I will henceforth refer to τ as 'price duration.' Probabilities of various outcomes of a random experiment can be defined by a probability density function *f* or the cumulative distribution function *F* given by:

$$f(y) = \lim_{dy \to 0} \frac{P[y < \tau \leq y + dy]}{dy} \quad \text{and} \qquad [3.1]$$

$$F(y) = P[\tau \leq y] \qquad [3.2]$$

where τ is the variable of interest. Since price duration is a nonnegative variable, the density and cumulative distribution functions satisfy the relationship

$$f(y) = \frac{dF(y)}{dy} \quad \text{and} \qquad [3.3]$$

$$F(y) = \int_0^{+} f(\tau) d\tau \, . \qquad [3.4]$$

The survivor function measures the probability that duration exceeds a constant time y , and is defined by:

$$S(y) = P[\tau > y], y \in \Re^+ \qquad [3.5]$$

and is a decreasing function with limiting values *S(0)* = +1, and *S(+∞)* = 0, satisfying

[57] Gourieroux and Jesiak (2002) present the process through times between trades, because they concentrate on the trade duration as opposed to the price duration used in this study.

$$S(y) = 1 - F(y) = \int_{y}^{+\infty} f(\tau) d\tau \,. \qquad [3.6]$$

The hazard or intensity function λ provides a measure of the instantaneous probability of occurrence of a price change after a time y has elapsed during which no price changes occurred, and is defined as

$$\lambda(y) = \lim_{dy \to 0} \frac{1}{dy} P\left[y < \tau \leq y + dy \mid \tau \geq y\right] \qquad [3.7]$$

$$= \lim_{dy \to 0} \frac{1}{dy} \frac{P\left[y < \tau \leq y + dy\right]}{P\left[\tau \geq y\right]}$$

$$= \frac{f(y)}{S(y)}$$

From the hazard function, one can derive an expression for the survivor function

$$\lambda(y) = -\frac{1}{S(y)} \frac{dS(y)}{dy} = -\frac{d \ln S(y)}{dy} \,, \qquad [3.8]$$

and therefore

$$S(y) = \exp\left\{- \int_{0}^{y} \lambda(\tau) d\tau \right\}. \qquad [3.9]$$

Initially, assume the hazard function is a constant $\lambda(y) = \lambda$, meaning that the occurrence of a price change is independent of the time already elapsed without a change. Under this condition, the duration distribution generating a fixed λ is easily derived:

$$\lambda(y) = \frac{-d \ln S(y)}{dy} = \lambda \qquad [3.10]$$

with solution

$$\ln S(y) = k - \lambda y \qquad [3.11]$$

and therefore

$$S(y) = K \exp(-\lambda y) \qquad [3.12]$$

where K is a constant of integration. Since the boundary condition is *S(0)*=1, this will imply K=1, and the solution for the associated duration distribution is:

$$S(y) = \exp(-\lambda y) \Leftrightarrow f(y) = \lambda \exp(-\lambda y)\,. \qquad [3.13]$$

That is duration is distributed exponential, with parameter $\lambda > 0$, mean $E\tau = \lambda^{-1}$ and variance $V\tau = \lambda^{-2}$. Furthermore, the ratio of its mean to its standard deviation is unity, avoiding the so-called property of "excess dispersion"[58].

Actual durations likely exhibit excess dispersion and non-constant hazard functions, so the exponential will rarely be an appropriate distribution choice. Alternatively, the gamma distribution, the Burr distribution, and the Weibull distributions have been used to describe the duration distribution. All of these are distributions for positive random variables. In what follows, I show that empirically the Weibull distribution provides the best fit so I now focus on that distribution.

Following Gourieroux and Jesiak (2002), the family of Weibull distributions is derived from the exponential distributions family by a deterministic time deformation. A Weibull distributed duration variable τ, with parameters γ and λ, denoted W(γ, λ) is equivalent to $(\lambda\tau)^{\gamma}$ following the exponential distribution γ(1, 1). The hazard, pdf, and survivor functions are respectively:

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[58] Actual trade and price durations exhibit "excess dispersion", defined as the sample standard deviation greater than the sample mean (Engle and Russell, 1998).

$$\lambda(y) = \gamma\lambda(\lambda y)^{\gamma-1}, \qquad [3.14]$$

$$f(y) = \gamma\lambda(\lambda y)^{\gamma-1} \exp-(\lambda y)^{\lambda}, \qquad [3.15]$$

$$S(y) = \exp-(\lambda y)^{\lambda}. \qquad [3.16]$$

The hazard function of a Weibull distributed duration variable could thus be a constant $\lambda(y) = \lambda$ in the case that $\gamma = 1$ [59], monotonically decreasing in *y* if $0 < \gamma < 1$, and increasing if $\gamma > 1$. In the former case, the distribution is said to have a negative duration dependence, and a positive duration dependence in the latter. A decreasing hazard function, in my duration context would imply that the longer we have gone without a price change, the lower the probability a price change will actually occur. In other words, the likelihood of a price change (or *failure*) at time y, conditional upon duration up to time *y*, is decreasing in *y*. Another appealing quality of the Weibull distribution is that unlike the exponential, it allows for excess dispersion since its mean and variance are:

$$E\tau = \frac{1}{\lambda}\Gamma(1+\frac{1}{\lambda}) \qquad [3.17]$$

$$V\tau = \lambda^{-2}\left[\Gamma(1+\frac{2}{\lambda}) - \Gamma(1+\frac{1}{\lambda})^2\right]. \qquad [3.18]$$

3.2. Autoregressive Conditional Duration Models

Engle and Russell (1998) develop and introduce the Autoregressive Conditional Duration model for a time series of durations. We can think of the model

[59] Note that the Weibull nests the exponential distribution when $\gamma = 1$.

as a time series model of time, or simply, as a GARCH process that models durations between events such as price changes. The model essentially looks at market volatility by tying it to the intensity of trading. Instead of modeling asset price behavior in calendar time, the model represents price movements as being driven by an underlying information arrival process, or "directing process" that eventually manifests itself in trading patterns. Having parameterized the conditional intensity function of the price durations, the model can be used to forecast price duration (price change) arrival rates. The conditional intensity can be parameterized as a function of only the time between past events, and the associated marks. The dependence of the arrival rate on past durations is the reason for the label Autoregressive Conditional Duration.

Consider a stochastic process, which is a sequence of arrival times $\{t_0, t_1, \ldots. t_n\}$. Let N(t) be a counting function of the number of events that have occurred by time t. N(t) is a step function, continuous from the left, with limits from the right. Now, let the stochastic process be a "marked point process" because associated with every arrival (trade arrival or alternatively price change arrival), there is a vector of characteristics, or marks. Furthermore, assume the process evolves with after-effects; i.e. we have a marked point process in which the realization of price durations at a given point in time depends on the sequence of price durations preceding it. In addition, assume the process is also conditionally orderly. That is, at time $t \geq t_0$ for a sufficiently small interval of time, and conditional on any event P defined by the realization of the process in the interval $[t_0, t)$, the probability of two or more events occurring is infinitesimal relative to the probability of one event. Furthermore, a "self-exciting process" is assumed, under which past evolution impacts the probability structure of future events. Such a conditionally orderly stochastic process can be described by the conditional intensity, conditional density of durations between times, and conditional survivor function, taking into account past information including at least arrival times and the count. Engle and Russell (1998) provide an alternative definition of the hazard function, which is the conditional intensity of such a process:

$$\lambda(t \mid N(t), t_1, \ldots t_{N(t)}) = \lim_{\Delta t \to 0} \frac{P(N(t+\Delta t) > N(t) \mid N(t), t_1 \ldots, t_{N(t)})}{\Delta t} \qquad [3.19]$$

If I let $\tau_i = t_i - t_{i-1}$ be the interval between two arrival times, duration, the density of τ_i conditional on past durations can be specified directly. Let ψ_i be the expectation of the i^{th} duration given as:

$$\mathrm{E}(\tau_i \mid \tau_{i-1}, \ldots \tau_1) = \psi_i\,(\tau_{i-1}, \ldots \tau_1; \theta) \equiv \psi_i, \qquad [3.20]$$

where θ is a vector of parameters that determine the conditional mean function.

The novelty of the ACD model lies in its ability to summarize the dependence of the conditional intensity on the past durations only through the conditional expected duration function ψ_i. The crucial assumption permitting that simplification is

$$\tau_i = \psi_i \varepsilon_i, \qquad [3.21]$$

where $\{\varepsilon_i\} \sim$ i.i.d. with density $p(\varepsilon, \phi)$ which must be specified. Gourieroux and Jasiak (2002), describe the simplification as introducing a path-dependent time deformation such that the durations expressed on the new time scale are i.i.d. Since all durations, both realized and conditional, have to be nonnegative, the multiplicative disturbance will have positive probability only for positive values, and it must have a mean of unity. We have to assume then that ε_i is independent of τ_i, and that $E(\varepsilon_i \mid I_{i-1}) = 1$, where I_{i-1} is the information set available at t_{i-1}.This assumption requires that "all the temporal dependence in the durations be captured by the mean function" (Peiris, Allen, Yang 2002). The assumption can be tested using the standardized residuals of the ACD model.

ACD models are obtained as different classes of parameterizations of the conditional expected duration function. The model is autoregressive because the probabilistic structure of τ_i resembles an autoregressive (AR) process. The conditional expectation of durations depends on past durations and other marks. Thus, the conditional intensity (hazard) of the duration process does not depend on any other conditioning information but the expected duration and the counting function. The temporal dependence in the duration series is thus entirely captured by the mean equation.

A multitude of ACD models can be developed using different functional specifications of the time deformation measured by the expected duration and ε's distribution family. Engle and Russell (1998) use the baseline hazard function of

$$\lambda_0(t) = \frac{f(t)}{S(t)} \qquad [3.22]$$

which is the ratio of the density function of ε and the survival function associated with ε_t. The conditional intensity of an ACD model based on the assumptions mentioned above is given in Engle and Russell (1998) as

$$\lambda(t \mid N(t), t_1, \ldots t_{N(t)}) = \lambda_0\left(\frac{t - t_{N(t)}}{\psi_{N(t)+1}}\right)\frac{1}{\psi_{N(t)+1}}. \qquad [3.23]$$

Past history thus influences conditional intensity through both a multiplicative effect and a shift in the baseline hazard, what the authors call an “accelerated failure time” model. One useful application of the model might be in predicting the rate of time flow from past event arrival times, through the function ψ.

In the simplest version of the model, the durations are conditionally exponential, the baseline hazard is one, and the conditional intensity is

$$\lambda = \frac{1}{\psi_{N(t)+1}}. \qquad [3.24]$$

Similarly, a host of alternative distributions can also be accommodated, the most important of which as discussed earlier, is the Weibull. The choice of error distribution $p(\varepsilon, \phi)$ will determine the density of τ, f($\tau \mid I, \Theta$), $\Theta = (\theta, \phi)$ [60].

Assume that only the past m durations and q conditional durations influence the conditional duration at time *t*. We refer to this as the ACD(m,q) model, which

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[60] The parameters θ of the conditional mean, and the parameters ϕ of the conditional density are assumed to be constant. If $\theta \in \Theta_\psi$ and $\phi \in \Phi$, then $\Theta \equiv (\theta, \phi) \in (\Theta\psi \otimes \Phi)$

proposes a type of ARMA dynamics for ψ_n. The parameterization of the conditional mean ψ_n in this model[61] is analogous to the parameterization of the conditional variance in the GARCH(m,q) model of Bollerslev (1986). The autoregressive linear specification for the conditional mean function is given by

$$\psi_n = \omega + \sum_{i=1}^{m} \alpha_i \tau_{n-i} + \sum_{j=1}^{q} \beta_j \psi_{n-j} \qquad [3.25]$$

where the parameters are nonnegative. Engle and Russell (1998) suggest the model is a convenient parameterization because it allows various moments to be calculated by expectation, regardless of the form of the baseline hazard. The conditional mean of τ_i is ψ_i, the conditional duration, but the unconditional mean is

$$E(\tau_i) = \mu = \frac{\omega}{(1 - \sum(\alpha_i + \beta_j))} \qquad [3.26]$$

if the duration process is stationary. Similarly, unconditional variances can be computed[62], depending on the distribution for the errors. If the errors follow an exponential distribution, the corresponding EACD(1,1) model, for example will have unconditional variance of

$$\sigma^2 = \mu^2 \left(\frac{1 - \beta^2 - 2\alpha\beta}{1 - \beta^2 - 2\alpha\beta - 2\alpha^2} \right). \qquad [3.27]$$

Alternatively, if the errors are Weibull distributed, the unconditional variance will be

[61] Note that if $\alpha_i = \beta_j = 0$ the model nests the Poisson constant arrival rate of durations.

[62] See, for example Engle and Russell (1998).

$$\sigma^2 = \mu^2 \sigma_\varepsilon \left(\frac{1 - 2\alpha\beta - \beta^2}{1 - \alpha^2 - \beta^2 - 2\alpha\beta - \alpha^2 \sigma_\varepsilon} \right) \qquad [3.28]$$

where $\sigma_\varepsilon = \dfrac{\Gamma(1 + \frac{2}{\gamma})}{\Gamma(1 + \frac{1}{\gamma})^2} - 1$

Thus under either error type, if $\alpha > 0$, the unconditional standard deviation will exceed the mean and the process will exhibit "excess dispersion." Notice that the distribution of the errors in the model will define the distribution of the durations, therefore the excess dispersion of the Weibull($1, \gamma$) errors, just like their non-constant hazard rate as seen later, simply gets transferred to the durations.

In addition, the autocorrelation function of τ_i for the ACD(1,1) model can be calculated through a recursive formula, similar to the standard GARCH model:

$$\rho_1 = \frac{\alpha(1 - \beta^2 - \alpha\beta)}{1 - \beta^2 - 2\alpha\beta}, \text{ and} \qquad [3.29]$$

$$\rho_n = (\alpha + \beta)\rho_{n-1} \text{ for } (n>1) \qquad [3.30]$$

Therefore the persistence effect and clustering of durations will be governed by $(\alpha + \beta)$, while a slowly decaying autocorrelation function requires β to be close to one. Refer to Figure 1.

Letting $\eta_i = \tau_i - \psi_i$, a martingale sequence by construction, the ACD(m,q) specification can easily be transformed into the following ARMA(z, q) model with highly autocorrelated innovations:

$$\tau_i = \omega + \sum_{i=1}^{z} (\alpha_i + \beta_i)\tau_{i-j} - \sum_{j=1}^{q} \beta_j \eta_{i-j} + \eta_i \qquad [3.31]$$

where $z = \max(m, q)$

Finally, the parameters of the model can be estimated using maximum-likelihood procedures. If the underlying distribution of the errors is unknown, similar to the Lee and Hansen (1994) proof in the GARCH context, Engle and Russell (1998) prove that a quasi-maximum likelihood estimation computed as if error terms are exponentially distributed will produce consistent, and asymptotically normal estimates. Naturally, the result is identical to maximum likelihood estimation of the ACD model when the errors are known to be exponentially distributed. The associated quasi log-likelihood function is

$$\log L(\theta) = -\sum_{i=1}^{N(t)} \left(\log \psi_i + \frac{\tau_i}{\psi_i} \right) \qquad [3.32]$$

and in case a QMLE is run, residuals can be smoothed to get a kernel estimator of the unknown error distribution. QMLE, however does not ensure efficiency of the estimates. Maximum likelihood with the correct density will be the more efficient estimator, giving the baseline hazard different parametric shapes according to specified error distributions. As already mentioned, the Weibull distribution has been widely used in the duration literature mainly because of its nonnegative range of support and the ability to exhibit a monotonically increasing or decreasing hazard rate as a function of time. Its survivor and hazard functions were computed earlier. Adopting the notation of Engle and Russell, the probability density function f and the corresponding survivor function S for the Weibull with parameters (k,γ) are respectively:

$$f(\tau)=\gamma k^{\gamma}\tau^{\gamma-1}\exp\left\{-(k\tau)^{\gamma}\right\} \quad \text{and} \qquad [3.33]$$

$$S(\tau)=\exp\left\{-(k\tau)^{\gamma}\right\}. \qquad [3.34]$$

And therefore the hazard will be:

$$\lambda(\tau)=\frac{f(\tau)}{S(\tau)}=\frac{\gamma k^{\gamma}\tau^{\gamma-1}\exp\left\{-(k\tau)^{\gamma}\right\}}{\exp\left\{-(k\tau)^{\gamma}\right\}}=\gamma k^{\gamma}\tau^{\gamma-1} \qquad [3.35]$$

Using the result of Engle and Russell (1998), in the context of the ACD(1,1) model, the conditional intensity of the durations with Weibull $(1,\gamma)$ distributed errors is

$$\lambda(t\mid\tau_{N(t)},....\tau_1)=\left(\Gamma(1+\frac{1}{\gamma})\psi_{N(t)+1}^{-1}\right)^{\gamma}\left(t-t_{N(t)}\right)^{\gamma-1}\gamma \qquad [3.36]$$

where $\Gamma(\cdot)$ is the gamma function and γ is the previously discussed Weibull parameter. Note that the conditional intensity is now a two parameter family, and can exhibit monotonically increasing or decreasing hazard functions depending on γ.

From the conditional intensity, the log-likelihood function associated with the Weibull distributed durations for the ACD(1,1) model, is

$$\log L(\theta)=\sum_{i=1}^{N(t)}\left\{\ln\left(\frac{\gamma}{\tau_i}\right)+\gamma\ln\left(\frac{\Gamma(1+1/\gamma)\tau_i}{\psi_i}\right)-\left(\frac{\Gamma(1+1/\gamma)\tau_i}{\psi_i}\right)^{\gamma}\right\} \qquad [3.37]$$

where

Γ is the Gamma function,

$\psi_i=\omega+\alpha\tau_{i-1}+\beta\psi_{i-1}$ for i>1

$$\psi_i = \frac{\omega}{1-\beta} \text{ for } i\text{=1}$$

$$\theta = (\omega, \alpha, \beta, \gamma), \alpha, \beta \geq 0, \omega > 0, \alpha + \beta < 1$$

Maximum likelihood estimates of the parameters in the specified mean (conditional duration) equation and of the Weibull parameter can then be obtained using standard MLE methods. Namely, the log likelihood function is maximized iteratively with respect to the parameters in θ subject to the stationarity and non-negativity conditions above.

The expected lengths of the price durations are estimated with ACD models and can be used as approximations of the inverse of expected volatility. As previously mentioned, the price formation evolution can be modeled as a marked point process with after effects and memory, dependent upon the latent information variable. The exact relation between expected price durations and standard measures of instantaneous volatility is derived[63] from the solution of the 'crossing time' problem for a continuous-time stochastic process by Engle and Russell (1998) as:

$$\tilde{\sigma}_i^2 = \frac{c^2}{\psi_i}, \qquad [3.38]$$

where c is the price duration threshold. The result carries a lot of intuitive appeal, since over a discretized price change, one can generally expect the longer it takes the price to move by an increment, the lower the expected volatility of the stock's price. In this way, an alternative statistic of (the inverse of) price volatility is

[63] Allen, Peiris, and Yang (2002) derive the relation by presenting the price process as a binomial process with increments of $\pm c$ and estimating the expected variance per unit of time.

obtained, which elegantly circumvents the price discreteness and calendar time problem by measuring the length of time between price changes rather than the usual deviation from average price. The construct shares a lot of similar features with the volatility specification in event time introduced by Cho and Frees (1988).

3.2.1. Extensions of the Standard ACD Model

The dynamic specification of the expected duration ψ_i can also be expanded to accommodate exogenous variables (marks), or it can be a non-linear function similar to the popular extensions of the GARCH model like EGARCH, and NGRACH.

3.2.1.1. The Log-ACD Model

Bauwens and Giot (2000) introduce a logarithmic ACD model called Log-ACD. The model's appealing feature is that it eliminates a potential problem, namely that if some of the exogenous explanatory variables or their coefficients are negative, MLE might produce a negative expected duration. That particular limitation can be handled with an exponential transformation of the exogenous variables (Copejans and Domowitz's (1999)), but it can also be handled by simply making sure none of the expected durations produced by the estimation are negative[64]. I will estimate a Log-ACD (1,1) model to check for robustness. The features of the Log-ACD model with

[64] The MLE estimation ceases on a negative ψ_i, so as long as estimations converge, negative expected durations must not have been a problem.

Weibull $(1,\gamma)$ distributed errors (ε_i) will now be presented. The description follows Bauwens and Giot (2000).

The logarithmic ACD model starts by modifying the mixing process for the observed duration to

$$\tau_i = e^{\psi_i}\varepsilon_i, \qquad [3.39]$$

where the errors are assumed i.i.d. The assumption, paired with the assumption that the errors have $\mu = 1$ will allow us to subsume the dependence in the duration process in the conditional expectation $E(\tau_i \mid I_{i-1}) = e^{\psi_i} \Rightarrow \psi_i = \ln E(\tau_i \mid I_{i-1})$ in such a way that:

$$\frac{\tau_i}{E(\tau_i \mid I_{i-1})} \text{ is i.i.d.} \qquad [3.40]$$

I now introduce one specification for an equation for the autoregressive model of the logarithm of the conditional durations:

$$\psi_i = \omega + \alpha \ln \tau_{i-1} + \beta\psi_{i-1} \qquad [3.41]$$

which can be rewritten as

$$\psi_i = \omega' + \alpha \ln \varepsilon_{i-1} + (\alpha+\beta)\psi_{i-1}, \qquad [3.42]$$

where $\omega' = \omega - \alpha \ln\left[\Gamma(1+\frac{1}{\gamma})\right]$.

The only restriction the model imposes is $|\alpha+\beta| < 1$, necessary for stationarity. More importantly, however, if the model also includes exogenous variables in the specification for the log of the conditional duration, I no longer need to worry about the possibility that a negative coefficient might give rise to a negative expected duration, since $e^{\psi_i} > 0$.

The density function of τ_i can be written as:

$$f(\tau_i) = \frac{\gamma}{\tau_i}\left(\frac{\tau_i \Gamma(1+1/\gamma)}{e^{\psi_i}}\right)^{\gamma} e^{-\left(\frac{\tau_i \Gamma(1+1/\gamma)}{e^{\psi_i}}\right)^{\gamma}} \qquad [3.43]$$

and the log likelihood function of the observed durations τ_i for *i* = 1, 2….*N* will be:

$$\log L(\theta) = \sum_{i=1}^{N}\left(\ln(\gamma) - \ln(\tau_i) + \gamma \ln\left[\tau_i \Gamma(1+1/\gamma)\right] - \gamma\psi_i - \left(\frac{\tau_i \Gamma(1+1/\gamma)}{e^{\psi_i}}\right)^{\gamma}\right) \qquad [3.44]$$

where ψ_i is as defined in the equation for the log of the conditional expected duration, which can be estimated by maximum likelihood methods.

3.2.1.2. Other Extensions

Ghysels, Gourieroux, and Jasiak (1997) present a stochastic volatility duration (SVD) model which accommodates stochastic volatility in the durations. Bauwens and Veredas (1999) establish the stochastic conditional duration model (SCD) which uses a stochastic volatility model for the durations rather than a GARCH-like specification.

Grammig and Maurer (1999) introduced an ACD model based on a Burr underlying error distribution, which nests the Weibull distribution and exhibits a non-monotonous hazard function because it depends on one more parameter.

Potential market microstructure candidate variables can be included in the specification, allowing new tests of the determinants of price formation and other market dynamics. One important set of variables are exogenous price-related variables. Including exogenous price-related variables will address the concern voiced by He and Chen (2003) that standard ACD model estimations assume the duration time process is exogenous to the price process, or the so-called "exogeneity problem."

4. Data Description and Transformations

This study utilizes NYSE TAQ (Trades and Quotes) data. The TAQ dataset evolved from the earlier TORQ dataset compiled by Joel Hasbrouck. The database records every transaction that occurred for the stocks traded on the NYSE, and is released in monthly increments[65]. The dataset consists of two separate time stamped parts: one lists the trades and the other the bid and ask quoted prices posted by NYSE specialists. The prevailing quotes can be determined for any given transaction and matched according to the time stamp. An important study by Lee and Ready (1991) suggests matching transactions with quotes that are at least five seconds old, since on the NYSE floor, quotes are posted more quickly than transactions. In addition, each transaction is classified as either a sale or a purchase based on a modified "midpoint" rule. If a transaction price is closer to the ask than to the bid matched quote, the transaction is termed a buy, otherwise it is a sell. If the transaction falls on the midpoint of the relevant ask and bid quotes, the "tick" rule is applied. If the

[65] Refer to http://www.nyse.com/taq

transaction price is greater than the previous price, it is classified as an uptick, and the transaction is classified as a buy. Downticks are classified as sells. Lee and Ready (1991)[66] found this process of transaction signing to be most accurate and best performing in a variety of simulated scenarios. The method has since become the norm in NYSE empirical microstructure works, and is also used by Engle and Lange (2001). Only transactions with a 'regular' TAQ database condition indicator are retained, and those occurring within normal business hours. Data is treated consecutively from day to day, discarding the first price change for each day to prevent overnight information episodes from entering the sample. In addition, because lagged duration marks will be used, the first durations from each day will also be purged later on.

Price durations are computed for every stock in the sample. Two alternative construction methods for price durations have been suggested in the literature. In the original Engle and Russell (1998) study of ACD models, trade-to-trade durations are used. Engle and Lange (2001) alternatively use the price durations defined by the time between significant price movements of predetermined size. Engle and Lange (2001) recommend using price movements measured between successive mid-quote prices to compute durations, where the mid-quote price is the mid-point of the bid and ask quote associated with the particular trade. They claim the mid-quote price provides an accurate indication of the asset's true market value, and more

[66] The Lee and Ready (1991) transaction signing algorithm has faced some criticism recently, namely by Grammig and Theissen (2002) who claim that trade misclassification could bias empirical studies employing in particular the Easley, Keifer, O'Hara, and Paperman (1996) methodology for estimating informed trading probability. Our empirical model is structured around price durations, so we hopefully circumvent the problem.

importantly, using it instead of the actual transaction price avoids the problem of bid-ask bounce and the negative serial correlation in price changes that it induces. Thus price discreteness noise is reduced. To make sure we exclude aberrations and that real price events are being isolated as durations, I require at least two consecutive trades with midpoint quote changes outside a preset threshold to signal the end of a price duration. Example 1 (enclosed at end) provides a sample duration construction. The use of that particular construction method is necessitated by the appealing feature of one of its associated marks - net directional volume over each duration (VNET). As described later on, VNET measures the realized market depth associated with a particular price deterioration, and is useful in measuring market liquidity.

For each of the price durations, a variety of summary measures are compiled. The choice of these characteristics, called marks is discussed in a later section.

One particular mark however, warrants a more detailed description and will be presented next.

4.1. Net Directional Volume (VNET)

VNET, net directional volume is defined by Engle and Lange (2001) as

$$VNET = \left| \sum_i d_i vol_i \right| \qquad [4.1]$$

where *d* is the direction of trade indicator (buy = 1 and sell = -1) and *vol* is the number of shares traded. Summation is over all transactions in a given price duration. VNET is thus an intraday measure of realized market liquidity, which is defined as the net directional volume associated with a price movement of a predefined, threshold magnitude. VNET provides a direct measure of ex-post market depth, corresponding to each particular price deterioration. Theories predicated on information asymmetries predict VNET will vary with volume, transactions, and volatility. The movements of this measure of net order imbalances can be interpreted as an interaction of the varying proportions of informed and uninformed traders and the cumulative change in specialist inventories. VNET is constructed in event time and is measured repeatedly throughout the trading day to capture the short run dynamics of market liquidity. VNET allows one to test if market depth is a function of the magnitude and timing of current and lagged transaction flows. However, the construct is predicated upon transaction price changes, and thus only follows quote revision dynamics while casting no light upon the behavior of the spread, since the quoted spread changes are subsumed in the aggregated duration marks. Actually, all spread-relevant marks resulting from the usage of price durations have to do with quoted spreads at each price change event. Since liquidity has both a spread and a depth dimension, the construct tends to relegate the former component while producing a meaningful measure of the latter.

Note that VNET does not differentiate whether the excess volume produced a price increase or a price decrease since price durations are constructed using the absolute price change in mid-quote prices over the duration interval. Based on Chordia, Roll, and Subrahmanyam (2001) I could expect the net directional volume to differ for a price increase than for a decrease, exhibiting some sort of asymmetric price stickiness. I conjecture that price decreases could be associated with a market maker's desire to get rid of excess inventory, and could provide some insights about the existence of inventory effects, and will therefore include a dummy for a price increase in the model of realized liquidity.

The bid-ask spread only measures market tightness for low volume orders. For a high volume order, there may be an inferior execution. Low realized liquidity occurs when high volume orders can not be executed at the current bid or ask. Liquidity is therefore reflected in the transaction price expected for various size buying or selling orders. The schedule of such prices is often called the market reaction curve. It illustrates depth, the maximum number of shares that can be traded at any given price. Slope of the curve is often estimated by net trading volume and the corresponding price change over a fixed interval of time. However, estimation over a fixed interval of time has numerous problems, stemming from the discreteness of the price change, and the likelihood that excess demand can be close to zero, depending on the length of the time period chosen. Further, using a fixed time interval would dissipate the advantage of using transactions data, since in effect, the short run dynamics of transactions prices and volumes are being discarded. VNET thus measures market depth directly as the number of shares that can be bought or sold within a given price range. Its measurement interval is therefore dependent on the price level, rather than on calendar time[67].

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[67] Re-computing average VNET over pre-specified price thresholds, allows a construction of implied market reaction curves. The slope and sensitivity of these curves provide direct inference about realized price elasticity and general liquidity patterns.

5. Data and Sample Construction

The NYSE completed the switch to decimal pricing of all its 3,525 listed issues on January 29, 2001. This ended a five-month test period during which a pilot sample of 158 select NYSE listed stocks traded in price increments of a penny, while the remainder traded in sixteenths of a dollar. The switch started on August 28, 2000 with 7 stocks (Phase I), then 57 more were added on September 25, 2000 (Phase IIA), and an additional 94 securities were added on December 5, 2000 (Phase IIB.)

The phased transition to decimal prices provides a natural experiment for an examination of changes in price formation dynamics, liquidity, and quote setting behavior. Chakravarty, Wood, and Van Ness (2002), Gibson, Singh, and Yerramilli (2002), Bacidore, Battalio, and Jennings (2001) investigate the effects of decimalization, by constructing a matched, non-decimal control sample for the pilot stocks. The use of such matched securities allows control for market effects occurring simultaneously with the decimalization of the pilot securities. Existing research and inferences however, have for the most part been based on a more descriptive analysis, and methods utilizing fixed-interval time-sampling. The usage of an ACD model in this natural experiment setting will provide further insight into the influence of decimalization, as well as provide basis for tests of hypothesized market microstructure effects in the price formation dynamics and the relative change in strength of the effects associated with the switch to decimal pricing. Moreover, this is the first study to examine the evolution of price and liquidity formation and the effects of decimalization in event-time, predicated upon the construct of price duration.

This study utilizes a matched sample of pilot and control stocks. The test sample period in this study will be similar to Chakravarty, Wood, and Van Ness (2002). I use 20 Phase IIA only (started on September 25, 2000) pilot stocks, however my test sample period starts 1 week after the beginning of the phase, on October 2, 2000. Chakravarty, Wood, and Van Ness (2002) report their communication with market participants indicated that significant "learning" was taking place in the first weeks of the decimal pilot as the parties involved were experimenting with the new system, looking for an equilibrium trading strategy. The end of the test sample period is January 26, 2001 because that is the last day of non-decimal trading for the control stocks.

Each of the pilot stocks is matched with the non-decimal stock, identified in Chakravarty, Wood, and Van Ness (2002). Their matching criteria make sure that at the time of selection (shortly before the date of decimalization), the control stock was similar[68] to the pilot stock on a number of criteria, with the only notable difference that it trades in sixteenths[69]. Selection criteria used also reflect the selection criteria used to identify the initial NYSE pilot stocks, and include: option availability, similar price, similar traded volume, similar volatility, similar market capitalization, similar

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[68] Similar within $\pm 10\%$.
[69] Bacidore, Battalio, and Jennings (2001) compute a score using the same criteria to identify matching stocks.

relative strength to the S&P 500 Index, similar recent price performance, similar industry (if possible), and same listing venue (NYSE).

In addition, a control sample period of all-decimal trading from February 08[70], 2001 until May 31, 2001 reflecting fully decimalized NYSE trading is also examined to test the robustness of my conclusions. The stocks in the sample and control sample along with the descriptive statistics of their trades over both the test and control periods are listed in Table 1.

I examine the change in the differences among pilot stock and matched control stock coefficients over the test sample period and the control sample period. Examining the change in differences allows me to control for imperfect matching. I do however, include proxies for traditional control variables such as market capitalization and average volatility in the estimated models. The ACD(1,1) model of expected price durations is in fact a model of expected volatility, allowing for the expectation to depend on past durations (reciprocals of volatility). In addition, some of the duration marks like trading volume proxy for market capitalization. I will thus be effectively controlling for average stock volatility and firm size, so arguably the differences among decimal and matched stocks over the individual sample period only will also have a reasonable degree of validity.

[70] Allowing 8 business days for "learning."

5.1. Construction of Price Series, Durations, and Associated Marks

I use the NYSE TAQ database to obtain tick-by-tick trades and quotes data for each of the pilot and control stocks for the test period October 2, 2000 till January 26, 2001, and the control period from February 08, 2001 till May 31, 2001. Transactions are matched to their prevailing quotes according to the time-stamp, and identified as either buys or sells following the Lee and Ready (1991) modified midpoint rule. Similar to Engle and Lange (2001), the data are filtered to promote consistency and isolate only intra-day price fluctuations. Since the opening mechanism of the NYSE resembles a one-shot auction, and excess volatility has been reported around the opening, the first five minutes of trading will be dropped. The filter is necessitated by the different information and price discovery and setting process characterizing the open. I also drop transactions that occurred after the regular closing time of 4:01 pm. In addition, as suggested in Chung, Van Ness, and Van Ness (2001), trades and quotes involving out of sequence time stamps, an obvious error in range, or a correction are discarded. Thus, quotes will be omitted if either the bid or the ask price is equal to or less than zero, or if the quoted depth is equal to or less than zero. As in Huang and Stoll (1997), quotes are also omitted if the quoted spread is greater than $4 or less than zero. In addition, those trades for which $|(p_t - p_{t-1})|/p_{t-1} > 0.1$ and quotes for which $|(a_t - a_{t-1})|/a_{t-1} > 0.1$ or $|(b_t - b_{t-1})|/b_{t-1} > 0.1$ will be dropped because they most likely arise because of data errors due to their size. Trades will be omitted if the price is less than or equal to zero. As discussed in Section 4., at least two consecutive data points containing a change in the midpoint of specialist's quotes by at least a pre-specified threshold size will trigger a price duration.

Contemporaneous and aggregated variables associated with each of the price durations are computed. These marks will include:

PTIME – length of duration in seconds

NPTIME – normalized,[71] de-seasonalized duration length

AVEVOL – the average transaction size per duration

VOLUME – volume transacted during a duration

NUMBER – the number of transactions in a duration

DUMSPR – a dummy equal to 1 if the nominal spread is greater than the modal spread for a stock

SPREAD – the nominal spread associated with the last transaction of a duration

NLSPRD – normalized, de-seasonalized lagged spread.

DSPREAD – the realized change in the nominal spread, measured from last duration. Will be used to proxy for spread revision.

PDSPREAD – realized percentage change in the nominal spread

ESPREAD – effective spread, equal to $| 2(P_t - M_t)/M_t |$, where P_t is the price, and M_t is the midpoint for the last trade in a duration. The usage of this spread definition allows estimation of actual execution costs paid by a trader when trades occur at prices inside the posted bid or ask price (Chung, Ness, and Ness (2002).)

[71] The details about the normalization process are described in section 7.1.

DESPREAD – the realized change in effective spread

PDESPREAD – realized percentage change in the effective spread

RSPREAD – realized spread, defined as $| 2_t (P_t - P_{t+1}) / M_t |$, where P_{t+1} is the price associated with the last transaction of the next duration, and the other variables are defined as above. The realized spread will provide a measure of the average price reversal after a trade, or "market making revenue net of losses to better informed investors" (Chung, Van Ness, and Van Ness (2002).)

DRSPREAD – the change in realized spread

PDRSPREAD – the percentage change in the realized spread

VOLNET = VOLUME minus VNET

TPRICE – the price of the trade signaling a duration's length

PRESID – realized price change over a duration

APRESID – absolute realized price change over a duration

DEPTH – combined quoted depth at SPREAD

Section 6 presents the formulation of models designed to test various microstructure hypotheses within the framework of the ACD models. The empirical specification of the hypothesized microstructure relations and decimalization's effect on these relations is also presented.[72] Finally, I formulate a test specification for commonality in liquidity within the ACD framework, and a proposal for examining decimalization's impact on commonality, measuring commonality's sensitivity to tick size. Section 7 presents the empirical results.

[72] Market reaction curves and their implied slopes and sensitivities could also be constructed to measure the shift in liquidity dynamics due to the lower tick size.

6. Testable Hypotheses - Empirical Specifications

6.1. Empirical Tests of Microstructure Hypotheses

6.1.1. Exogenous Variables

Conditional expected duration series is an efficiently measured proxy for conditional volatility, one that circumvents the problems associated with fixed-interval price change measurement. Denoting the conditional expectation of a normalized duration ψ_i as ENPTIME, a self-contained ACD(1,1) model can be represented as:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} \qquad [6.1]$$

I initially estimate both an exponential error ACD(1,1) and a Weibull error, WACD(1,1) QMLE model with the directly specified likelihood functions described in Section 3.

Including exogenous variables in the specification will allow the conditional expectation of a duration assessed at t_0 to reflect possible relevant information available to market participants at t_0. Without the exogenous variables, the model's specification would be self-contained. Adding exogenous variables however, has to be done in a manner that ensures the conditional expected normalized duration as well as the durations succeeding it will be positive numbers. This requires a specification which allows exogenous variables to have negative estimated coefficients while still retaining the non-negativity of the expected durations. As mentioned before, this is not an issue as long as MLE convergence is achieved.

Copejans and Domowitz (1999) suggest an alternative specification which is formulated to avoid the negativity problem:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \exp(\kappa' z_t) \qquad [6.2]$$

where z_t is a vector of exogenous variables, and κ' is the vector of coefficients associated with them. This specification is also estimated for robustness. I find it generally produces equivalent results in terms of coefficients and model performance. I also estimate the Weibull Log-ACD(1,1) model. The Weibull Log-ACD model provides a specification far better suited for handling possible negative exogenous variable coefficients and never gives rise to negative durations.

6.1.1.1. Specification of the ACD Model

a) Volume

As hypothesized by Easley and O'Hara (1987), large trades will reflect a higher probability of informed trading, since informed agents try to capitalize on their fleeting informational advantage and are more likely to trade large sizes. Their theory predicts either the lag of AVEVOL or VOLUME, or both will be negatively related to ENPTIME. The reason being that informed trading leads to price revisions, higher volatility, and therefore a lower conditional expected price duration. Kyle (1985), and Hasbrouck (1988), also hypothesize a negative relation as do Blume, Easley, and O'Hara (1994), and Easley, Keifer, O'Hara and Paperman (1996) who suggest that volume provides information which is not contained in past prices, and can generally be interpreted as a signal for the quality of information. These models predict that high volume will signify a higher probability of informed trading, and a negative relation between VOLUME and expected duration. The Mixture of Distributions Hypothesis (MDH),(Gallant, Rossi, and Tauchen (1992), Tauchen and Pitts (1983), and Epps and Epps (1976)) suggests on the other hand that volume is positively related to conditional volatility, and therefore negatively related to the conditional expectation of price duration[73].

b) Number of Transactions

Theory suggests the lagged number of transactions may be negatively related to conditional volatility. Foster and Viswanathan (1995), Easley and O'Hara (1992), Jones, Kaul, and Lipson (1994), claim it is the pace of trading as evidenced by the number of transactions that leads to an increase in price volatility by helping revise the market maker's belief about being faced with an informed trader. In addition, the number of transactions can be used as a proxy for informed trading if informed traders indeed split their large trades to disguise their informational advantage and minimize price impact. These arguments all suggest a negative relation between the lagged number of transactions and expected conditional duration.

In contrast, a large lagged number of transactions might help market makers arrive at a less noisy estimate of the true price, leading to lower expected volatility, and therefore a higher conditional expectation of duration, as suggested by the work of French and Roll (1986), Garbade and Silber (1979), and Mendelson (1982). Also,

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[73] So do McInish and Wood (1992) who find that trade size increases bid-ask spread, and therefore volatility.

consistent with Admati and Pfleiderer (1988), a low number of transactions could be interpreted as informed trades only because uninformed trading is deterred by short sale constraints, and therefore lead to longer durations.

c) Transaction Arrival Rate

The average rate of transaction arrivals during the previous duration interval might also affect the conditional expectation of duration. The empirical relation is however ambiguous, because the existing literature suggests opposing effects. On the one hand, the trading process itself may introduce noise into prices (French and Roll (1986)), so less frequent trading (larger lagged average transaction arrival rate) could actually reduce conditional volatility, and thus result in a positive relation between the arrival rate and expected duration. On the other hand, even though only relevant to auction length, Amihud and Mendelson (1987), and Madhavan (1992) suggest a large lagged average transaction arrival rate could delay the price discovery process if it implies increased uncertainty and noise, thus increasing volatility and decreasing expected duration, resulting in a negative relation between the arrival rate and conditional expected duration.

d) Accumulated Order Imbalances

The summation of past net directional volumes (VNETs) is a noisy approximation of the net change in specialist inventory. In spite of its crudeness however, including summed lagged imbalances as an exogenous variable in my

ACD(1,1) specification will provide an indirect measure of inventory effects. Models developed by Stoll (1978), and Ho and Stoll (1981) suggest a negative relation between inventory level and expected duration, because the higher the inventory level, the greater the inventory risk, and the more willing the specialist will be to change (mid-quote of) prices, thus the lower the conditional expectation of duration.

e) The Spread

The quoted spread for each duration will always be a multiple of the minimum tick size. The lagged spread variables would all be expected to enter the ACD(1,1) model with a negative coefficient, as suggested in Roll (1984), Hasbrouck (1991), and Stoll (1989) who all document the relation between bid-ask spreads and short term prices. Bagehot (1971), Kyle (1985), and Glosten and Milgrom (1985) predict that dealers adjust the spread upwards if they are faced with an increased probability of informed trading. Therefore, a high lagged spread is predicted to be associated with a higher propensity of dealers to change mid-quote prices, a higher expected volatility, and therefore lower duration. The effect is however indirect because I do not directly model the actual dynamics of spread setting behavior. Testing explicitly for the size of the hypothesized information, order-processing, or inventory-based models of the spread can not be carried out within the price duration framework[74].

[74] Filtering out only those durations which were accompanied by a major change in spread however, as done in Kallimipalli and Warga (2002) for example will provide us with a set of spread change price durations. Ordered-probit models can then be used to predict the behavior of the spread, and test explicitly for the significance of each of the hypothesized components of the bid-ask spread, and the effect of recent market history and volatility.

6.1.2. Models Explaining Net Directional Volume: VNET

Net directional volume is a direct measure of liquidity since it measures the realized market depth associated with particular event-time price deformations. Based upon identification of the optimal specification of the ACD(1,1) model, I construct an estimated series of expected conditional durations. These estimates, along with other exogenous marks will be used as explanatory variables in a model of realized market depth measured over each duration interval, proxied by VNET:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \kappa' M \qquad [6.3]$$

where M_t is a vector of duration mark logs, and κ is their coefficient vector. The model is estimated in logs, after Engle and Lange (2001).

The regression will model realized liquidity or the net directional volume that can be transacted before prices have adjusted and how it moves with volume, volatility and other duration marks.

6.1.2.1. Specification of the VNET Model

Asymmetric information theories[75] predict that higher transaction intensity reflects an influx of informed traders and therefore negatively impacts liquidity. These theories predict a negative relation between the lagged number of transactions and VNET.

Similarly, a high lagged VOLUME could also signify increased transaction intensity and a higher level of informed trading. However, it could also signify an

[75] Kyle (1985), Glosten and Milgrom (1985), and others.

abundance of trading, in which specialists support a higher net order imbalance (Diamond and Verrechia (1987), and Madhavan and Smidt (1993).) Generally, Engle and Lange (2001) detect a positive relation between lagged VOLUME and VNET, which is always less than unity. Their results suggest that market depth responds to volume less than proportionately, reflecting the increased risk of informed trading associated with high volumes.

Escribano, Pascual, and Tapia (2002), Chordia, Roll, and Subrahmanyam (2001) and virtually all of the informational asymmetry microstructure works predict a negative relation between depth and expected volatility, implying a positive relation between depth and expected duration. A low expected duration would be associated with increased expected volatility and the potential for informed trading, and therefore lower market liquidity.

Lagged spread is expected to enter the VNET equation with a negative sign if large spreads evidence high informational asymmetry and low liquidity. In other words when the market is tight it usually will lack depth. Lee, Mucklow and Ready (1993) and Engle and Lange (2001) document the above relation. Alternatively, the relation may depend on the size of the firm as found for NASDAQ stocks by Chung and Zhao (2003).

In addition, I also include summed lagged VNET's as an independent variable serving as indirect proxy for inventory effects on market depth. I hypothesize that increased specialist inventory will provide support for larger realized depth, for the market maker will be able to accommodate larger order imbalances, aiding him in the effort to unload extra inventory and reduce inventory risk.

Chordia, Roll, and Subrahmanyam (2001) hypothesize that signed order imbalances will be higher after market declines, and lower after market increases. The coefficient of lagged price change (PRESID) is therefore hypothesized to have a negative relation with VNET. In addition, I form an asymmetric PRESID specification testing for asymmetric liquidity response to price decreases and increases.

I also form the NPTIME_ERR variable defined as the log of (NPTIME/ENPTIME). If significant, even though it is a contemporaneous variable, Engle and Lange (2001) claim it can be used as a measure of impatience. Since a trader can influence this shock term by trading on one side of the market and thus influencing the contemporaneous NPTIME, the variable is weakly exogenous. A positive coefficient on the variable would suggest the market "interprets impatience" to reflect a high likelihood of asymmetric information. Thus, rapid trading would reduce the volume that could otherwise be traded at a particular price, and a positive coefficient would mean that traders who spread their trades over longer than the time they expect duration to last would face higher market depth, all else equal.

6.2. Empirical Tests for Decimalization Effects

Comparing the coefficients of the pilot and control samples in the above referenced ACD and VNET models will provide a useful test of the effects of decimalization. I compare the coefficients on the matched stocks individual regressions, as well as the coefficient estimates from pooled across securities regressions. This allows me to directly test how decimalization influenced conditional volatility and realized liquidity. The ACD and VNET models will isolate the effect of the switch in trading regime respectively upon the formation of conditional duration expectation and market liquidity. The shift in the sensitivity of liquidity to changes in the VNET variables brought about by decimalization will also be examined.

Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997) predict that if the minimum tick size is reduced (or in the extreme case, prices are decimalized altogether), market depth and liquidity will decline. The reason as described in the literature review section is that investors will be discouraged from placing limit orders as their quotes can be “stepped in front of” or “picked off.” Brown, Laux, and Schachter (1991) and Cordella and Foucault (1996), hypothesize that an optimal tick size exists for every security, and thus decimalization would end up reducing liquidity. They claim an optimal tick size reduces negotiating costs and the probability of errors, encourages dealers to make a market by posting spreads, and encourages them to conduct more research on their assigned stock. Anshuman and Kalay (1998), Bernhardt and Hughson (1996), and Kandel and Marx (1996) claim such an optimal tick size arises due to market frictions in Bertrand competition among liquidity providers. Angel (1997), Ball and Chordia (1998), and Goldstein and Kavajec (2000) find evidence of liquidity decline after the NYSE switch to sixteenths in 1997.

The above findings are in disagreement with the widely held belief and claims by Hart (1995), Peake (1995), and O'Connell (1997) that reducing the tick size will increase liquidity through enabling better price comparison, competition, and integration of markets. The argument seems to work for the bid-ask spread, but not for market depth. Little research has been conducted testing which components of the bid ask spread in particular have changed with decimalization, how large is the adverse affect on market depth and the change of its sensitivity to different trading characteristics, and how the changes in the price formation and quote setting process could come to impact large volume traders.

I examine these questions by identifying the process for and estimating separate ACD and VNET models during the pilot and post-pilot sample periods. Decimalization's impact upon the model's coefficients will provide direct evidence about how the equilibrium price formation and quote setting processes changed as a result of the new minimum tick size. Modeling the realized market depths and comparing the difference among coefficients in the VNET regression brought about by decimalization will give me an estimate of the structural change in liquidity characteristics.[76]

[76] As mentioned before, a thinned price duration process which only filters the price changes accompanied by a significant change in the spread could also be applied. The size of the bid-ask spread components and the dynamics of the quote setting process can then be better modeled through the application of ordered probit models, including ACD predicted durations and proxy variables for the different components as explanatory variables. Comparing matched stock coefficients or pooled coefficients between the two samples in my natural experiment setting could throw light upon the impact of the minimum tick size change on the important bid-ask spread component of liquidity.

6.3. Empirical Tests for Commonality in Liquidity

The major measure of liquidity in my model is VNET, the realized net order imbalance. VNET can alternatively be viewed as the realized market depth associated with each price change of at least a predetermined size. As previously discussed, my regression of VNET on a set of explanatory microstructure variables will help model and forecast market depth. The orthogonalized residuals from the VNET regression model will be used to construct a series of individual stock liquidity shocks obtained in event time. These residuals by constructions have been cleansed of potential stock-specific cross sectional influences due to microstructure and conditional volatility effects. The residuals will therefore represent a proxy for exogenous shocks to liquidity. I treat each stock as a cross-sectional unit in the multivariate exploration for whether common factors influence the variability of the residual series. I conduct principal component and common factor analysis on the multivariate set of residuals. These methods allow me to test for the presence of underlying systematic driving forces behind liquidity formation as well as document the liquidity commonality phenomenon from the unique perspective of real (possibly informational) event time. The simultaneity of the stock price durations can't be obtained across the sample of 40 stocks. I therefore aggregate the residuals from the realized market depth regressions across fixed time intervals[77] and investigate the resulting time-consistent cumulated residual series for common factors. I argue that since the two-staged event time analysis of expected duration (ACD model) and realized market depth (VNET)

[77] Daily aggregation is utilized, but the results from more frequent aggregations are computed to check for robustness.

has already been applied around individual price changes, the duration setup allows a more efficient estimation of liquidity. Aggregation is then applied to ensure a larger-scale simultaneity and time-consistency. The methodology is thus a viable, if not even superior alternative to a straightforward fixed-interval (15 minutes as in Hasbrouck and Seppi (2001) and Harford and Kaul (2004)) analysis because an attempt to model the subsumed conditional volatility and its dynamics and effect upon realized market depth is made at the micro level of stock-specific price durations and events first, thus more closely tracing the real-time price and liquidity formation co-evolution.

The procedure used to explore for common factors in liquidity is similar to the principal component factor analysis of Hasbrouck and Seppi (2001) and Harford and Kaul(2004). My approach however, benefits from the use of the unexplained isolated realized market depths associated with each of the respective real price changes, instead of working with an arbitrarily set fixed-interval series which is unlikely to coincide with real individual stock price events and net order imbalances. Utilizing the VNET marks associated with price durations and the residuals from my individual stock VNET regressions will arguably constitute a less ambiguous and problematic liquidity commonality estimation framework. This results because the approach also addresses the Hasbrouck and Seppi (2001) concern of segregating transitory and permanent liquidity by providing a model of realized depth which will filter my liquidity measure of most cross-sectional variation by controlling for stock-specific microstructure and volatility effects. More importantly, the analysis could reconcile the findings of differential explanatory power of the liquidity principal component in the liquidity measures of Harford and Kaul (2004) with the changes in liquidity measures used by Chordia et al, (2000).

My analysis is an example of the alternative estimation and aggregation technique Harford and Kaul (2004) call for, because it is an event-time based estimation of the synthetic co-evolution of price changes and corresponding liquidity measures, accounting for an array of microstructure variables and separately modeled concurrent conditional volatility (ACD) effects. Concentrating on the price duration construct synthetically binds the dynamics of price changes and associated liquidity measures more closely to real life price and trading cost formation patterns. The traditional fixed-interval analysis of Hasbrouck and Seppi (2001) and Harford and Kaul (2004) assumes that synchronous trading activity will move prices, and tries to detect the correlation between return and order flow in the fixed-interval aggregates. The duration-based approach is a unified setting centered around the event-time co-evolution of price and liquidity formation, and is thus better suited to incorporating and detecting the non-synchronous microstructure and conditional volatility patterns that might affect its progression.

The usage of event-time adjusted residuals addresses the concern voiced by Lo and MacKinlay (1988, 1990) who develop a statistical model of non-synchronous trading and show that when fixed-interval analytical techniques are applied to it, spurious autocorrelation, cross correlation, and most importantly cross autocorrelation will inevitably be detected. Lo and MacKinlay's (1990) model is constructed around the probability of trades and is designed to purge a series of concomitant returns of spurious autocorrelation. My cumulated residuals are measured over fixed-intervals, but the price duration framework estimation of expected duration and VNET has already specifically adjusted them for non-synchronicity and non-simultaneous stock price events.

One could argue that since the transaction data exhibits non-conforming time patterns across stocks, I can not expect whatever might induce commonality such as macroeconomic information or shocks to be impounded into prices simultaneously for all stocks, or at least not be detectable in arbitrarily aggregated, albeit ex-post contemporaneous fixed intervals. Commonality in liquidity would thus more likely not give rise to concurrent liquidity changes, but the liquidity residuals from the individual events aggregated over a reasonable fixed-interval could still manifest the co-variation induced by commonality. Traders might be slow to respond, market frictions might exist, or some stocks might trade more frequently and would thus be faster or harder hit by market wide informational asymmetries. Furthermore, similar to Cao's (2003) argument, market maker front running might also give rise to non-contemporaneous correlated liquidity, so aggregation in that case is the correct approach to investigate for commonality[78].

The common factor analysis or principal components results should therefore be interpreted in terms of an ex-post rationalization of the evolution of price event defined raw and unexplained cumulated liquidity, rather than an attempt to predict

[78] Alternatively, I could only use the thinned series of realized market depth residuals displaying certain characteristics most likely attributed to the effect of a systematic liquidity shock, idiosyncratic liquidity shock, or information shock. The formulation would provide a direct test for the driving force behind liquidity commonality.

liquidity movements disjoint in time. Some caution should therefore be exercised in using the results to predict liquidity co-movement or devise portfolio trading cost minimization strategies or hedges.

Detecting common factors driving the variability of the adjusted market depth series will confirm or test the findings[79] of the theoretical and empirical literature on commonality in liquidity. In addition, I analyze the consequences of decimalization on the strength of the common factors and thus test whether the trading process characteristics are in any way conducive to liquidity commonality.

7. Results

I present both individual security estimation results as well as pooled regression results. The results of various robustness tests are also reported.

7.1. Durations and Marks

7.1.1. Duration Calculations

I initially estimate the price durations using a common threshold of \$1/16th for all stocks over both the test and control time periods, as this is the minimum tick size for the non-decimal stocks. The characteristics of the resulting durations are presented in Tables 2a and 2b. The 1/16th threshold results in a more disperse distribution of durations across stocks than is desired.

To obtain a workable, consistent series of price durations for each stock, Engle and Lange (2001) recommend using a price threshold resulting in roughly 15

[79] Hasbrouck and Seppi (2001), Harfod and Kaul (2004), Chordia, Roll, and Subrahmanyam (2000).

durations per day for every stock, or a total of about 1170 durations per stock for my sample. I calibrated the price change threshold for each decimal and control stock to obtain a comparable number of durations for each decimal stock and its control stock match over each of the two time periods.[80] The thresholds and the characteristics of the resulting raw durations are presented in Tables 3a and 3b.

7.1.2. Marks Calculation

The marks of each duration are computed as outlined in Section 5. The computations of the normalized duration length and spread deserve some specific attention.

NPTIME – Extant empirical research[81] documents a prominent inverted U-shaped pattern in durations, bid-ask spreads, and volume within the day. The average frequencies of my duration data (Figure 2a) exhibit a clear U-shaped time-of-day pattern. The plot of the average duration lengths over each quarter-hour interval (Figure 2b) confirms the inverted U-shaped pattern of the time-of-day effects. I adjust the duration times for each stock will therefore be adjusted for seasonality effects by running a regression of durations upon an exhaustive set of quarter-hour dummies,

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[80] The resulting price thresholds are not uniform across the two sample time periods for the matched control stocks due to a couple of reasons. First, during the control time period, the matched control stocks were trading in \$1/16[ths] which necessitated that the mid-quote price threshold be a multiple of the minimum tick size. Applying those same price thresholds over the control time period resulted in too few durations for the matched stocks since some of them (PKI, UNH) went through stock splits, but mainly because thy were now trading in decimals. (see Table 3a) They therefore had to be recalibrated.
On the other hand, using the same thresholds for the decimal stocks gave me an average of exactly 15 durations per day for a stock. The fact, coupled with the lack of stock splits in the decimal stocks allowed me to use the same price thresholds as in the test period.
[81] Harris (1986), Madhavan, Richardson and Roomans (1997), and Wood, McInish, and Ord (1985), Engle and Russell (1998.)

with no intercept. The dummy variable coefficients, which will be the model's predicted duration values for any quarter-hour will just be equal to the mean durations over each quarter[82]. The normalized seasonally-adjusted duration NPTIME is computed by dividing realized durations by the predicted duration for each relevant quarter of the trading day. The resulting normalized durations will be my major variable τ_i . Their statistics are described in Table 4, confirming the documented empirical result of excess dispersion.

NLSPREAD – The procedure used to de-seasonalize the spread will be the same as for the time-of-day adjustment of NPTIME. Figure 3 plots the quarter-hour time-of-day effects[83] for average spread, confirming the U-shaped pattern and strength of seasonal factors.

Figure 4a plots the pooled all-stocks raw duration histogram, and presents the corresponding exponential function fit. Figure 4b presents the histogram for normalized durations. Longer normalized durations are also increasingly less likely. An exponential distribution, however, assumes a constant hazard rate, meaning that the likelihood of a price change is independent of the time elapsed without a price change. Furthermore, the exponential distribution implies no excess dispersion (mean equal to standard deviation) which is obviously not the case as evidenced by the means and standard deviations in Tables 3 and 4. Since the sample duration data exhibits excess dispersion, a Weibull distribution might provide a better fit (plotted in

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[82] The coefficients for all the quarterly dummies are significant. Results are currently omitted for the sake of brevity.
[83] All the quarterly dummies are significant. Results are currently omitted for brevity.

Figure 4b) because it can accommodate the greater volatility of durations and allows for an increasing hazard function ($\gamma > 1$) which would account for the longer durations. Excess dispersion also implies that the data exhibits a greater proportion of large durations than an exponential distribution would predict (refer to Figures 4a and 4b percentile plots). The Weibull could explicitly model for that possibility.

Running a T-test for unity mean and standard deviation[84] on the standardized residuals from my ACD models would help determine which error distribution provides a better fit to the duration data. Furthermore, I can examine the standardized (squared) residuals for autocorrelation. Since the Exponential model implies i.i.d. $\varepsilon = \frac{\tau}{\psi}$, the Weibull implies i.i.d. $\varepsilon^{\gamma} = \left(\frac{\tau}{\psi}\right)^{\gamma}$ and the Logarithmic-Weibull implies $\varepsilon = \frac{\tau}{e^{\varphi}}$ is i.i.d. I will compute Q-statistics and determine which model does the best job of filtering the residuals of autocorrelation. This will be one of my tools for cross-model comparison.

7.2. ACD Models

Both the raw and the normalized durations exhibit a significant degree of autocorrelation, as evidenced by the correlograms of the merged durations in Table 5. The durations are autocorrelated and non-normal[85]. The setting thus calls for the use

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[84] In the case of the Weibull ACD(1,1) model, ε^{γ} should be distributed exponentially, so the same test can be applied to the residuals of the model raised to the power equal to the estimated gamma coefficient.

[85] As also evidenced by the (not reported) values of Jarque-Bera statistics and skewness and kurtosis.

of ACD(1,1) models to better describe the conditional expectation of time until the next price deterioration.

The results are presented in two parts. The first part examines and tests whether the errors for three alternative specifications conform to the underlying theoretical distributional assumptions implicit in the underlying statistical assumption. The second part focuses on the economic interpretation of the coefficients.

The maximum likelihood estimation of the models will be carried out in EViews 4.1, using the log-likelihood object routine, with Marquardt[86] optimization algorithm. Bollerslev-Woolridge robust errors were also used[87] for tests of the null hypotheses that the coefficients equal zero.

7.2.1. Results for a Simple Model

I initially estimate Exponential, Weibull, and Logarithmic-Weibull ACD(1,1) models for the test time period, with only the lagged spread as an exogenous variable. The model estimated is[88]:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1} \qquad [7.1]$$

Engle and Russell(1998) found this specification to be reasonable for their analysis of durations for the stock of IBM. The (1,1) autoregressive structure proves to be the optimal specification[89] for each distributional assumption and model.

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86 Berndt-Hall-Hall-Hausman (BHHH) algorithm is also used as a check for robustness of results.
87 Seldom differed from those produced using the default estimated variance-covariance matrix.
88 For the Log-Weibull ACD model, the specification is
$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

The results for the Exponential, Weibull, and Logarithmic-Weibull models are reported in Tables 6a, 6b, and 6c respectively. The overwhelming majority (about 92% of the cases) of the stocks exhibit statistically significant positive α_1 and β_1. The finding denotes a persistent process, meaning that the conditional expectation of time until the next price change is dependent upon past durations and expected durations. Expected volatility is thus conditioned upon the current information set, containing both past realized and conditional durations. The process therefore describes the observed autocorrelation in the duration data. For the decimal stocks, the three models produce an average α_1 of 0.11 and average β_1 is 0.57, and the matched control stocks produce an average α_1 of 0.15 and an average β_1 of 0.57. The resulting autocorrelation functions describing the persistence of the processes are plotted in Figure 5. The coefficient for the lagged spread is consistently negative and significant. The finding is in agreement with the theoretical research relating increased volatility to wider bid-ask spreads (refer to section 6).

[89] Within each model, different autoregressive structures are nested specifications, so an optimal can be selected based on log-likelihood values and information criteria. The finding is similar to GARCH studies finding (1,1) to be the optimal specification. As mentioned above, note that comparison across Exponential, Weibull, and Logarithmic-Weibull ACD models based on log-likelihood values and information criteria are generally not possible due to their different likelihood functions. The only exception is the Weibull ACD model which nests the Exponential ACD if $\gamma = 1$. Instead, the cleanliness of the (squared) residuals is the appropriate yardstick for cross-model comparisons.

7.2.2. Complete Model Specification

Having considered different ACD autoregressive structures, and based upon the previously described theories, I chose the following optimal specification[90]:

$$\begin{aligned} ENPTIME_t &= \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) \\ &+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1} \end{aligned} \quad [7.2]$$

where $I_N^{PRESID_{t-1}}$ is an indicator variable equal to 1 if the price declined during the previous duration and zero if it increased, allowing for an asymmetric effect $(\gamma_P + \gamma_N)$ of past negative price changes compared to positive (γ_P) price changes on conditional duration. The rest of the exogenous mark variables are as defined in Section 5.1. For the moment I concentrate on the error structure of the model. Section 7.2.3. focuses on the economic interpretation of the estimated coefficients.

Three types of ACD(1,1) models are estimated testing different error distributions or conditional duration setups: Exponential, Weibull, and Logarithmic-Weibull. Models are estimated separately for both the test time period of pilot decimalization and the control time period of full decimalization. The results are reported in Tables 7(a, b, c).

The autoregressive coefficients α_1 and β_1 are once again strongly positive significant for virtually all of the cases. The processes modeled are therefore strongly

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[90] For the Log-Weibull ACD model, the specification is:

$$\begin{aligned} ENPTIME_t &= \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) \\ &+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1} \end{aligned}$$

persistent, and the results reconfirm that expectation of time till next price change is in fact conditioned upon past durations and expected durations. The inverse of expected volatility is therefore also conditioned upon the current information set. The process therefore captures the observed autocorrelation and clusters of normalized duration data. Across the three models, test period decimal stocks have an average α_1 of 0.1395 and average β_1 is 0.6496, while the matched control stocks produce average α_1 of 0.1545 and average β_1 of 0.584. The resulting autocorrelation functions describing the persistence of the processes are plotted in Figure 6. As expected from the size of the coefficients, the decimal stocks process displays a higher degree of persistence, indicating that shocks linger a bit longer than for the stocks with fractional trading[91]. The decay patterns don't differ by as much across models because the α_1 and β_1 coefficients are fairly uniform across models, unlike the other variables' coefficients.

7.2.2.1. Criteria for Cross Model Comparison

The Log-Likelihood estimation of the Weibull-based models provides an estimate of γ, which allows a direct initial test of whether the durations and therefore the model's errors are exponentially distributed. As Table 6d reports, for about half of the stocks I can reject the null hypothesis that $\gamma = 1$ in my simple starting point model thus ruling in favor of a Weibull model. Most of the stocks for which the Exponential

[91] As expected, under the fully decimal control time period, the decay patterns of both groups of stocks display similar persistence, and dissipate in a similar longer interval.

null is rejected exhibit $\gamma > 1$, translating into an increasing hazard function. Thus, the longer a stock has gone without a price change, the higher the probability that one will occur. The exponential distribution, on the other hand, exhibits a constant hazard function, meaning that the probability of a price change is independent of the time a stock has gone without one.

For cross-model comparison, finding the best model and specification in the case of different likelihood functions and non-nested models can be carried out by an examination of the standardized (squared) residuals. The primary reason I resorted to ACD models was that actual measured durations were autocorrelated and non-normal. If an ACD model does a good job of capturing that autocorrelation, the standardized residuals should be i.i.d. and free of autocorrelation as discussed above. The degree of autocorrelation remaining can be estimated and the Q-statistics and correlograms reported. Furthermore, for the exponential model, I can test the hypothesis that both the mean and the standard deviation of the standardized residuals are equal to unity, since the exponential distribution would imply no excess dispersion. The same test can be performed using the Weibull standardized residuals raised to the power equal to the estimated γ coefficient since these transformed residuals should be exponentially distributed under the Weibull distributional assumption.

For brevity, I omit the results from tests on the residuals for the models reported in the prior section. An initial examination of the convergence behavior, coefficient significance, likelihoods, and residuals from the starting point specification tends to favor the Logarithmic Weibull (1,1) error models.

7.2.2.2. Cross-Model Comparisons

7.2.2.2.1. Error Distribution Tests

I test the distributional assumptions of the three models. I identify the best performing model, and for brevity, only discuss the sign and magnitude of its decimal stock coefficients and how they differ from the control stock coefficients. I later use only the predicted durations from that optimal model as an explanatory variable in my VNET regressions.

Just as I did with the simple spread-only model, I test whether the Weibull and Logarithmic-Weibull models produce a coefficient $\gamma = 1$[92]. This is an appropriate initial test of whether the Weibull is the better-fitting duration distribution. If the null of $\gamma = 1$ can not be rejected, the Weibull ACD model reduces to the nested Exponential ACD model. Table 8 reports the results and once again, the exponential null is rejected for about half the stocks in the Weibull model, and ¾ of the stocks with the Logarithmic-Weibull model. Since the Weibull specification nests the Exponential ACD, there is an improved log-likelihood value whenever we relax the constraint of γ=1. The test is thus equivalent to a Likelihood Ratio test. The conditional probability of a price change is increasing in the time elapsed without a

[92] This is the γ coefficient of the Weibull log-likelihood function, estimated simultaneously by the MLE. It is not any of the coefficients appealing in the ACD specifications.

price change whenever $\gamma > 1$. The function also indirectly makes longer durations increasingly less likely. For the cases in which the null is not rejected, ruling in favor of exponentially distributed errors and durations, a constant hazard rate adequately describes the instantaneous probability of a price change, independent of the time elapsed without one.

The Weibull ACD model tends to increase the average Log-Likelihood value compared to the Exponential ACD model for virtually all cases, thus again ruling in favor of the Weibull distribution. A standard Likelihood Ratio test of whether the Logarithmic-Weibull model is better than the Weibull would in this case be meaningless since the two do not share a nested specification, and do not even have a common likelihood function. I can, however, examine the Akaike and Schwartz Information Criteria for cross model comparison of non-nested models[93]. I will infer that the model with the lowest information criteria is the best performing model. Examining the results in Table 7(*a*, *b*, and *c*), the Exponential model has the highest average AIC and SIC values, the Weibull being slightly better, while the Logarithmic-Weibull model consistently exhibits the lowest average information criteria. Based on these tests, I conclude the Logarithmic –Weibull model performs best.

The next test will utilize the models' standardized residuals. First, I examine the Exponential ACD residuals. According to the multiplicative error assumptions of

[93] According to Greene (2003), page 159.

the model, the standardized residuals $\varepsilon = \frac{\tau}{\psi}$ should be i.i.d. exponential, with a mean and standard deviation of unity. If the Weibull model is in fact a better fit, as predicted by the results in Table 8, I should reconfirm that finding here. The results of the mean and variance equality tests and empirical Watson, and Anderson –Darling[94] tests of exponential distribution are reported in Table 9. Once again, the results reject the exponential-null quite strongly for all cases, as well as the null of no excess dispersion $(\mu = \sigma = 1)$.

I also examine the Weibull ACD model standardized residuals $\varepsilon = \left(\frac{\tau}{\psi}\right)$, and the Logarithmic-Weibull ACD model residuals $\varepsilon = \frac{\tau}{e^{\varphi}}$. As was the case with the Exponential ACD model residuals, the mean of the residuals is in fact close to unity[95]. If the residuals are Weibull(1,γ) distributed, raising them to the estimated power γ, should produce an exponential distribution. I conduct Kolmogorov and Watson exponential tests on the residuals and compare exponential quantiles to empirical quantiles. The results (reported in Table 10) confirm that for the majority of the stocks, I fail to reject the null hypothesis of exponentially distributed ε^{γ}, thus ruling in favor of the Weibull(1,γ) distribution for the errors. The Logarithmic-Weibull ACD(1,1) model seems to do a marginally better job of producing Weibull residuals.

[94] See Anderson and Darling (1952) and D'Agostino and Stephens (1986) for description of the tests and the associated statistics.
[95] Test results omitted for brevity.

In addition, I also look at the quantile plots of ε^{γ} , compared to an empirical quantile plot. For the majority of the stocks, I discover an empirical distribution closely resembling the exponential, with the majority of the quantiles lying very close to or on the 45° line, thus close to the hypothetical exponential quantile. Figure 7 shows the Weibull and Logarithmic-Weibull model ε^{γ} quantiles , for stocks HIT and RCL, with the remaining stocks' plots exhibiting similar distributions. The finding reconfirms the Weibull as a better error assumption, and hints once again that the Logarithmic-Weibull might be the better model, since its ε^{γ} quantile plots closer to the 45° line.

7.2.2.2.2. Autocorrelation Results

I now turn to an examination of the time series properties of the models' standardized residuals and squared residuals. Table 11 reports the Ljung-Box Portmanteau Q-statistics and the results of the test of zero autocorrelation at a particular lag for the first 15 autocorrelations and partial autocorrelations for stock CLB. The results are generally quite similar for the rest of the stocks in the sample. In general, the tests confirm that the Logarithmic-Weibull model is marginally better than the Weibull model, which in turn is a bit better than the Exponential model in filtering out autocorrelation.

The collective results suggest strongest support for the Logarithmic-Weibull model. It allows for a flexible specification permitting negative values (or negative coefficients of) exogenous variables, converges faster regardless of starting values, produces the assumed Weibull disturbances, does a good job of filtering autocorrelation, has lowest AIC and SIC values and highest LL values, and its ML estimation was in general more stable and robust.

7.2.3. ACD Results

I now turn to a more formal interpretation of the results of my best, Logarithmic-Weibull (1,γ), ACD (1,1) specification of the model.[96] The estimation results are reported in Table 7c. The full model is:

$$\begin{aligned} ENPTIME_t &= \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) \\ &+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1} \end{aligned} \quad [7.3]$$

7.2.3.1. Tests of Microstructure Hypotheses

The signs and magnitudes of the ω, α_1, and β_1 coefficients are overwhelmingly positive significant and virtually indistinguishable across decimal and non-decimal stocks. Both decimal and control stocks thus have similar autocorrelation functions and decay patterns, as discussed in Section 7.2.2.

The γ_0 coefficient of normalized lagged spread is consistently negative, and significant for about half of the stocks. The coefficient's sign supports the documented relation between bid-ask spreads and short term prices of Roll (1984), Hasbrouck (1991), and Stoll (1989). In addition, the finding is consistent with the hypothesis that higher spreads are associated with an increased probability of informed trading making dealers more eager to change prices, translating into higher

[96] Found to be the optimal model, but note that all other models would produce identical conclusions.

expected volatility and thus a lower expected price duration as suggested by Kyle (1985), Glosten and Milgrom (1985), and Bagehot (1971).

The models of Easley and O'Hara (1987), Hasbrouck (1988) suggest that informed trading is manifested in greater transactions volume, and in turn leads to a quicker revision of prices, higher conditional volatility, and therefore lower expected price duration. In addition, Blume, Easley, and O'Hara (1994), and Easley, Keifer, O'Hara, and Paperman (1996) also predict that volume conveys a signal about information quality not contained in prices, and thus also hypothesize a negative coefficient[97].

The estimated γ_1 coefficient is consistently negative, and significant for about 30% of the stocks. Larger lagged (average) volume does in fact lead to a higher conditional volatility and lower expected duration.

A positive lagged spread change would indicate market makers have increased the spread possibly to shield themselves in the face of costly informed trading. They would thus perceive to be in an informed trading environment and be more willing to revise prices, thus increasing conditional volatility and decreasing expected duration. In agreement with the theoretical arguments presented above, the γ_2 coefficient is negative and significant for roughly 90% of the stocks.

Lagged quoted depth enters my specification in order to provide a preliminary inspection of the relation between the depth component of liquidity and price

[97] So do McInish and Wood (1992) and a host of papers focusing on the Mixture of Distributions Hypothesis (Tauchen and Pitts (1983), and Epps and Epps (1976)) claiming volume is positively related to conditional volatility, and thus negatively related to expected duration.

volatility. A lower lagged depth could indicate a higher degree of uncertainty and informed trading, thus translating into a higher conditional volatility and lower expected duration. It is important to note however, that quoted depth is not generally a very meaningful number, for it generally applies to only small trades. There is no predominant sign for the γ_3 coefficient; the average coefficient is negative however, and a few of the negative coefficients are significant. I therefore find that lagged quoted depth generally exerts a mild negative influence on expected duration. The result could be a attributed to a more complicated spread/depth quoting dealer behavior. For example if market makers set quoted depth high in the face of informed trading. Conversely, quoted depth may simply not be a useful proxy variable for informed trading; quoted depth arguably measures the thinnest range of the limit order book and may not be the best marker of the depth facet of liquidity. This assertion is confirmed later in my analysis of models explaining the behavior of net directional volume, VNET.

The γ_4 coefficient of lagged number of transactions offers a direct test of the assertions by Foster and Viswanathan (1995), Easley and O'Hara (1992), and Jones, Kaul, and Lipson (1994.) These authors argue that the pace of trading proxies for informed trading and increases if informed investors split up their trades, or when public information is released. If true, the dealer adjusts prices more quickly, giving rise to higher volatility. In contrast, works like French and Roll (1986) and Mendelson (1982) argue that more transactions enable the dealer to obtain a less noisy estimate of the true price and thus will result in lower volatility, hypothesizing a positive coefficient. Similarly, Admati and Pfleiderer (1988) claim a low number of transactions might reveal more informed trading if uninformed trades are deterred, thus again leading to a positive γ_4 coefficient prediction.

The γ_4 coefficient is overwhelmingly negative, and significant for roughly half the stocks. Lagged number of transactions thus tends to have a negative effect on conditional duration, possibly due to a higher degree of informed trading and market maker willingness to revise quotes.

The last set of coefficients γ_P and γ_N allow a test of whether absolute lagged price change asymmetrically affects the quote revision process. I argue that if the previous duration was associated with a large absolute price change, it might indicate a heightened level of informational asymmetry and a more volatile trading environment. The conjecture would be consistent with expected duration being negatively associated with ($\gamma_P<0$, and $\gamma_P+\gamma_N<0$) a large lagged absolute price change. I incorporate a standard asymmetric setup to test whether negative or positive lagged price changes exert higher pressure on the conditional quote formation process. The effect of a positive lagged price change on expected duration is thus γ_P, and that of a negative price change is $\gamma_P+\gamma_N$.

Virtually all of the estimated γ_P coefficients are negative (average coefficient value = -1.08), with about 82% of them being significant. About half of the γ_N coefficients are negative, and the other half are positive, with roughly 50% of each group being significant. The results are therefore inconclusive. Lagged absolute price changes tend to be associated with upward changes in conditional volatility and give rise to a negative effect upon expected mid-quote duration. Negative and positive lagged price changes affect expected duration in a seemingly uniform fashion. It is thus only the magnitude and not the direction of the past price change that affects the conditional quote formation process.

7.2.3.2. Decimal vs. Control Stock Coefficients

7.2.3.2.1. Initial Tests for between Group Coefficient Equality

I now compare the coefficients of the decimal stock sample to the coefficients of the control stock sample over both time periods. I initially conduct two-tailed equality of mean t-tests assuming both equal and unequal variances. The next section reports results for a pooled regression specification. The mean equality test results are reported in Table 12 (a and b). During the test sample time period, I can not reject (at the 5% significance level) the null hypothesis that decimal and non-decimal stock coefficients have equal means for all of my exogenous variables. The coefficient of lagged depth γ_3 is the only exception, where the test rejects the null at roughly the 8% level. The tests over the control time period confirm the validity of the matching system, failing to detect differences in both groups means when all stocks traded in decimals. The exception is the coefficient for the lagged change in spread γ_2, which is more negative for the stocks originally trading in decimals.

Even though the two sets of sample means are largely indistinguishable, an interesting observation can be made from the t-statistics. During the test time period, the mean coefficients for the decimal stocks were larger in absolute value than the coefficients of the control stocks[98]. Thus virtually all of the t-statistics in Table 12a are positive. The finding does not extend to the fully decimal time period results, presented in Table 12b. Assuming comparable average exogenous variables across stock samples the larger decimal coefficients are consistent with a higher average expected price duration and thus lower conditional volatility for decimal stocks. This would be consistent with the argument that the refined pricing grid enables smoother and more stable price quoting, thus making the expected average time for a predetermined price change higher and expected conditional volatility lower[99].

7.2.3.2.2. Pooled Regression Tests

In order to test the robustness of the prior results, I also estimate the following pooled, 40-stock Logarithmic-Weibull ACD(1,1) model:

$$\begin{aligned} ENPTIME_t &= \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) \\ &+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1} + \\ &\gamma_{10} NLSPRD_{t-1} I^C + \gamma_{11} \log(AVEVOL_{t-1}) I^C + \gamma_{12} DSPREAD_{t-1} I^C + \gamma_{13} \log(DEPTH_{t-1}) I^C + \\ &\gamma_{14} NUMBER_{t-1} I^C + (\gamma_{1P} + \gamma_{1N} I_N^{PRESID_{t-1}}) APRESID_{-1} I^C \end{aligned} \qquad [7.4]$$

where I^C is an indicator variable equal to 1 if the stock is a control stock and zero otherwise. The specification allows for common persistence parameters but a separate set of exogenous mark coefficients for the control stocks. Results of the

[98] A single-factor ANOVA of the differences between the coefficient pairs, excluding outliers tends to reject the hypothesis that mean coefficients are equal for all the exogenous variables.

[99] The argument is also confirmed by the examination of the average control stock coefficients. They show a significantly higher average over the decimal time period compared to their non-decimal trading period.

estimation over the test sample period and the fully decimal control sample period are reported in Table 12c.

The estimation confirms the previous observation that the ω, α_1, and β_1 coefficients are quite stable across time periods. The estimation over the test sample period reinforces my findings of the sign and magnitudes of the coefficients of the exogenous microstructure variables. All un-interacted coefficients are similar to the means of the individual stock ACD estimates. The exceptions are γ_3, which is now insignificant but nevertheless positive, and γ_4 which is now positive and significant.

The positive γ_3 coefficient is now in agreement with microstructure predictions that higher lagged depth is indicative of lower informational asymmetry, and thus lower conditional volatility and higher expected duration. The insignificance of the γ_3 coefficient however, strengthens the conclusion that quoted depth might not be a very meaningful mark in the context of price duration because it only applies to small trades.

The positive and significant γ_4 coefficient lends support to the claims of French and Roll (1986), and Mendelson (1982) who argue that more transactions help the dealer arrive at a less noisy estimate of the true price and thus give rise to lower expected volatility and higher conditional expected duration. Furthermore, Admati and Pfleiderer (1988) would also predict a positive coefficient. Their model predicts a low number of transactions might be due to the uninformed trades being deterred and thus a higher degree of informational asymmetry, and a lower conditional duration and higher volatility. Overall, the pooled estimation presents evidence that the effects hypothesized by this body of work dominate the negative hypothesized relation predicted by Foster and Viswanathan (1995), Easley and O'Hara (1992), and Jones, Kaul, and Lipson (1994).

Three of the interacted control stock coefficients are significantly different from zero, indicating divergence from their decimal stock counterparts.

The γ_{10} coefficient of lagged normalized spread is negative and significant, thus lagged spreads decrease conditional expected duration and increase expected volatility more for fractionally trading stocks. The finding is in agreement with the predictions of Roll (1984), Hasbrouck (1991), and Stoll (1989), and Bagehot (1971), Kyle (1985), and Glosten and Milgrom (1985). Fractionally trading stocks are thus more sensitive to lagged normalized spreads, translating into a lower conditional expected duration and thus higher conditional volatility. The finding lends support to the claim that a refinement of the pricing grid affected the quote revision process and made prices less volatile.

The γ_{12} coefficient on lagged change in spread is also negative and significant for the control stocks. The decrease in the conditional expectation of price duration is thus smaller for a comparable increase in lagged spread for control stocks. Once again, everything else equal, the formation dynamics of expected duration for decimal stocks would give rise to higher durations and thus lower volatility.

Finally, the coefficient of γ_{1P} is positive and significant. Lagged absolute price change thus does not seem to impact the mid-quote revision process and the expected duration for control stocks by as much as it does for decimal stocks. A Wald test fails to reject the null that $\gamma_P + \gamma_{1P}$=0, thus only decimal stock mid-quote formation is in fact dependent upon the magnitude of the past price change. The finding can be attributed to the refined pricing grid making mid-quote revision less sticky and price formation faster and more efficient with decimal pricing.

The estimation over the control sample period generally confirms the hypothesized expected convergence of the more important microstructure coefficients, since all stocks are now trading in decimals. The only exceptions are the differences in control stock coefficients of lagged depth and price change. These results might possibly be attributed to market makers still learning the new system and adjusting their price quotation process. Excluding the lagged absolute price change,[100] a Wald test does not reject the joint null that the interacted, control stock coefficients are equal to zero, confirming the robustness of the matching sample and the experimental setting.

In general, the results suggest the switch to decimalization affects the dynamics of the mid-quote price formation and price revision processes. After the complete switch to decimalization, the price formation process adjusted to the new trading regime, and the dynamics of expected conditional duration became stable and uniform in terms of the new ACD model coefficients. Decimalization seems to have reduced conditional mid-quote price volatility by making the average conditional expectation of time necessary for a predetermined price change slightly larger. The

[100] Since the new trading regime forces the control stocks to now trade within finer increments, we can expect the dynamics of mid-quote price formation to be in the process of equilibrating, and probably be slightly different from those of the decimal stocks which have traded in decimals for a longer time.

finding is in direct agreement with the argument of decimalization advocates who argued that a refined pricing grid leads to more continuous, correct, and generally less volatile pricing. The results also suggest that conditional intraday volatility has declined with decimalization, confirming the arguments of Bessembinder (2003) and Chakravarty, Wood, and van Ness (2004). I do not however, directly test whether this change occurred for my sample.

7.3. VNET Based Model of Realized Market Depth

I now turn to a model of ex-post realized market depth (VNET) over each price duration. This model is designed to capture the dynamics of event-time varying liquidity as a function of proxies for information asymmetry and other market characteristic variables. Engle and Lange (2001) propose and test a simpler version of the model proposed here.

Testing a host of relevant hypothesized microstructure variables for each of the individual stocks and each time period, I isolated the model specification resulting in most statistically significant coefficients for the most stocks[101]. Using F-tests, AIC, and SIC, I isolate the most parsimonious and robust specification. The resulting model is:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) \\ & + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID1_{t-1}}\end{aligned} \qquad [7.5]$$

[101] Potential microstructure proxy variables tested include: duration average volume, duration volume, number of transactions, nominal spread, normalized nominal spread, change in nominal spread, (%, change in) effective spread, (%, change in) realized spread, balanced volume, price at duration's last trade, (absolute) price change over a duration, and quoted depth.

where $I^{+/-}_{PRESID_{t-1}}$ is an indicator variable equal to 1 if the preceding price change was positive and -1 if it was negative.

The regression equation is estimated separately for each stock, for both sample periods. The estimated coefficients and their significance are reported in Tables 13a and 13b.

In addition, I also estimate another specification, over the pooled, cumulated sample periods. The model includes the same independent variables as above, but I also add the interaction of all right hand side variables with a dummy variable (I^{CP}) equal to 1 for the fully decimal control time period. The pooled regression equation is:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID|_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID|_{t-1}} I^{CP}\end{aligned} \qquad [7.6]$$

The pooled specification directly allows an estimate of a pooled individual stock model across the two time samples, and enables a test for shifts in intercept and other coefficients after the regime shift to decimalization. A Wald test of whether the interacted coefficients are equal to zero is in fact identical to the standard Chow test of a structural break after decimalization[102]. The pooled regression results are reported in Table 14, and Wald and Chow statistics are reported in Table 15.

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[102] The Chow test of a structural change at start of decimal trading, estimated on the pooled time samples data and the standard regression model without interacted terms. For a description of the Chow test, see Greene (2003), page 133.

The dependent variable's lag is never significant even though VNET does exhibit some autocorrelation, in agreement with the claim of Chordia and Subrahmanyam (2002). I attribute the result to the set of explanatory variables being a proper proxy for past depths. Interestingly, the cumulated signed order imbalances never entered the specification significantly and so might either not constitute a proper proxy for inventory effects, or the realized market depth component of liquidity is not significantly influenced by inventory effects. Furthermore, the model's residuals are generally free of autocorrelation.

7.3.1. VNET Model Individual Stock Regression Results

The coefficient of conditional duration β_1 given the current information set is predominantly positive and significant in both Tables 13 and 14 over both the test time period and the control time period[103]. Market depth thus deteriorates if market makers perceive higher conditional volatility (lower expected duration,) possibly due to an increase in informed traders. The finding is consistent with the predictions of Escribano, Pascual, and Tapia (2002), and Chordia, Roll, and Subrahmanyam (2001).

The coefficient on the number of lagged transactions β_2 is predominantly negative and marginally significant during both sample time periods. Its sign is consistent with the conjecture that more intensified trading can potentially signal informed trading and thus lead to a decrease in market depth, in line with the

[103] The interpretation of the coefficients for the control time period in Table 14 can be carried out by examining the sign and significance of the sum of the pooled coefficient and the corresponding interacted coefficient, in this case β_1 and β_8.

informational asymmetry models of Kyle (1985) and Glosten and Milgrom (1985). The marginal significance of the coefficient in the individual stock regression setting suggests, however, the offsetting effect of more transactions making the market more liquid, and thus increasing supported market depth, as hypothesized by Diamond and Verrechia (1987), and Madhavan and Smidt (1993).

The coefficient of lagged spread β_3 is overwhelmingly negative and significant over each sample period. I also estimated models that included lagged change in spread and other spread related exogenous marks but they generally led to similar conclusions, with lagged nominal spread representing spread effects best. In general, the result is consistent with the results of Lee, Mucklow and Ready (1993) and Engle and Lange (2001) that tight market depth goes hand in hand with wide spreads, representing a negative relation between these two facets of liquidity.

The coefficient of lagged volume β_4, is predominantly positive and significant. The finding suggests that increased total volume is probably a poor proxy for informed trading. Rather, it may be an indicator of decreased order imbalance due to more offsetting trades. In light of this result, it seems that the offsetting effect hypothesized by Diamond and Verrechia (1987), and Madhavan and Smidt (1993) and mentioned above does in fact dominate. Since VNET is an absolute value, and the regression is set in logs however, the finding of a coefficient less than unity can be interpreted[104] as a less than proportional response of VNET to VOLUME. Increased volume is thus associated with a proportionately smaller increase in order

[104] As noted by Engle and Lange (2001).

imbalance percentage, possibly due to increased market maker concerns of informed trading.

The coefficient of the weakly exogenous[105] PTIME_ERR variable β_5 is strongly significant and uniformly positive across the sample stocks. Because trading moves prices, the variable is weakly exogenous when for example we try to forecast VNET conditional on time to conduct trading. Since the variable can be influenced by trading on one side of the market, the coefficient can be interpreted as the reward for "patience." For a stock with the average $\beta_5 = 0.5$, a trader willing to increase trading time by 100% will face a 50% more favorable market depth. The sign of the estimated coefficient is consistent with the prediction that market makers condition their quote setting behavior on, among other things, the degree of impatience they are faced with, and will raise their estimates of informed trading, and in turn readjust quotes, and move spreads up, and realized depth down.

Finally, the β_6 coefficient of $\log(APRESID_{t-1}) * I^{+/-}_{PRESID1_{t-1}}$ is mainly positive, but rarely significant in the individual stock regressions. The magnitude of the previous price change dos not in general affect net directional volume. I also tested a specification allowing for asymmetric effects of positive and negative price changes on VNET but the model failed to detect any significant asymmetric response factor, or depth "stickiness". The positive coefficient in the individual stock regressions thus fails to provide any support for the Chordia, Roll, and Subrahmanyam (2001) claim that signed order imbalances will be higher after market declines, and lower after

[105] The variable is considered weakly exogenous because it is contemporaneous but it can be affected by heavy one-sided trading.

market increases. It should be noted however, that I only test the immediate (lag one) market movements effect on order imbalance level and not general market trends.

7.3.2. Pooled Regression results

The regression coefficients are also estimated in a pooled regression setting, to exploit maximum information. I allow for stock specific intercepts, similar to a panel fixed effect treatment due to each stock's differing average duration volume and price threshold. In the pooled-stock equivalent of the individual regression reported in Table 13, I thus include a 40-element intercept vector of fully exhaustive stock dummies to control for cross-sectional heterogeneity. The results for the stock pools across the test time period and control time period samples are reported in Table 16. I also estimated a pooled specification within each time period with interactive dummies allowing a test for whether the control sample stocks' (the stocks trading in $1/16^{th}$ increments) coefficients shifted. The results of that specification (Table 17b) are discussed further in the next section. As Engle and Lange (2001) point out, this pooled model forces constant and identical elasticities across stocks.

The pooled regression for the test time period (Table 16a) produces an unambiguously significant set of individual intercepts and strongly significant set of coefficients for the explanatory variables, with the exception of β_2. On the other hand, β_6 is now strongly significant. Despite that, the remaining coefficients have the same signs and magnitudes as estimated by the averages in the individual stock regressions. The pooled regression for the control time period (Table 16b) also produces a set of strongly significant individual intercept coefficients, and a set of significant coefficients with signs and magnitudes once again similar to the average individual stock regression estimates, except for β_6 which is now insignificant but still positive[106].

The findings of the pooled regressions reconfirm the directions of the relations described in the preceding section dealing with individual stock regressions. They suggest the results are relatively robust.

7.3.3. Decimal vs. Control Stock Coefficients

7.3.3.1. Individual stock regressions

In this section, I investigate whether decimalization brought about a shift in market depth formation dynamics. I first examine the difference in coefficient size from the individual stock regressions. I report t-tests for mean differences, and F-tests for variance explained. The results are reported in Table 18 (a and b). In light of the limited number of observations and hence power of the associated t-tests and ANOVAs however, I also estimate an interaction specification (results reported in Table 14, 17a, and 20) which will allow a more efficient Wald test for equality of coefficients.

The average coefficients of the decimal stocks are not statistically different from those for the control stocks during the test time period. Table 18a reports that

[106] Once again, in order to make similar conclusions based on the results in Table 17a, at this point I only look at the sign and significance of the summed non-interacted and interacted coefficients, for I am not discussing decimalization effects and differences between decimal and control (non-decimal) stocks as of yet.

equal and unequal variance t-tests, as well as paired two-sample tests fail to reject the hypothesis of equal average coefficients for each of the variables across both groups of stocks. Furthermore, a single factor ANOVA of the differences in coefficient pairs fails to reject the null of a zero mean. The coefficients are remarkably consistent and stable across decimal and control stocks, reconfirming the finding of Engle and Lange (2001) pertaining to the effect of the change in ticker from 1/8th to 1/16th. Table 18b reconfirms the finding of constant and stable coefficients, where those tests fail to reject the null of equal means for all coefficients but β_1[107]. Overall, based on these tests, I infer that individual stocks exhibit quite stable coefficients in terms of sign and significance across trading regime characteristics and sample periods. The results strengthen the model's robustness and hint that in fact, the model is adequately describing the dynamics of the formation of duration-bound realized order imbalances. In addition, same stock coefficients across the two sample periods are also stable and remarkably similar (Table 19.)

I now turn to the results of my other individual stock regression (Table 14), this time pooled across the two sample periods, allowing for a decimalization structural change in all coefficients. A Wald test of the joint null hypothesis that the coefficients of the interacted terms are zero is a test of the impact of the new trading regime on all stocks. The results are reported in Table 15. Note that this particular Wald test is equivalent to a regular Chow test for a structural break in a pooled sample period individual stock regression of the regular, non-interacted RHS

[107] The finding could be ascribed to outliers though.

variables only. Table 15 also reports the results from these Chow tests, but the estimation results from the 40 individual stock regressions are omitted for brevity. As anticipated, one would expect to find no evidence of a structural change for the pilot stocks, already trading in decimals over both sample time periods. The tests in Table 15 fail to reject the null of no structural shift for about half of the stocks. In contrast, the control sample stocks exhibit a more pronounced structural shift, for I can only reject the null for 30% of the stocks. There is thus, significant evidence that the decimal trading regime change affected the depth formation process of the control stocks[108]. In particular, decimalization brought about a sizable significantly positive change in the coefficient of expected duration. In view of the previous conclusion from the ACD models that decimalization might have increased expected duration, the finding supports the predictions of Hart (1995), Peake (1995), and O'Connell (1997) who hypothesize that decimalization will increase liquidity through enabling better price comparison and competition. There also seems to be some evidence that the coefficient of lagged transaction number has gone down due to decimalization, and since the actual number of average transactions is virtually identical for both pre-decimalization and post-decimalization, the finding thus favors the predictions of Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997) who predict that if the minimum tick is lowered market depth and liquidity will suffer. The coefficient of impatience has also fallen, meaning that the reward for patience has decreased.

[108] In addition, both the Chow and Wald tests from stock pooled regressions reported in Table 17a and 20 and discussed later, soundly reject the null that the change in trading regime exerted no change on control stock, decimal stock, and all stocks' depth formation dynamics.

7.3.3.2. Pooled Regressions

A reexamination of the 40 stock pool regression coefficients within each sample period reported in Table 16, at first glance suggests stability in sign for decimal and control stocks within the two sample periods. In addition, I also calculate separate pools for the 20-stock sample of decimal and control stocks within each period. The results are also reported in Table 16.

Testing whether decimal stock coefficients differed from their control stock counterparts during the test sample period, simple t-tests fail to reject the zero mean difference null for each coefficient except for the coefficients of spread and impatience. The setting, however, is not the most appropriate, given the limitations of such a test.

The more sophisticated structural break tests allowed by the regressions in Table 14 suggest that decimalization might have brought about a possible shift in realized depth formation dynamics, even though the effects have potentially offsetting implications for the resulting change in liquidity formation. I now examine the control stocks pool and all stocks pool for a structural break in coefficients on January 29, 2001, using an interacted model which is the pooled equivalent of the model in Table 14:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}\end{aligned} \qquad [7.7]$$

where β_o and β_7 are stock specific intercept vectors of size 20 for my control stock pool and 40 for the pool of all (Table 20) stocks.

The results from the pooled regression estimation for the control stocks (reported in Table 17a.) once again indicate that the universal switch to decimal trading affected the liquidity formation dynamics of the stocks in the control stock sample. Interestingly though, only the β_8 coefficient is significant, meaning that decimalization only brought about a discernible positive change in the coefficient of expected duration. Since there are no significant offsetting effects from other interacted coefficients, the finding is somewhat unambiguous regarding improvement in liquidity formation dynamics. In addition, a Wald test soundly rejects the joint null of zero interacted coefficients, and a Chow test in an un-interacted regression also rejects the null of no structural break at January 29, 2001.

Pooled regression estimation (Table 20) for the sample of both the decimal and control stocks also reveals the switch to decimalization seems to have affected the liquidity formation process of all stocks, even the decimal stocks that traded in penny increments during the pilot sample period. Once again, the β_8 coefficient of interacted expected duration is positive and significant, and so is the β_{10} coefficient of lagged spread. The conclusion is that dynamics of realized depth were positively affected by the universal switch to decimal prices. It seems like liquidity was improved by the lower impact of volatility and adverse selection. Results from the corresponding Wald and Chow tests also confirm the hypothesis of a decimalization structural break in all stocks' liquidity formation.

In order to better test whether the pooled stock coefficients of decimal and control stocks were different within each sample period, I resort to the following model (reported in Table 17b) allowing for a 40-element individual stock intercept vector.

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\ & + \beta_7 \log(ENPTIME_t) I^C + \beta_8 \log(NUMBER_{t-1}) I^C + \beta_9 \log(SPREAD_{t-1}) I^C \\ & + \beta_{10} \log(VOLUME_{t-1}) I^C + \beta_{11} \log(NPTIME\_ERR_t) I^C \\ & + \beta_{12} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^C \end{aligned} \qquad [7.8]$$

The useful feature of this regression specification is that I can now directly test for the significance of the difference in liquidity formation dynamics between decimal and fractionally trading stocks, using the full information of the variance-covariance matrix. As anticipated, during the fractional trading period, the control stocks exhibited differing formation dynamics than the matched pilot stocks trading in decimals. The pooled estimation reveals a significant positive difference in the coefficient of lagged spread and a negative difference in the coefficient of impatience. Notice that the magnitude of the difference (0.054 for the spread coefficient and -0.048 for the impatience coefficient) is the same as the magnitude of the difference in these respective coefficients in Table 16a, the advantage of the present test being that a more robust significance test of the difference can be carried out in the context of the regression in Table 17b. The larger (by 50%) negative coefficient of lagged spread for decimal stocks suggests a decrease in the predicted realized depth and a partial decline in depth and liquidity, consistent with the predictions of Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997). It is useful to note however, that the mean spread for decimal stocks during the fractional pilot time sample period was exactly 50% smaller (refer to Table 1). The finding could not therefore be interpreted as an unambiguous decline in liquidity due to decimalization, but rather as a re-equilibration of a remarkably stable functional relation of the dynamics of realized depth.

Considering the joint determination of the spread and depth facets of liquidity, I am inclined to conclude that the shift to decimalization did not necessarily impact inversely liquidity formation. On the other hand, the difference in the impatience coefficient suggests that decimal stocks tended to reward impatience by more during the pilot time period. The finding would support the claim that decimal trading makes market makers follow prices more closely and update quotes in a timelier fashion based on current information set. Rapid trading would thus reduce the volume that could otherwise be transacted at a particular price by more for stocks trading in decimals. The difference thus presents a slightly increased market impact for trades in decimal stocks, supporting the claim of reduced liquidity by Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997). Overall, a Wald test soundly rejects the null of no structural break between decimal and control stocks during the pilot sample time period. In light of the individual coefficient shifts, both would tend to support the claim that decimal stocks' realized depth was slightly impaired.

Turning my attention to the fully decimal trading sample period (Table 16 b, and Table 17b), I now fail to detect differences in liquidity formation dynamics among pilot and control stocks. The finding is reassuring because we would in fact expect to find no differences in that control sample period due to the equivalence of the trading regime. The only significant coefficient difference is the increased coefficient of expected duration for control stocks[109].

Overall, my findings confirm that the major underlying dynamics of realized depth formation are quite stable, and are not unambiguously affected to a considerable degree by changes in trading regime characteristics. The findings support the idea of fairly constant, time invariant depth elasticity with respect to the right hand side explanatory marks. In addition, the signs of the coefficients are consistent with the relations between liquidity (realized depth) and exogenous marks suggested by information asymmetry arguments. My proxy for inventory effects never entered any of the specifications significantly.

In terms of decimalization's impact on realized market depth, there is moderate evidence that over the test sample period, liquidity formation dynamics were in fact affected negatively by the decimal pricing grid. In particular, the liquidity formation process for decimal stocks was hampered by the larger negative coefficient of lagged spread, and the higher market impact of trades in decimal-trading stocks compared to fractionally trading stocks, as evidenced by the different coefficient of

[109] Therefore, an increase in instantaneous volatility would decrease depth by more for control (now freshly decimal) stocks, at least in these initial weeks of fully decimal trading, possibly due to market makers still learning how to adjust price quotations towards a more stable coefficient like the one for pilot stocks.

impatience. The results seem to favor the conclusions in Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997), who predict that if the minimum tick is lowered market depth and liquidity will go down, and the empirical descriptive findings of Chakravarty, Wood, and Van Ness (2004).

In addition, the universal switch to decimal trading on January 29, 2001 also affected the realized depth formation process of both control stocks and all stocks in the sample. The results of my individual and pooled interacted and non-interacted specifications suggest that decimalization brought about a sizable significantly positive change in the coefficient of expected duration, and since decimalization might have increased expected duration, the finding supports the claims of Hart (1995), Peake (1995), and O'Connell (1997) who hypothesize decimalization will increase liquidity through enabling better price comparison and competition.

7.4. Commonality in Liquidity

My duration based approach has allowed me to isolate particular price durations in real, event time and model their concurrent characteristics and formation process. The analysis started with a model of conditional expected duration as a function of the lagged hypothesized microstructure variables, and estimated the dynamics of expected conditional duration, or conditional volatility formation, predicated on the real price event intervals. Each of these price events (durations) constituted a significant mid-quote price change and its associated market quality and characteristics marks were also computed over the corresponding time interval. The ensuing analysis of realized market depth, or net directional volume (VNET) associated with each of the price change events, specifically subsumed and incorporated the effects of expected conditional duration, or conditional volatility and also allowed for variables predicted to affect liquidity formation. The market depth model focuses on the evolution of liquidity formation by synthetically binding and subsuming the concomitant price and liquidity formation dynamics within the common duration construct, thus tracking market depth in real event time as a process that is not disjoint from but is rather predicated upon price formation. The analysis is thus an alternative to the fixed-interval intra-day estimation procedures that simply assume the relation between liquidity and price formation will manifest itself in the arbitrarily formed intervals. My approach is therefore a direct answer to the concerns of Harford and Kaul (2004).

This section utilizes data from the aforementioned results in a multivariate analysis of the constructed series of market liquidity and liquidity shock measures. In particular, I examine the data for common factors driving the co-variance and standardized covariance structures of realized market depths and the residuals from the market depth models. The liquidity commonality phenomenon and its ramifications and implications for asset pricing are described in sections 2.3 and 6.3. The commonality in liquidity analysis presented here is a direct but more unified extension of the empirical work in Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Harford and Kaul (2004). A key difference in my analysis is the direct control for microstructure and conditional volatility effects, and the reliance on event-time defined meaningful price change episodes to model piece and liquidity co-formation. The examination presented here follows a unified estimation approach which includes a liquidity model allowing for volatility and microstructure effects and circumvents the pitfall of disjoint trade and price formation processes assumed in the econometrically problematic fixed-interval analysis.

7.4.1. Liquidity Variable Choice and Data Aggregation

I examine several alternative market liquidity series constructed around each significant price movement. The first series (VNETL) is the log of the absolute value of the cumulated signed net order imbalance associated with each price duration. VNETL is the dependent variable in my VNET regression, and is a direct ex-post measure of the market supported depth for each price event. Alternatively, since it measures an actual number of shares, the series of the cumulated signed net order imbalance (NNET) transacted during a particular duration will also be used.

I also use the series of residuals (RES) from each of the individual stock VNET regressions in which the dependent variable is the logged realized market depth. These residual series therefore control for market microstructure and conditional volatility effects. RES is thus a proxy for actual liquidity shocks net of cross-sectional and stock specific influences. Since the VNET regression was set in log levels, I will also construct a residual series representing liquidity shock to realized market depth in actual shares by taking the exponent of the absolute value of the residual from the log regression, and then keeping the sign of the residual in order to retain the direction of the shock. The resulting series (EXRES) thus provides a measure of the magnitude in actual shares as well as the signs of the errors.

As discussed in Section 6.3, factor analysis requires the input variables be concomitant and time-synchronous in order to obtain a conforming data matrix. I achieve conformity by aggregating my relevant liquidity measures over individual business days. I thus obtain standardized series of individual stock liquidity and liquidity shocks for each of 78 business days during my test and control sample periods[110].

7.4.2. Common Factor Analysis

I conduct standard principal component analysis and maximum likelihood common factor analysis using as a basis the cross-sectional correlation matrix defined by the relevant measure of liquidity. The following discussion of the two methods follows Dillon and Goldstein (1984).

Principal component analysis is a data reduction technique that isolates a parsimonious set of mutually orthogonal linear combinations (components) which explain the majority of the variation present within a large set of concomitant data series. The components are extracted so that the first component accounts for the largest amount of variation in the data, the second component is uncorrelated with the

[110] For thinly traded stocks, in the cases a particular duration spanned more than one business day, the aggregation method records a zero measure for liquidity and shocks on the inactive day. The results from the ensuing factor analysis remain unchanged if I recode the data and substitute the mean value of the series instead of the zero. The results are thus robust to my substitution choice, either because the mean for most of the series is close to zero, or the transformation does not affect the pattern of deviations from the mean and the general covariance structure of the series.

first and explains the largest proportion of the remaining residual variation, and so on. Algebraically, the first principal component (C^1) is the linear combination of the observed variables X_i , i = 1, 2, …,p

$$C^1 = w_1^1 X_1 + w_2^1 X_2 + \cdots + w_P^1 X_P \quad [7.9]$$

and the weights $w_1^1, w_2^1, \ldots, w_P^1$ are chosen to maximize the ratio of the variance of C^1 to total variance, subject to the normalization constraint $\sum_{i=1}^{P} \left(w_i^1 w_i^1 \right) = 1$. The next component C^2 is the linear combination orthogonal to C^1 that explains the maximum amount of the residual variation, and so on. Up to *p* components can be extracted, where p is the rank of the covariance (or correlation) matrix. The goal of the analysis is typically to identify a parsimonious representation explaining variation in the data with as few components as possible.

Maximum Likelihood factor analysis, on the other hand begins with the assumption that a set of unobservable common factors and a single latent unique factor explain all the variation in a given variable. The assumed model is:

$$\begin{aligned} X_1 &= v_1^1 CF^1 + v_1^2 CF^2 + \cdots + v_1^m CF^m + e_1 \\ &\vdots \\ X_P &= v_P^1 CF^1 + v_P^2 CF^2 + \cdots + v_P^m CF^m + e_P \end{aligned} \quad [7.10]$$

where up to $m \le p$ common factors (CF) can be extracted, and $v_i^j,\ i = 1,2,\ldots p,\ j = 1,2,\ldots m$ are the weights of the jth common factor associated with the ith observable variable, and the $e_j,\ j = 1,2\ldots p$ are the unique residual effects.

A primary difference in estimating the two models is that principal components extraction is simply a mathematical calculation. The method makes nor requires any assumptions about the multivariate statistical distribution governing the data. In contrast, ML Factor analysis as it is generally implemented presumes the underlying data are multivariate normal. The distinction in terms of interpretation is that PC analysis (without making any assumptions about an underlying multivariate distribution) provides no statistical theory that can be used to 'test' for the number of factors while ML factor analysis (based on multivariate normality) provides such a test. The analyses utilize the standardized variables, and thus the correlation matrix rather than the covariance matrix, removing differences due to the individual variable means and dispersions.[111]

7.4.3. Principal Components and ML Factor Analysis Results

Table 21 reports the results from the analysis based upon the liquidity series and the liquidity residual series of the 40 sample stocks over the pilot and fully decimal period, as well as over the merged time period. The percentage of variation explained by each factor is obtained by dividing the respective eigenvalue of the correlation matrix associated with each respective factor by 40, the number of series. The rank of the correlation matrix equals 40, implying the matrix has 40 positive eigenvalues.

[111] In the literature, this adjustment is most commonly necessitated by differing units of measurement among the data sample series. In the present case however, the units of measurement are uniform but the rather uneven variances of the series necessitate the adjustment.

The results from the realized market depth series VNETL and NNET generally confirm the findings of mild commonality in liquidity detected of Hasbrouck and Seppi (2001) and Huberman and Halka (2001). Up to 15% of the variation in aggregated logged net directional volumes associated with each price duration can be explained by the first factor. The finding is very close to the 13% found by Hasbrouck and Seppi (2001) from their analysis of transactions realized within fixed, 15 minute intervals. Assuming multivariate normality, the standard error of that first eigenvalue is 1.34 and is thus statistically significant[112]. The VNETL and NNET scree-plots in Table 22 also confirm the finding of a single common factor governing liquidity co-variation[113].

The evidence of commonality disappears when the residuals from the liquidity regressions are examined. The eigenvalues and the associated percentage of variation explained by the first three factors in the analysis of the RES and EXRES series are small[114]. In addition, an examination of the RES and EXRES scree-plots in Table 22 confirms the absence of a common dominating factor. The findings strengthen the validity of the individual VNET regressions. In particular, the impact of RHS variables accounting for microstructure and conditional volatility effects on liquidity account for the manifestation of a common factor liquidity structure. The finding

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[112] With n observations $\sqrt{n}\left(l_i - \psi_i\right) \overset{asy.dist.}{\sim} N(0, 2\psi_i^2)$ where ψ_i and l_i are the population and sample value of the i[th] eigenvalue. Standard error of the eigenvalue of 6 is therefore $\sqrt{\frac{2(6)^2}{40}} = 1.34$

[113] Scree-plots (after Cattell, 1966) are simply a plot of the eigenvalues in descending order. The number of relevant factors (the scree) is marked by the point where the subsequent eigenvalues plot as a straight line.

[114] Assuming multivariate normality none are significant.

provides evidence against the claim that systematic liquidity shocks give rise to correlated liquidity, and therefore have potentially important implications for the discussion of liquidity effects in asset pricing. The results suggest common driving forces in terms of microstructure and volatility effects on individual-stock liquidity formation processes are what drives commonality in liquidity. Furthermore, they support the claim of Fernando (2003) that systematic common liquidity shocks do not give rise to liquidity commonality.

The results on commonality suggest the characteristics of the trading process, namely the individual stock price and liquidity formation dynamics ultimately give rise to and account for the bulk of liquidity commonality. While the common factor analysis does not help pinpoint precise identity of the effects giving rise to a common liquidity factor, a task left for future research, the results make it reasonable to surmise that their origin is rooted at the microstructural level of price, liquidity, and conditional volatility formation. Moreover, the event-time, price-duration based analysis undertaken in this study is in fact particularly well-suited for and relevant in delineating the actual liquidity formation process and modeling the synthetic co-evolution of price and liquidity.

7.4.3.1. Pilot Stocks vs. Control Stocks

Comparing the common factor analysis results of the pilot, decimally trading stocks with those of the control stocks over each of my sample test periods provides a way to assess how minimum tick trading regime changes affected stock liquidity formation dynamics, and liquidity commonality.

Table 23 reports the results of the principal component factor analyses on the two stock groups over each sample period. The results reconfirm the finding from the previous section of a single factor explaining from 14% to 19% of the co-variation in the raw liquidity measures VNETL and NNET. The evidence of a common factor again however disappears in the results of the RES and EXRES orthogonalized residuals.

The difference in the strength of the common factor behind pilot and control stocks is quite small and virtually indistinguishable. In general however, decimal/pilot stocks do exhibit a slightly higher explained proportion of co-variation. I conclude decimalization had no influence on liquidity commonality, and if anything, it seems to have made liquidity variations more related and uniform. The latter argument agrees with the argument made by decimalization proponents that switching to penny pricing increments would encourage price continuity and standardization and contribute to a smoother, less fragmented trading environment.

8. Conclusion

This study utilized the construct of price duration, defined as the time necessary for prices to move in either direction by at least a pre-specified increment. The appealing feature of the construct is that it provides an event time segregation of real price/information events rather than relying on fixed-interval analysis. Having predicated the duration construct on the change in price, the concomitant levels of or changes in other market characteristics, called marks, are subsumed and synchronized to the real price events they relate to. The price duration construct thus allows for a unique microstructural examination of the interrelated formation processes of price, liquidity, and volatility while tracing their developments within the confines of individual stock real price events. The study first proceeded by parameterising the conditional duration/volatility process of 40 NYSE stocks through the estimation of various multiplicative error Autoregressive Conditional Duration models. Having isolated the proper functional form and most suitable empirical distributional assumptions, I used the model's output to generate the series of expected conditional durations, representing a proxy for the inverse of expected volatility, conditioned on past durations and an array of lagged exogenous microstructural marks.

The process allowed me to test an array of hypothesized informational market microstructure relations, confirming the significance and direction of their hypothesized impact on volatility formation dynamics. The results strongly support the hypothesized sign and significance of informational microstructure variables affecting price and volatility development[115].

The purpose of this study was to then shed some light upon the effect of the trading regime change in minimum ticker size upon price, volatility, and liquidity formation. In addition, the expected durations were used in a regression modeling the

[115] Individual works tested include Roll (1984), Hasbrouck (1991), Stoll (1989), Kyle (1985), Glosten and Milgrom (1985), Bagehot (1971), Blume, Easley, and O'Hara (1994), Easley, Keifer, O'Hara, and Paperman (1996), Easley and O'Hara (1987), Hasbrouck (1988), Foster and Viswanathan (1995), Easley and O'Hara (1992), and Jones, Kaul, and Lipson (1994).

realized market depth, or net directional volume transacted over particular price duration. This is the only study which approaches the issues through the event time construct of price duration as opposed to fixed-interval analysis.

There is evidence that the switch to decimalization affected the dynamics of the mid-quote price formation and price revision. After the complete switch to decimalization, the price formation process adjusted to the new trading regime, and the dynamics of expected conditional duration remained quite stable and uniform in terms of the new ACD model coefficients. Decimalization seems to have reduced conditional mid-quote price volatility by making the average conditional expectation of time necessary for a predetermined price change slightly larger. The finding is in direct agreement with the argument of decimalization advocates claiming that a refined pricing grid will lead to more continuous, correct, and generally less volatile pricing. Evidence thus seems to point that conditional intraday volatility has declined with decimalization, confirming the claims of Bessembinder (2003) and Chakravarty, Wood, and van Ness (2004).

In addition, my liquidity analysis confirms that the underlying dynamics of realized depth formation are quite stable, and are not unambiguously affected to a considerable degree by changes in trading regime characteristics. The findings support the idea of fairly constant, time invariant depth elasticity with respect to the right hand side explanatory marks. In addition, the signs of the coefficients confirm the information asymmetry microstructure works[116] predicted relations between liquidity (realized depth) and exogenous microstructure marks. My proxy for inventory effects never enters significantly any of the liquidity analysis specifications.

In terms of decimalization's impact, there is moderate evidence that over the test sample period, liquidity formation dynamics were in fact affected negatively by the decimal pricing grid. In particular, the liquidity formation process for decimal stocks was hampered by the larger negative coefficient of lagged spread, and the higher market impact of trades in decimal-trading stocks compared to fractionally trading stocks, as evidenced by the different coefficient of impatience. The results seem to favor the conjectured relations in Harris (1991, 1994), Grossman and Miller (1988), and Seppi (1997), who predict that if the minimum tick is lowered market depth and liquidity will go down, and the empirical descriptive findings of Chakravarty, Wood, and Van Ness (2004).

In addition, the universal switch to decimal trading on January 29, 2001 also affected the realized depth formation process of both control stocks and all stocks in the sample. The results of both the individual and pooled interacted and un-interacted specifications mildly support the claims of the microstructure works of Hart (1995), Peake (1995), and O'Connell (1997) who hypothesize decimalization would increase liquidity through enabling better price comparison and competition.

[116] Works tested include Kyle (1985), Glosten and Milgrom (1985), Diamond and Verrechia (1987), Madhavan and Smidt (1993), Lee, Mucklow and Ready (1993), Engle and Lange (2001), Chordia, Roll, and Subrahmanyan (2001), Escribano, Pascual, and Tapia (2002), and Chordia and Subrahmanyam (2002).

Finally, I conduct a common factor analysis on the aggregated realized market depth and orthogonalized residuals series. My results confirm the findings of Hasbrouck and Seppi (2001) of a single latent factor explaining about 15% of liquidity co-variation. Interestingly, the evidence of commonality disappears after controlling for concomitant microstructure and volatility effects. In particular, the impact of RHS variables accounting for microstructure and conditional volatility effects on liquidity, or their subsumed interrelated formation dynamics could well account for the manifestation of a common factor liquidity structure. The finding provides evidence against the claim that systematic liquidity shocks give rise to correlated liquidity[117], at least not in a direct way but possibly through their impact on price and volatility dynamics, and could therefore have potentially important implications about liquidity effects on asset pricing. Rather, it seems like the common driving forces in terms of microstructure and volatility effects behind individual-stock liquidity formation processes are the very reason commonality in liquidity is detected. The interpretation of the finding tends to support an argument that the trading process characteristics, namely the individual stock price and volatility formation dynamics ultimately give rise to and account for the bulk of the traditionally documented liquidity commonality.

In light of the results, the precise identity of the common liquidity factor is not directly pinpointed, but it would be quite reasonable to surmise that its origin is rooted at the microstructural determination of price, liquidity, and conditional

[117] Confirming the theoretical conclusions from the model in Fernando (2003).

volatility formation. Moreover, the event-time, price-duration based analysis undertaken in this study could in fact be particularly well-suited for and pertinent to the delineation of the actual liquidity formation process and the modeling of the synthetic co-evolution of price and liquidity.

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[i] Madhavan (2000) provides a definition of market microstructure as the "area of finance concerned with the process by which investors' latent demands are ultimately translated into transactions." He splits the general area into four sub areas:

1) *Price formation and price discovery,* examines the static properties of execution costs and their determinants, as well as the dynamic models of price formation by which latent demands ultimately translate into trading prices and volumes that reflect available information.
2) *Market structure and design issues,* dealing with the effect of alternative trading protocols and regulations upon the price formation process, market liquidity, and quality.
3) *Information and disclosure,* concerned primarily with the effect of the price formation process' characteristics upon traders' strategies and behavior. The issue of market transparency is the core of this research area.
4) *Relation of microstructure informational issues to other finance areas* like corporate finance, investments, and international finance.

Example 1.
A sample duration for a hypothetical set of transactions and their matched quotes.

Threshold=$.0625

Duration = 72 seconds
VNET = 100
Volume = 900

Transaction Time	Transaction Price	Bid Quote	Ask Quote	Mid-Quote Price	Trade Indicator	Direction d_i	Volume vol_i
10:01:00	$ 5.1250	$ 5.1250	$ 5.375	$ 5.2500	S	1	300
10:01:05	$ 5.3125	$ 5.1250	$ 5.375	$ 5.2500	B	-1	200
10:01:12	$ 5.3750	$ 5.1250	$ 5.375	$ 5.2500	B	-1	100
10:01:25	$ 5.1250	$ 5.1250	$ 5.375	$ 5.2500	S	1	100
10:02:12	$ 5.5000	$ 5.1250	$ 5.500	$ 5.3125	B	-1	200
10:02:20	$ 5.5000	$ 5.1250	$ 5.500	$ 5.3125	B	-1	200

$$VNET = \left| \sum_i d_i vol_i \right|$$

Figure 1.
Autocorrelation functions of an ACD(1,1) process for different values of alpha and beta.

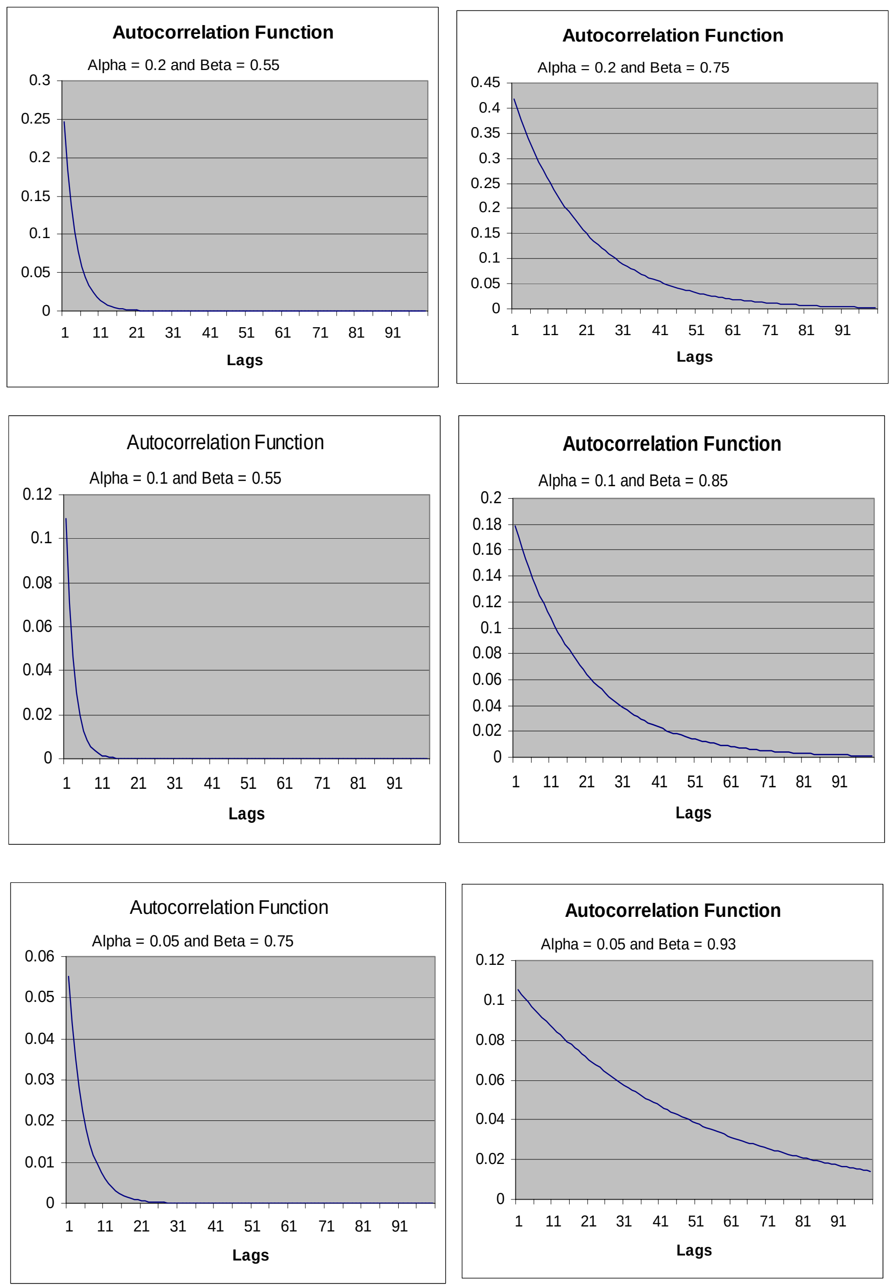


Figure 2.
Time-of-day effects of raw durations. Quarter-hours reported on horizontal axis.

October 2, 2000 till January 26, 2001.

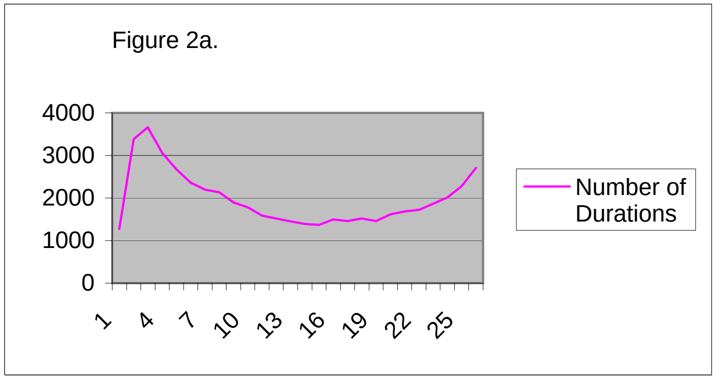


Figure 2a.

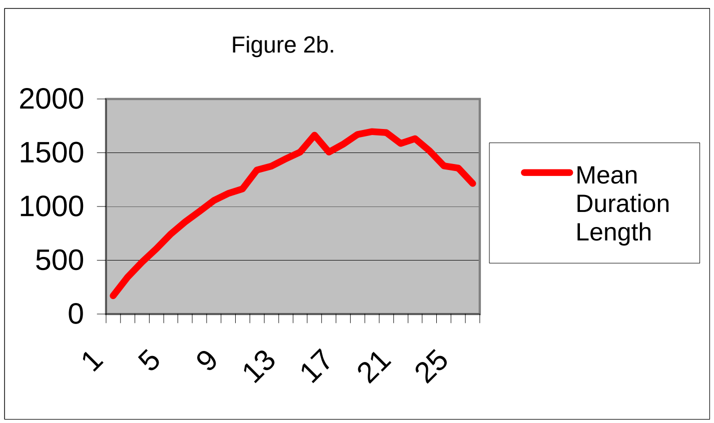


Figure 2b.

February 8, 2001 till May 31, 2001.

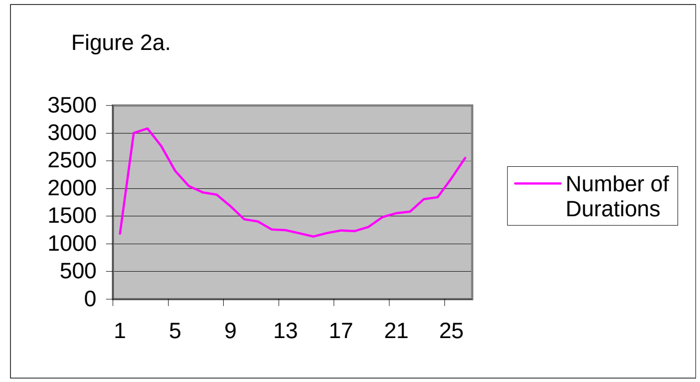


Figure 2a.

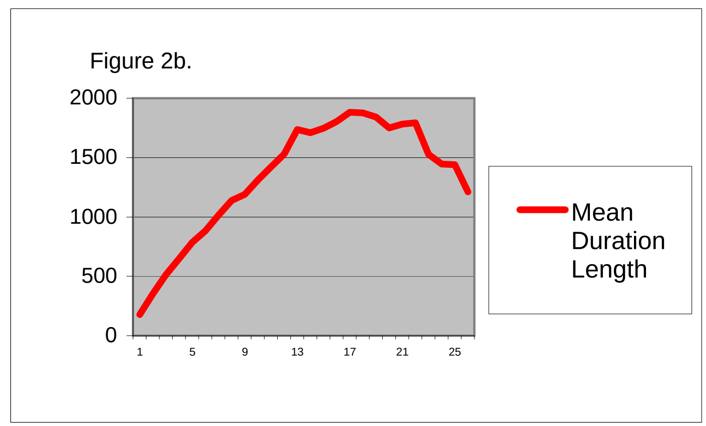
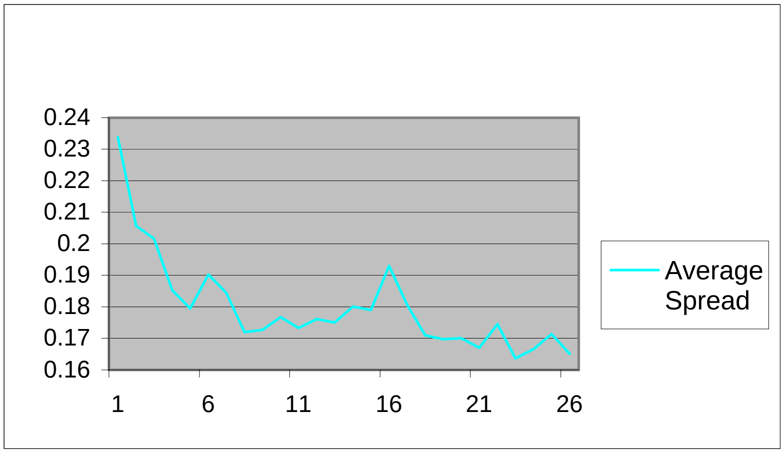


Figure 2b.

Figure 3.
Time-of-day effects of average spread. Quarter-hours reported on horizontal axis.

October 2, 2000 till January 26, 2001.



February 8, 2001 till May 31, 2001.

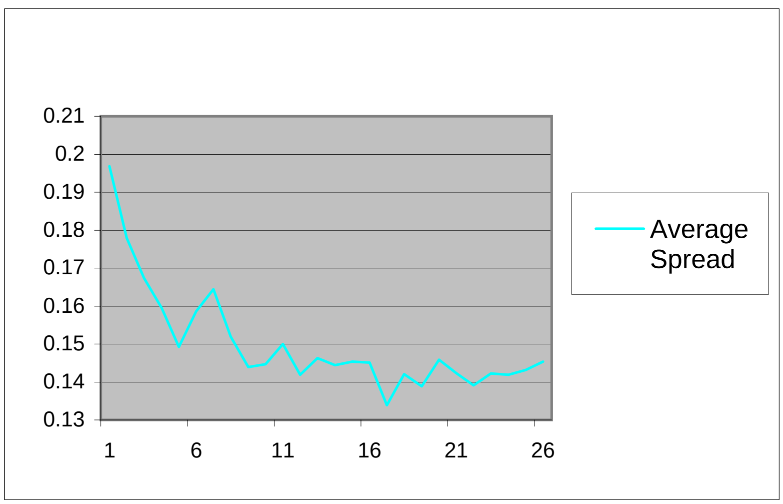


Figure 4a.
Histogram and probability plot of raw durations against exponential distribution.

October 2, 2000 till January 26, 2001. **February 8, 2001 till May 31, 2001.**

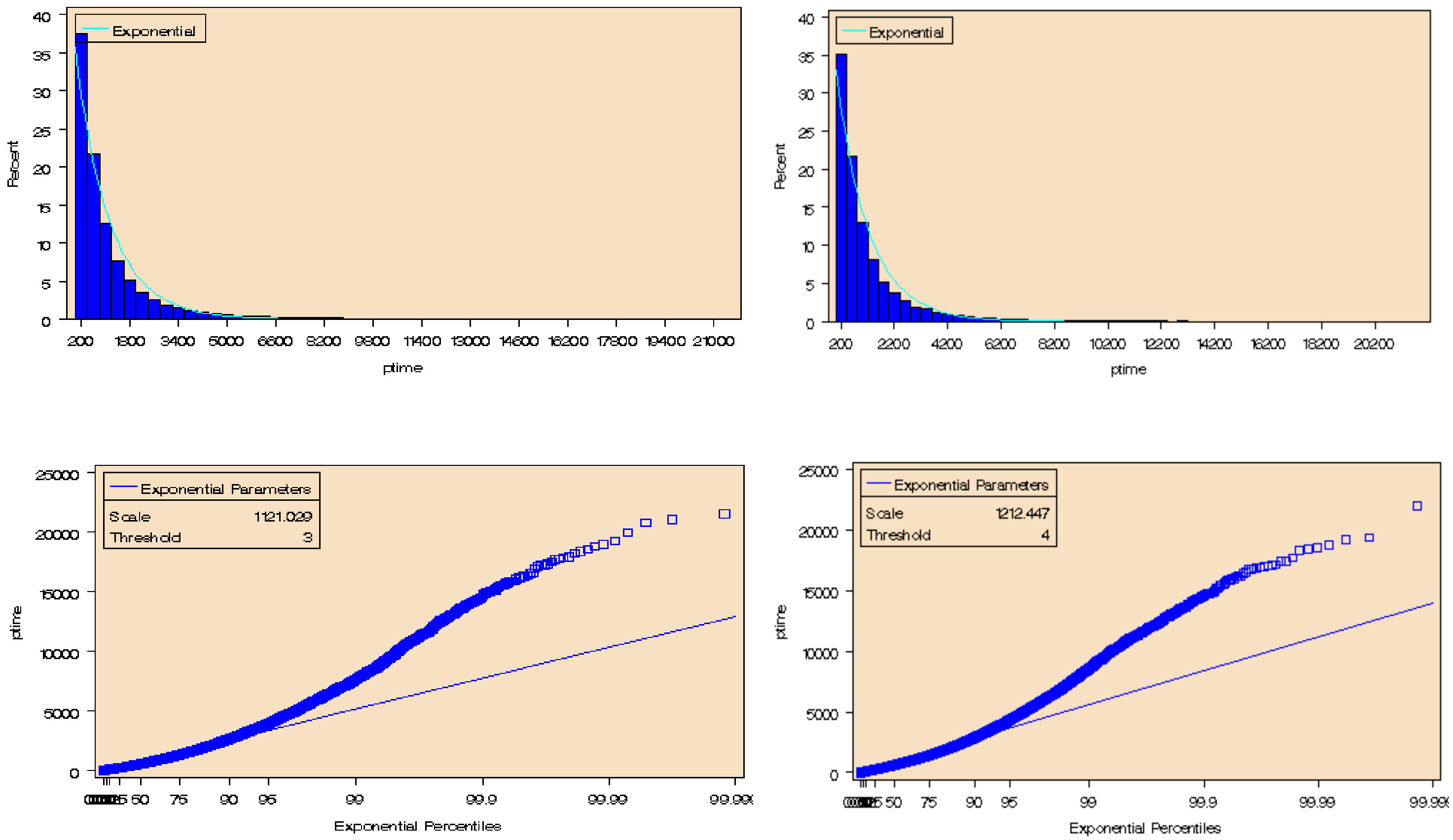


Figure 4b.
Histograms and probability plots of the normalized durations against the Exponential and Weibull distributions.

October 2, 2000 till January 26, 2001.

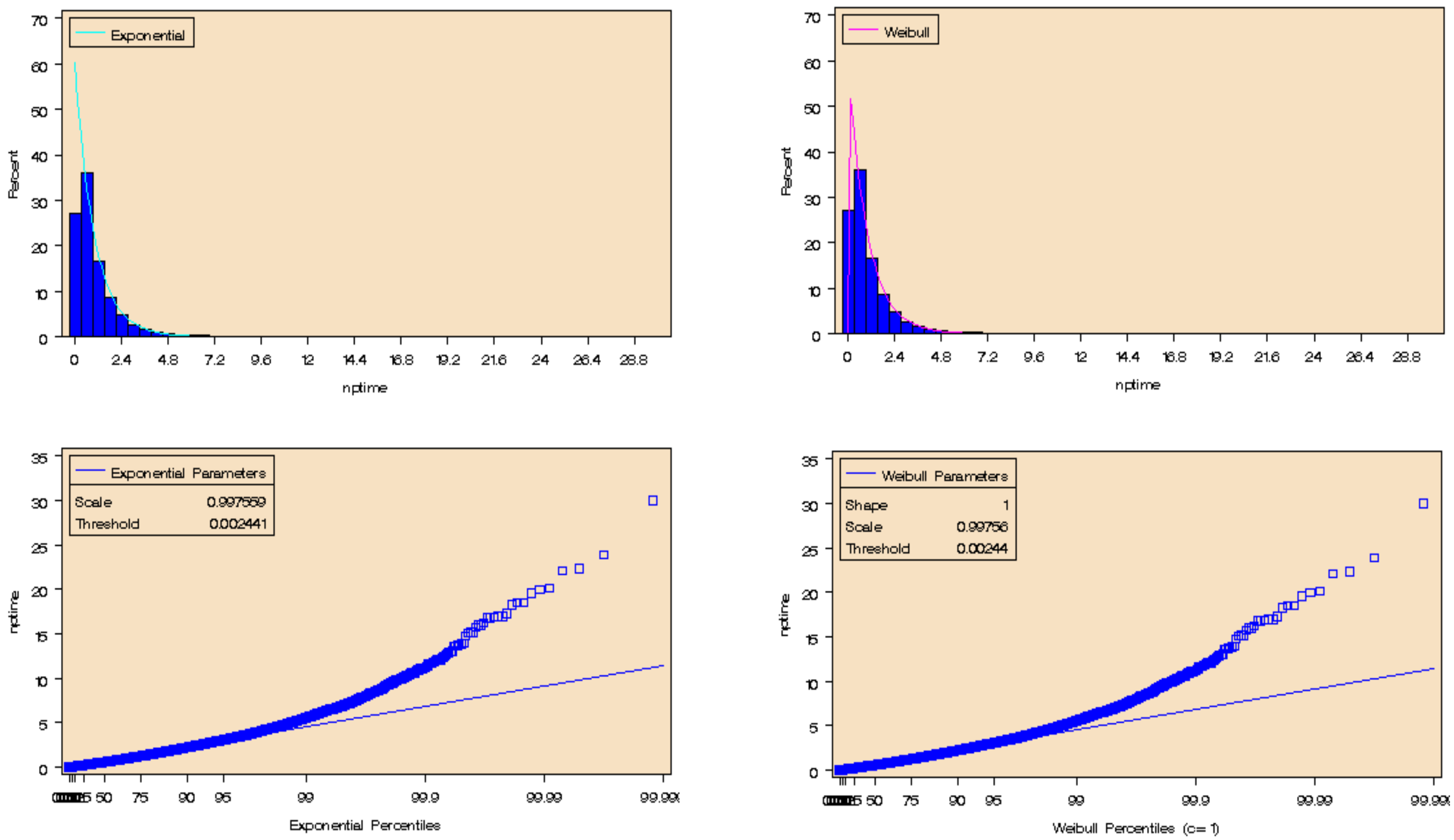


Figure 4b.
Histograms and probability plots of the normalized durations against the Exponential and Weibull distributions.

February 8, 2001 till May 31, 2001.

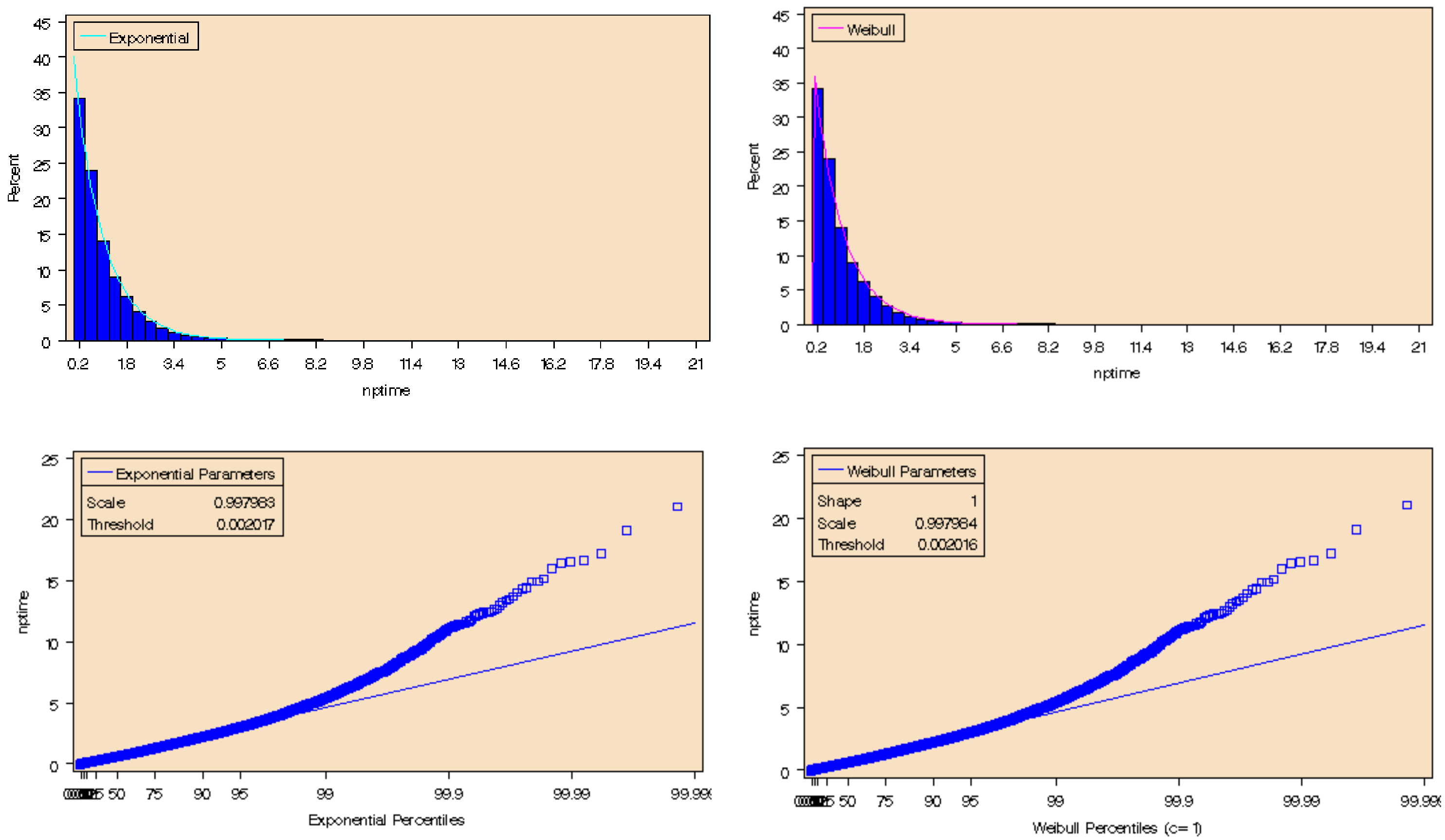
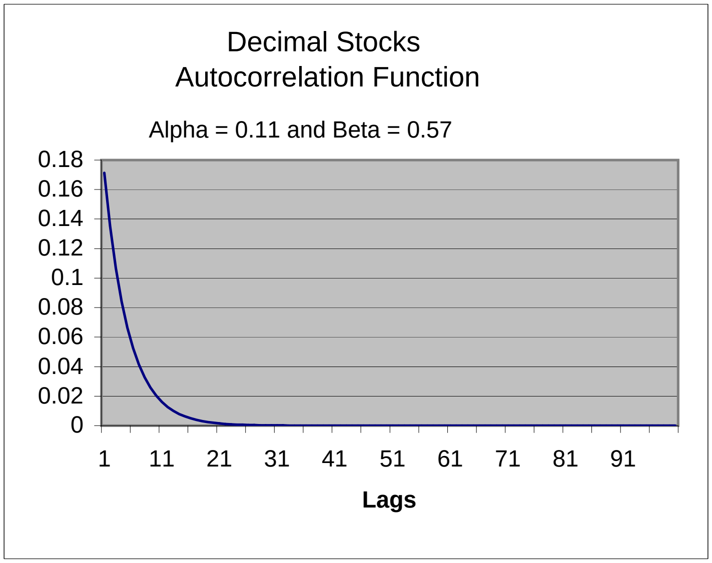


Figure 5. Autocorrelation functions of the simple starting point estimated ACD(1,1) models. Sample period October 2, 2000 till January 26, 2001.

Model is: $ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

Where ENPTIME is the conditional expected normalized duration, NPTIME is the normalized actual duration, and SPREAD is nominal spread associated with the particular duration.



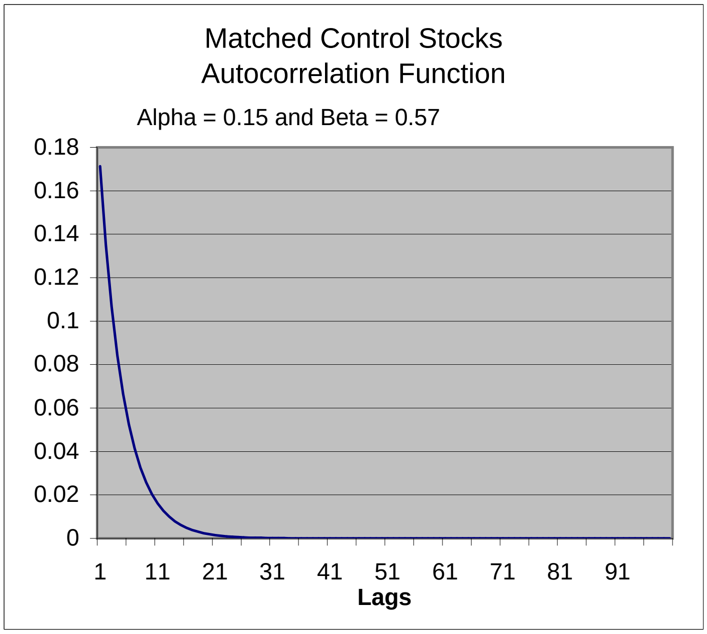
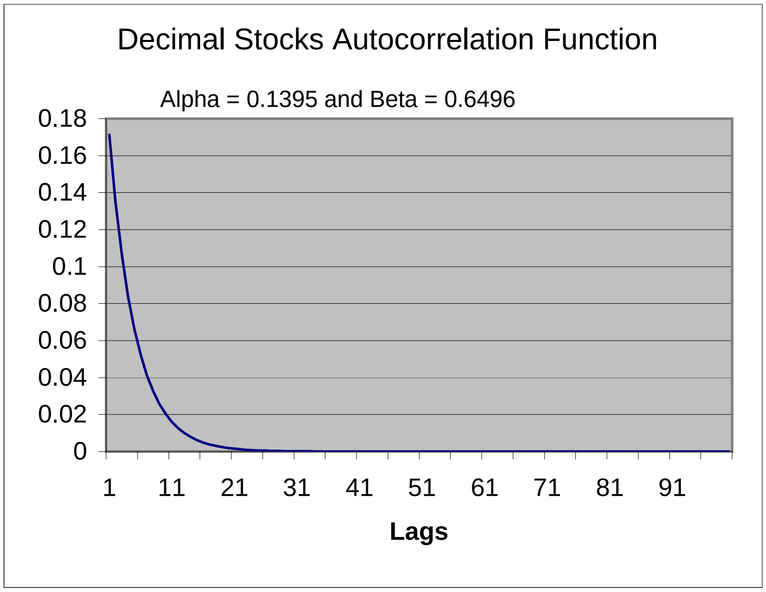
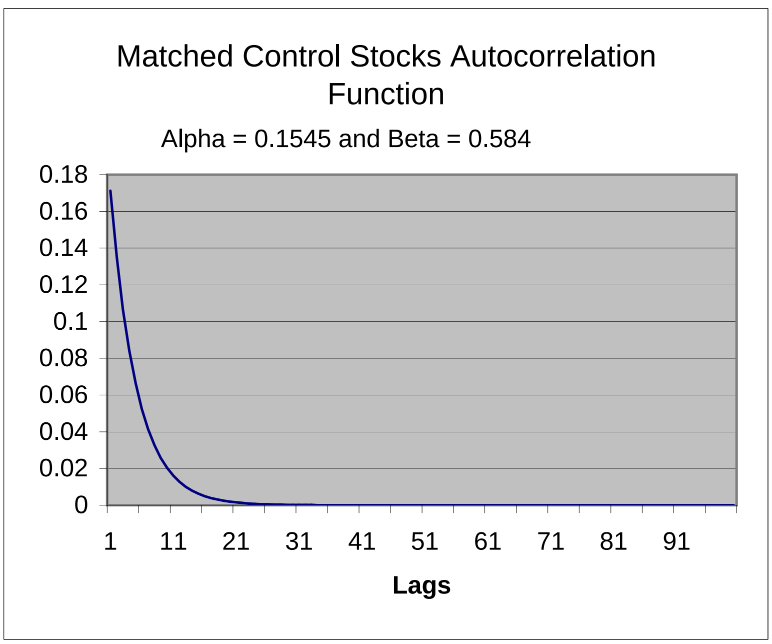


Figure 6. Autocorrelation functions of the optimal estimated ACD(1,1) models.
Sample period October 2, 2000 till January 26, 2001.

Model is:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$





* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Figure 7. Empirical distribution tests of the standardized residuals from the WACD and WLACD models for stocks HIT and RCL.
Sample time period October 2, 2000 till January 26, 2001.

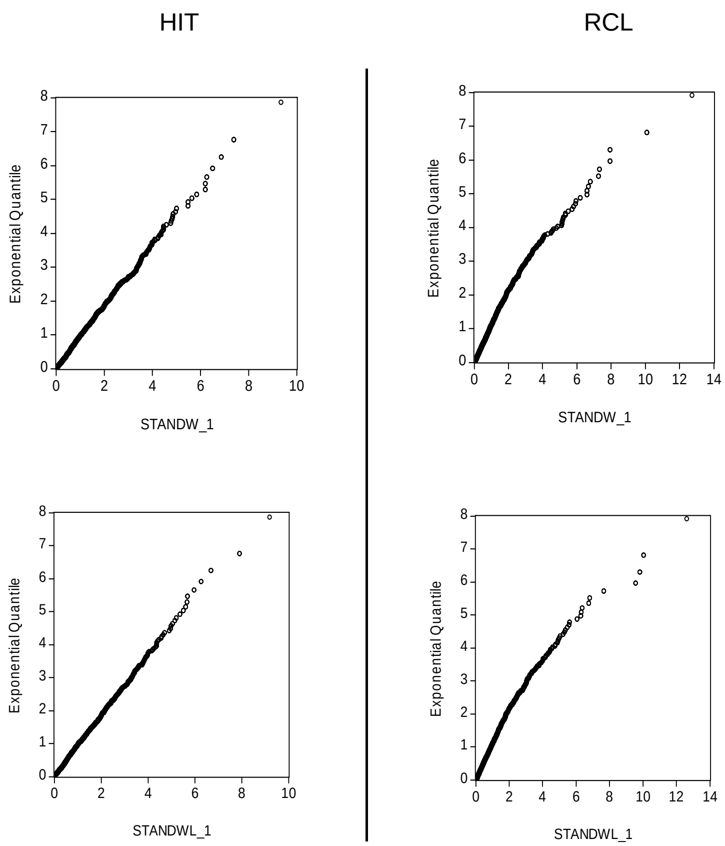


Table 1. Company Descriptives

Ticker symbols and names of the decimal and matched control sample companies.

Decimal Pilot Stocks		Matched Control Stock	
Ticker	*Company Name*	*Ticker*	*Company Name*
AOL	AMERICA ONLINE	**WMT**	WAL-MART STORES
ASF	ADMINISTAFF INC	**CCN**	CHRIS-CRAFT INDS
BEN	FRANKLIN RESOURCES INC	**AOC**	AON CORP
CI	CIGNA CORP	**UNH**	UNITEDHEALTH GROUP INC
CL	COLGATE-PALMOLIVE CO	**KO**	COCA-COLA CO
CPQ	AOL TIME WARNER INC	**T**	AT&T CORP
DCX	DAIMLERCHRYSLER AG	**DOV**	DOVER CORP
GMH	GENERAL MOTORS CL H	**ALL**	ALLSTATE INSURANCE
GT	GOODYEAR TIRE & RUBBER CO	**GP**	GEORGIA-PACIFIC CORP
HAR	HARMAN INTERNATIONAL INDS	**PHM**	PULTE HOMES INC
KF	KOREA FUND	**APF**	MORGAN STAN ASIA PACIFIC FD
LE	LANDS END	**CLB**	CORE LABORATORIES NV
LMT	LOCKHEED MARTIN CORP	**MRO**	MARATHON OIL CORP
MLM	MARTIN MARIETTA MATERIALS	**HTN**	HOUGHTON MIFFLIN CO
RCL	ROYAL CARIBBEAN CRUISES LTD	**CNF**	CNF INC
S	SEARS ROEBUCK Co	**NKE**	NIKE INC -CL B
SGY	STONE ENERGY CORP	**AMG**	AFFILIATED MANAGERS GRP INC
STT	STATE STREET CORP	**PKI**	PERKINELMER INC
UBS	UBS AG	**HIT**	HITACHI LTD -ADR
VAL	VALSPAR CORP	**AGX**	AGRIBRANDS INTERNATIONAL INC

Table 1 (cont'd) Company Descriptives

Descriptive statistics for the decimal pilot sample and control sample stocks and their trades.

Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE						
	Market Cap end 2000	Average Daily Volume	Mean Daily Trades	Mean Price	Price Var.	Mean Trans. Spread		Market Cap end 2000	Av. Daily Volume (thous.)	Mean Daily Trades	Mean Price	Price Var.	Mean Trans. Spread
AOL	80,614	12547	1954	47.43	41.51	0.0807	**WMT**	237,469	7303	2173	49.66	12.77	0.0993
ASF	746	215	246	36.21	215.83	0.1575	**CCN**	2,328	63	95	71.38	14.3	0.2412
BEN	9,286	493	495	38.96	4.04	0.0719	**AOC**	8,912	1408	431	33.81	12.82	0.1219
CI	20,111	740	788	120.69	51.93	0.2092	**UNH**	19,471	1446	958	96.97	633*	0.1543
CL	36,578	1594	839	56.99	15.32	0.063	**KO**	151,416	3685	1381	58.8	4.54	0.0942
CPQ	25,419	11172	2048	22.56	23.6	0.0527	**T**	64,863	15271	2276	21.84	9.65	0.0876
DCX	41,335	577	423	43.35	6.42	0.0849	**DOV**	8,242	716	520	40.94	4.92	0.1314
GMH	29,831	3384	797	26.83	13.05	0.0712	**ALL**	31,714	2443	949	38.02	9.29	0.107
GT	3,623	906	525	19.56	8.25	0.0513	**GP**	6,329	1922	718	26.68	7.99	0.1056
HAR	1,243	200	194	37.6	22.31	0.1756	**PHM**	1,754	310	307	37.86	16.67	0.1485
KF	528	140	58	11.2	0.59	0.0693	**APF**	556	97	37	8.89	0.08	0.0849
LE	736	168	184	24.74	7.6	0.1006	**CLB**	880	100	73	22.49	3.06	0.1825
LMT	14,632	1102	606	33.09	1.35	0.0832	**MRO**	8,554	1183	525	27.5	0.7	0.0901
MLM	1,979	154	176	38.65	9.81	0.1093	**HTN**	1,335	176	142	38.47	16.08	0.1474
RCL	5,070	573	216	23.56	7.93	0.1024	**CNF**	1,645	360	258	29.02	15.6	0.1401
S	11,579	1366	690	32.95	6.3	0.0613	**NKE**	14,991	1172	632	46.89	47.47	0.1225
SGY	1,197	137	190	56.78	16.75	0.147	**AMG**	1,209	154	226	54.12	18.7	0.2012
STT	20,086	688	955	120.52	72.4	0.2046	**PKI**	5,226	549	784	100.5	75.12	0.2929
UBS	69,602	220	222	147.25	218.85	0.1957	**HIT**	28,727	33	86	101.44	113	0.4371
VAL	1,367	96	143	27.78	5.85	0.0882	**AGX**	1,345	56	31	50.25	22.68	0.134
Mean	***18778.074***	***1823.5503***	***587.3751***	***48.335***	***37.485***	***0.10898***	***Mean***	***29848***	***1922.3391***	***630.1***	***47.777***	***51.922***	***0.15619***

* UNH went through a stock split, explaining the large variance, and the difference in mean sample volatility

Table 1. (cont'd) Company Descriptives

Descriptive statistics for the trades of the decimal pilot sample and control sample.

Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE						MATCHED CONTROL SAMPLE					
	Average Daily Volume (thous.)	Mean Daily Trades	Mean Price	Price Variance	Mean Trans. Spread		Average Daily Volume (thous.)	Mean Daily Trades	Mean Price	Price Variance	Mean Trans. Spread
AOL	12567	2177	46.10	30.07	0.0689	**WMT**	5516	2160	50.90	3.68	0.0523
ASF	193	195	22.48	12.08	0.1083	**CCN**	62	113	68.88	14.41	0.1459
BEN	567	697	41.74	5.35	0.0633	**AOC**	918	530	34.30	1.66	0.0727
CI	1076	1085	102.10	53.46	0.1379	**UNH**	2093	1116	58.45	7.56	0.0703
CL	1431	1148	55.79	6.16	0.0591	**KO**	3916	1521	48.57	18.71	0.0487
CPQ	8983	1792	18.90	4.88	0.0414	**T**	9127	1812	21.96	0.77	0.0351
DCX	457	318	48.45	5.10	0.0758	**DOV**	671	678	38.65	5.06	0.0758
GMH	2982	814	21.70	4.51	0.0576	**ALL**	1907	1250	41.50	2.70	0.0508
GT	886	678	25.43	3.03	0.0525	**GP**	1516	760	30.96	5.09	0.0576
HAR	153	180	31.21	14.51	0.1361	**PHM**	414	455	40.12	19.40	0.0957
KF	130	41	10.25	0.93	0.0643	**APF**	61	32	8.43	0.18	0.0607
LE	123	173	29.25	16.36	0.0983	**CLB**	100	90	22.28	5.41	0.1570
LMT	1404	805	36.67	1.79	0.0734	**MRO**	1296	806	29.61	4.50	0.0446
MLM	173	184	45.97	7.36	0.0984	**HTN**	154	208	47.37	26.62	0.0964
RCL	889	319	23.09	10.32	0.0733	**CNF**	270	307	31.31	5.51	0.0810
S	1381	829	37.50	5.38	0.0549	**NKE**	1296	777	41.69	22.92	0.0673
SGY	179	271	52.30	16.04	0.1364	**AMG**	169	278	51.63	17.00	0.1550
STT	871	1233	98.52	84.69	0.1375	**PKI**	545	739	64.43	137.44	0.1468
UBS	79	157	148.91	90.17	0.3084	**HIT**	37	100	92.51	117.43	0.3529
VAL	171	222	30.87	30.87	0.0816	**AGX**	24	28	54.00	0.05	0.0596
Mean	***1734.724***	***666***	***46.3615***	***20.153***	***0.09637***	***Mean***	***1504.6103***	***687.93846***	***43.8775***	***20.805***	***0.096***

Table 2a.
Characteristics of durations computed using a fixed $1/16 price threshold for all stocks.
Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE						MATCHED CONTROL SAMPLE				
	Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Percentage Price Threshold (%)			Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Percentage Price Threshold (%)
AOL	13374	0.0625	47.48	0.13163		**WMT**	13990	0.0625	50.17	0.12458
ASF	2957	0.0625	35.48	0.17616		**CCN**	881	0.0625	72.06	0.08673
BEN	4269	0.0625	38.96	0.16042		**AOC**	2943	0.0625	34.66	0.18032
CI	5221	0.0625	118.29	0.05284		**UNH**	12620	0.0625	100.35	0.06228
CL	6154	0.0625	57.08	0.10950		**KO**	9632	0.0625	58.77	0.10635
CPQ	4686	0.0625	23.35	0.26767		**T**	6195	0.0625	22.58	0.27679
DCX	2866	0.0625	43.69	0.14305		**DOV**	6035	0.0625	41.02	0.15236
GMH	3998	0.0625	27.05	0.23105		**ALL**	6519	0.0625	37.75	0.16556
GT	1474	0.0625	19.64	0.31823		**GP**	5069	0.0625	26.94	0.23200
HAR	2738	0.0625	37.71	0.16574		**PHM**	4207	0.0625	38.02	0.16439
KF	166	0.0625	10.97	0.56974		**APF**	108	0.0625	8.86	0.70542
LE	2240	0.0625	25.13	0.24871		**CLB**	1081	0.0625	22.56	0.27704
LMT	4640	0.0625	33.11	0.18876		**MRO**	3401	0.0625	27.58	0.22661
MLM	1862	0.0625	38.52	0.16225		**HTN**	1900	0.0625	38.69	0.16154
RCL	1976	0.0625	23.56	0.26528		**CNF**	3378	0.0625	28.96	0.21581
S	3982	0.0625	33.13	0.18865		**NKE**	4194	0.0625	47.32	0.13208
SGY	3155	0.0625	57.07	0.10951		**AMG**	4916	0.0625	54.59	0.11449
STT	9281	0.0625	120.77	0.05175		**PKI**	15673	0.0625	100.75	0.06203
UBS	3490	0.0625	149.36	0.04185		**HIT**	1294	0.0625	100.86	0.06197
VAL	902	0.0625	27.59	0.22653		**AGX**	296	0.0625	47.94	0.13037
Mean	***3972***	***0.0625***	***48.40***	***0.1905***		***Mean***	***5217***	***0.0625***	***48.02***	***0.1819***

Table 2a.
Characteristics of durations computed using a fixed $ 1/16 price threshold for all stocks.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE					MATCHED CONTROL SAMPLE				
	Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Price Threshold (%)		Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Price Threshold (%)
AOL	11235	0.0625	44.93	0.1391	**WMT**	7948	0.0625	50.64	0.1234
ASF	1943	0.0625	22.78	0.2744	**CCN**	443	0.0625	67.80	0.0922
BEN	4343	0.0625	41.57	0.1503	**AOC**	2381	0.0625	34.42	0.1816
CI	8276	0.0625	102.95	0.0607	**UNH**	5544	0.0625	58.32	0.1072
CL	6054	0.0625	55.88	0.1118	**KO**	4132	0.0625	48.77	0.1282
CPQ	2937	0.0625	19.31	0.3237	**T**	2779	0.0625	21.97	0.2845
DCX	2086	0.0625	48.28	0.1295	**DOV**	3541	0.0625	38.38	0.1628
GMH	3249	0.0625	21.77	0.2871	**ALL**	4118	0.0625	41.38	0.1510
GT	2646	0.0625	25.16	0.2484	**GP**	3666	0.0625	30.63	0.2040
HAR	1978	0.0625	31.43	0.1989	**PHM**	2750	0.0625	39.19	0.1595
KF	89	0.0625	9.96	0.6275	**APF**	33	0.0625	8.37	0.7467
LE	1757	0.0625	28.92	0.2161	**CLB**	675	0.0625	22.11	0.2827
LMT	4370	0.0625	36.56	0.1710	**MRO**	1573	0.0625	29.46	0.2122
MLM	1551	0.0625	45.29	0.1380	**HTN**	1829	0.0625	46.10	0.1356
RCL	1639	0.0625	23.67	0.2640	**CNF**	1861	0.0625	31.39	0.1991
S	3842	0.0625	37.22	0.1679	**NKE**	2329	0.0625	41.85	0.1493
SGY	3391	0.0625	52.68	0.1186	**AMG**	3093	0.0625	51.36	0.1217
STT	10778	0.0625	97.71	0.0640	**PKI**	6601	0.0625	66.13	0.0945
UBS	2560	0.0625	148.55	0.0421	**HIT**	1104	0.0625	91.14	0.0686
VAL	1627	0.0625	30.71	0.2035	**AGX**	72	0.0625	53.94	0.1159
Mean	***3818***	***0.0625***	***46.2665***	***0.1968***	***Mean***	***2823.6***	***0.0625***	***43.6675***	***0.1860***

Table 2b.
Descriptives of raw durations computed using a fixed $ 1/16 price threshold for all stocks.
Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Duration (seconds)	Duration Standard Deviation	Median	Min.	Max.			Mean Duration (seconds)	Duration Standard Deviation	Median	Min.	Max.
AOL	147	163	98	5	11560		**WMT**	133	156	83	2	3401
ASF	534	820	245	7	9070		**CCN**	981	1159	538	8	10012
BEN	452	543	276	6	6934		**AOC**	475	666	280	5	11560
CI	187	221	121	5	3741		**UNH**	137	157	87	2	2849
CL	304	348	194	5	6256		**KO**	172	196	108	3	2949
CPQ	342	474	194	8	8119		**T**	291	402	166	6	7734
DCX	576	741	339	8	7569		**DOV**	330	415	201	4	4996
GMH	376	464	227	6	7430		**ALL**	249	325	148	3	5317
GT	859	1207	465	7	15561		**GP**	332	466	191	5	10808
HAR	639	730	391	5	7311		**PHM**	455	594	266	5	10103
KF	4401	4485	2695	33	18743		**APF**	5952	5285	4050	114	21096
LE	858	1224	445	6	17018		**CLB**	1492	1954	848	5	20026
LMT	407	475	252	3	6185		**MRO**	498	641	278	5	7677
MLM	923	1098	563	5	16544		**HTN**	1024	1304	574	6	14263
RCL	926	1298	492	9	14416		**CNF**	549	728	311	3	9963
S	456	569	268	5	7315		**NKE**	288	371	166	4	4914
SGY	653	875	328	5	8272		**AMG**	428	613	208	4	7151
STT	134	171	79	3	2924		**PKI**	121	150	75	3	5215
UBS	469	771	219	4	10912		**HIT**	1031	988	762	3	7922
VAL	1324	1674	786	12	15050		**AGX**	3746	3797	2336	46	17399
Mean	***748.35***	***918***	***433.85***	***7***	***10047***		***Mean***	***934.2***	***1018***	***583.8***	***12***	***9268***

Table 2b.
Descriptives of raw durations computed using a fixed $ 1/16 price threshold for all stocks.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Duration (seconds)	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**			**Mean Duration (seconds)**	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**
AOL	164	265	107	3	14881		**WMT**	210	238	136	5	4092
ASF	865	1343	374	2	15581		**CCN**	1124	1300	715	18	10050
BEN	410	474	260	4	5859		**AOC**	588	726	364	4	10646
CI	187	233	117	4	4644		**UNH**	274	331	167	8	4212
CL	293	342	185	4	6501		**KO**	316	368	199	7	4984
CPQ	475	591	286	10	8082		**T**	619	865	347	10	14534
DCX	746	962	440	5	10508		**DOV**	479	590	281	4	5916
GMH	511	628	307	7	7445		**ALL**	389	481	236	7	7156
GT	640	803	366	5	8203		**GP**	459	542	279	4	5661
HAR	814	1011	492	4	11776		**PHM**	544	655	326	5	7200
KF	5333	5505	2878	60	20450		**APF**	6567	5295	4829	324	19680
LE	1041	1359	598	9	16092		**CLB**	1763	2120	1043	5	14705
LMT	392	535	231	6	14098		**MRO**	891	1216	487	7	20219
MLM	1022	1265	596	3	10341		**HTN**	937	1174	572	10	12251
RCL	888	1187	522	12	15987		**CNF**	846	1140	490	5	11799
S	461	602	273	7	14161		**NKE**	404	579	231	7	9633
SGY	527	655	298	5	7700		**AMG**	534	818	254	3	14380
STT	135	163	83	3	2246		**PKI**	212	240	134	4	3345
UBS	638	920	308	4	8703		**HIT**	1120	1192	784	4	8891
VAL	1020	1422	539	11	15182		**AGX**	4682	4642	2598	99	18536
Mean	***828.1095***	***1013***	***463***	***8***	***10922***		***Mean***	***1147.9***	***1226***	***723.6***	***27***	***10395***

Table 3a.
Characteristics of durations computed after calibrating the stock specific price threshold for all stocks.
Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE					MATCHED CONTROL SAMPLE				
	Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Percentage Price Threshold (%)		Number of Durations	Nominal Price Threshold ($)	Average Midquote Price	Percentage Price Threshold (%)
AOL	1806	0.28	47.21	0.5931	**WMT**	1523	0.25	50.47	0.4953
ASF	1408	0.15	36.09	0.4156	**CCN**	1341	0.03125	72.11	0.0433
BEN	1800	0.13	39.05	0.3329	**AOC**	1685	0.09375	34.67	0.2704
CI	1479	0.25	118.74	0.2105	**UNH**	1608	0.34375	103.62	0.3317
CL	1466	0.19	57.24	0.3319	**KO**	1264	0.21875	58.69	0.3727
CPQ	1302	0.15	23.46	0.6394	**T**	1082	0.15625	22.77	0.6862
DCX	1241	0.12	43.63	0.2750	**DOV**	1295	0.1875	40.93	0.4581
GMH	1413	0.14	27.06	0.5174	**ALL**	1127	0.1875	37.71	0.4972
GT	1312	0.07	19.7	0.3553	**GP**	1248	0.15625	27.04	0.5778
HAR	1338	0.15	37.68	0.3981	**PHM**	1462	0.15625	38.07	0.4104
KF	781	0.01	11.12	0.0899	**APF**	348	0.005	8.86	0.0564
LE	1081	0.13	25.13	0.5173	**CLB**	1081	0.0625	22.56	0.2770
LMT	1298	0.17	33.09	0.5138	**MRO**	1597	0.09375	27.61	0.3396
MLM	1336	0.09	38.52	0.2336	**HTN**	1247	0.09375	38.76	0.2419
RCL	1365	0.09	23.56	0.3820	**CNF**	1119	0.15625	29.26	0.5340
S	1126	0.16	33.15	0.4827	**NKE**	1287	0.15625	47.41	0.3296
SGY	1380	0.16	57.08	0.2803	**AMG**	1332	0.25	54.75	0.4566
STT	1279	0.42	121.05	0.3470	**PKI**	1328	0.625	100.34	0.6229
UBS	1392	0.19	148.83	0.1277	**HIT**	1294	0.0625	100.86	0.0620
VAL	1103	0.05	27.59	0.1812	**AGX**	570	0.005	48.79	0.0102
Mean	***1335***	***0.155***	***48.449***	***0.3612***	***Mean***	***1242***	***0.1645625***	***48.264***	***0.3537***

Table 3a.
Characteristics of durations computed with recalibrated price thresholds for the matched stocks.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE					MATCHED CONTROL SAMPLE				
	Number of Durations	**Nominal Price Threshold ($)**	**Average Midquote Price**	**Percentage Price Threshold (%)**		**Number of Durations**	**Nominal Price Threshold ($)**	**Average Midquote Price**	**Percentage Price Threshold (%)**
AOL	1268	0.28	44.31	0.63191	**WMT**	1437	0.20	50.51	0.39596
ASF	787	0.15	23.04	0.65104	**CCN**	845	0.02	67.67	0.02956
BEN	1646	0.13	41.39	0.31409	**AOC**	1514	0.09	34.48	0.26102
CI	1878	0.25	103.68	0.24113	**UNH**	1880	0.15	58.23	0.25760
CL	1145	0.19	55.78	0.34062	**KO**	1063	0.16	48.91	0.32713
CPQ	744	0.15	19.39	0.77359	**T**	733	0.14	21.97	0.63723
DCX	889	0.12	48.2	0.24896	**DOV**	847	0.17	38.21	0.44491
GMH	950	0.14	21.81	0.64191	**ALL**	942	0.16	41.24	0.38797
GT	2358	0.07	25.16	0.27822	**GP**	2026	0.10	30.62	0.32658
HAR	862	0.15	31.36	0.47832	**PHM**	910	0.16	39.04	0.40984
KF	631	0.01	10.15	0.09852	**APF**	592	0.004	8.38	0.04773
LE	789	0.13	28.72	0.45265	**CLB**	686	0.06	22.14	0.27100
LMT	1035	0.17	36.52	0.46550	**MRO**	1085	0.08	29.38	0.27229
MLM	1080	0.09	45.24	0.19894	**HTN**	1163	0.10	46.06	0.21711
RCL	1015	0.09	23.73	0.37927	**CNF**	1107	0.10	31.46	0.31786
S	902	0.16	37.17	0.43045	**NKE**	943	0.13	41.98	0.30967
SGY	1379	0.16	52.82	0.30292	**AMG**	1413	0.15	51.31	0.29234
STT	1049	0.42	96.99	0.43303	**PKI**	1056	0.32	67.18	0.47633
UBS	1104	0.19	148.18	0.12822	**HIT**	1135	0.06	91.08	0.06588
VAL	1951	0.05	30.75	0.16260	**AGX**	754	0.004	53.98	0.00741
Mean	***1173.1***	***0.155***	***46.2195***	***0.38259***	***Mean***	***1106.55***	***0.1179***	***43.6915***	***0.28777***

Table 3a.
Characteristics of durations computed with test-period calibrated stock specific price threshold for all stocks.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE					MATCHED CONTROL SAMPLE				
	Number of Durations	**Nominal Price Threshold ($)**	**Average Midquote Price**	**Percentage Price Threshold (%)**		**Number of Durations**	**Nominal Price Threshold ($)**	**Average Midquote Price**	**Percentage Price Threshold (%)**
AOL	1268	0.28	44.31	0.6319	**WMT**	954	0.25	50.44	0.4956
ASF	787	0.15	23.04	0.6510	**CCN**	646	0.03125	67.77	0.0461
BEN	1646	0.13	41.39	0.3141	**AOC**	1445	0.09375	34.47	0.2720
CI	1878	0.25	103.68	0.2411	**UNH**	477	0.34375	58.2	0.5906
CL	1145	0.19	55.78	0.3406	**KO**	620	0.21875	49.02	0.4462
CPQ	744	0.15	19.39	0.7736	**T**	552	0.15625	21.96	0.7115
DCX	889	0.12	48.2	0.2490	**DOV**	716	0.1875	38.26	0.4901
GMH	950	0.14	21.81	0.6419	**ALL**	690	0.1875	41.24	0.4547
GT	2358	0.07	25.16	0.2782	**GP**	962	0.15625	30.55	0.5115
HAR	862	0.15	31.36	0.4783	**PHM**	929	0.15625	39.03	0.4003
KF	631	0.01	10.15	0.0985	**APF**	480	0.005	8.39	0.0596
LE	789	0.13	28.72	0.4526	**CLB**	675	0.0625	22.11	0.2827
LMT	1035	0.17	36.52	0.4655	**MRO**	835	0.09375	29.43	0.3186
MLM	1080	0.09	45.24	0.1989	**HTN**	1220	0.09375	46.05	0.2036
RCL	1015	0.09	23.73	0.3793	**CNF**	564	0.15625	31.46	0.4967
S	902	0.16	37.17	0.4305	**NKE**	737	0.15625	41.83	0.3735
SGY	1379	0.16	52.82	0.3029	**AMG**	793	0.25	51.21	0.4882
STT	1049	0.42	96.99	0.4330	**PKI**	350	0.625	67.36	0.9279
UBS	1104	0.19	148.18	0.1282	**HIT**	1104	0.0625	91.14	0.0686
VAL	1951	0.05	30.75	0.1626	**AGX**	641	0.005	53.98	0.0093
Mean	***1173.1***	***0.155***	***46.2195***	***0.3826***	***Mean***	***769.5***	***0.1645625***	***43.695***	***0.3824***

Table 3b.
Descriptive statistics of the raw durations with calibrated stock specific price thresholds for all stocks.
Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Duration (seconds)	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**			**Mean Duration (seconds)**	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**
AOL	948	1242	563	5	13588		**WMT**	1042	1287	586	19	11579
ASF	966	1398	436	12	11685		**CCN**	766	966	441	6	17945
BEN	963	1225	541	8	11141		**AOC**	772	1083	420	6	16352
CI	568	753	330	11	7456		**UNH**	857	1251	464	19	17297
CL	1105	1323	662	14	15007		**KO**	1100	1281	694	16	13454
CPQ	1082	1485	595	19	16085		**T**	1082	1763	790	25	19024
DCX	1174	1578	627	9	15124		**DOV**	1271	1681	664	12	15609
GMH	968	1282	538	17	12631		**ALL**	1163	1657	617	11	18817
GT	943	1421	496	9	15561		**GP**	1172	1567	591	9	11770
HAR	1123	1531	643	6	18235		**PHM**	1095	1497	595	6	14828
KF	1773	2025	1121	23	16586		**APF**	3343	3402	2391	20	21579
LE	1507	2008	764	6	17728		**CLB**	1492	1955	848	5	20026
LMT	1252	1576	745	15	17540		**MRO**	979	1292	522	11	10734
MLM	1214	1443	728	7	18433		**HTN**	1398	1398	811	9	16247
RCL	1256	1824	630	9	17804		**CNF**	1403	1826	793	4	14090
S	1396	1724	787	17	12768		**NKE**	801	1137	444	16	13670
SGY	1264	1761	620	9	16981		**AMG**	1216	1839	549	9	14165
STT	782	1121	406	19	13222		**PKI**	1004	1419	564	13	20840
UBS	978	1501	443	8	15377		**HIT**	1031	988	763	3	7922
VAL	1133	1351	714	12	15050		**AGX**	2836	3250	1682	46	19310
Mean	***1119.75***	***1478.6***	***619.45***	***12***	***14900***		***Mean***	***1291.15***	***1626.95***	***761.45***	***13***	***15763***

Table 3b.
Descriptive statistics of the raw durations computed after re-calibrating the matched stock price thresholds.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Duration (seconds)	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**			**Mean Duration (seconds)**	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**
AOL	1249	1575	753	11	19391		**WMT**	1035	1200	653	10	16521
ASF	1733	2651	727	8	17452		**CCN**	709	878	423	13	7227
BEN	984	1219	595	17	17101		**AOC**	1249	1574	753	11	19391
CI	711	878	423	13	7227		**UNH**	745	921	448	20	11932
CL	1338	1710	777	17	15854		**KO**	1110	1409	674	14	13173
CPQ	1628	1993	1023	37	19234		**T**	1916	2439	1126	48	21975
DCX	1592	2031	871	9	15181		**DOV**	1683	2093	922	15	13841
GMH	1575	1936	865	16	13617		**ALL**	1514	1952	859	17	16954
GT	714	965	402	5	11216		**GP**	791	979	450	7	9475
HAR	1591	2055	937	5	15406		**PHM**	1459	1763	818	15	12163
KF	2594	2744	1775	9	16905		**APF**	2168	2155	1446	8	17400
LE	1990	2592	1087	17	18761		**CLB**	1721	2119	997	5	14705
LMT	1351	1793	743	13	18455		**MRO**	1225	1587	641	7	15486
MLM	1344	1854	737	6	15285		**HTN**	1349	1619	828	13	14183
RCL	1307	1704	727	14	13691		**CNF**	1320	1717	716	5	14705
S	1686	2249	860	10	16822		**NKE**	921	1355	513	12	15627
SGY	1108	1459	597	5	13214		**AMG**	1007	1595	451	8	15531
STT	1057	1441	586	18	15843		**PKI**	1090	1531	609	6	17166
UBS	1207	1821	580	5	16149		**HIT**	1097	1161	762	4	8891
VAL	881	1176	493	9	13647		**AGX**	2039	2307	1132	10	13288
Mean	***1382***	***1792***	***777.9***	***12***	***15523***		***Mean***	***1307***	***1618***	***761.05***	***12***	***14482***

Table 4.
Descriptive statistics of the normalized durations computed after calibrating the stock specific price threshold for all stocks.
Sample time period October 2, 2000 till January 26, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Stand. Duration	Duration Standard Deviation	Median	Min.	Max.			Mean Stand. Duration	Duration Standard Deviation	Median	Min.	Max.
AOL	1	1.2203	0.6424	0.0067	17.33		**WMT**	1	1.1594	0.627	0.0135	18.53
ASF	1	1.3516	0.5475	0.0083	20.16		**CCN**	1	1.1597	0.6516	0.0067	22.15
BEN	1	1.1164	0.6536	0.0112	13.96		**AOC**	1	1.2768	0.5959	0.0092	20.04
CI	1	1.166	0.5996	0.0187	9.43		**UNH**	1	1.337	0.6241	0.0101	30.02
CL	1	1.138	0.648	0.0168	16.90		**KO**	1	1.0548	0.7054	0.0238	10.43
CPQ	1	1.2451	0.6114	0.0186	15.83		**T**	1	1.1331	0.6064	0.0156	11.84
DCX	1	1.1926	0.6066	0.0093	13.78		**DOV**	1	1.297	0.5737	0.0083	18.57
GMH	1	1.1588	0.6255	0.0211	10.62		**ALL**	1	1.3407	0.5951	0.0078	22.41
GT	1	1.3027	0.5734	0.0156	13.89		**GP**	1	1.3088	0.5779	0.0111	16.83
HAR	1	1.2732	0.6358	0.0089	13.24		**PHM**	1	1.1912	0.611	0.0043	12.96
KF	1	0.9608	0.7101	0.0106	7.26		**APF**	1	0.8377	0.8595	0.0059	5.67
LE	1	1.2704	0.5901	0.0058	17.01		**CLB**	1	1.2145	0.6401	0.0032	18.32
LMT	1	1.1131	0.6442	0.0065	11.27		**MRO**	1	1.2263	0.6057	0.0067	16.06
MLM	1	1.0976	0.6964	0.0049	17.02		**HTN**	1	1.1492	0.6421	0.0067	12.46
RCL	1	1.2775	0.582	0.0059	14.85		**CNF**	1	1.1653	0.6193	0.0029	12.15
S	1	1.1373	0.6409	0.0098	10.65		**NKE**	1	1.2404	0.5897	0.0187	15.25
SGY	1	1.2577	0.5728	0.0045	11.75		**AMG**	1	1.3163	0.5389	0.0094	13.67
STT	1	1.3235	0.6006	0.0228	19.65		**PKI**	1	1.3161	0.6076	0.0168	23.93
UBS	1	1.2142	0.5936	0.0066	16.82		**HIT**	1	0.8892	0.7402	0.0024	7.24
VAL	1	1.0721	0.6958	0.0066	10.47		**AGX**	1	1.0216	0.6426	0.0129	7.05
Mean	***1***	***1.194445***	***0.62352***	***0.011***	***14.1***		***Mean***	***1***	***1.181755***	***0.63***	***0.010***	***15.78***

Table 4.
Descriptive statistics of the normalized durations computed after calibrating the stock specific price threshold for all stocks.
Sample time period February 8, 2001 till May 31, 2001.

PILOT DECIMAL SAMPLE							MATCHED CONTROL SAMPLE					
	Mean Stand. Duration	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**		**Mean Stand. Duration**	**Duration Standard Deviation**	**Median**	**Min.**	**Max.**
AOL	1	1.1403	0.6478	0.0127	16.67	**WMT**	1	1.0722	0.6708	0.0172	16.53
ASF	1	1.4655	0.4504	0.0057	15.16	**CCN**	1	1.0046	0.6724	0.0126	8.13
BEN	1	1.1623	0.6648	0.0152	13.49	**AOC**	1	1.1238	0.6747	0.0029	10.99
CI	1	1.1623	0.6393	0.0116	14.05	**UNH**	1	1.0424	0.6557	0.0151	10.82
CL	1	1.1523	0.6721	0.0132	14.43	**KO**	1	1.0709	0.6752	0.0120	11.48
CPQ	1	1.0302	0.6983	0.0177	8.56	**T**	1	1.2230	0.6427	0.0226	14.95
DCX	1	1.0661	0.6357	0.0088	8.06	**DOV**	1	1.0832	0.6491	0.0085	7.83
GMH	1	1.0675	0.6320	0.0112	8.19	**ALL**	1	1.1358	0.6151	0.0098	9.91
GT	1	1.1905	0.6357	0.0084	14.31	**GP**	1	1.0995	0.6375	0.0090	12.40
HAR	1	1.1457	0.6579	0.0031	10.62	**PHM**	1	1.0198	0.6755	0.0074	8.36
KF	1	0.9581	0.7707	0.0020	8.82	**APF**	1	0.9211	0.7084	0.0039	8.68
LE	1	1.2431	0.6277	0.0057	11.44	**CLB**	1	1.0592	0.6698	0.0048	8.54
LMT	1	1.1680	0.6407	0.0086	12.33	**MRO**	1	1.0879	0.6069	0.0142	9.28
MLM	1	1.3671	0.5862	0.0029	17.21	**HTN**	1	1.1144	0.6481	0.0071	12.12
RCL	1	1.1446	0.6307	0.0121	11.38	**CNF**	1	1.1497	0.6509	0.0020	16.45
S	1	1.1595	0.6081	0.0064	8.90	**NKE**	1	1.3135	0.5983	0.0155	14.94
SGY	1	1.1486	0.6585	0.0091	12.46	**AMG**	1	1.4723	0.5581	0.0052	21.05
STT	1	1.1769	0.5988	0.0186	13.19	**PKI**	1	1.1962	0.6172	0.0053	11.21
UBS	1	1.2816	0.5938	0.0066	11.74	**HIT**	1	0.9613	0.7244	0.0039	7.39
VAL	1	1.1691	0.6218	0.0100	12.96	**AGX**	1	0.9402	0.6791	0.0063	7.77
Mean	***1***	***1.169965***	***0.63355***	***0.009***	***12.20***	***Mean***	***1***	***1.10455***	***0.65***	***0.01***	***11.44***

Table 5.

Correlograms of the first 15 autocorrelations and partial autocorrelations of the raw and normalized durations.The correlations are computed for the dataset of all merged durations for ease of presentation. The durations for the 40 individual stocks, however exhibit the same autocorrelation pattern.

Q-statistics and p-values test the null of zero autocorrelation at the specified lag.

October 2, 2000 till January 26, 2001.				
Raw Durations				
	Autocorr.	Partial Corr.	Q-Stat	Prob
1	0.217	0.217	2418.4	*0.00*
2	0.135	0.092	3357.9	*0.00*
3	0.103	0.06	3909.4	*0.00*
4	0.088	0.047	4308.2	*0.00*
5	0.079	0.04	4627.9	*0.00*
6	0.063	0.024	4833.2	*0.00*
7	0.062	0.028	5032.7	*0.00*
8	0.072	0.039	5298.7	*0.00*
9	0.077	0.041	5607.6	*0.00*
10	0.082	0.042	5950	*0.00*
11	0.081	0.037	6284.4	*0.00*
12	0.072	0.026	6549	*0.00*
13	0.078	0.034	6860.3	*0.00*
14	0.082	0.036	7204.7	*0.00*
15	0.083	0.035	7557.2	*0.00*

February 8, 2001 till May 31, 2001.				
Raw Durations				
	Autocorr.	Partial Corr.	Q-Stat	Prob
1	0.224	0.224	2283.6	*0.00*
2	0.151	0.106	3317.2	*0.00*
3	0.112	0.062	3892.5	*0.00*
4	0.096	0.05	4316.8	*0.00*
5	0.085	0.041	4649.6	*0.00*
6	0.08	0.037	4941.3	*0.00*
7	0.079	0.037	5225.2	*0.00*
8	0.087	0.045	5573	*0.00*
9	0.082	0.036	5882.7	*0.00*
10	0.097	0.051	6310.5	*0.00*
11	0.09	0.037	6679.2	*0.00*
12	0.082	0.027	6982.4	*0.00*
13	0.09	0.039	7353.8	*0.00*
14	0.099	0.045	7799.6	*0.00*
15	0.093	0.034	8195.4	*0.00*

October 2, 2000 till January 26, 2001.				
Normalized Durations, adjusted for Time-of-day effects				
	Autocorr.	Partial Corr.	Q-Stat	Prob
1	0.145	0.145	1081.6	*0.00*
2	0.096	0.076	1553.9	*0.00*
3	0.079	0.057	1874.9	*0.00*
4	0.069	0.045	2120.6	*0.00*
5	0.066	0.042	2344.3	*0.00*
6	0.056	0.031	2506.8	*0.00*
7	0.053	0.029	2651.5	*0.00*
8	0.052	0.028	2792.5	*0.00*
9	0.058	0.034	2968.1	*0.00*
10	0.054	0.028	3118.7	*0.00*
11	0.045	0.018	3222.1	*0.00*
12	0.042	0.017	3312.8	*0.00*
13	0.049	0.025	3437.3	*0.00*
14	0.046	0.02	3545	*0.00*
15	0.041	0.015	3630.4	*0.00*

February 8, 2001 till May 31, 2001.				
Normalized Durations, adjusted for Time-of-day effects				
	Autocorr.	Partial Corr.	Q-Stat	Prob
1	0.143	0.143	938.11	*0.00*
2	0.106	0.087	1449.5	*0.00*
3	0.087	0.063	1798.5	*0.00*
4	0.083	0.057	2113.6	*0.00*
5	0.071	0.041	2340.6	*0.00*
6	0.064	0.035	2529.9	*0.00*
7	0.048	0.019	2635.9	*0.00*
8	0.055	0.029	2775.5	*0.00*
9	0.047	0.021	2878	*0.00*
10	0.059	0.033	3034.8	*0.00*
11	0.044	0.016	3123.8	*0.00*
12	0.04	0.013	3195.5	*0.00*
13	0.043	0.018	3279.3	*0.00*
14	0.047	0.022	3380.5	*0.00*
15	0.044	0.018	3469.1	*0.00*

Table 6a. ML estimation of a WACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $ENPTIME_{t} = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

	Decimal Pilot Stocks						
	ω	**α**	**β**	**δ**	**LogL**	**AIC**	**SIC**
AOL	0.086	0.180	0.740	-0.152	-1734.030	1.926	1.938
p-value	*0.040*	*0.000*	*0.000*	*0.085*			
ASF	0.325	0.125	0.661	-0.521	-1354.700	1.931	1.946
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
BEN	0.237	0.091	0.731	-0.503	-1769.049	1.971	1.983
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
CI	0.278	0.116	0.720	-0.275	-1419.094	1.926	1.940
p-value	*0.000*	*0.010*	*0.000*	*0.118*			
CL	0.726	0.131	0.252	-0.920	-1434.295	1.964	1.978
p-value	*0.000*	*0.000*	*0.052*	*0.000*			
CPQ	0.110	0.051	0.868	-0.459	-1225.029	1.889	1.905
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
DCX	0.132	0.164	0.734	-0.182	-1188.828	1.924	1.940
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
GMH	1.351	-0.003	-0.155	-2.891	-1370.299	1.947	1.961
p-value	*NA*	*NA*	*NA*	*NA*			
GT	0.882	0.158	0.108	-1.600	-1262.509	1.932	1.948
p-value	*0.000*	*0.000*	*0.258*	*0.000*			
HAR	0.229	0.117	0.726	-0.285	-1280.763	1.922	1.937
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
KF	0.139	0.156	0.737	-0.396	-753.014	1.941	1.965
p-value	*0.002*	*0.000*	*0.000*	*0.152*			
LE	0.611	0.179	0.496	-1.524	-1032.204	1.919	1.937
p-value	*0.117*	*0.213*	*0.141*	*0.200*			
LMT	0.187	0.070	0.802	-0.402	-1272.434	1.968	1.984
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
MLM	0.572	0.108	0.418	-0.610	-1312.363	1.972	1.988
p-value	*0.000*	*0.001*	*0.000*	*0.000*			
RCL	0.590	0.103	0.649	-1.735	-1255.476	1.847	1.862
p-value	*0.000*	*0.003*	*0.000*	*0.000*			
S	0.118	0.066	0.848	-0.311	-1082.548	1.932	1.950
p-value	*0.000*	*0.001*	*0.000*	*0.000*			
SGY	0.583	0.141	0.457	-0.721	-1298.817	1.890	1.905
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
STT	0.135	0.098	0.829	-0.228	-1242.702	1.951	1.967
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
UBS	0.252	0.241	0.557	-0.160	-1306.546	1.884	1.899
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
VAL	0.487	-0.153	0.615	-1.300	-1043.372	1.901	1.919
p-value	*0.197*	*0.343*	*0.069*	*0.273*			
Mean	**0.402**	**0.107**	**0.590**	**-0.76**	**-1281.9**	**1.927**	**1.943**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6a. ML estimation of a EACD(1,1) model. Sample time period October 2, 2000 (cont'd) till January 26, 2001.

Model is*: $ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

	Matched Control Stocks						
	ω	α	β	δ	LogL	AIC	SIC
WMT	0.484	0.208	0.461	-0.716	-1452.202	1.914	1.928
p-value	*0.000*	*0.000*	*0.000*	*0.002*			
CCN	0.384	0.437	0.231	-0.150	-1215.002	1.819	1.835
p-value	*0.000*	*0.000*	*0.000*	*0.040*			
AOC	0.241	0.132	0.739	-0.744	-1598.153	1.903	1.916
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
UNH	0.116	0.125	0.811	-0.239	-1528.452	1.907	1.921
p-value	*0.000*	*0.000*	*0.000*	*0.003*			
KO	0.088	0.052	0.884	-0.208	-1251.545	1.988	2.004
p-value	*0.030*	*0.001*	*0.000*	*0.216*			
T	0.197	0.075	0.865	-1.243	-1011.142	1.878	1.897
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
DOV	0.439	0.270	0.486	-1.054	-1234.298	1.914	1.930
p-value	*0.025*	*0.000*	*0.004*	*0.105*			
ALL	0.349	0.157	0.640	-0.959	-1072.465	1.912	1.930
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
GP	0.195	0.059	0.850	-0.757	-1203.358	1.936	1.953
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
PHM	0.271	0.087	0.771	-0.480	-2086.811	2.862	2.877
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
APF	1.237	0.122	-0.092	-2.904	-338.590	1.975	2.019
p-value	*0.003*	*0.220*	*0.819*	*0.024*			
CLB	0.395	0.353	0.383	-0.509	-1024.613	1.905	1.923
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
MRO	0.346	0.098	0.697	-1.296	-1552.556	1.951	1.964
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
HTN	0.193	0.100	0.801	-0.538	-1200.727	1.934	1.950
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
CNF	0.100	0.100	0.858	-0.306	-1183.623	2.125	2.143
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
NKE	0.416	0.151	0.602	-0.953	-1273.585	1.987	2.003
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
AMG	0.793	0.126	0.314	-0.934	-1258.076	1.896	1.912
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
PKI	0.172	0.077	0.818	-0.157	-1279.550	1.935	1.950
p-value	*0.000*	*0.000*	*0.000*	*0.000*			
HIT	0.343	0.255	0.465	-0.128	-1245.440	1.933	1.949
p-value	*0.000*	*0.000*	*0.000*	*0.058*			
AGX	0.516	0.262	0.241	-0.127	-548.021	1.940	1.971
p-value	*0.001*	*0.000*	*0.162*	*0.654*			
Mean	**0.364**	**0.162**	**0.591**	**-0.72**	**-1227.91**	**1.981**	**1.999**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6b. ML estimation of a WACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

	Decimal Pilot Stocks							
	ω	**α**	**β**	**δ**	**γ**	**LogL**	**AIC**	**SIC**
AOL	0.041	0.094	0.879	-0.074	1.074	-1670.7	1.857	1.872
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
ASF	0.164	0.080	0.808	-0.245	0.939	-1373.9	1.960	1.979
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
BEN	0.223	0.088	0.745	-0.471	1.055	-1784.2	1.989	2.004
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
CI	2.263	0.029	-0.569	-0.637	1.052	-1406.9	1.911	1.928
p-value	*0.000*	*0.497*	*0.085*	*0.106*	*0.000*			
CL	0.779	0.102	0.286	-1.201	1.065	-1423.7	1.950	1.968
p-value	*0.000*	*0.002*	*0.026*	*0.000*	*0.000*			
CPQ	0.090	0.060	0.888	-0.430	1.056	-1453.9	2.243	2.263
p-value	*0.000*	*0.015*	*0.000*	*0.000*	*0.000*			
DCX	0.133	0.164	0.734	-0.183	0.998	-1188.8	1.926	1.946
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
GMH	0.868	0.022	0.169	-2.607	0.883	-1701.2	2.417	2.435
p-value	*NA*	*NA*	*NA*	*NA*	*NA*			
GT	0.685	0.211	0.272	-1.755	1.029	-1647.1	2.520	2.540
p-value	*0.335*	*0.418*	*0.672*	*0.116*	*0.000*			
HAR	0.348	0.087	0.688	-0.540	0.986	-1458.4	2.189	2.208
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
KF	0.137	0.150	0.744	-0.394	1.123	-744.4	1.922	1.951
p-value	*0.000*	*0.000*	*0.000*	*0.076*	*0.000*			
LE	0.608	0.173	0.509	-1.552	1.110	-1577.6	2.931	2.954
p-value	*0.056*	*0.141*	*0.064*	*0.139*	*0.000*			
LMT	0.184	0.069	0.806	-0.398	1.045	-1270.1	1.966	1.986
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
MLM	0.405	0.109	0.542	-0.341	1.029	-1313.3	1.975	1.994
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
RCL	0.591	0.105	0.646	-1.736	0.965	-1422.3	2.093	2.112
p-value	*0.000*	*0.006*	*0.000*	*0.000*	*0.000*			
S	0.117	0.065	0.850	-0.309	1.042	-1080.9	1.930	1.953
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
SGY	0.416	0.164	0.530	-0.412	0.902	-1358.2	1.977	1.996
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
STT	0.088	0.069	0.872	-0.096	0.989	-1231.8	1.936	1.956
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
UBS	0.259	0.248	0.546	-0.170	0.948	-1302.9	1.880	1.899
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
VAL	0.667	-0.146	0.376	-1.733	1.119	-4514.5	8.202	8.225
p-value	*0.017*	*0.293*	*0.079*	*0.200*	*0.000*			
Mean	**0.453**	**0.097**	**0.566**	**-0.76**	**1.021**	**-1546**	**2.389**	**2.409**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6b. (cont'd) ML estimation of a WACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$$

	Matched Control Stocks							
	ω	α	β	δ	γ	LogL	AIC	SIC
WMT	0.692	0.201	0.397	-1.559	1.059	-1774.35	2.338	2.356
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
CCN	0.388	0.429	0.234	-0.149	1.055	-1211.66	1.816	1.835
p-value	*0.000*	*0.000*	*0.000*	*0.025*	*0.000*			
AOC	0.237	0.131	0.742	-0.736	1.021	-1597.40	1.903	1.919
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
UNH	0.110	0.124	0.815	-0.225	1.051	-1524.77	1.904	1.921
p-value	*0.000*	*0.000*	*0.000*	*0.002*	*0.000*			
KO	0.075	0.052	0.893	-0.159	1.114	-1238.67	1.969	1.990
p-value	*0.014*	*0.000*	*0.000*	*0.236*	*0.000*			
T	0.195	0.074	0.868	-1.239	1.102	-1002.26	1.864	1.887
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
DOV	0.570	0.246	0.342	-0.813	1.001	-1231.61	1.911	1.931
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
ALL	0.347	0.158	0.641	-0.956	1.013	-1072.30	1.913	1.936
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
GP	0.175	0.039	0.890	-0.762	0.951	-1192.38	1.920	1.941
p-value	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*			
PHM	0.336	0.077	0.744	-0.578	1.000	-1350.51	1.856	1.874
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
APF	1.272	0.111	-0.125	-2.856	1.219	-328.75	1.924	1.979
p-value	*0.000*	*0.105*	*0.665*	*0.001*	*0.000*			
CLB	0.445	0.369	0.338	-0.603	0.946	-1021.57	1.901	1.924
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
MRO	0.284	0.091	0.753	-1.188	0.975	-1552.43	1.952	1.969
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
HTN	0.198	0.101	0.798	-0.551	0.977	-1200.11	1.934	1.955
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
CNF	0.236	0.154	0.746	-0.668	0.997	-1051.41	1.890	1.912
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
NKE	0.510	0.167	0.490	-1.040	1.038	-1304.26	2.036	2.056
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
AMG	0.792	0.133	0.303	-0.929	0.893	-1286.24	1.940	1.960
p-value	*0.000*	*0.001*	*0.002*	*0.000*	*0.000*			
PKI	0.169	0.076	0.821	-0.154	1.004	-1279.53	1.936	1.956
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
HIT	0.306	0.231	0.520	-0.117	1.188	-1216.15	1.889	1.909
p-value	*0.000*	*0.000*	*0.000*	*0.012*	*0.000*			
AGX	0.508	0.252	0.258	-0.114	1.085	-544.81	1.933	1.971
p-value	*0.000*	*0.000*	*0.092*	*0.649*	*0.000*			
Mean	**0.392**	**0.161**	**0.573**	**-0.770**	**1.034**	**-1199.1**	**1.936**	**1.959**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6c. (cont'd) ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

	Decimal Pilot Stocks							
	ω	α	β	δ	γ	LogL	AIC	SIC
AOL	0.058	0.069	0.896	-0.190	1.082	-1655.7	1.840	1.855
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
ASF	0.385	0.167	0.193	-1.509	0.878	-1289.9	1.841	1.859
p-value	*0.000*	*0.000*	*0.025*	*0.000*	*0.000*			
BEN	0.090	0.104	0.649	-0.367	1.043	-1762.7	1.965	1.981
p-value	*0.000*	*0.000*	*0.000*	*0.005*	*0.000*			
CI	0.165	0.126	0.653	-0.321	1.045	-1393.2	1.892	1.910
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
CL	0.019	0.036	0.930	-0.028	1.062	-1439.2	1.972	1.990
p-value	*0.002*	*0.000*	*0.000*	*0.560*	*0.000*			
CPQ	0.265	0.176	0.437	-2.118	1.039	-1202.1	1.856	1.875
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
DCX	0.067	0.123	0.762	-0.052	1.001	-1185.0	1.919	1.940
p-value	*0.000*	*0.000*	*0.000*	*0.412*	*0.000*			
GMH	0.220	0.155	0.446	-1.464	1.046	-1348.7	1.917	1.936
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
GT	0.285	0.186	0.116	-2.325	0.965	-1247.1	1.910	1.930
p-value	*0.000*	*0.000*	*0.154*	*0.000*	*0.000*			
HAR	0.397	0.180	0.006	-1.393	0.998	-1231.8	1.850	1.870
p-value	*0.000*	*0.000*	*0.931*	*0.000*	*0.000*			
KF	0.053	0.094	0.828	-0.199	1.135	-737.7	1.904	1.934
p-value	*0.009*	*0.000*	*0.000*	*0.414*	*0.000*			
LE	0.225	0.202	0.425	-0.870	0.966	-1010.3	1.880	1.903
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
LMT	0.087	0.059	0.813	-0.405	1.046	-1271.0	1.968	1.988
p-value	*0.000*	*0.000*	*0.000*	*0.002*	*0.000*			
MLM	0.165	0.112	0.402	-0.723	1.034	-1303.0	1.960	1.979
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
RCL	0.117	0.089	0.828	-0.461	0.963	-1264.5	1.861	1.881
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
S	0.088	0.068	0.844	-0.562	1.044	-1077.8	1.925	1.947
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
SGY	0.299	0.144	0.352	-1.138	0.923	-1290.3	1.879	1.898
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
STT	0.040	0.052	0.916	-0.054	0.995	-1224.9	1.925	1.945
p-value	*0.000*	*0.000*	*0.000*	*0.085*	*0.000*			
UBS	0.116	0.177	0.590	-0.104	0.948	-1300.0	1.876	1.895
p-value	*0.000*	*0.000*	*0.000*	*0.169*	*0.000*			
VAL	0.194	0.169	0.488	-1.139	1.084	-1024.0	1.868	1.890
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
Mean	**0.167**	**0.124**	**0.579**	**-0.771**	**1.015**	**-1262.9**	**1.900**	**1.920**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6c. (cont'd) ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \delta Spread_{t-1}$

	Matched Control Stocks							
	ω	α	β	δ	γ	LogL	AIC	SIC
WMT	0.242	0.177	0.508	-1.224	1.088	-1439.0	1.897	1.915
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
CCN	0.130	0.274	0.285	-0.117	1.044	-1220.3	1.829	1.848
p-value	*0.000*	*0.000*	*0.000*	*0.304*	*0.000*			
AOC	0.188	0.120	0.728	-0.921	1.025	-1590.7	1.895	1.911
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
UNH	0.084	0.106	0.830	-0.181	1.048	-1523.0	1.902	1.918
p-value	*0.000*	*0.000*	*0.000*	*0.043*	*0.000*			
KO	0.014	0.033	0.940	-0.005	1.116	-1237.5	1.968	1.988
p-value	*0.307*	*0.000*	*0.000*	*0.965*	*0.000*			
T	0.206	0.073	0.859	-1.643	1.101	-1000.7	1.861	1.884
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
DOV	0.286	0.194	0.567	-1.169	0.990	-1198.6	1.860	1.880
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
ALL	0.234	0.159	0.615	-1.132	1.019	-1065.4	1.901	1.924
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
GP	0.332	0.096	0.657	-2.147	0.979	-1174.7	1.892	1.913
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
PHM	0.306	0.147	0.530	-1.191	0.971	-1352.1	1.858	1.876
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
APF	0.289	0.061	-0.147	-3.031	1.216	-329.1	1.925	1.981
p-value	*0.025*	*0.065*	*0.641*	*0.006*	*0.000*			
CLB	0.350	0.286	0.063	-1.129	0.961	-997.2	1.856	1.879
p-value	*0.000*	*0.000*	*0.397*	*0.000*	*0.000*			
MRO	0.214	0.103	0.656	-1.537	0.980	-1549.7	1.948	1.965
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
HTN	0.109	0.072	0.814	-0.422	0.976	-1201.7	1.937	1.957
p-value	*0.000*	*0.000*	*0.000*	*0.002*	*0.000*			
CNF	0.123	0.095	0.837	-0.424	1.001	-1039.5	1.869	1.891
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
NKE	0.358	0.144	0.452	-1.773	0.997	-1207.7	1.886	1.906
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
AMG	0.340	0.117	0.437	-1.132	0.888	-1242.8	1.875	1.894
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
PKI	0.060	0.054	0.893	-0.081	1.005	-1280.0	1.937	1.956
p-value	*0.000*	*0.000*	*0.000*	*0.020*	*0.000*			
HIT	0.085	0.148	0.584	-0.069	1.185	-1219.1	1.893	1.913
p-value	*0.001*	*0.000*	*0.000*	*0.198*	*0.000*			
AGX	0.029	0.166	0.352	0.205	1.075	-547.1	1.941	1.979
p-value	*0.618*	*0.000*	*0.012*	*0.525*	*0.000*			
Mean	**0.199**	**0.131**	**0.573**	**-0.956**	**1.033**	**-1171**	**1.896**	**1.919**

* ENPTIME = exp. duration, NPTIME = norm. duration, Spread = nominal spread.

Table 6d. Model*: $ENPTIME_{t} = \omega + \alpha_{1} NPTIME_{t-1} + \beta_{1} ENPTIME_{t-1} + \delta Spread_{t-1}$

Gamma coefficients from the Weibull ACD(1,1) and the Weibull-Logarithmic ACD(1,1) models
with lagged spread as the only exogenous variable. Sample period October 2, 2000 till January 26, 2001.
The goodness of the Weibull distributional assumption in both cases can be tested by H_0: γ=1, which describes
the nested exponential distribution.

PILOT DECIMAL SAMPLE				
	WACD(1,1) H_0: γ=1		**Log-WACD(1,1) H_0: γ=1**	
	γ	**p-value**	**γ**	**p-value**
AOL	1.0744	*0.0000*	1.0819	*0.0000*
ASF	0.9389	*0.0047*	0.8783	*0.0000*
BEN	1.0548	*0.0073*	1.0433	*0.0170*
CI	1.0522	*0.4188*	1.0448	*0.0400*
CL	1.0653	*0.0059*	1.0623	*0.0010*
CPQ	1.0557	*0.1064*	1.0388	*0.0411*
DCX	0.9979	*0.9135*	1.0008	*0.9663*
GMH	0.8835	*NA*	1.0458	*0.0362*
GT	1.0292	*0.8024*	0.9653	*0.0856*
HAR	0.9860	*0.7080*	0.9983	*0.9238*
KF	1.1228	*0.0001*	1.1353	*0.0000*
LE	1.1097	*0.2829*	0.9663	*0.1177*
LMT	1.0454	*0.0285*	1.0456	*0.0337*
MLM	1.0292	*0.1240*	1.0336	*0.0759*
RCL	0.9651	*0.2888*	0.9634	*0.0536*
S	1.0420	*0.0680*	1.0445	*0.0590*
SGY	0.9022	*0.0000*	0.9232	*0.0000*
STT	0.9893	*0.5488*	0.9946	*0.7795*
UBS	0.9481	*0.0095*	0.9477	*0.0099*
VAL	1.1188	*0.3667*	1.0839	*0.0010*
Number of rejections at 5%		***8***		***12***
Number of rejections at 10%		***9***		***16***

MATCHED CONTROL SAMPLE				
	WACD(1,1) H_0: γ=1		**Log-WACD(1,1) H_0: γ=1**	
	γ	**p-value**	**γ**	**p-value**
WMT	1.0588	*0.0085*	1.0876	*0.000*
CCN	1.0554	*0.0071*	1.0443	*0.0278*
AOC	1.0208	*0.2301*	1.0246	*0.1657*
UNH	1.0509	*0.0047*	1.0477	*0.0077*
KO	1.1140	*0.0000*	1.1155	*0.0000*
T	1.1018	*0.0001*	1.1014	*0.0001*
DOV	1.0005	*0.9771*	0.9903	*0.6033*
ALL	1.0126	*0.5278*	1.0193	*0.3594*
GP	0.9510	*0.021*	0.9789	*0.2542*
PHM	0.9995	*0.9861*	0.9715	*0.1244*
APF	1.2187	*0.0000*	1.2162	*0.0000*
CLB	0.9458	*0.0055*	0.9610	*0.0249*
MRO	0.9750	*0.1471*	0.9804	*0.2620*
HTN	0.9766	*0.2347*	0.9755	*0.2145*
CNF	0.9972	*0.9135*	1.0010	*0.9662*
NKE	1.0384	*0.0958*	0.9969	*0.8849*
AMG	0.8927	*0.0000*	0.8880	*0.0000*
PKI	1.0040	*0.8200*	1.0048	*0.7898*
HIT	1.1883	*0.0000*	1.1853	*0.0000*
AGX	1.0853	*0.0222*	1.0748	*0.0423*
Number of rejections at 5%		***11***		***10***
Number of rejections at 10%		***12***		***10***

* Where ENPTIME is the conditional expected normalized duration, NPTIME is the normalized actual duration, and SPREAD is nominal spread associated with the particular duration.

Table 7a. ML Estimation of an Exponential ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
AOL	0.210	0.107	0.853	-0.039	-0.027	-0.296	0.013	0.000	0.278	-0.142	-1662.33	1.85	1.88
p-value	*0.010*	*0.000*	*0.000*	*0.000*	*0.006*	*0.000*	*0.098*	*0.099*	*0.001*	*0.001*			
ASF	1.213	0.341	-0.097	-0.249	0.038	-1.219	0.013	-0.019	-1.406	-1.245	-1337.98	1.92	1.95
p-value	*0.234*	*0.042*	*0.740*	*0.118*	*0.820*	*0.022*	*0.892*	*0.253*	*0.364*	*0.171*			
BEN	0.625	0.158	0.617	-0.011	-0.026	-0.256	-0.051	-0.002	-0.491	0.683	-1759.09	1.97	2.00
p-value	*0.000*	*0.000*	*0.000*	*0.516*	*0.082*	*0.000*	*0.000*	*0.151*	*0.002*	*0.000*			
CI	1.023	0.237	0.228	-0.290	-0.001	-0.962	-0.001	-0.012	1.072	-1.145	-1413.71	1.93	1.96
p-value	*0.367*	*0.111*	*0.324*	*0.158*	*0.994*	*0.043*	*0.995*	*0.149*	*0.439*	*0.047*			
CL	0.179	0.053	0.884	-0.007	0.014	-0.757	-0.007	0.000	-0.765	-0.069	-1429.01	1.96	2.00
p-value	*0.005*	*0.003*	*0.000*	*0.470*	*0.178*	*0.000*	*0.474*	*0.400*	*0.000*	*0.395*			
CPQ	0.291	0.099	0.745	-0.063	-0.014	-0.619	0.002	0.000	0.070	0.038	-1217.54	1.89	1.93
p-value	*0.012*	*0.000*	*0.000*	*0.000*	*0.311*	*0.000*	*0.893*	*0.258*	*0.784*	*0.795*			
DCX	0.812	0.097	0.743	0.074	-0.050	0.177	-0.002	0.001	-2.376	-0.252	-1172.42	1.91	1.95
p-value	*0.000*	*0.017*	*0.000*	*0.001*	*0.015*	*0.418*	*0.922*	*0.460*	*0.000*	*0.285*			
GMH	0.347	0.193	0.588	-0.065	0.002	-0.468	0.000	-0.002	-0.081	-0.120	-1533.46	2.19	2.22
p-value	*0.840*	*0.575*	*0.374*	*0.846*	*0.994*	*0.824*	*0.999*	*0.886*	*0.982*	*0.971*			
GT	0.486	0.309	0.490	0.064	0.013	-1.020	0.004	-0.009	-2.816	0.207	-1257.37	1.93	1.97
p-value	*0.335*	*0.017*	*0.003*	*0.344*	*0.845*	*0.122*	*0.909*	*0.036*	*0.139*	*0.839*			
HAR	0.202	-0.042	0.921	0.005	-0.009	-0.623	0.013	0.007	-1.284	1.529	-1254.42	1.89	1.93
p-value	*0.000*	*0.046*	*0.000*	*0.868*	*0.602*	*0.012*	*0.383*	*0.000*	*0.006*	*0.000*			
KF	0.342	0.168	0.718	0.000	-0.033	-0.748	0.038	-0.025	-1.293	-1.456	-737.33	1.92	1.98
p-value	*0.084*	*0.000*	*0.000*	*0.991*	*0.129*	*0.227*	*0.087*	*0.006*	*0.251*	*0.142*			
LE	-0.202	0.081	1.043	0.124	0.105	0.524	-0.053	-0.028	-1.832	1.295	-1112.64	2.08	2.13
p-value	*0.885*	*0.507*	*0.000*	*0.525*	*0.597*	*0.806*	*0.583*	*0.027*	*0.230*	*0.133*			
LMT	0.751	0.371	0.233	-0.093	0.017	-1.055	0.001	-0.005	-1.455	0.301	-1275.14	1.98	2.02
p-value	*0.029*	*0.005*	*0.099*	*0.223*	*0.623*	*0.008*	*0.982*	*0.176*	*0.025*	*0.330*			
MLM	0.116	0.610	0.413	-0.027	0.054	-0.933	-0.064	-0.021	-0.623	0.798	-1296.61	1.96	2.00
p-value	*0.805*	*0.001*	*0.005*	*0.802*	*0.354*	*0.096*	*0.174*	*0.113*	*0.546*	*0.301*			
RCL	0.317	0.154	0.793	-0.046	-0.009	-0.491	0.010	-0.008	-0.853	0.189	-1252.90	1.85	1.89
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.335*	*0.000*	*0.335*	*0.000*	*0.000*	*0.196*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a. cont'd ML Estimation of an Exponential ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
S	0.307	-0.027	0.919	-0.089	-0.011	-0.685	-0.019	0.001	-0.071	0.037	-1082.13	1.94	1.99
p-value	*0.451*	*0.763*	*0.000*	*0.099*	*0.860*	*0.330*	*0.577*	*0.625*	*0.960*	*0.923*			
SGY	0.637	0.187	0.488	-0.007	-0.017	-0.903	0.013	-0.015	-0.496	0.413	-1321.93	1.93	1.97
p-value	*0.325*	*0.049*	*0.021*	*0.946*	*0.866*	*0.000*	*0.743*	*0.251*	*0.537*	*0.222*			
STT	0.017	0.042	0.920	-0.022	0.002	-0.822	0.014	0.001	-0.024	-0.093	-1286.23	2.03	2.07
p-value	*0.895*	*0.052*	*0.000*	*0.138*	*0.924*	*0.000*	*0.076*	*0.300*	*0.866*	*0.019*			
UBS	0.107	0.116	0.849	0.011	-0.004	-0.295	-0.006	-0.002	-0.163	0.216	-1290.56	1.87	1.91
p-value	*0.113*	*0.000*	*0.000*	*0.311*	*0.689*	*0.000*	*0.333*	*0.088*	*0.199*	*0.000*			
VAL	1.116	0.087	0.415	-0.291	-0.142	-1.559	0.129	-0.021	2.086	-0.526	-1100.78	2.02	2.06
p-value	*0.359*	*0.765*	*0.571*	*0.375*	*0.444*	*0.420*	*0.452*	*0.375*	*0.551*	*0.798*			
Mean	**0.445**	**0.167**	**0.638**	**-0.051**	**-0.005**	**-0.651**	**0.002**	**-0.01**	**-0.63**	**0.033**	**-1289.68**	**1.95**	**1.99**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a. cont'd. ML Estimation of an Exponential ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
WMT	1.234	0.199	0.476	-0.045	-0.066	-0.805	-0.011	0.000	1.000	-0.133	*-1455.01*	*1.93*	1.96
p-value	*0.001*	*0.005*	*0.000*	*0.488*	*0.194*	*0.015*	*0.721*	*0.958*	*0.372*	*0.594*			
CCN	1.665	0.373	0.233	-0.482	-0.020	-0.410	-0.204	-0.141	1.082	-0.850	*-1196.414*	*1.801*	*1.839*
p-value	*0.090*	*0.058*	*0.403*	*0.167*	*0.894*	*0.432*	*0.249*	*0.188*	*0.723*	*0.744*			
AOC	0.360	0.147	0.751	-0.054	0.000	-1.326	-0.014	-0.003	-1.018	0.090	-1584.80	1.89	*1.93*
p-value	*0.000*	*0.000*	*0.000*	*0.016*	*0.979*	*0.000*	*0.187*	*0.094*	*0.001*	*0.598*			
UNH	0.294	0.101	0.820	-0.028	-0.005	-0.616	-0.013	0.001	-0.427	0.157	-1519.48	1.90	*1.94*
p-value	*0.010*	*0.000*	*0.000*	*0.181*	*0.715*	*0.000*	*0.255*	*0.306*	*0.007*	*0.006*			
KO	0.366	0.066	0.857	-0.008	-0.010	-0.936	0.017	-0.001	-0.882	-0.390	*-1242.43*	*1.98*	2.02
p-value	*0.061*	*0.013*	*0.000*	*0.781*	*0.552*	*0.028*	*0.171*	*0.221*	*0.195*	*0.002*			
T	0.614	0.038	0.670	-0.094	0.046	-1.664	-0.028	0.000	-3.441	-0.106	*-1001.62*	*1.87*	1.92
p-value	*0.267*	*0.709*	*0.000*	*0.305*	*0.446*	*0.138*	*0.428*	*0.815*	*0.031*	*0.849*			
DOV	0.158	0.185	0.731	-0.094	0.021	-0.694	-0.010	-0.002	-0.400	0.407	-1222.47	1.90	*1.94*
p-value	*0.136*	*0.000*	*0.000*	*0.000*	*0.135*	*0.000*	*0.386*	*0.043*	*0.124*	*0.001*			
ALL	0.432	0.095	0.817	-0.017	-0.025	-0.979	0.019	-0.001	-0.775	-0.227	*-1062.64*	*1.91*	1.95
p-value	*0.002*	*0.001*	*0.000*	*0.471*	*0.075*	*0.000*	*0.120*	*0.205*	*0.049*	*0.126*			
GP	0.642	0.101	0.707	-0.146	-0.001	-1.527	-0.016	-0.001	-1.304	0.201	-1194.65	1.93	*1.97*
p-value	*0.006*	*0.019*	*0.000*	*0.002*	*0.967*	*0.001*	*0.452*	*0.669*	*0.072*	*0.394*			
PHM	0.400	0.105	0.755	-0.188	0.017	-0.982	-0.016	-0.004	-0.266	-0.168	*-1412.12*	*1.95*	1.98
p-value	*0.164*	*0.005*	*0.000*	*0.000*	*0.652*	*0.000*	*0.582*	*0.256*	*0.591*	*0.506*			
APF	1.727	0.203	0.011	-0.122	-0.088	-1.635	-0.027	-0.009	1.039	-3.935	-335.73	1.99	*2.10*
p-value	*0.013*	*0.094*	*0.969*	*0.540*	*0.047*	*0.263*	*0.732*	*0.644*	*0.799*	*0.185*			
CLB	0.792	0.299	0.190	-0.066	-0.051	-0.706	0.177	-0.041	-1.866	-0.594	-994.47	1.86	*1.91*
p-value	*0.021*	*0.000*	*0.160*	*0.633*	*0.293*	*0.217*	*0.006*	*0.044*	*0.008*	*0.346*			
MRO	0.140	0.072	0.894	-0.048	-0.012	-2.190	0.039	-0.003	-0.878	0.022	*-1520.64*	*1.92*	1.95
p-value	*0.043*	*0.000*	*0.000*	*0.032*	*0.185*	*0.000*	*0.000*	*0.000*	*0.081*	*0.903*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a. cont'd. ML Estimation of an Exponential ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
HTN	0.593	0.109	0.708	-0.114	-0.014	-0.882	-0.008	-0.005	-1.258	0.313	*-1189.52*	*1.93*	1.97
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.436*	*0.000*	*0.595*	*0.028*	*0.000*	*0.092*			
CNF	0.470	0.150	0.792	-0.091	-0.034	-0.829	0.009	-0.006	-0.308	0.319	-1031.49	1.86	1.91
p-value	*0.005*	*0.000*	*0.000*	*0.020*	*0.148*	*0.000*	*0.626*	*0.008*	*0.291*	*0.091*			
NKE	1.074	0.185	0.340	-0.255	0.071	-1.394	-0.048	-0.004	-3.418	1.075	-1199.45	1.88	*1.92*
p-value	*0.019*	*0.004*	*0.010*	*0.003*	*0.138*	*0.000*	*0.182*	*0.204*	*0.000*	*0.002*			
AMG	1.583	0.169	0.030	-0.379	-0.010	-1.155	-0.095	0.002	-0.531	0.251	-1252.74	1.90	*1.94*
p-value	*0.001*	*0.011*	*0.844*	*0.000*	*0.849*	*0.000*	*0.007*	*0.804*	*0.232*	*0.214*			
PKI	0.058	0.059	0.880	-0.012	-0.003	-0.130	-0.039	0.000	0.240	-0.086	-1279.26	1.94	*1.98*
p-value	*0.824*	*0.032*	*0.000*	*0.764*	*0.911*	*0.264*	*0.005*	*0.828*	*0.352*	*0.178*			
HIT	0.868	0.305	0.337	-0.017	-0.097	-0.004	0.083	-0.037	-0.297	-0.069	-1226.52	1.91	*1.95*
p-value	*0.000*	*0.000*	*0.001*	*0.683*	*0.000*	*0.971*	*0.021*	*0.000*	*0.156*	*0.728*			
AGX	0.652	0.259	0.256	0.057	-0.061	-0.446	0.065	-0.026	-0.112	0.434	-541.48	1.94	*2.01*
p-value	*0.020*	*0.000*	*0.083*	*0.498*	*0.105*	*0.277*	*0.037*	*0.029*	*0.891*	*0.639*			
Mean	**0.706**	**0.161**	**0.563**	**-0.110**	**-0.017**	**-0.965**	**-0.006**	**-0.014**	**-0.691**	**-0.164**	**-1173.146**	**1.910**	**1.955**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a. ML Estimation of an Exponential ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
AOL	0.900	0.188	0.646	0.011	-0.041	-0.290	-0.018	0.000	-0.767	-0.235	-1573.45	2.500	2.540
p-value	*0.004*	*0.002*	*0.000*	*0.583*	*0.154*	*0.042*	*0.196*	*0.340*	*0.046*	*0.026*			
ASF	0.148	0.154	0.827	-0.135	0.014	-0.712	0.034	-0.007	-0.401	-0.224	-773.15	1.993	2.052
p-value	*0.831*	*0.028*	*0.000*	*0.170*	*0.787*	*0.423*	*0.662*	*0.000*	*0.845*	*0.710*			
BEN	0.073	0.111	0.840	0.014	-0.017	0.346	-0.017	0.007	-0.282	-0.169	-1911.08	2.336	2.369
p-value	*0.389*	*0.000*	*0.000*	*0.337*	*0.358*	*0.236*	*0.050*	*0.000*	*0.248*	*0.020*			
CI	0.043	0.065	0.880	-0.008	0.018	-0.332	-0.004	0.000	-0.252	0.017	-1786.15	1.914	1.943
p-value	*0.461*	*0.000*	*0.000*	*0.429*	*0.041*	*0.000*	*0.548*	*0.415*	*0.008*	*0.762*			
CL	-0.119	-0.057	0.931	0.063	0.177	2.082	-0.025	0.001	-4.417	-0.991	-1192.47	2.102	2.146
p-value	*0.807*	*0.268*	*0.000*	*0.191*	*0.058*	*0.021*	*0.789*	*0.363*	*0.198*	*0.179*			
CPQ	0.311	0.076	0.714	-0.019	0.004	-1.325	-0.035	0.000	0.139	-0.528	-722.47	1.972	2.034
p-value	*0.279*	*0.147*	*0.000*	*0.700*	*0.893*	*0.001*	*0.139*	*0.707*	*0.887*	*0.081*			
DCX	0.185	0.119	0.800	-0.026	0.010	-1.287	-0.011	-0.003	-0.331	-0.059	-847.50	1.931	1.985
p-value	*0.157*	*0.000*	*0.000*	*0.136*	*0.547*	*0.000*	*0.392*	*0.037*	*0.024*	*0.771*			
GMH	0.508	0.073	0.715	0.020	-0.080	0.178	0.050	0.005	-0.268	-0.651	-1095.27	2.329	2.380
p-value	*0.000*	*0.001*	*0.000*	*0.003*	*0.000*	*0.272*	*0.000*	*0.000*	*0.049*	*0.000*			
GT	0.723	0.186	0.701	-0.047	-0.024	-0.542	-0.039	-0.005	-1.577	-0.374	-2267.56	1.933	1.957
p-value	*0.000*	*0.001*	*0.000*	*0.022*	*0.281*	*0.080*	*0.055*	*0.024*	*0.024*	*0.353*			
HAR	0.415	0.074	0.665	-0.084	0.041	-0.963	-0.085	-0.001	-0.346	-0.153	-835.30	1.964	2.019
p-value	*0.280*	*0.204*	*0.000*	*0.246*	*0.307*	*0.000*	*0.004*	*0.694*	*0.539*	*0.585*			
KF	1.174	0.244	-0.069	-0.078	-0.020	-2.355	0.000	-0.022	-0.712	-1.463	-611.18	1.972	2.043
p-value	*0.005*	*0.003*	*0.699*	*0.273*	*0.608*	*0.000*	*0.999*	*0.292*	*0.689*	*0.363*			
LE	0.708	0.289	0.560	-0.031	-0.031	-0.442	-0.032	-0.008	-0.828	0.039	-717.92	1.848	1.907
p-value	*0.000*	*0.000*	*0.000*	*0.330*	*0.200*	*0.000*	*0.157*	*0.008*	*0.016*	*0.838*			
LMT	0.799	0.280	0.085	-0.092	-0.016	-1.073	-0.020	0.001	0.298	-1.020	-1055.87	2.062	2.109
p-value	*0.173*	*0.074*	*0.654*	*0.228*	*0.801*	*0.001*	*0.680*	*0.807*	*0.819*	*0.008*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a. ML Estimation of an Exponential ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*: $ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$

$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$

Decimal Pilot Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
MLM	0.192	0.162	0.537	-0.066	0.050	-1.078	-0.011	-0.002	-0.615	-0.193	-1028.92	1.926	1.972
p-value	*0.247*	*0.002*	*0.000*	*0.123*	*0.047*	*0.000*	*0.693*	*0.678*	*0.093*	*0.462*			
RCL	0.814	0.237	0.519	-0.089	-0.010	-0.567	-0.061	-0.006	-0.817	-0.061	-974.89	1.943	1.991
p-value	*0.005*	*0.001*	*0.000*	*0.071*	*0.718*	*0.123*	*0.022*	*0.131*	*0.143*	*0.873*			
S	1.782	0.038	0.521	0.002	-0.121	-0.928	-0.050	0.001	-1.926	0.181	-850.25	1.910	1.963
p-value	*0.005*	*0.770*	*0.061*	*0.981*	*0.092*	*0.317*	*0.422*	*0.544*	*0.102*	*0.751*			
SGY	-0.108	0.095	0.752	-0.033	0.068	-0.704	-0.006	0.000	-0.580	0.043	-1328.10	1.942	1.980
p-value	*0.352*	*0.000*	*0.000*	*0.209*	*0.005*	*0.000*	*0.729*	*0.988*	*0.020*	*0.642*			
STT	0.198	0.146	0.799	-0.063	-0.018	-0.225	0.007	-0.001	0.142	-0.058	-976.07	1.882	1.929
p-value	*0.221*	*0.000*	*0.000*	*0.000*	*0.377*	*0.042*	*0.618*	*0.247*	*0.479*	*0.269*			
UBS	0.238	0.192	0.704	-0.085	-0.001	-0.165	-0.022	-0.004	0.262	-0.227	-1025.93	1.878	1.924
p-value	*0.018*	*0.000*	*0.000*	*0.000*	*0.962*	*0.014*	*0.089*	*0.130*	*0.028*	*0.055*			
VAL	0.617	0.306	0.426	-0.053	-0.019	-0.531	-0.021	-0.014	-0.459	0.257	-1839.76	1.897	1.926
p-value	*0.000*	*0.000*	*0.000*	*0.001*	*0.209*	*0.000*	*0.102*	*0.000*	*0.001*	*0.198*			
Mean	**0.480**	**0.149**	**0.628**	**-0.040**	**-0.001**	**-0.546**	**-0.018**	**-0.003**	**-0.687**	**-0.293**	**-1170.7**	**2.012**	**2.058**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a cont'd. ML Estimation of an Exponential ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
WMT	0.051	0.066	0.812	-0.023	0.040	-0.159	-0.026	0.000	-0.865	0.255	-1373.50	1.927	1.964
p-value	*0.738*	*0.032*	*0.000*	*0.186*	*0.039*	*0.433*	*0.033*	*0.374*	*0.034*	*0.106*			
CCN	0.474	0.252	0.584	-0.030	-0.026	-0.024	0.009	-0.040	-0.846	0.359	-789.17	1.894	1.950
p-value	*0.007*	*0.000*	*0.000*	*0.357*	*0.286*	*0.932*	*0.700*	*0.004*	*0.043*	*0.454*			
AOC	0.396	0.055	0.818	-0.053	-0.013	-0.891	-0.003	-0.001	-0.923	0.354	-1464.19	1.949	1.984
p-value	*0.000*	*0.015*	*0.000*	*0.003*	*0.224*	*0.000*	*0.736*	*0.298*	*0.000*	*0.059*			
UNH	-0.438	0.054	0.759	-0.114	0.108	-2.378	-0.020	0.000	0.118	0.138	-1831.28	1.960	1.989
p-value	*0.165*	*0.470*	*0.000*	*0.133*	*0.054*	*0.000*	*0.359*	*0.776*	*0.923*	*0.681*			
KO	0.094	0.009	0.883	0.013	0.005	-0.655	-0.009	0.001	-0.264	-0.260	-1021.67	1.943	1.990
p-value	*0.688*	*0.918*	*0.000*	*0.828*	*0.886*	*0.091*	*0.712*	*0.566*	*0.800*	*0.233*			
T	0.318	0.091	0.801	-0.084	0.022	-0.801	-0.019	0.000	-1.687	0.084	-682.20	1.891	1.954
p-value	*0.098*	*0.020*	*0.000*	*0.012*	*0.341*	*0.174*	*0.312*	*0.477*	*0.105*	*0.782*			
DOV	0.587	0.251	0.530	-0.078	-0.027	-0.711	0.006	-0.002	-1.003	1.251	-802.83	1.922	1.978
p-value	*0.031*	*0.000*	*0.000*	*0.051*	*0.426*	*0.002*	*0.810*	*0.098*	*0.004*	*0.000*			
ALL	0.399	0.173	0.652	-0.069	0.013	-0.435	0.013	-0.004	-0.385	-0.886	-1139.14	2.442	2.494
p-value	*0.593*	*0.158*	*0.002*	*0.414*	*0.881*	*0.577*	*0.705*	*0.003*	*0.868*	*0.211*			
GP	0.212	0.042	0.883	0.006	-0.008	-0.802	0.002	0.001	-0.948	0.253	-1993.54	1.979	2.007
p-value	*0.112*	*0.098*	*0.000*	*0.782*	*0.542*	*0.023*	*0.827*	*0.569*	*0.048*	*0.305*			
PHM	1.064	0.110	0.502	-0.119	-0.077	-0.526	-0.042	-0.001	0.392	0.027	-886.91	1.973	2.026
p-value	*0.003*	*0.027*	*0.000*	*0.005*	*0.081*	*0.002*	*0.160*	*0.586*	*0.308*	*0.915*			
APF	0.723	0.333	0.294	0.139	-0.061	1.043	0.015	-0.037	-4.302	5.558	-561.34	1.933	2.008
p-value	*0.005*	*0.000*	*0.013*	*0.060*	*0.030*	*0.363*	*0.566*	*0.087*	*0.019*	*0.045*			
CLB	1.893	0.161	0.366	0.172	-0.193	0.223	-0.059	0.004	0.447	-2.042	-661.45	1.960	2.027
p-value	*0.009*	*0.214*	*0.089*	*0.139*	*0.004*	*0.625*	*0.435*	*0.859*	*0.737*	*0.073*			
MRO	1.212	0.184	0.283	-0.003	-0.019	-1.228	-0.038	-0.001	-3.403	-0.929	-1048.04	1.952	1.998
p-value	*0.000*	*0.000*	*0.019*	*0.928*	*0.575*	*0.000*	*0.123*	*0.597*	*0.001*	*0.043*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7a cont'd. ML Estimation of an Exponential ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	LogL	AIC	SIC
HTN	0.155	0.059	0.896	0.010	-0.013	-0.395	0.015	-0.005	-0.428	0.474	-1118.90	1.943	1.987
p-value	*0.238*	*0.002*	*0.000*	*0.699*	*0.527*	*0.066*	*0.472*	*0.008*	*0.035*	*0.030*			
CNF	0.500	0.178	0.375	-0.030	0.054	0.007	-0.028	-0.005	-2.145	1.210	-1067.53	1.949	1.994
p-value	*0.013*	*0.000*	*0.000*	*0.327*	*0.065*	*0.959*	*0.280*	*0.039*	*0.000*	*0.000*			
NKE	0.480	0.132	0.784	0.024	-0.041	-0.502	0.022	-0.002	-0.785	-0.199	-904.11	1.941	1.992
p-value	*0.000*	*0.000*	*0.000*	*0.334*	*0.008*	*0.007*	*0.073*	*0.008*	*0.054*	*0.298*			
AMG	0.863	0.187	0.407	-0.126	0.013	-0.472	-0.089	-0.009	-0.458	0.189	-1303.98	1.861	1.898
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.511*	*0.000*	*0.000*	*0.000*	*0.001*	*0.133*			
PKI	-0.126	0.127	0.830	-0.029	0.035	-0.391	-0.024	-0.001	0.116	0.089	-999.68	1.914	1.961
p-value	*0.289*	*0.000*	*0.000*	*0.232*	*0.063*	*0.000*	*0.071*	*0.131*	*0.580*	*0.153*			
HIT	0.948	0.284	0.224	-0.061	-0.031	-0.163	-0.017	-0.044	0.278	-0.706	-1107.21	1.970	2.015
p-value	*0.000*	*0.000*	*0.078*	*0.032*	*0.361*	*0.049*	*0.581*	*0.001*	*0.310*	*0.007*			
AGX	0.381	0.489	0.093	0.064	-0.011	0.080	0.056	-0.046	-1.650	0.151	-698.07	1.881	1.942
p-value	*0.058*	*0.000*	*0.395*	*0.242*	*0.724*	*0.914*	*0.040*	*0.010*	*0.288*	*0.917*			
Mean	**0.509**	**0.162**	**0.589**	**-0.020**	**-0.011**	**-0.459**	**-0.012**	**-0.010**	**-0.937**	**0.268**	**-1072.7**	**1.959**	**2.008**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b ML estimation of a Weibull ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
AOL	0.203	0.107	0.858	-0.038	-0.026	-0.287	0.012	0.000	0.273	-0.139	1.087	-1651.2	1.842	1.875
p-value	*0.003*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*	*0.057*	*0.037*	*0.000*	*0.000*	*0.000*			
ASF	1.189	0.330	-0.050	-0.248	0.038	-1.238	0.007	-0.019	-1.402	-1.214	1.130	-1324.1	1.898	1.939
p-value	*0.144*	*0.011*	*0.830*	*0.045*	*0.773*	*0.003*	*0.934*	*0.153*	*0.259*	*0.088*	*0.000*			
BEN	0.594	-0.124	0.923	0.024	-0.032	-0.729	-0.091	0.009	-0.619	0.496	1.329	-1746.4	1.954	1.987
p-value	*0.008*	*0.001*	*0.000*	*0.719*	*0.000*	*0.278*	*0.017*	*0.003*	*0.605*	*0.154*	*0.000*			
CI	0.997	0.239	0.221	-0.297	0.004	-0.976	0.000	-0.012	1.088	-1.151	1.075	-1411.3	1.925	1.964
p-value	*0.316*	*0.070*	*0.276*	*0.109*	*0.968*	*0.020*	*0.999*	*0.103*	*0.367*	*0.022*	*0.000*			
CL	0.193	0.056	0.881	-0.007	0.014	-0.741	-0.005	-0.001	-0.822	-0.075	1.073	-1422.4	1.957	1.997
p-value	*0.013*	*0.001*	*0.000*	*0.490*	*0.132*	*0.000*	*0.545*	*0.218*	*0.002*	*0.293*	*0.000*			
CPQ	0.287	-0.176	1.096	-0.240	0.005	-3.998	0.005	-0.001	-0.469	1.377	1.370	-1269.3	1.968	2.012
p-value	*0.274*	*0.000*	*0.000*	*0.001*	*0.969*	*0.215*	*0.966*	*0.159*	*0.927*	*0.001*	*0.000*			
DCX	0.813	0.098	0.742	0.073	-0.050	0.177	-0.002	0.001	-2.367	-0.254	0.988	-1171.4	1.907	1.953
p-value	*0.000*	*0.020*	*0.000*	*0.002*	*0.019*	*0.433*	*0.908*	*0.476*	*0.000*	*0.300*	*0.000*			
GMH	0.352	0.119	0.557	-0.100	0.011	-0.495	0.000	-0.001	-0.232	-0.388	0.925	-1388.8	1.983	2.024
p-value	*0.854*	*0.733*	*0.485*	*0.732*	*0.955*	*0.825*	*0.998*	*0.937*	*0.958*	*0.904*	*0.000*			
GT	0.509	0.308	0.496	0.065	0.008	-1.024	0.004	-0.009	-2.756	0.133	1.077	-1263.1	1.944	1.987
p-value	*0.254*	*0.007*	*0.001*	*0.282*	*0.890*	*0.078*	*0.882*	*0.022*	*0.109*	*0.881*	*0.000*			
HAR	0.384	-0.008	0.870	0.026	-0.031	-0.478	-0.002	0.005	-1.056	1.217	1.037	-1262.6	1.905	1.948
p-value	*0.000*	*0.793*	*0.000*	*0.564*	*0.000*	*0.026*	*0.916*	*0.063*	*0.000*	*0.000*	*0.000*			
KF	0.387	0.189	0.666	-0.002	-0.035	-0.798	0.045	-0.029	-1.511	-1.626	1.151	-727.2	1.893	1.958
p-value	*0.019*	*0.000*	*0.000*	*0.946*	*0.054*	*0.095*	*0.017*	*0.000*	*0.111*	*0.046*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b. cont'd ML estimation of a Weibull ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
LE	0.391	0.187	0.757	-0.097	0.101	-1.429	-0.058	-0.027	-2.504	1.251	1.207	-1023.3	1.915	1.966
p-value	*0.737*	*0.048*	*0.000*	*0.633*	*0.492*	*0.207*	*0.438*	*0.003*	*0.091*	*0.136*	*0.000*			
LMT	0.141	0.078	0.851	-0.025	0.013	-0.281	-0.001	-0.001	-0.517	0.005	1.050	-1267.5	1.971	2.015
p-value	*0.091*	*0.002*	*0.000*	*0.153*	*0.184*	*0.050*	*0.895*	*0.206*	*0.076*	*0.965*	*0.000*			
MLM	0.098	0.635	0.406	-0.025	0.053	-0.937	-0.053	-0.022	-0.641	0.703	1.123	-1295.3	1.957	2.000
p-value	*0.801*	*0.000*	*0.001*	*0.774*	*0.264*	*0.024*	*0.172*	*0.038*	*0.453*	*0.269*	*0.000*			
RCL	0.321	0.156	0.790	-0.046	-0.009	-0.491	0.009	-0.008	-0.863	0.193	0.976	-1252.4	1.852	1.895
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.352*	*0.000*	*0.380*	*0.000*	*0.000*	*0.208*	*0.000*			
S	0.266	-0.047	0.921	-0.095	-0.007	-0.675	-0.021	0.002	0.052	0.060	1.279	-1072.4	1.926	1.975
p-value	*0.302*	*0.411*	*0.000*	*0.004*	*0.861*	*0.136*	*0.333*	*0.289*	*0.953*	*0.809*	*0.000*			
SGY	2.198	-0.111	0.543	-0.584	-0.310	-5.101	0.245	-0.121	5.987	2.533	1.113	-1270.0	1.858	1.900
p-value	*0.459*	*0.585*	*0.014*	*0.493*	*0.475*	*0.270*	*0.519*	*0.012*	*0.301*	*0.230*	*0.000*			
STT	0.048	0.013	0.938	-0.019	0.000	-0.471	-0.004	0.002	-0.040	-0.033	1.028	-1212.0	1.914	1.958
p-value	*0.552*	*0.295*	*0.000*	*0.101*	*0.982*	*0.000*	*0.525*	*0.001*	*0.694*	*0.231*	*0.000*			
UBS	0.125	0.121	0.842	0.012	-0.005	-0.286	-0.006	-0.003	-0.190	0.200	0.964	-1288.8	1.869	1.910
p-value	*0.099*	*0.000*	*0.000*	*0.278*	*0.626*	*0.000*	*0.414*	*0.104*	*0.175*	*0.003*	*0.000*			
VAL	0.402	0.243	0.322	-0.035	-0.027	-0.415	0.003	-0.040	3.596	-0.119	1.288	-1042.3	1.912	1.962
p-value	*0.829*	*0.760*	*0.889*	*0.952*	*0.921*	*0.916*	*0.994*	*0.687*	*0.697*	*0.993*	*0.002*			
Mean	**0.495**	**0.121**	**0.681**	**-0.083**	**-0.014**	**-1.034**	**0.004**	**-0.014**	**-0.250**	**0.158**	**1.113**	**-1268.1**	**1.917**	**1.961**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b. cont'd ML estimation of a Weibull ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
WMT	1.229	0.210	0.477	-0.042	-0.066	-0.821	-0.011	0.000	-0.764	-0.124	1.064	-1455.3	1.93	1.97
p-value	*0.000*	*0.001*	*0.000*	*0.466*	*0.144*	*0.006*	*0.701*	*0.848*	*0.327*	*0.580*	*0.000*			
CCN	1.611	0.347	0.271	-0.553	-0.013	-0.491	-0.192	-0.138	0.888	-0.351	1.196	-1196.1	1.80	1.84
p-value	*0.017*	*0.013*	*0.167*	*0.033*	*0.906*	*0.190*	*0.123*	*0.077*	*0.665*	*0.836*	*0.000*			
AOC	0.309	0.134	0.775	-0.049	0.002	-1.305	-0.014	-0.003	-0.903	0.061	1.030	-1579.7	1.89	1.92
p-value	*0.000*	*0.000*	*0.000*	*0.015*	*0.780*	*0.000*	*0.146*	*0.110*	*0.001*	*0.696*	*0.000*			
UNH	0.287	0.102	0.823	-0.026	-0.004	-0.615	-0.013	0.001	-0.423	0.153	1.058	-1514.8	1.90	1.94
p-value	*0.004*	*0.000*	*0.000*	*0.156*	*0.698*	*0.000*	*0.195*	*0.255*	*0.003*	*0.003*	*0.000*			
KO	0.352	0.069	0.863	-0.004	-0.008	-0.904	0.016	-0.001	-0.886	-0.383	1.129	-1226.5	1.96	2.00
p-value	*0.020*	*0.001*	*0.000*	*0.858*	*0.518*	*0.008*	*0.102*	*0.068*	*0.099*	*0.000*	*0.000*			
T	0.608	0.030	0.661	-0.083	0.048	-1.717	-0.026	0.000	-3.596	-0.119	1.228	-1005.9	1.88	1.93
p-value	*0.119*	*0.666*	*0.000*	*0.189*	*0.259*	*0.032*	*0.298*	*0.668*	*0.002*	*0.762*	*0.000*			
DOV	0.365	0.265	0.607	-0.098	0.009	-0.620	-0.020	-0.003	-0.396	0.303	0.975	-1223.0	1.91	1.95
p-value	*0.022*	*0.000*	*0.000*	*0.002*	*0.634*	*0.001*	*0.185*	*0.025*	*0.243*	*0.038*	*0.000*			
ALL	0.751	0.143	0.745	-0.027	-0.011	-1.370	0.024	-0.002	-2.745	0.133	0.990	-1059.8	1.90	1.95
p-value	*0.001*	*0.001*	*0.000*	*0.533*	*0.582*	*0.000*	*0.164*	*0.026*	*0.000*	*0.563*	*0.000*			
GP	0.644	0.102	0.707	-0.146	-0.002	-1.529	-0.016	-0.001	-1.312	0.202	1.008	-1164.6	1.89	1.93
p-value	*0.006*	*0.017*	*0.000*	*0.002*	*0.963*	*0.001*	*0.458*	*0.666*	*0.073*	*0.391*	*0.000*			
PHM	0.373	0.112	0.753	-0.184	0.021	-0.893	-0.004	-0.005	-0.418	-0.216	1.034	-1357.3	1.87	1.91
p-value	*0.112*	*0.002*	*0.000*	*0.000*	*0.503*	*0.000*	*0.872*	*0.085*	*0.291*	*0.249*	*0.000*			
APF	1.704	0.183	-0.024	-0.121	-0.083	-1.641	-0.022	-0.008	1.148	-3.727	1.232	-324.9	1.94	2.06
p-value	*0.001*	*0.029*	*0.907*	*0.382*	*0.010*	*0.101*	*0.703*	*0.548*	*0.687*	*0.073*	*0.000*			
CLB	0.826	0.319	0.161	-0.058	-0.056	-0.605	0.181	-0.042	-1.886	-0.556	0.936	-994.5	1.86	1.91
p-value	*0.036*	*0.000*	*0.271*	*0.719*	*0.301*	*0.354*	*0.011*	*0.073*	*0.021*	*0.442*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b. cont'd ML estimation of a Weibull ACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*: $$ENPTIME_{t} = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
MRO	0.160	0.078	0.881	-0.057	-0.012	-2.180	0.042	-0.003	-0.921	0.016	1.007	-1519.8	1.92	1.96
p-value	*0.029*	*0.000*	*0.000*	*0.017*	*0.194*	*0.000*	*0.000*	*0.000*	*0.081*	*0.930*	*0.000*			
HTN	0.664	0.118	0.672	-0.118	-0.020	-0.880	-0.007	-0.006	-1.315	0.344	0.983	-1189.7	1.93	1.97
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.326*	*0.000*	*0.676*	*0.032*	*0.000*	*0.091*	*0.000*			
CNF	0.600	0.194	0.717	-0.113	-0.050	-0.858	0.023	-0.008	-0.157	0.156	1.015	-1082.2	1.96	2.00
p-value	*0.002*	*0.000*	*0.000*	*0.014*	*0.052*	*0.000*	*0.251*	*0.007*	*0.660*	*0.458*	*0.000*			
NKE	1.067	0.185	0.336	-0.256	0.072	-1.379	-0.046	-0.004	-3.437	1.082	1.015	-1195.6	1.88	1.92
p-value	*0.017*	*0.003*	*0.009*	*0.002*	*0.122*	*0.000*	*0.194*	*0.195*	*0.000*	*0.002*	*0.000*			
AMG	0.559	0.115	0.676	-0.098	-0.038	-0.286	0.009	-0.002	-0.157	0.183	0.886	-1252.9	1.90	1.94
p-value	*0.002*	*0.000*	*0.000*	*0.001*	*0.138*	*0.007*	*0.544*	*0.462*	*0.455*	*0.052*	*0.000*			
PKI	-0.269	0.052	0.900	-0.051	0.005	-0.375	-0.064	0.001	0.755	-0.124	1.003	-1260.9	1.92	1.96
p-value	*0.190*	*0.020*	*0.000*	*0.145*	*0.881*	*0.000*	*0.000*	*0.304*	*0.000*	*0.018*	*0.000*			
HIT	0.869	0.282	0.374	-0.017	-0.097	0.032	0.074	-0.035	-0.298	-0.030	1.214	-1190.4	1.86	1.90
p-value	*0.000*	*0.000*	*0.000*	*0.559*	*0.000*	*0.696*	*0.003*	*0.000*	*0.044*	*0.833*	*0.000*			
AGX	1.663	0.358	0.074	-0.092	-0.100	-0.439	-0.030	-0.094	-0.770	0.800	1.170	-528.4	1.90	1.98
p-value	*0.000*	*0.000*	*0.527*	*0.116*	*0.030*	*0.354*	*0.447*	*0.000*	*0.068*	*0.400*	*0.000*			
Mean	**0.72**	**0.17**	**0.57**	**-0.11**	**-0.02**	**-0.94**	**0.00**	**-0.02**	**-0.88**	**-0.11**	**1.06**	**-1166.1**	**1.90**	**1.95**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b. ML estimation of a Weibull ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
AOL	0.868	0.188	0.675	0.007	-0.040	-0.292	-0.017	-0.001	-0.727	-0.239	1.164	-1543.7	2.454	2.499
p-value	*0.000*	*0.000*	*0.000*	*0.612*	*0.048*	*0.007*	*0.072*	*0.096*	*0.010*	*0.002*	*0.000*			
ASF	0.458	0.082	0.740	0.017	-0.006	-0.394	0.020	-0.003	-1.348	-0.186	0.757	-679.0	1.756	1.821
p-value	*0.245*	*0.530*	*0.000*	*0.942*	*0.949*	*0.798*	*0.875*	*0.434*	*0.581*	*0.808*	*0.000*			
BEN	0.160	0.115	0.861	-0.004	0.013	-0.348	0.004	-0.003	-0.713	-0.492	1.066	-1567.4	1.919	1.955
p-value	*0.378*	*0.000*	*0.000*	*0.854*	*0.611*	*0.332*	*0.779*	*0.011*	*0.355*	*0.021*	*0.000*			
CI	0.042	0.065	0.880	-0.008	0.018	-0.333	-0.004	0.000	-0.250	0.017	1.030	-1784.7	1.913	1.946
p-value	*0.441*	*0.000*	*0.000*	*0.401*	*0.029*	*0.000*	*0.522*	*0.373*	*0.006*	*0.754*	*0.000*			
CL	0.130	0.069	0.789	-0.016	0.002	-0.438	-0.018	0.001	-0.054	0.093	1.070	-1139.2	2.011	2.059
p-value	*0.794*	*0.453*	*0.000*	*0.823*	*0.969*	*0.497*	*0.756*	*0.447*	*0.983*	*0.831*	*0.000*			
CPQ	0.403	0.060	0.773	-0.039	-0.016	-1.244	-0.044	0.000	0.719	-0.348	1.189	-720.3	1.968	2.037
p-value	*0.046*	*0.059*	*0.000*	*0.218*	*0.379*	*0.000*	*0.004*	*0.868*	*0.231*	*0.126*	*0.000*			
DCX	0.164	0.119	0.806	-0.026	0.011	-1.284	-0.010	-0.003	-0.343	-0.014	1.044	-845.9	1.930	1.989
p-value	*0.171*	*0.000*	*0.000*	*0.102*	*0.428*	*0.000*	*0.399*	*0.018*	*0.012*	*0.942*	*0.000*			
GMH	0.240	0.135	0.659	-0.055	0.008	-0.871	-0.016	0.000	0.125	0.006	1.051	-916.2	1.954	2.010
p-value	*0.119*	*0.005*	*0.000*	*0.073*	*0.662*	*0.000*	*0.326*	*0.954*	*0.775*	*0.981*	*0.000*			
GT	1.626	0.066	0.638	-0.158	-0.117	-0.840	-0.052	-0.008	-1.209	1.204	1.038	-2260.2	1.927	1.954
p-value	*0.000*	*0.503*	*0.000*	*0.016*	*0.013*	*0.227*	*0.168*	*0.051*	*0.486*	*0.042*	*0.000*			
HAR	1.697	0.178	0.086	-0.221	-0.038	-1.077	-0.125	0.000	-0.741	0.199	0.987	-845.4	1.989	2.050
p-value	*0.002*	*0.072*	*0.667*	*0.038*	*0.466*	*0.000*	*0.009*	*0.979*	*0.343*	*0.648*	*0.000*			
KF	1.106	0.248	0.153	-0.226	-0.013	-2.916	0.025	-0.051	-2.621	-3.397	1.210	-611.4	1.976	2.053
p-value	*0.004*	*0.002*	*0.429*	*0.005*	*0.755*	*0.000*	*0.611*	*0.000*	*0.235*	*0.063*	*0.000*			
LE	1.441	0.344	0.362	0.038	-0.045	-1.080	-0.109	-0.008	-2.665	0.156	1.003	-741.1	1.909	1.974
p-value	*0.003*	*0.001*	*0.000*	*0.735*	*0.522*	*0.006*	*0.055*	*0.498*	*0.058*	*0.837*	*0.000*			
LMT	0.804	0.283	0.071	-0.094	-0.015	-1.078	-0.018	0.001	0.275	-1.013	1.059	-1013.5	1.982	2.034
p-value	*0.132*	*0.048*	*0.676*	*0.174*	*0.791*	*0.000*	*0.680*	*0.789*	*0.812*	*0.004*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b. Cont'd   ML estimation of a Weibull ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
MLM	0.255	0.202	0.548	-0.052	0.035	-0.715	-0.031	-0.003	-0.604	-0.170	0.988	-1026.4	1.923	1.974
p-value	*0.145*	*0.000*	*0.000*	*0.171*	*0.168*	*0.000*	*0.224*	*0.530*	*0.073*	*0.522*	*0.000*			
RCL	0.820	0.241	0.515	-0.088	-0.010	-0.557	-0.060	-0.006	-0.834	-0.051	1.066	-962.7	1.920	1.974
p-value	*0.002*	*0.000*	*0.000*	*0.045*	*0.675*	*0.092*	*0.012*	*0.079*	*0.098*	*0.881*	*0.000*			
S	1.725	0.059	0.523	0.001	-0.120	-0.967	-0.042	0.001	-1.798	0.152	1.057	-855.5	1.923	1.982
p-value	*0.018*	*0.643*	*0.066*	*0.990*	*0.112*	*0.260*	*0.475*	*0.664*	*0.127*	*0.772*	*0.000*			
SGY	-0.049	0.087	0.781	-0.020	0.049	-0.724	-0.005	0.001	-0.499	0.028	1.032	-1351.1	1.977	2.019
p-value	*0.817*	*0.017*	*0.000*	*0.578*	*0.204*	*0.000*	*0.820*	*0.822*	*0.070*	*0.824*	*0.000*			
STT	0.177	0.143	0.803	-0.064	-0.015	-0.210	0.006	-0.001	0.149	-0.058	1.099	-967.7	1.868	1.920
p-value	*0.197*	*0.000*	*0.000*	*0.000*	*0.390*	*0.026*	*0.603*	*0.166*	*0.364*	*0.173*	*0.000*			
UBS	0.248	0.192	0.701	-0.089	0.002	-0.134	-0.026	-0.006	0.288	-0.239	0.950	-1011.9	1.855	1.905
p-value	*0.010*	*0.000*	*0.000*	*0.000*	*0.915*	*0.040*	*0.067*	*0.055*	*0.010*	*0.012*	*0.000*			
VAL	1.822	0.420	0.407	0.065	-0.179	0.397	-0.050	-0.048	-1.318	-0.148	1.051	-1836.3	1.895	1.926
p-value	*0.000*	*0.000*	*0.000*	*0.219*	*0.000*	*0.359*	*0.113*	*0.000*	*0.161*	*0.829*	*0.000*			
Mean	**0.71**	**0.16**	**0.59**	**-0.05**	**-0.02**	**-0.76**	**-0.03**	**-0.01**	**-0.71**	**-0.22**	**1.05**	**-1134**	**1.95**	**2.00**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7b cont'd. ML estimation of a Weibull ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 NPTIME_{t-1} + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
WMT	0.062	0.070	0.813	-0.022	0.035	-0.144	-0.024	0.000	-0.771	0.263	1.140	-1349	1.893	1.934
p-value	*0.596*	*0.003*	*0.000*	*0.100*	*0.014*	*0.354*	*0.007*	*0.327*	*0.014*	*0.030*	*0.000*			
CCN	0.474	0.247	0.588	-0.030	-0.027	0.004	0.012	-0.039	-0.841	0.381	1.169	-773	1.858	1.920
p-value	*0.000*	*0.000*	*0.000*	*0.219*	*0.120*	*0.985*	*0.505*	*0.000*	*0.007*	*0.283*	*0.000*			
AOC	0.387	0.054	0.823	-0.052	-0.013	-0.869	-0.003	-0.001	-0.911	0.351	1.062	-1459	1.944	1.982
p-value	*0.000*	*0.007*	*0.000*	*0.001*	*0.170*	*0.000*	*0.733*	*0.247*	*0.000*	*0.037*	*0.000*			
UNH	0.056	0.216	0.822	-0.126	0.078	-1.518	-0.063	-0.008	-0.363	0.257	1.140	-1845	1.975	2.008
p-value	*0.878*	*0.004*	*0.000*	*0.031*	*0.066*	*0.000*	*0.003*	*0.000*	*0.734*	*0.383*	*0.000*			
KO	1.533	0.304	0.787	0.287	0.052	4.065	-0.209	-0.005	-7.135	0.700	1.370	-990	1.886	1.937
p-value	*0.387*	*0.078*	*0.000*	*0.063*	*0.733*	*0.234*	*0.008*	*0.054*	*0.409*	*0.536*	*0.000*			
T	0.299	0.088	0.816	-0.086	0.022	-0.829	-0.020	0.000	-1.566	0.067	1.116	-675	1.873	1.942
p-value	*0.043*	*0.003*	*0.000*	*0.002*	*0.220*	*0.072*	*0.180*	*0.486*	*0.055*	*0.780*	*0.000*			
DOV	0.576	0.250	0.533	-0.078	-0.028	-0.693	0.008	-0.002	-0.974	1.268	1.062	-795	1.906	1.967
p-value	*0.018*	*0.000*	*0.000*	*0.030*	*0.368*	*0.001*	*0.732*	*0.064*	*0.002*	*0.000*	*0.000*			
ALL	0.853	0.090	0.676	-0.227	-0.017	-1.441	0.056	-0.003	-1.326	-1.108	1.346	-975	2.096	2.152
p-value	*0.100*	*0.484*	*0.000*	*0.052*	*0.812*	*0.116*	*0.200*	*0.090*	*0.616*	*0.183*	*0.000*			
GP	0.395	0.093	0.797	-0.028	-0.009	-0.710	-0.013	-0.001	-0.968	0.274	1.069	-1972	1.958	1.989
p-value	*0.000*	*0.000*	*0.000*	*0.029*	*0.306*	*0.000*	*0.105*	*0.040*	*0.000*	*0.060*	*0.000*			
PHM	1.016	0.200	0.567	-0.052	-0.096	-0.537	-0.030	-0.003	0.290	0.021	1.178	-895	1.993	2.051
p-value	*0.010*	*0.016*	*0.000*	*0.128*	*0.066*	*0.000*	*0.445*	*0.189*	*0.489*	*0.949*	*0.000*			
APF	0.755	0.306	0.303	0.128	-0.065	0.872	0.016	-0.034	-3.516	5.072	1.192	-547	1.888	1.969
p-value	*0.000*	*0.000*	*0.001*	*0.018*	*0.001*	*0.314*	*0.404*	*0.036*	*0.020*	*0.013*	*0.000*			
CLB	2.036	0.153	0.330	0.172	-0.206	0.219	-0.064	0.005	0.588	-2.273	1.087	-666	1.977	2.050
p-value	*0.001*	*0.182*	*0.051*	*0.087*	*0.000*	*0.586*	*0.345*	*0.800*	*0.628*	*0.026*	*0.000*			
MRO	1.247	0.191	0.255	-0.004	-0.019	-1.229	-0.040	-0.001	-3.389	-0.945	1.046	-1046	1.950	2.001
p-value	*0.000*	*0.000*	*0.026*	*0.905*	*0.550*	*0.000*	*0.080*	*0.493*	*0.000*	*0.025*	*0.000*			

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Table 7b cont'd. ML estimation of a Weibull ACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

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$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
HTN	0.153	0.059	0.897	0.009	-0.012	-0.380	0.014	-0.005	-0.425	0.468	1.046	-1121	1.949	1.997
p-value	*0.200*	*0.001*	*0.000*	*0.691*	*0.507*	*0.057*	*0.452*	*0.003*	*0.027*	*0.020*	*0.000*			
CNF	0.482	0.176	0.382	-0.030	0.055	0.012	-0.027	-0.005	-2.146	1.229	1.023	-1067	1.949	1.999
p-value	*0.015*	*0.000*	*0.000*	*0.295*	*0.056*	*0.928*	*0.278*	*0.032*	*0.000*	*0.000*	*0.000*			
NKE	0.482	0.132	0.784	0.023	-0.041	-0.501	0.021	-0.002	-0.787	-0.198	0.991	-904	1.943	1.999
p-value	*0.000*	*0.000*	*0.000*	*0.361*	*0.009*	*0.009*	*0.081*	*0.012*	*0.057*	*0.309*	*0.000*			
AMG	0.847	0.192	0.395	-0.124	0.016	-0.464	-0.090	-0.009	-0.451	0.201	0.902	-1289	1.842	1.883
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.531*	*0.000*	*0.000*	*0.003*	*0.006*	*0.192*	*0.000*			
PKI	-0.072	0.097	0.872	-0.038	0.021	-0.419	-0.028	-0.001	0.256	0.055	1.009	-999	1.914	1.966
p-value	*0.441*	*0.000*	*0.000*	*0.022*	*0.120*	*0.000*	*0.003*	*0.033*	*0.121*	*0.230*	*0.000*			
HIT	1.597	0.263	0.221	-0.147	-0.118	-0.478	-0.076	-0.044	0.924	-0.989	1.133	-1085	1.933	1.981
p-value	*0.000*	*0.000*	*0.122*	*0.016*	*0.006*	*0.001*	*0.046*	*0.032*	*0.078*	*0.015*	*0.000*			
AGX	0.354	0.470	0.111	0.057	-0.009	0.058	0.060	-0.047	-1.304	0.381	1.208	-677	1.828	1.895
p-value	*0.013*	*0.000*	*0.168*	*0.083*	*0.673*	*0.711*	*0.002*	*0.000*	*0.240*	*0.716*	*0.000*			
Mean	**0.68**	**0.18**	**0.59**	**-0.02**	**-0.02**	**-0.25**	**-0.02**	**-0.01**	**-1.24**	**0.27**	**1.11**	**-1056**	**1.93**	**1.98**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c. ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
AOL	0.228	0.087	0.886	-0.008	-0.015	-0.533	0.003	0.000	-0.053	-0.191	1.089	-1644	1.834	1.867
p-value	*0.001*	*0.000*	*0.000*	*0.513*	*0.119*	*0.000*	*0.684*	*0.025*	*0.631*	*0.001*	*0.000*			
ASF	0.273	0.182	0.462	-0.145	0.062	-1.360	-0.055	-0.011	-0.812	0.017	0.884	-1276	1.829	1.870
p-value	*0.236*	*0.000*	*0.000*	*0.023*	*0.098*	*0.000*	*0.009*	*0.001*	*0.036*	*0.932*	*0.000*			
BEN	0.322	0.121	0.597	0.010	-0.013	-0.382	-0.040	-0.001	-0.523	0.429	1.047	-1756	1.964	1.998
p-value	*0.005*	*0.000*	*0.000*	*0.627*	*0.417*	*0.006*	*0.003*	*0.321*	*0.018*	*0.013*	*0.000*			
CI	0.379	0.161	0.665	-0.093	0.000	-0.412	-0.012	-0.004	-0.307	-0.081	1.053	-1382	1.885	1.924
p-value	*0.012*	*0.000*	*0.000*	*0.000*	*0.999*	*0.000*	*0.406*	*0.000*	*0.046*	*0.363*	*0.000*			
CL	0.794	0.133	0.537	-0.031	-0.011	-0.930	0.009	-0.001	-2.796	0.036	1.079	-1415	1.947	1.987
p-value	*0.000*	*0.000*	*0.000*	*0.211*	*0.645*	*0.000*	*0.520*	*0.069*	*0.000*	*0.812*	*0.000*			
CPQ	0.101	0.060	0.860	-0.055	0.009	-1.720	-0.006	0.000	-0.473	-0.012	1.045	-1201	1.864	1.908
p-value	*0.248*	*0.000*	*0.000*	*0.010*	*0.477*	*0.000*	*0.554*	*0.188*	*0.129*	*0.933*	*0.000*			
DCX	0.630	0.132	0.706	0.065	-0.070	-0.084	-0.006	0.000	-0.604	-0.251	1.012	-1172	1.908	1.954
p-value	*0.000*	*0.000*	*0.000*	*0.002*	*0.002*	*0.277*	*0.684*	*0.957*	*0.002*	*0.275*	*0.000*			
GMH	0.871	0.145	0.634	-0.038	-0.038	-0.865	-0.029	-0.001	-1.752	-0.171	1.054	-1340	1.914	1.955
p-value	*0.000*	*0.000*	*0.000*	*0.150*	*0.066*	*0.002*	*0.066*	*0.031*	*0.000*	*0.342*	*0.000*			
GT	0.830	0.198	0.352	-0.014	-0.065	-1.571	0.011	-0.001	-3.648	1.361	0.979	-1235	1.901	1.944
p-value	*0.000*	*0.000*	*0.000*	*0.717*	*0.017*	*0.000*	*0.604*	*0.197*	*0.001*	*0.017*	*0.000*			
HAR	0.585	0.162	0.515	-0.141	-0.003	-1.163	-0.051	-0.008	-0.902	0.284	1.006	-1221	1.843	1.886
p-value	*0.000*	*0.000*	*0.000*	*0.002*	*0.880*	*0.000*	*0.006*	*0.007*	*0.000*	*0.048*	*0.000*			
KF	0.206	0.100	0.805	-0.002	-0.029	-1.108	0.039	-0.021	-0.621	-1.921	1.161	-723	1.881	1.946
p-value	*0.103*	*0.000*	*0.000*	*0.942*	*0.052*	*0.072*	*0.026*	*0.001*	*0.511*	*0.029*	*0.000*			
LE	0.812	0.250	0.437	-0.022	0.000	-0.191	-0.076	-0.013	-1.679	0.209	0.985	-995	1.862	1.913
p-value	*0.000*	*0.000*	*0.000*	*0.632*	*0.992*	*0.444*	*0.007*	*0.000*	*0.000*	*0.472*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c. cont'd ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
LMT	0.079	0.058	0.798	-0.041	0.013	-0.699	0.002	0.000	-0.576	-0.006	1.046	-1269	1.974	2.017
p-value	*0.460*	*0.003*	*0.000*	*0.066*	*0.293*	*0.001*	*0.906*	*0.956*	*0.146*	*0.965*	*0.000*			
MLM	0.492	0.140	0.310	-0.055	-0.028	-0.745	0.020	-0.006	-1.436	-0.105	1.040	-1295	1.957	2.000
p-value	*0.008*	*0.000*	*0.002*	*0.276*	*0.269*	*0.001*	*0.325*	*0.082*	*0.001*	*0.726*	*0.000*			
RCL	0.185	0.090	0.854	-0.049	-0.009	-1.168	0.020	-0.005	-0.548	0.376	0.980	-1248	1.846	1.888
p-value	*0.008*	*0.000*	*0.000*	*0.010*	*0.366*	*0.000*	*0.094*	*0.001*	*0.066*	*0.071*	*0.000*			
S	0.056	0.069	0.857	-0.031	0.019	-0.820	-0.003	0.000	-0.663	0.001	1.046	-1078	1.936	1.986
p-value	*0.604*	*0.001*	*0.000*	*0.099*	*0.207*	*0.004*	*0.805*	*0.999*	*0.040*	*0.997*	*0.000*			
SGY	1.246	0.185	0.171	-0.137	-0.054	-0.830	-0.086	-0.009	-1.676	0.256	0.929	-1279	1.871	1.913
p-value	*0.000*	*0.000*	*0.064*	*0.015*	*0.121*	*0.000*	*0.004*	*0.005*	*0.000*	*0.188*	*0.000*			
STT	0.073	0.041	0.926	0.002	-0.003	-0.605	0.002	0.000	-0.125	-0.010	1.005	-1212	1.914	1.958
p-value	*0.301*	*0.000*	*0.000*	*0.871*	*0.800*	*0.000*	*0.802*	*0.159*	*0.171*	*0.778*	*0.000*			
UBS	0.022	0.078	0.879	0.008	0.003	-0.639	-0.014	-0.001	0.070	0.163	0.964	-1282	1.858	1.900
p-value	*0.772*	*0.000*	*0.000*	*0.565*	*0.800*	*0.000*	*0.112*	*0.386*	*0.663*	*0.049*	*0.000*			
VAL	0.876	0.214	0.341	-0.128	-0.079	-1.089	-0.026	-0.009	-1.040	0.785	1.086	-1018	1.868	1.918
p-value	*0.000*	*0.000*	*0.000*	*0.001*	*0.040*	*0.000*	*0.397*	*0.049*	*0.069*	*0.121*	*0.000*			
Mean	**0.453**	**0.130**	**0.630**	**-0.045**	**-0.016**	**-0.846**	**-0.015**	**-0.005**	**-1.008**	**0.059**	**1.024**	**-1252**	**1.893**	**1.937**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c cont'd. ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
WMT	0.788	0.185	0.550	-0.073	-0.009	-0.636	-0.022	0.000	-1.588	-0.232	1.090	-1439	1.906	1.944
p-value	*0.000*	*0.000*	*0.000*	*0.030*	*0.706*	*0.003*	*0.186*	*0.697*	*0.000*	*0.075*	*0.000*			
CCN	0.561	0.288	0.297	0.047	-0.027	-0.054	-0.046	-0.065	-0.391	-0.783	1.056	-1203	1.812	1.855
p-value	*0.000*	*0.000*	*0.000*	*0.182*	*0.212*	*0.735*	*0.089*	*0.001*	*0.228*	*0.018*	*0.000*			
AOC	0.249	0.105	0.777	-0.061	0.004	-2.034	-0.012	0.000	-1.073	0.080	1.032	-1575	1.884	1.919
p-value	*0.001*	*0.000*	*0.000*	*0.023*	*0.739*	*0.000*	*0.328*	*0.760*	*0.006*	*0.703*	*0.000*			
UNH	0.383	0.090	0.831	-0.001	-0.009	-0.591	-0.019	0.001	-0.719	0.151	1.056	-1511	1.895	1.931
p-value	*0.001*	*0.000*	*0.000*	*0.955*	*0.442*	*0.003*	*0.076*	*0.041*	*0.000*	*0.021*	*0.000*			
KO	0.277	0.035	0.925	0.024	-0.001	-0.635	0.003	0.000	-1.084	-0.289	1.127	-1227	1.961	2.006
p-value	*0.027*	*0.003*	*0.000*	*0.213*	*0.890*	*0.041*	*0.645*	*0.405*	*0.027*	*0.000*	*0.000*			
T	0.328	0.045	0.903	-0.096	0.009	-2.069	0.019	0.000	-2.459	-0.057	1.115	-994	1.860	1.910
p-value	*0.027*	*0.001*	*0.000*	*0.008*	*0.482*	*0.000*	*0.033*	*0.362*	*0.000*	*0.730*	*0.000*			
DOV	0.483	0.265	0.559	-0.130	0.021	-1.257	-0.029	-0.005	-0.694	-0.182	1.000	-1189	1.855	1.899
p-value	*0.008*	*0.000*	*0.000*	*0.012*	*0.403*	*0.000*	*0.123*	*0.000*	*0.072*	*0.378*	*0.000*			
ALL	0.775	0.122	0.779	-0.030	-0.055	-1.044	0.030	-0.001	-1.634	-0.186	1.036	-1055	1.893	1.942
p-value	*0.000*	*0.000*	*0.000*	*0.308*	*0.000*	*0.001*	*0.020*	*0.045*	*0.003*	*0.284*	*0.000*			
GP	0.555	0.057	0.760	-0.167	0.019	-1.979	-0.027	0.001	-2.737	0.547	0.996	-1160	1.879	1.924
p-value	*0.002*	*0.002*	*0.000*	*0.000*	*0.405*	*0.000*	*0.129*	*0.303*	*0.000*	*0.006*	*0.000*			
PHM	0.174	0.117	0.744	-0.043	0.028	-1.270	0.005	-0.002	-1.260	-0.179	0.987	-1336	1.844	1.884
p-value	*0.214*	*0.000*	*0.000*	*0.121*	*0.151*	*0.000*	*0.722*	*0.119*	*0.000*	*0.220*	*0.000*			
APF	0.911	0.096	-0.198	-0.187	-0.083	-1.961	-0.024	-0.003	1.877	-4.018	1.232	-325	1.937	2.059
p-value	*0.060*	*0.019*	*0.379*	*0.273*	*0.040*	*0.093*	*0.691*	*0.837*	*0.539*	*0.080*	*0.000*			
CLB	0.626	0.282	0.320	-0.024	-0.022	-1.492	0.002	-0.027	-2.938	1.062	0.996	-969	1.814	1.865
p-value	*0.004*	*0.000*	*0.000*	*0.712*	*0.438*	*0.000*	*0.935*	*0.002*	*0.000*	*0.019*	*0.000*			
MRO	0.226	0.088	0.826	-0.052	-0.022	-2.840	0.060	-0.003	-1.671	-0.007	1.005	-1522	1.921	1.958
p-value	*0.062*	*0.000*	*0.000*	*0.103*	*0.130*	*0.000*	*0.000*	*0.000*	*0.026*	*0.979*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c cont'd. ML estimation of a WLACD(1,1) model. Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
HTN	0.449	0.089	0.684	-0.082	-0.014	-1.133	0.014	-0.005	-2.120	0.355	0.985	-1188	1.925	1.970
p-value	*0.002*	*0.000*	*0.000*	*0.040*	*0.540*	*0.000*	*0.477*	*0.098*	*0.000*	*0.216*	*0.000*			
CNF	0.487	0.139	0.796	-0.032	-0.043	-0.896	0.046	-0.007	-0.853	0.058	1.022	-1022	1.848	1.898
p-value	*0.001*	*0.000*	*0.000*	*0.363*	*0.032*	*0.000*	*0.003*	*0.000*	*0.008*	*0.708*	*0.000*			
NKE	0.693	0.144	0.504	-0.234	-0.013	-1.880	0.027	-0.002	-2.208	0.324	1.004	-1199	1.882	1.926
p-value	*0.003*	*0.000*	*0.000*	*0.000*	*0.609*	*0.000*	*0.191*	*0.123*	*0.000*	*0.139*	*0.000*			
AMG	0.458	0.105	0.622	-0.134	0.007	-0.988	-0.017	-0.001	-0.940	0.145	0.893	-1239	1.879	1.922
p-value	*0.030*	*0.000*	*0.000*	*0.004*	*0.836*	*0.000*	*0.396*	*0.865*	*0.004*	*0.221*	*0.000*			
PKI	0.186	0.060	0.868	-0.008	0.007	-0.174	-0.039	0.000	-0.100	-0.067	1.016	-1268	1.928	1.971
p-value	*0.170*	*0.000*	*0.000*	*0.700*	*0.690*	*0.021*	*0.000*	*0.950*	*0.497*	*0.076*	*0.000*			
HIT	0.792	0.163	0.507	-0.007	-0.127	0.051	0.046	-0.026	-0.461	0.132	1.210	-1196	1.867	1.911
p-value	*0.000*	*0.000*	*0.000*	*0.820*	*0.000*	*0.612*	*0.058*	*0.006*	*0.023*	*0.468*	*0.000*			
AGX	0.194	0.179	0.282	0.128	-0.063	0.034	0.068	-0.034	-0.291	0.452	1.089	-539	1.933	2.017
p-value	*0.476*	*0.000*	*0.048*	*0.171*	*0.096*	*0.949*	*0.024*	*0.006*	*0.743*	*0.600*	*0.000*			
Mean	**0.480**	**0.133**	**0.617**	**-0.058**	**-0.020**	**-1.142**	**0.004**	**-0.009**	**-1.167**	**-0.135**	**1.047**	**-1158**	**1.886**	**1.935**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c ML estimation of a WLACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks														
Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
AOL	0.483	0.121	0.783	-0.023	-0.017	-0.992	-0.013	0.000	-0.610	-0.029	1.140	-1164.414	1.855	1.900
p-value	*0.001*	*0.000*	*0.000*	*0.151*	*0.279*	*0.000*	*0.149*	*0.400*	*0.033*	*0.705*	*0.000*			
ASF	0.770	0.209	0.534	-0.231	0.038	-1.413	-0.051	-0.007	-2.089	-0.136	0.848	-622.673	1.612	1.678
p-value	*0.002*	*0.000*	*0.000*	*0.001*	*0.304*	*0.000*	*0.073*	*0.001*	*0.000*	*0.608*	*0.000*			
BEN	0.152	0.072	0.836	0.009	-0.009	-1.124	-0.001	0.001	-0.601	-0.009	1.069	-1568.014	1.920	1.956
p-value	*0.070*	*0.000*	*0.000*	*0.567*	*0.479*	*0.000*	*0.911*	*0.018*	*0.012*	*0.957*	*0.000*			
CI	0.239	0.099	0.713	-0.038	0.020	-0.520	0.000	0.000	-0.802	-0.125	1.036	-1771.030	1.899	1.931
p-value	*0.032*	*0.000*	*0.000*	*0.047*	*0.171*	*0.000*	*0.997*	*0.414*	*0.000*	*0.238*	*0.000*			
CL	0.037	0.091	0.732	0.042	0.024	-0.843	-0.021	0.001	-0.767	-0.072	1.052	-1106.826	1.954	2.003
p-value	*0.794*	*0.000*	*0.000*	*0.149*	*0.218*	*0.002*	*0.263*	*0.172*	*0.038*	*0.700*	*0.000*			
CPQ	0.026	0.083	0.761	-0.090	0.015	-1.634	-0.034	0.000	0.720	-0.313	1.144	-702.657	1.921	1.989
p-value	*0.890*	*0.004*	*0.000*	*0.037*	*0.457*	*0.001*	*0.060*	*0.934*	*0.401*	*0.276*	*0.000*			
DCX	0.634	0.139	0.598	-0.034	-0.041	-1.746	0.000	-0.003	-1.228	0.107	1.038	-848.347	1.935	1.995
p-value	*0.007*	*0.000*	*0.000*	*0.369*	*0.179*	*0.000*	*0.986*	*0.030*	*0.000*	*0.736*	*0.000*			
GMH	0.143	0.181	0.526	-0.041	0.033	-1.829	-0.022	-0.001	-1.152	0.229	1.062	-906.500	1.934	1.990
p-value	*0.458*	*0.000*	*0.000*	*0.333*	*0.166*	*0.000*	*0.286*	*0.262*	*0.103*	*0.447*	*0.000*			
GT	0.698	0.098	0.678	-0.064	-0.021	-1.040	-0.036	-0.001	-3.378	0.148	1.045	-2226.595	1.899	1.926
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.165*	*0.000*	*0.002*	*0.145*	*0.000*	*0.634*	*0.000*			
HAR	0.717	0.137	0.391	-0.106	-0.024	-0.978	-0.013	-0.002	-1.767	0.235	1.011	-820.140	1.931	1.991
p-value	*0.005*	*0.000*	*0.000*	*0.100*	*0.498*	*0.000*	*0.652*	*0.371*	*0.001*	*0.368*	*0.000*			
KF	0.313	0.118	0.256	-0.051	-0.032	-1.836	0.046	-0.017	-2.918	-1.924	1.163	-602.046	1.946	2.024
p-value	*0.184*	*0.000*	*0.086*	*0.380*	*0.302*	*0.005*	*0.194*	*0.233*	*0.035*	*0.157*	*0.000*			
LE	0.748	0.146	0.741	0.074	-0.111	-0.378	0.018	-0.001	-0.715	0.390	1.004	-705.424	1.818	1.884
p-value	*0.000*	*0.000*	*0.000*	*0.069*	*0.000*	*0.301*	*0.474*	*0.733*	*0.041*	*0.120*	*0.000*			
LMT	0.221	0.111	0.691	-0.086	0.001	-1.767	-0.028	0.000	0.184	-0.326	1.009	-985.352	1.927	1.980
p-value	*0.208*	*0.000*	*0.000*	*0.006*	*0.962*	*0.000*	*0.095*	*0.465*	*0.716*	*0.151*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c. cont'd ML estimation of a WLACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Decimal Pilot Stocks (cont'd)														
Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
MLM	0.141	0.115	0.552	-0.142	0.028	-1.611	-0.012	0.001	-0.523	-0.697	0.973	-1008.787	1.890	1.941
p-value	*0.395*	*0.000*	*0.000*	*0.001*	*0.288*	*0.000*	*0.582*	*0.663*	*0.308*	*0.020*	*0.000*			
RCL	0.545	0.148	0.656	-0.037	-0.038	-0.927	0.007	-0.002	-1.295	-0.021	1.058	-961.477	1.918	1.971
p-value	*0.000*	*0.000*	*0.000*	*0.326*	*0.049*	*0.004*	*0.700*	*0.117*	*0.029*	*0.950*	*0.000*			
S	1.013	0.126	0.684	0.009	-0.091	-1.257	-0.059	-0.001	-0.667	0.634	1.030	-853.067	1.918	1.977
p-value	*0.000*	*0.000*	*0.000*	*0.771*	*0.002*	*0.002*	*0.003*	*0.214*	*0.202*	*0.015*	*0.000*			
SGY	-0.130	0.073	0.786	-0.025	0.048	-0.726	0.001	0.001	-0.639	0.070	1.026	-1331.646	1.949	1.990
p-value	*0.262*	*0.000*	*0.000*	*0.382*	*0.032*	*0.000*	*0.976*	*0.443*	*0.047*	*0.509*	*0.000*			
STT	-0.022	0.017	0.978	-0.034	-0.008	-0.241	0.011	0.000	0.276	-0.139	1.118	-963.967	1.861	1.913
p-value	*0.701*	*0.007*	*0.000*	*0.000*	*0.270*	*0.009*	*0.008*	*0.245*	*0.011*	*0.000*	*0.000*			
UBS	0.329	0.141	0.725	-0.104	-0.019	-0.268	-0.004	-0.005	0.230	-0.394	0.950	-1014.365	1.859	1.909
p-value	*0.009*	*0.000*	*0.000*	*0.001*	*0.407*	*0.012*	*0.842*	*0.093*	*0.150*	*0.002*	*0.000*			
VAL	0.352	0.162	0.611	-0.059	-0.024	-1.122	0.009	-0.006	-0.574	0.011	0.998	-1834.204	1.893	1.924
p-value	*0.001*	*0.000*	*0.000*	*0.007*	*0.171*	*0.000*	*0.478*	*0.014*	*0.017*	*0.969*	*0.000*			
Mean	**0.370**	**0.119**	**0.662**	**-0.052**	**-0.011**	**-1.113**	**-0.010**	**-0.002**	**-0.916**	**-0.118**	**1.039**	**-1099.9**	**1.892**	**1.944**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c. cont'd ML estimation of a WLACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks														
Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
WMT	0.041	0.059	0.895	-0.023	0.016	-0.594	-0.025	0.000	-0.194	0.013	1.161	-1339.813	1.881	1.922
p-value	*0.566*	*0.000*	*0.000*	*0.030*	*0.077*	*0.000*	*0.000*	*0.753*	*0.074*	*0.883*	*0.000*			
CCN	0.416	0.156	0.668	-0.020	-0.053	0.177	0.024	-0.019	-0.860	0.551	1.154	-781.064	1.877	1.939
p-value	*0.001*	*0.000*	*0.000*	*0.448*	*0.010*	*0.481*	*0.206*	*0.065*	*0.044*	*0.250*	*0.000*			
AOC	0.362	0.067	0.774	-0.062	-0.014	-1.142	-0.008	-0.001	-1.264	0.377	1.063	-1455.630	1.939	1.977
p-value	*0.000*	*0.000*	*0.000*	*0.004*	*0.261*	*0.000*	*0.467*	*0.424*	*0.000*	*0.100*	*0.000*			
UNH	0.344	0.174	0.554	-0.095	-0.005	-1.684	-0.009	-0.001	-0.506	0.076	1.117	-1788.308	1.915	1.948
p-value	*0.019*	*0.000*	*0.000*	*0.000*	*0.807*	*0.000*	*0.462*	*0.029*	*0.200*	*0.644*	*0.000*			
KO	0.261	0.064	0.693	-0.048	0.020	-1.246	-0.051	0.000	-0.997	-0.217	1.111	-991.267	1.888	1.939
p-value	*0.173*	*0.007*	*0.000*	*0.130*	*0.423*	*0.000*	*0.003*	*0.395*	*0.016*	*0.274*	*0.000*			
T	0.254	0.076	0.861	-0.077	0.015	-0.867	-0.023	0.000	-1.047	-0.203	1.118	-673.806	1.871	1.940
p-value	*0.092*	*0.000*	*0.000*	*0.009*	*0.380*	*0.112*	*0.115*	*0.785*	*0.237*	*0.446*	*0.000*			
DOV	0.480	0.131	0.694	-0.056	-0.055	-1.279	-0.017	0.000	-0.002	0.553	1.057	-794.797	1.905	1.967
p-value	*0.021*	*0.000*	*0.000*	*0.098*	*0.060*	*0.000*	*0.485*	*0.628*	*0.996*	*0.032*	*0.000*			
ALL	0.956	0.162	0.381	-0.139	-0.025	-1.357	-0.034	-0.001	-1.442	-1.759	1.048	-889.883	1.915	1.971
p-value	*0.002*	*0.000*	*0.000*	*0.005*	*0.525*	*0.001*	*0.155*	*0.319*	*0.155*	*0.000*	*0.000*			
GP	0.549	0.128	0.242	-0.085	0.004	-0.788	-0.027	-0.001	-2.544	0.150	1.063	-1977.991	1.964	1.995
p-value	*0.003*	*0.000*	*0.022*	*0.009*	*0.843*	*0.000*	*0.063*	*0.319*	*0.000*	*0.581*	*0.000*			
PHM	1.096	0.078	0.226	-0.178	-0.103	-0.764	-0.063	-0.001	-0.207	0.125	1.086	-884.093	1.969	2.028
p-value	*0.001*	*0.025*	*0.140*	*0.001*	*0.031*	*0.000*	*0.053*	*0.599*	*0.595*	*0.621*	*0.000*			
APF	0.548	0.283	0.151	0.169	-0.092	1.191	0.007	-0.023	-1.684	4.766	1.209	-538.686	1.860	1.942
p-value	*0.020*	*0.000*	*0.104*	*0.011*	*0.001*	*0.244*	*0.809*	*0.230*	*0.445*	*0.044*	*0.000*			
CLB	0.516	0.113	0.240	0.073	-0.038	0.031	-0.006	-0.004	-1.679	-0.744	1.025	-667.366	1.981	2.053
p-value	*0.037*	*0.000*	*0.085*	*0.231*	*0.273*	*0.903*	*0.875*	*0.529*	*0.009*	*0.145*	*0.000*			

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 7c. cont'd ML estimation of a WLACD(1,1) model. Sample time period February 8, 2001 till May 31, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1}) + \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

Matched Control Stocks (cont'd)

Stock	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
MRO	0.393	0.040	0.887	0.041	-0.009	-1.641	-0.023	0.000	-2.745	-0.156	1.052	-1039.655	1.938	1.989
p-value	*0.000*	*0.004*	*0.000*	*0.026*	*0.403*	*0.000*	*0.035*	*0.420*	*0.001*	*0.616*	*0.000*			
HTN	0.141	0.050	0.895	-0.035	0.001	-0.612	-0.029	-0.002	-0.376	0.786	1.042	-1106.740	1.924	1.972
p-value	*0.166*	*0.000*	*0.000*	*0.043*	*0.936*	*0.001*	*0.040*	*0.052*	*0.015*	*0.000*	*0.000*			
CNF	0.056	0.106	0.509	-0.045	0.052	-0.149	-0.012	-0.002	-2.182	1.108	1.014	-1072.516	1.959	2.009
p-value	*0.752*	*0.000*	*0.000*	*0.259*	*0.097*	*0.449*	*0.644*	*0.201*	*0.000*	*0.003*	*0.000*			
NKE	0.532	0.164	0.690	0.040	-0.039	-1.019	0.031	-0.002	-1.454	-0.309	1.000	-895.226	1.924	1.981
p-value	*0.000*	*0.000*	*0.000*	*0.280*	*0.091*	*0.001*	*0.052*	*0.013*	*0.014*	*0.255*	*0.000*			
AMG	0.420	0.135	0.493	-0.163	0.060	-0.864	-0.105	-0.008	-1.314	0.685	0.909	-1274.650	1.821	1.862
p-value	*0.019*	*0.000*	*0.000*	*0.000*	*0.030*	*0.000*	*0.000*	*0.005*	*0.000*	*0.001*	*0.000*			
PKI	-0.005	0.059	0.874	-0.043	0.007	-0.602	-0.037	0.000	0.246	0.119	0.996	-1008.034	1.932	1.984
p-value	*0.967*	*0.000*	*0.000*	*0.042*	*0.612*	*0.000*	*0.002*	*0.798*	*0.232*	*0.106*	*0.000*			
HIT	0.591	0.176	-0.030	-0.171	0.001	-0.159	-0.056	-0.028	-0.565	-0.357	1.115	-1092.428	1.946	1.995
p-value	*0.015*	*0.000*	*0.818*	*0.005*	*0.987*	*0.184*	*0.106*	*0.001*	*0.038*	*0.141*	*0.000*			
AGX	-0.090	0.251	0.330	0.042	-0.003	0.465	0.071	-0.035	-1.180	-0.152	1.196	-685.504	1.850	1.917
p-value	*0.562*	*0.000*	*0.000*	*0.330*	*0.908*	*0.485*	*0.002*	*0.008*	*0.377*	*0.914*	*0.000*			
Mean	**0.39**	**0.12**	**0.55**	**-0.04**	**-0.01**	**-0.65**	**-0.02**	**-0.01**	**-1.10**	**0.27**	**1.08**	**-1047.87**	**1.91**	**1.87**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 8. Optimal Specification Model.
Sample time period October 2, 2000 till January 26, 2001.
Gamma coefficients from the Weibull ACD(1,1) and the Weibull-Logarithmic ACD(1,1) models.The goodness of the Weibull distributional assumption in both cases can be tested by H_0: γ=1, which describes the nested exponential distribution.

PILOT SAMPLE				
Sample period Oct. 2, 2000 till Jan. 26, 2001				
	WACD(1,1) H_0: γ=1		**WLACD(1,1) H_0: γ=1**	
	γ	p-value	**γ**	p-value
AOL	1.087	*0.000*	1.089	*0.000*
ASF	1.130	*0.169*	0.884	*0.000*
BEN	1.329	*0.018*	1.047	*0.013*
CI	1.075	*0.281*	1.053	*0.021*
CL	1.073	*0.001*	1.079	*0.000*
CPQ	1.370	*0.233*	1.045	*0.037*
DCX	0.988	*0.690*	1.012	*0.572*
GMH	0.925	*0.716*	1.054	*0.016*
GT	1.077	*0.156*	0.979	*0.331*
HAR	1.037	*0.331*	1.006	*0.778*
KF	1.151	*0.000*	1.161	*0.000*
LE	1.207	*0.077*	0.985	*0.533*
LMT	1.050	*0.017*	1.046	*0.026*
MLM	1.123	*0.028*	1.040	*0.051*
RCL	0.976	*0.263*	0.980	*0.331*
S	1.279	*0.000*	1.046	*0.071*
SGY	1.113	*0.422*	0.929	*0.000*
STT	1.028	*0.270*	1.005	*0.777*
UBS	0.964	*0.084*	0.964	*0.095*
VAL	1.288	*0.488*	1.086	*0.001*
Number of rejections at 5%		***7***		***11***
Number of rejections at 10%		***9***		***14***

MATCHED CONTROL SAMPLE				
Sample period Feb. 8, 2001 till May 31, 2001				
	WACD(1,1) H_0: γ=1		**WLACD(1,1) H_0: γ=1**	
	γ	p-value	**γ**	p-value
WMT	1.140	*0.026*	1.161	*0.000*
CCN	1.169	*0.089*	1.154	*0.009*
AOC	1.062	*0.097*	1.063	*0.079*
UNH	1.140	*0.002*	1.117	*0.004*
KO	1.370	*0.000*	1.111	*0.000*
T	1.116	*0.001*	1.118	*0.000*
DOV	1.062	*0.210*	1.057	*0.988*
ALL	1.346	*0.724*	1.048	*0.136*
GP	1.069	*0.769*	1.063	*0.859*
PHM	1.178	*0.299*	1.086	*0.500*
APF	1.192	*0.000*	1.209	*0.000*
CLB	1.087	*0.120*	1.025	*0.878*
MRO	1.046	*0.693*	1.052	*0.815*
HTN	1.046	*0.417*	1.042	*0.452*
CNF	1.023	*0.585*	1.014	*0.359*
NKE	0.991	*0.661*	1.000	*0.865*
AMG	0.902	*0.000*	0.909	*0.000*
PKI	1.009	*0.927*	0.996	*0.422*
HIT	1.133	*0.000*	1.115	*0.000*
AGX	1.208	*0.001*	1.196	*0.019*
Number of rejections at 5%		***8***		***9***
Number of rejections at 10%		***10***		***10***

Table 9. Optimal Specification Model.
Sample time period October 2, 2000 till January 26, 2001.
Test of the standardized residuals from the Exponential ACD(1,1) model.
The goodness of the Exponential distributional assumption in both cases is tested by H_0: μ=1, H_0: σ =1, and an empirical Watson (W) and Anderson-Darling (AD) test of exponential distribution.

PILOT SAMPLE				
	EACD(1,1)		W test	AD test
	H_0: μ=1	H_0: σ =1	Exponential null	
	p-val.	p-val.	p-val.	p-val.
AOL	0.9573	0.0000	0.0000	0.0000
ASF	0.4630	0.0000	0.0000	0.0000
BEN	0.9941	0.0000	0.0000	0.0000
CI	0.8287	0.0000	0.0000	0.0000
CL	0.8699	0.0000	0.0000	0.0000
CPQ	0.9304	0.0000	0.0000	0.0000
DCX	0.6496	0.0000	0.0000	0.0000
GMH	0.5393	0.0000	0.0000	0.0000
GT	0.3238	0.0000	0.0000	0.0000
HAR	0.8027	0.0000	0.0000	0.0000
KF	0.9349	0.0001	0.0001	0.0000
LE	0.0002	0.0000	0.0000	0.0000
LMT	0.5808	0.0000	0.0000	0.0000
MLM	0.7684	0.0006	0.0000	0.0000
RCL	0.9012	0.0000	0.0000	0.0000
S	0.6549	0.0000	0.0000	0.0000
SGY	0.0212	0.0000	0.0000	0.0000
STT	0.4667	0.0000	0.0000	0.0000
UBS	0.9723	0.0000	0.0000	0.0000
VAL	0.5398	0.0195	0.0000	0.0000

MATCHED CONTROL SAMPLE				
	EACD(1,1)		W test	AD test
	H_0: μ=1	H_0: σ =1	Exponential null	
	p-val.	p-val.	p-val.	p-val.
WMT	0.9982	0.0000	0.0000	0.0000
CCN	0.0504	0.0000	0.0000	0.0000
AOC	0.9283	0.0000	0.0000	0.0000
UNH	0.9999	0.0000	0.0000	0.0000
KO	0.9209	0.4174	0.0000	0.0000
T	0.2268	0.0077	0.0000	0.0000
DOV	0.9822	0.0000	0.0000	0.0000
ALL	0.6798	0.0000	0.0000	0.0000
GP	0.0319	0.0000	0.0000	0.0000
PHM	0.5833	0.0000	0.0000	0.0000
APF	0.9999	0.0000	0.0000	0.0000
CLB	0.4405	0.0002	0.0000	0.0000
MRO	0.9711	0.0000	0.0000	0.0000
HTN	0.9947	0.0000	0.2107	0.0005
CNF	0.7713	0.0000	0.0000	0.0000
NKE	0.1651	0.0000	0.0000	0.0000
AMG	0.9261	0.0000	0.0000	0.0000
PKI	0.0027	0.0000	0.0000	0.0000
HIT	0.9903	0.0000	0.0000	0.0000
AGX	0.9971	0.4009	0.0043	0.0000

Table 10. Optimal Specification Model.
Sample time period October 2, 2000 till January 26, 2001.
Test of stand. residuals from the Weibull and Logarithmic-Weibull ACD(1,1) models.
The goodness of the Weibull distributional assumption in both cases can be tested by running an empirical Kolmogorov (K) and Watson (W) tests of exponential distribution with mean 1 upon both models' standardized residuals, raised to power γ.

PILOT SAMPLE				
	WACD(1,1)		WLACD(1,1)	
e^{γ}	Expon.null		Expon.null	
p-values	K	W	K	W
AOL	0.011	0.000	0.005	0.000
ASF	0.004	0.000	0.219	0.000
BEN	0.000	0.000	0.017	0.000
CI	0.326	0.000	0.086	0.000
CL	0.016	0.000	0.021	0.000
CPQ	0.899	0.000	0.073	0.000
DCX	0.044	0.000	0.173	0.000
GMH	0.000	0.000	0.007	0.000
GT	0.377	0.000	0.354	0.000
HAR	0.336	0.029	0.057	0.000
KF	0.258	0.574	0.309	0.591
LE	0.009	0.000	0.757	0.010
LMT	0.077	0.005	0.101	0.001
MLM	0.365	0.333	0.304	0.051
RCL	0.192	0.000	0.207	0.001
S	0.008	0.000	0.228	0.004
SGY	0.235	0.000	0.113	0.000
STT	0.065	0.000	0.108	0.000
UBS	0.253	0.000	0.157	0.000
VAL	0.001	0.000	0.629	0.505
Failed rej. at 5%	***11***	***2***	***16***	***3***
Failed rej. at 10%	***9***	***2***	***13***	***2***

MATCHED CONTROL SAMPLE				
	WACD(1,1)		WLACD(1,1)	
e^{γ}	Expon.null		Expon.null	
p-values	K	W	K	W
WMT	0.009	0.000	0.007	0.000
CCN	0.134	0.035	0.271	0.055
AOC	0.032	0.000	0.019	0.000
UNH	0.052	0.000	0.038	0.000
KO	0.131	0.000	0.133	0.006
T	0.071	0.000	0.160	0.005
DOV	0.340	0.000	0.338	0.000
ALL	0.011	0.000	0.030	0.000
GP	0.056	0.000	0.032	0.000
PHM	0.741	0.010	0.115	0.090
APF	0.063	0.101	0.072	0.065
CLB	0.143	0.068	0.410	0.253
MRO	0.040	0.000	0.014	0.000
HTN	0.153	0.121	0.286	0.145
CNF	0.646	0.000	0.317	0.002
NKE	0.202	0.000	0.176	0.000
AMG	0.666	0.000	0.338	0.000
PKI	0.181	0.000	0.223	0.000
HIT	0.041	0.301	0.048	0.292
AGX	0.165	0.197	0.134	0.364
Failed rej. at 5%	***15***	***5***	***13***	***7***
Failed rej. at 10%	***11***	***4***	***12***	***4***

Table 11 Stock CLB.

Sample time period October 2, 2000 till January 26, 2001.

Correlograms of 15 ACs and PACs of EACD, WACD, and WLACD residuals

Q-statistics and p-values test the null of zero autocorrelation at the specified lag.

EACD Standardized residuals					EACD Squared Standardized Resids				
	AC	PAC	Q-stat	p-value		AC	PAC	Q-stat	p-value
1	0.025	0.025	0.6684	*0.414*	**1**	-0.017	-0.017	0.3021	*0.583*
2	-0.059	-0.06	4.4986	*0.105*	**2**	-0.031	-0.031	1.3574	*0.507*
3	-0.007	-0.004	4.5452	*0.208*	**3**	0.007	0.006	1.408	*0.704*
4	0.071	0.068	9.98	*0.041*	**4**	0.044	0.043	3.4944	*0.479*
5	0.029	0.025	10.911	*0.053*	**5**	-0.01	-0.009	3.6115	*0.607*
6	0.012	0.019	11.071	*0.086*	**6**	-0.009	-0.007	3.6974	*0.718*
7	0.009	0.012	11.156	*0.132*	**7**	-0.017	-0.018	4.001	*0.780*
8	0.027	0.024	11.925	*0.155*	**8**	0	-0.003	4.0011	*0.857*
9	-0.008	-0.012	11.998	*0.213*	**9**	-0.017	-0.017	4.2983	*0.891*
10	-0.007	-0.007	12.055	*0.281*	**10**	-0.015	-0.015	4.5381	*0.920*
11	0.056	0.053	15.445	*0.163*	**11**	0.008	0.008	4.6042	*0.949*
12	-0.039	-0.048	17.124	*0.145*	**12**	-0.026	-0.026	5.3232	*0.946*
13	-0.056	-0.049	20.572	*0.082*	**13**	-0.027	-0.026	6.1317	*0.941*
14	-0.027	-0.028	21.35	*0.093*	**14**	-0.025	-0.027	6.7975	*0.942*
15	0.048	0.036	23.851	*0.068*	**15**	0.007	0.004	6.8571	*0.961*

WACD Standardized residuals					WACD Squared Standardized residuals				
	AC	PAC	Q-stat	p-value		AC	PAC	Q-stat	p-value
1	0.029	0.029	0.8907	*0.345*	**1**	-0.018	-0.018	0.3365	*0.562*
2	-0.058	-0.059	4.5342	*0.104*	**2**	-0.034	-0.035	1.6035	*0.449*
3	-0.005	-0.002	4.5607	*0.207*	**3**	0.012	0.01	1.7471	*0.627*
4	0.069	0.066	9.7123	*0.046*	**4**	0.05	0.049	4.4183	*0.352*
5	0.032	0.028	10.847	*0.054*	**5**	-0.009	-0.007	4.5096	*0.479*
6	0.015	0.021	11.086	*0.086*	**6**	-0.008	-0.005	4.5843	*0.598*
7	0.014	0.017	11.291	*0.126*	**7**	-0.017	-0.019	4.8838	*0.674*
8	0.027	0.024	12.089	*0.147*	**8**	0.002	-0.002	4.8872	*0.770*
9	-0.007	-0.011	12.148	*0.205*	**9**	-0.017	-0.017	5.2058	*0.816*
10	-0.007	-0.007	12.198	*0.272*	**10**	-0.016	-0.015	5.4714	*0.858*
11	0.058	0.055	15.815	*0.148*	**11**	0.01	0.01	5.5801	*0.900*
12	-0.04	-0.049	17.564	*0.130*	**12**	-0.028	-0.029	6.4306	*0.893*
13	-0.056	-0.049	21.055	*0.072*	**13**	-0.031	-0.029	7.4533	*0.877*
14	-0.026	-0.027	21.774	*0.083*	**14**	-0.027	-0.029	8.2254	*0.877*
15	0.047	0.036	24.214	*0.062*	**15**	0.01	0.006	8.3341	*0.910*

WLACD Standardized residuals					WLACD Squared Standardized residuals				
	AC	PAC	Q-stat	p-value		AC	PAC	Q-stat	p-value
1	0.033	0.033	1.1923	*0.275*	**1**	-0.004	-0.004	0.0147	*0.903*
2	-0.037	-0.039	2.7143	*0.257*	**2**	-0.017	-0.017	0.3371	*0.845*
3	0.009	0.011	2.7935	*0.425*	**3**	0.037	0.037	1.8052	*0.614*
4	0.064	0.062	7.1806	*0.127*	**4**	0.046	0.046	4.135	*0.388*
5	0.04	0.037	8.9099	*0.113*	**5**	-0.006	-0.004	4.1697	*0.525*
6	0.028	0.03	9.7534	*0.135*	**6**	0.006	0.006	4.2127	*0.648*
7	0.013	0.013	9.9501	*0.191*	**7**	-0.015	-0.018	4.4484	*0.727*
8	0.043	0.04	11.949	*0.153*	**8**	0.027	0.025	5.2349	*0.732*
9	-0.021	-0.028	12.419	*0.191*	**9**	-0.026	-0.027	5.9957	*0.740*
10	-0.027	-0.028	13.237	*0.211*	**10**	-0.023	-0.022	6.5873	*0.764*
11	0.057	0.053	16.819	*0.113*	**11**	0.021	0.02	7.0731	*0.793*
12	-0.016	-0.028	17.097	*0.146*	**12**	-0.001	-0.002	7.0743	*0.853*
13	-0.034	-0.029	18.362	*0.144*	**13**	-0.024	-0.018	7.6841	*0.864*
14	-0.024	-0.022	18.998	*0.165*	**14**	-0.022	-0.023	8.2301	*0.877*
15	0.05	0.046	21.7	*0.116*	**15**	0.024	0.022	8.8452	*0.885*

Table 12a. Decimal vs. control stock coefficient comparison in WLACD(1,1) model.
Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_{t} = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

t-Test: Two-Sample Assuming Equal Variances

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.45	0.13	0.63	-0.05	-0.02	-0.85	-0.01	0.00	-1.01	0.06	1.02	-1252.05	1.89	1.94
Variance	0.13	0.00	0.05	0.00	0.00	0.19	0.00	0.00	0.87	0.36	0.00	47678.09	0.00	0.00
Pooled Variance	0.09	0.00	0.06	0.01	0.00	0.42	0.00	0.00	1.04	0.67	0.01	69672.16	0.00	0.00
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00
t Stat	-0.28	-0.11	0.16	0.56	0.37	1.45	-1.82	1.10	0.49	0.75	-1.02	-1.13	0.51	0.08
P(T<=t) one-tail	0.39	0.46	0.44	0.29	0.36	0.08	0.04	0.14	0.31	0.23	0.16	0.13	0.31	0.47
t Crit.one-tail	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69
P(T<=t) two-tail	0.78	0.92	0.87	0.58	0.72	0.16	0.08	0.28	0.62	0.46	0.32	0.27	0.61	0.94
t Crit. two-tail	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02

t-Test: Two-Sample Assuming Unequal Variances

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.45	0.13	0.63	-0.05	-0.02	-0.85	-0.01	0.00	-1.01	0.06	1.02	-1252.05	1.89	1.94
Variance	0.13	0.00	0.05	0.00	0.00	0.19	0.00	0.00	0.87	0.36	0.00	47678.09	0.00	0.00
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	32.00	36.00	37.00	33.00	37.00	29.00	38.00	23.00	37.00	31.00	36.00	35.00	38.00	37.00
t Stat	-0.28	-0.11	0.16	0.56	0.37	1.45	-1.82	1.10	0.49	0.75	-1.02	-1.13	0.51	0.08
P(T<=t) one-tail	0.39	0.46	0.44	0.29	0.36	0.08	0.04	0.14	0.31	0.23	0.16	0.13	0.31	0.47
t Crit.one-tail	1.69	1.69	1.69	1.69	1.69	1.70	1.69	1.71	1.69	1.70	1.69	1.69	1.69	1.69
P(T<=t) two-tail	0.78	0.92	0.87	0.58	0.72	0.16	0.08	0.28	0.62	0.46	0.32	0.27	0.61	0.94
t Crit. two-tail	2.04	2.03	2.03	2.03	2.03	2.05	2.02	2.07	2.03	2.04	2.03	2.03	2.02	2.03

t-test paired

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.45	0.13	0.63	-0.05	-0.02	-0.85	-0.01	0.00	-1.01	0.06	1.02	-1252.05	1.89	1.94
Variance	0.13	0.00	0.05	0.00	0.00	0.19	0.00	0.00	0.87	0.36	0.00	47678.09	0.00	0.00
Pooled Variance	#N/A	0.40	0.08	-0.38	-0.06	0.09	0.11	0.39	0.40	0.83	0.48	0.80	0.54	0.43
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
t Stat	-0.27	-0.14	0.17	0.48	0.35	1.50	-1.93	1.27	0.64	1.45	-1.39	-2.30	0.75	0.10
P(T<=t) one-tail	0.40	0.45	0.43	0.32	0.36	0.07	0.03	0.11	0.27	0.08	0.09	0.02	0.23	0.46
t Crit.one-tail	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73
P(T<=t) two-tail	0.79	0.89	0.87	0.63	0.73	0.15	0.07	0.22	0.53	0.16	0.18	0.03	0.46	0.92
t Crit. two-tail	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 12a. Cont'd ANOVA of differences in decimal vs. control stock coefficients during the test sample period.
Sample time period October 2, 2000 till January 26, 2001.

Model is*:

$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

ANOVA SUMMARY

Groups	Count	Sum	Average	Variance
ω	18.00	-0.10	-0.01	0.19
α	18.00	-0.19	-0.01	0.00
β	18.00	-0.34	-0.02	0.06
γ0	18.00	-0.08	0.00	0.01
γ1	18.00	0.11	0.01	0.00
γ2	18.00	4.67	0.26	0.85
γ3	18.00	-0.48	-0.03	0.00
γ4	18.00	0.11	0.01	0.00
γp	18.00	6.59	0.37	0.87
γn	18.00	0.95	0.05	0.14
γ	18.00	-0.37	-0.02	0.01

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.11	10	0.31	1.60	0.11	1.88
Within Groups	36.27	187	0.19			
Total	39.4	197				

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 12b. Decimal vs. control stock coefficient comparison in WLACD(1,1) model.
Sample time period February 8, 2001 till May 31, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

t-Test: Two-Sample Assuming Equal Variances

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.37	0.12	0.66	-0.05	-0.01	-1.11	-0.01	0.00	-0.92	-0.12	1.04	-1099.9	1.89	1.94
Variance	0.10	0.00	0.03	0.00	0.00	0.27	0.00	0.00	1.04	0.26	0.01	191125	0.01	0.01
Pooled Variance	0.09	0.00	0.05	0.01	0.00	0.40	0.00	0.00	0.86	0.88	0.01	164321	0.00	0.00
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00	38.00
t Stat	-0.23	-0.24	1.51	-0.32	0.12	-2.33	0.95	1.63	0.63	-1.31	-1.66	-0.41	-1.09	-1.20
P(T<=t) one-tail	0.41	0.41	0.07	0.38	0.45	0.01	0.17	0.06	0.27	0.10	0.05	0.34	0.14	0.12
t Crit.one-tail	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69
P(T<=t) two-tail	0.82	0.81	0.14	0.75	0.90	0.02	0.35	0.11	0.53	0.20	0.10	0.69	0.28	0.24
t Crit. two-tail	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02

t-Test: Two-Sample Assuming Unequal Variances

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.37	0.12	0.66	-0.05	-0.01	-1.11	-0.01	0.00	-0.92	-0.12	1.04	-1099.9	1.89	1.94
Variance	0.10	0.00	0.03	0.00	0.00	0.27	0.00	0.00	1.04	0.26	0.01	191125	0.01	0.01
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	38.00	32.00	30.00	35.00	38.00	34.00	33.00	25.00	36.00	26.00	38.00	37.00	30.00	30.00
t Stat	-0.23	-0.24	1.51	-0.32	0.12	-2.33	0.95	1.63	0.63	-1.31	-1.66	-0.41	-1.09	-1.20
P(T<=t) one-tail	0.41	0.41	0.07	0.38	0.45	0.01	0.17	0.06	0.27	0.10	0.05	0.34	0.14	0.12
t Crit.one-tail	1.69	1.69	1.70	1.69	1.69	1.69	1.69	1.71	1.69	1.71	1.69	1.69	1.70	1.70
P(T<=t) two-tail	0.82	0.81	0.14	0.75	0.90	0.03	0.35	0.12	0.53	0.20	0.10	0.69	0.29	0.24
t Crit. two-tail	2.02	2.04	2.04	2.03	2.02	2.03	2.03	2.06	2.03	2.06	2.02	2.03	2.04	2.04

t-test paired

	ω	α	β	γ_0	γ_1	γ_2	γ_3	γ_4	γ_p	γ_n	γ	LogL	AIC	SIC
Mean	0.37	0.12	0.66	-0.05	-0.01	-1.11	-0.01	0.00	-0.92	-0.12	1.04	-1099.9	1.89	1.94
Variance	0.10	0.00	0.03	0.00	0.00	0.27	0.00	0.00	1.04	0.26	0.01	191125	0.01	0.01
Pooled Variance	0.30	0.42	0.45	0.19	0.34	0.04	-0.04	0.70	0.29	-0.81	0.05	0.78	-0.02	-0.01
Hyp. Mean Dif.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
df	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
t Stat	-0.28	-0.31	1.92	-0.35	0.15	-2.38	0.94	2.25	0.74	-1.04	-1.71	-0.84	-1.08	-1.19
P(T<=t) one-tail	0.39	0.38	0.04	0.37	0.44	0.01	0.18	0.02	0.23	0.16	0.05	0.21	0.15	0.12
t Crit.one-tail	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73
P(T<=t) two-tail	0.78	0.76	0.07	0.73	0.88	0.03	0.36	0.04	0.47	0.31	0.10	0.41	0.29	0.25
t Crit. two-tail	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09	2.09

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 12b. Cont'd ANOVA of differences in decimal vs. control stock coefficients during the control sample period.
Sample time period February 8, 2001 till May 31, 2001.

Model is*:
$$ENPTIME_t = \omega + \alpha_1 \log(NPTIME_{t-1}) + \beta_1 ENPTIME_{t-1} + \gamma_0 NLSPRD_{t-1} + \gamma_1 \log(AVEVOL_{t-1})$$
$$+ \gamma_2 DSPREAD_{t-1} + \gamma_3 \log(DEPTH_{t-1}) + \gamma_4 NUMBER_{t-1} + (\gamma_P + \gamma_N I_N^{PRESID_{t-1}}) APRESID_{t-1}$$

ANOVA SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
ω	20.00	-0.45	-0.02	0.13
α	20.00	-0.08	0.00	0.00
β	20.00	2.21	0.11	0.07
γ0	20.00	-0.15	-0.01	0.01
γ1	20.00	0.03	0.00	0.00
γ2	20.00	-9.35	-0.47	0.77
γ3	20.00	0.19	0.01	0.00
γ4	20.00	0.08	0.00	0.00
γp	20.00	3.68	0.18	1.23
γn	20.00	-7.77	-0.39	2.78
γ	20.00	-0.76	-0.04	0.01

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	7.66	10.00	0.77	1.68	0.09	1.88
Within Groups	95.03	209	0.45			
Total	102.7	219				

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 12c. Interacted stock pooled ACD estimation, testing for differences in control stock coefficients.

Model is*:

$$psiwl\_1 = \omega + \alpha*\log(NPTIME_{t-1}) + \beta*ENPTIME_{t-1} + \gamma_0*NLSPRD_{t-1} + \gamma_1*\log(AVEVOL_{t-1}) + \gamma_2*DSPREAD_{t-1} + \gamma_3*\log(DEPTH_{t-1}) + \gamma_4*NUMBER_{t-1} + (\gamma_p + \gamma_n*I^{-}_{PRESID)})*APRESID_{t-1} + \gamma_{10}*NLSPRD_{t-1}*I^{C} + \gamma_{11}*\log(AVEVOL_{t-1})*I^{C} + \gamma_{12}*DSPREAD_{t-1}*I^{C} + \gamma_{13}*\log(DEPTH_{t-1})*I^{C} + \gamma_{14}*NUMBER_{t-1}*I^{C} + (\gamma_{1p}*I^{C} + \gamma_{1n}*I^{C}*I^{-}_{PRESID})*APRESID_{t-1}$$

	Oct. 2, 2000 till Jan. 26, 2001. Method: ML (Marquardt) Included observations: 51543			
	Coeff.	Std. Err.	z-Stat.	p-val.
ω	0.15	0.01	17.25	*0.00*
α	0.11	0.00	49.53	*0.00*
β	0.76	0.01	148.4	*0.00*
γ_0	-0.03	0.00	-8.12	*0.00*
γ_1	-0.01	0.00	-4.29	*0.00*
γ_2	-0.55	0.01	-53.06	*0.00*
γ_3	0.00	0.00	-1.62	*0.11*
γ_4	0.00	0.00	2.08	*0.04*
γ_p	-0.08	0.02	-4.72	*0.00*
γ_n	0.03	0.02	1.11	*0.27*
γ_{10}	-0.02	0.01	-3.38	*0.00*
γ_{11}	0.00	0.00	-0.67	*0.50*
γ_{12}	-0.12	0.03	-3.77	*0.00*
γ_{13}	0.00	0.00	1.53	*0.13*
γ_{14}	0.00	0.00	-0.37	*0.71*
γ_{1p}	0.06	0.02	2.70	*0.01*
γ_{1n}	-0.03	0.03	-0.85	*0.39*
γ	1.01	0.00	346.5	*0.00*

LogL	***-49292.5***
Avg. LogL	***-0.9563***
# of Coef.	***18***
AIC	***1.913***
SIC	***1.916***

	Feb. 8, 2001 till May 31, 2001. Method: ML (Marquardt) Included observations: 45592			
	Coeff.	Std. Err.	z-Stat.	p-val.
ω	0.17	0.01	15.67	*0.00*
α	0.10	0.00	42.12	*0.00*
β	0.74	0.01	110.21	*0.00*
γ_0	-0.04	0.00	-11.52	*0.00*
γ_1	-0.01	0.00	-3.22	*0.00*
γ_2	-0.72	0.03	-21.15	*0.00*
γ_3	-0.01	0.00	-2.48	*0.01*
γ_4	0.00	0.00	3.40	*0.00*
γ_p	-0.01	0.02	-0.62	*0.54*
γ_n	-0.12	0.03	-4.23	*0.00*
γ_{10}	0.00	0.01	0.87	*0.38*
γ_{11}	0.00	0.00	1.32	*0.19*
γ_{12}	0.01	0.05	0.28	*0.78*
γ_{13}	-0.01	0.00	-2.13	*0.03*
γ_{14}	0.00	0.00	-0.79	*0.43*
γ_{1p}	-0.13	0.03	-3.80	*0.00*
γ_{1n}	0.23	0.05	5.01	*0.00*
γ	1.03	0.00	312.11	*0.00*

LogL	**-43814**
Avg. LogL	**-0.9610**
# of Coef.	**18.000**
AIC	**1.923**
SIC	**1.926**

* ENPTIME = exp. duration, NPTIME = norm. duration, NLSPRD = norm. nominal spread, AVEVOL = avg. transaction volume, DSPREAD = change in nominal spread, DEPTH = quoted depth, NUMBER = # of transactions, APRESID = |price change|.

Table 13a. Individual stock VNET regression.
Sample period Oct. 2, 2000 till Jan. 26, 2001.

Model is*: $$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Decimal Pilot Stocks							
	β_0	β_1	β_2	β_3	β_4	β_5	β_6
AOL	7.537	0.163	-0.218	-0.092	0.313	0.381	-0.054
p-value	*0.000*	*0.099*	*0.000*	*0.024*	*0.000*	*0.000*	*0.085*
ASF	5.234	0.003	-0.079	-0.293	0.187	0.402	0.015
p-value	*0.000*	*0.982*	*0.367*	*0.000*	*0.003*	*0.000*	*0.614*
BEN	7.288	-0.589	0.188	-0.153	-0.023	0.556	-0.005
p-value	*0.000*	*0.006*	*0.010*	*0.001*	*0.665*	*0.000*	*0.804*
CI	7.878	0.688	0.066	-0.125	-0.057	0.731	0.038
p-value	*0.000*	*0.000*	*0.426*	*0.005*	*0.383*	*0.000*	*0.363*
CL	7.164	0.252	0.016	-0.153	0.130	0.423	-0.034
p-value	*0.000*	*0.211*	*0.815*	*0.001*	*0.025*	*0.000*	*0.173*
CPQ	8.251	0.415	-0.117	-0.124	0.210	0.436	-0.037
p-value	*0.000*	*0.001*	*0.045*	*0.025*	*0.001*	*0.000*	*0.085*
DCX	6.499	0.093	-0.048	-0.135	0.176	0.518	0.038
p-value	*0.000*	*0.603*	*0.623*	*0.005*	*0.010*	*0.000*	*0.141*
GMH	8.259	0.286	0.079	-0.293	0.032	0.636	-0.025
p-value	*0.000*	*0.085*	*0.305*	*0.000*	*0.591*	*0.000*	*0.289*
GT	6.488	0.872	-0.099	-0.243	0.140	0.851	0.021
p-value	*0.000*	*0.001*	*0.384*	*0.001*	*0.065*	*0.000*	*0.413*
HAR	7.077	0.660	0.039	-0.094	-0.028	0.577	-0.051
p-value	*0.000*	*0.000*	*0.679*	*0.194*	*0.671*	*0.000*	*0.165*
KF	4.765	-0.352	0.041	-0.299	0.067	0.653	0.011
p-value	*0.000*	*0.319*	*0.844*	*0.053*	*0.548*	*0.000*	*0.733*
LE	7.599	0.180	0.244	-0.093	-0.090	0.483	0.038
p-value	*0.000*	*0.205*	*0.026*	*0.141*	*0.272*	*0.000*	*0.218*
LMT	7.004	0.815	-0.093	-0.123	0.179	0.678	0.021
p-value	*0.000*	*0.005*	*0.246*	*0.022*	*0.003*	*0.000*	*0.475*
MLM	6.626	0.503	0.122	-0.053	-0.009	0.623	0.025
p-value	*0.000*	*0.113*	*0.264*	*0.414*	*0.905*	*0.000*	*0.391*
RCL	6.520	-0.022	-0.013	-0.268	0.108	0.756	0.052
p-value	*0.000*	*0.888*	*0.893*	*0.000*	*0.090*	*0.000*	*0.082*
S	5.962	0.212	-0.138	-0.194	0.293	0.432	-0.036
p-value	*0.000*	*0.163*	*0.069*	*0.000*	*0.000*	*0.000*	*0.154*
SGY	7.311	0.176	0.024	-0.145	-0.047	0.437	0.003
p-value	*0.000*	*0.259*	*0.792*	*0.041*	*0.511*	*0.000*	*0.911*
STT	6.587	0.390	-0.183	0.034	0.210	0.337	0.023
p-value	*0.000*	*0.001*	*0.018*	*0.393*	*0.003*	*0.000*	*0.649*
UBS	5.254	-0.321	-0.248	-0.185	0.251	0.439	0.054
p-value	*0.000*	*0.012*	*0.007*	*0.000*	*0.000*	*0.000*	*0.138*
VAL	7.198	-0.133	0.255	-0.146	-0.204	0.433	0.057
p-value	*0.000*	*0.555*	*0.061*	*0.074*	*0.034*	*0.000*	*0.032*
Mean	**6.825**	**0.215**	**-0.008**	**-0.159**	**0.092**	**0.539**	**0.008**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 13a. cont'd. Individual stock VNET regression.
Sample period Oct. 2, 2000 till Jan. 26, 2001.

Model is*: $\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$
$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$

Matched Control Stocks							
	β_0	β_1	β_2	β_3	β_4	β_5	β_6
WMT	6.967	0.293	-0.313	-0.290	0.316	0.515	0.003
p-value	*0.000*	*0.069*	*0.000*	*0.000*	*0.000*	*0.000*	*0.928*
CCN	4.641	-0.280	-0.043	0.163	0.039	0.194	0.018
p-value	*0.000*	*0.113*	*0.796*	*0.126*	*0.612*	*0.006*	*0.534*
AOC	6.092	0.208	0.046	-0.092	0.157	0.860	0.028
p-value	*0.000*	*0.320*	*0.626*	*0.488*	*0.007*	*0.000*	*0.272*
UNH	5.700	0.413	-0.258	-0.042	0.350	0.355	0.023
p-value	*0.000*	*0.000*	*0.000*	*0.511*	*0.000*	*0.000*	*0.489*
KO	8.215	0.298	-0.185	-0.005	0.182	0.352	-0.037
p-value	*0.000*	*0.130*	*0.005*	*0.943*	*0.003*	*0.000*	*0.092*
T	7.637	0.203	-0.083	-0.106	0.269	0.395	-0.012
p-value	*0.000*	*0.073*	*0.252*	*0.326*	*0.000*	*0.000*	*0.589*
DOV	7.188	0.179	0.026	-0.209	0.065	0.515	0.011
p-value	*0.000*	*0.175*	*0.755*	*0.031*	*0.286*	*0.000*	*0.697*
ALL	8.209	0.254	-0.029	-0.292	0.058	0.576	0.021
p-value	*0.000*	*0.091*	*0.729*	*0.002*	*0.404*	*0.000*	*0.473*
GP	6.770	-0.006	-0.010	-0.334	0.159	0.464	0.024
p-value	*0.000*	*0.964*	*0.898*	*0.001*	*0.015*	*0.000*	*0.308*
PHM	6.677	0.587	-0.096	-0.197	0.055	0.564	0.012
p-value	*0.000*	*0.000*	*0.300*	*0.031*	*0.415*	*0.000*	*0.692*
APF	5.235	2.023	0.045	0.345	0.117	0.917	-0.065
p-value	*0.002*	*0.251*	*0.905*	*0.583*	*0.575*	*0.000*	*0.361*
CLB	6.226	-0.008	0.130	-0.202	-0.117	0.502	0.018
p-value	*0.000*	*0.970*	*0.408*	*0.245*	*0.162*	*0.000*	*0.634*
MRO	6.803	0.404	-0.018	-0.153	0.126	0.752	0.013
p-value	*0.000*	*0.034*	*0.840*	*0.254*	*0.083*	*0.000*	*0.558*
HTN	5.671	-0.351	0.053	-0.038	0.064	0.565	-0.021
p-value	*0.000*	*0.198*	*0.704*	*0.788*	*0.462*	*0.000*	*0.528*
CNF	6.704	0.101	-0.028	-0.291	0.082	0.550	0.018
p-value	*0.000*	*0.381*	*0.773*	*0.003*	*0.264*	*0.000*	*0.550*
NKE	6.419	-0.019	0.058	-0.346	0.101	0.558	0.013
p-value	*0.000*	*0.920*	*0.495*	*0.002*	*0.096*	*0.000*	*0.645*
AMG	6.470	0.308	0.019	-0.238	0.018	0.306	0.039
p-value	*0.000*	*0.067*	*0.833*	*0.007*	*0.783*	*0.000*	*0.285*
PKI	7.617	0.108	0.077	-0.088	-0.013	0.330	-0.047
p-value	*0.000*	*0.415*	*0.313*	*0.088*	*0.844*	*0.000*	*0.615*
HIT	4.366	-0.060	-0.133	0.055	0.088	0.185	-0.032
p-value	*0.000*	*0.801*	*0.357*	*0.564*	*0.344*	*0.002*	*0.292*
AGX	6.508	-0.665	0.474	0.464	-0.201	0.367	0.139
p-value	*0.000*	*0.177*	*0.038*	*0.047*	*0.096*	*0.003*	*0.001*
Mean	**6.506**	**0.200**	**-0.013**	**-0.095**	**0.096**	**0.491**	**0.008**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 13b. Individual stock VNET regression
Sample period Feb. 8, 2001 till May 31, 2001.

Model is*:
$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$$
$$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Decimal Pilot Stocks

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
AOL	7.929	0.181	-0.231	-0.067	0.302	0.364	-0.008
p-value	*0.000*	*0.144*	*0.000*	*0.130*	*0.000*	*0.000*	*0.803*
ASF	5.345	0.076	-0.268	-0.385	0.225	0.398	0.037
p-value	*0.000*	*0.542*	*0.024*	*0.000*	*0.015*	*0.000*	*0.413*
BEN	5.972	0.350	-0.327	-0.098	0.291	0.445	0.008
p-value	*0.000*	*0.010*	*0.000*	*0.014*	*0.000*	*0.000*	*0.658*
CI	7.205	0.575	-0.003	-0.163	0.061	0.759	0.012
p-value	*0.000*	*0.000*	*0.968*	*0.000*	*0.270*	*0.000*	*0.721*
CL	6.747	0.098	-0.124	-0.049	0.249	0.390	-0.001
p-value	*0.000*	*0.539*	*0.055*	*0.279*	*0.000*	*0.000*	*0.980*
CPQ	9.660	0.926	-0.065	-0.110	0.076	0.407	-0.004
p-value	*0.000*	*0.000*	*0.452*	*0.117*	*0.381*	*0.000*	*0.876*
DCX	7.869	-0.459	0.197	-0.270	-0.067	0.533	0.017
p-value	*0.000*	*0.052*	*0.109*	*0.000*	*0.460*	*0.000*	*0.550*
GMH	8.393	0.737	-0.123	-0.135	0.138	0.574	-0.006
p-value	*0.000*	*0.000*	*0.132*	*0.040*	*0.038*	*0.000*	*0.803*
GT	6.090	0.424	-0.124	-0.148	0.185	0.732	0.013
p-value	*0.000*	*0.005*	*0.097*	*0.001*	*0.001*	*0.000*	*0.464*
HAR	6.798	-0.128	0.139	-0.110	-0.031	0.502	-0.011
p-value	*0.000*	*0.612*	*0.248*	*0.168*	*0.704*	*0.000*	*0.793*
KF	4.544	0.637	-0.444	-0.044	0.253	0.530	-0.011
p-value	*0.000*	*0.347*	*0.055*	*0.805*	*0.027*	*0.000*	*0.760*
LE	7.262	-0.064	0.186	-0.102	-0.076	0.517	0.057
p-value	*0.000*	*0.665*	*0.145*	*0.165*	*0.450*	*0.000*	*0.114*
LMT	8.157	0.418	-0.098	-0.132	0.093	0.694	-0.002
p-value	*0.000*	*0.050*	*0.271*	*0.053*	*0.201*	*0.000*	*0.960*
MLM	6.711	0.179	0.276	-0.009	-0.046	0.618	0.016
p-value	*0.000*	*0.507*	*0.017*	*0.919*	*0.540*	*0.000*	*0.625*
RCL	7.293	0.171	0.100	-0.197	0.060	0.759	0.006
p-value	*0.000*	*0.480*	*0.339*	*0.006*	*0.387*	*0.000*	*0.831*
S	7.293	0.027	-0.198	-0.034	0.234	0.445	-0.035
p-value	*0.000*	*0.851*	*0.018*	*0.461*	*0.001*	*0.000*	*0.152*
SGY	7.735	0.649	0.203	-0.151	-0.157	0.459	-0.023
p-value	*0.000*	*0.001*	*0.010*	*0.010*	*0.017*	*0.000*	*0.412*
STT	6.137	0.087	-0.214	-0.050	0.288	0.262	-0.051
p-value	*0.000*	*0.441*	*0.006*	*0.175*	*0.000*	*0.000*	*0.328*
UBS	6.200	-0.135	0.077	-0.182	-0.020	0.402	-0.065
p-value	*0.000*	*0.351*	*0.457*	*0.001*	*0.789*	*0.000*	*0.138*
VAL	6.873	-0.090	0.381	-0.018	-0.163	0.535	0.023
p-value	*0.000*	*0.588*	*0.000*	*0.758*	*0.020*	*0.000*	*0.262*
Mean	**7.011**	**0.233**	**-0.033**	**-0.123**	**0.095**	**0.516**	**-0.001**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 13b. cont'd Individual stock VNET regression
Sample period Feb. 8, 2001 till May 31, 2001.

Model is*:
$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$$
$$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Matched Control Stocks							
	β_0	β_1	β_2	β_3	β_4	β_5	β_6
WMT	8.691	0.388	-0.118	-0.054	0.143	0.378	-0.007
p-value	*0.000*	*0.002*	*0.032*	*0.142*	*0.018*	*0.000*	*0.768*
CCN	4.836	0.121	0.011	0.065	0.053	0.294	-0.032
p-value	*0.000*	*0.661*	*0.956*	*0.452*	*0.612*	*0.001*	*0.308*
AOC	7.137	0.857	-0.104	-0.108	0.113	0.855	0.032
p-value	*0.000*	*0.000*	*0.223*	*0.089*	*0.068*	*0.000*	*0.191*
UNH	6.811	0.358	-0.120	-0.140	0.190	0.588	0.047
p-value	*0.000*	*0.034*	*0.055*	*0.001*	*0.000*	*0.000*	*0.018*
KO	8.451	1.066	-0.164	-0.150	0.133	0.518	-0.045
p-value	*0.000*	*0.000*	*0.038*	*0.009*	*0.096*	*0.000*	*0.118*
T	9.395	0.797	-0.307	0.064	0.242	0.339	-0.037
p-value	*0.000*	*0.000*	*0.000*	*0.313*	*0.003*	*0.000*	*0.103*
DOV	7.707	0.425	0.000	-0.042	0.069	0.540	0.014
p-value	*0.000*	*0.026*	*0.999*	*0.513*	*0.436*	*0.000*	*0.669*
ALL	7.174	0.375	-0.184	-0.040	0.242	0.511	-0.013
p-value	*0.000*	*0.097*	*0.044*	*0.478*	*0.002*	*0.000*	*0.714*
GP	6.657	1.147	-0.188	-0.081	0.217	0.774	0.025
p-value	*0.000*	*0.000*	*0.011*	*0.083*	*0.000*	*0.000*	*0.215*
PHM	5.556	1.027	-0.145	-0.074	0.262	0.447	0.045
p-value	*0.000*	*0.001*	*0.215*	*0.224*	*0.006*	*0.000*	*0.153*
APF	4.693	0.197	-0.063	-0.003	0.103	0.338	-0.038
p-value	*0.000*	*0.624*	*0.806*	*0.988*	*0.397*	*0.011*	*0.218*
CLB	7.566	0.150	0.391	-0.232	-0.279	0.508	0.053
p-value	*0.000*	*0.743*	*0.021*	*0.032*	*0.006*	*0.000*	*0.236*
MRO	6.742	0.681	-0.081	-0.161	0.183	0.555	-0.006
p-value	*0.000*	*0.000*	*0.294*	*0.004*	*0.008*	*0.000*	*0.752*
HTN	6.729	0.228	0.200	-0.138	-0.083	0.517	0.028
p-value	*0.000*	*0.214*	*0.056*	*0.022*	*0.301*	*0.000*	*0.323*
CNF	6.819	0.799	0.005	-0.211	0.012	0.670	0.001
p-value	*0.000*	*0.005*	*0.962*	*0.000*	*0.882*	*0.000*	*0.984*
NKE	7.023	0.107	-0.017	-0.089	0.125	0.561	0.080
p-value	*0.000*	*0.604*	*0.864*	*0.185*	*0.100*	*0.000*	*0.009*
AMG	5.305	0.227	-0.123	-0.092	0.189	0.282	0.001
p-value	*0.000*	*0.109*	*0.148*	*0.117*	*0.004*	*0.000*	*0.980*
PKI	7.035	0.610	-0.006	-0.060	0.067	0.559	-0.037
p-value	*0.000*	*0.001*	*0.954*	*0.233*	*0.412*	*0.000*	*0.476*
HIT	4.929	-0.099	0.173	-0.066	-0.017	0.188	-0.002
p-value	*0.000*	*0.733*	*0.211*	*0.310*	*0.849*	*0.002*	*0.963*
AGX	3.740	0.400	-0.091	-0.169	0.025	0.343	-0.030
p-value	*0.000*	*0.223*	*0.662*	*0.203*	*0.797*	*0.003*	*0.279*
Mean	**6.650**	**0.493**	**-0.047**	**-0.089**	**0.100**	**0.488**	**0.004**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 14. Individual stock restricted regressions over pooled sample period.

Model is*:

$$
\begin{aligned}
\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\
& + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\
& + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\
& + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\
& + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}
\end{aligned}
$$

Decimal Stocks

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}
AOL	7.519	0.164	-0.219	-0.091	0.314	0.380	-0.053	0.398	0.017	-0.012	0.025	-0.011	-0.016	0.045
p-value	*0.000*	*0.079*	*0.000*	*0.017*	*0.000*	*0.000*	*0.071*	*0.664*	*0.917*	*0.881*	*0.685*	*0.898*	*0.772*	*0.322*
ASF	5.230	0.004	-0.080	-0.293	0.188	0.402	0.015	0.133	0.070	-0.183	-0.091	0.034	-0.001	0.019
p-value	*0.000*	*0.980*	*0.377*	*0.000*	*0.004*	*0.000*	*0.632*	*0.864*	*0.702*	*0.202*	*0.430*	*0.753*	*0.991*	*0.711*
BEN	7.298	-0.573	0.185	-0.152	-0.023	0.556	-0.006	-1.321	0.918	-0.511	0.053	0.312	-0.111	0.015
p-value	*0.000*	*0.004*	*0.006*	*0.000*	*0.641*	*0.000*	*0.766*	*0.018*	*0.000*	*0.000*	*0.371*	*0.000*	*0.033*	*0.614*
CI	7.888	0.694	0.064	-0.125	-0.058	0.730	0.036	-0.683	-0.118	-0.067	-0.038	0.119	0.029	-0.024
p-value	*0.000*	*0.000*	*0.416*	*0.003*	*0.356*	*0.000*	*0.368*	*0.266*	*0.578*	*0.523*	*0.517*	*0.162*	*0.623*	*0.646*
CL	7.152	0.248	0.015	-0.152	0.131	0.422	-0.034	-0.386	-0.128	-0.142	0.102	0.117	-0.031	0.035
p-value	*0.000*	*0.189*	*0.818*	*0.000*	*0.016*	*0.000*	*0.150*	*0.613*	*0.618*	*0.139*	*0.122*	*0.188*	*0.559*	*0.325*
CPQ	8.391	0.426	-0.112	-0.122	0.198	0.435	-0.037	1.256	0.508	0.047	0.014	-0.120	-0.029	0.032
p-value	*0.000*	*0.000*	*0.054*	*0.028*	*0.001*	*0.000*	*0.088*	*0.257*	*0.045*	*0.653*	*0.878*	*0.255*	*0.666*	*0.373*
DCX	6.488	0.094	-0.048	-0.135	0.178	0.517	0.038	1.374	-0.545	0.244	-0.134	-0.243	0.015	-0.022
p-value	*0.000*	*0.593*	*0.616*	*0.005*	*0.009*	*0.000*	*0.133*	*0.063*	*0.058*	*0.076*	*0.108*	*0.016*	*0.822*	*0.582*
GMH	8.254	0.285	0.078	-0.293	0.033	0.636	-0.025	0.145	0.455	-0.201	0.159	0.105	-0.062	0.019
p-value	*0.000*	*0.073*	*0.289*	*0.000*	*0.567*	*0.000*	*0.267*	*0.865*	*0.096*	*0.080*	*0.065*	*0.253*	*0.326*	*0.599*
GT	6.491	0.871	-0.100	-0.243	0.140	0.851	0.021	-0.400	-0.449	-0.024	0.095	0.045	-0.120	-0.008
p-value	*0.000*	*0.000*	*0.366*	*0.000*	*0.056*	*0.000*	*0.393*	*0.556*	*0.123*	*0.857*	*0.253*	*0.623*	*0.066*	*0.786*
HAR	7.074	0.658	0.040	-0.095	-0.028	0.577	-0.051	-0.269	-0.768	0.094	-0.012	-0.003	-0.076	0.039
p-value	*0.000*	*0.000*	*0.662*	*0.172*	*0.660*	*0.000*	*0.152*	*0.705*	*0.013*	*0.547*	*0.914*	*0.979*	*0.330*	*0.484*

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 14. cont'd Individual stock restricted regressions over pooled sample period.

Model is*:

$$
\begin{aligned}
\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\
& + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\
& + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\
& + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\
& + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}
\end{aligned}
$$

Decimal Stocks

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}
KF	4.783	-0.343	0.045	-0.305	0.063	0.650	0.012	-0.232	0.813	-0.481	0.238	0.180	-0.095	-0.026
p-value	*0.000*	*0.328*	*0.830*	*0.047*	*0.570*	*0.000*	*0.715*	*0.857*	*0.284*	*0.124*	*0.312*	*0.261*	*0.552*	*0.587*
LE	7.580	0.180	0.252	-0.091	-0.089	0.481	0.039	-0.313	-0.242	-0.067	-0.011	0.013	0.034	0.017
p-value	*0.000*	*0.208*	*0.023*	*0.151*	*0.281*	*0.000*	*0.208*	*0.719*	*0.236*	*0.687*	*0.913*	*0.917*	*0.644*	*0.713*
LMT	6.998	0.805	-0.093	-0.124	0.180	0.678	0.022	1.133	-0.370	-0.011	-0.004	-0.081	0.017	-0.022
p-value	*0.000*	*0.005*	*0.244*	*0.021*	*0.003*	*0.000*	*0.467*	*0.138*	*0.299*	*0.930*	*0.968*	*0.387*	*0.797*	*0.625*
MLM	6.624	0.506	0.123	-0.053	-0.008	0.623	0.024	0.093	-0.320	0.153	0.046	-0.038	-0.005	-0.008
p-value	*0.000*	*0.114*	*0.268*	*0.421*	*0.909*	*0.000*	*0.397*	*0.896*	*0.441*	*0.337*	*0.663*	*0.714*	*0.952*	*0.858*
RCL	6.460	-0.026	-0.037	-0.274	0.117	0.763	0.050	0.833	0.197	0.137	0.078	-0.057	-0.005	-0.044
p-value	*0.000*	*0.861*	*0.696*	*0.000*	*0.051*	*0.000*	*0.075*	*0.276*	*0.516*	*0.356*	*0.446*	*0.555*	*0.954*	*0.291*
S	5.957	0.221	-0.142	-0.192	0.296	0.431	-0.035	1.334	-0.191	-0.057	0.160	-0.061	0.013	0.000
p-value	*0.000*	*0.122*	*0.046*	*0.000*	*0.000*	*0.000*	*0.140*	*0.083*	*0.363*	*0.623*	*0.019*	*0.537*	*0.809*	*0.996*
SGY	7.327	0.174	0.023	-0.144	-0.049	0.436	0.003	0.404	0.473	0.179	-0.004	-0.107	0.023	-0.026
p-value	*0.000*	*0.261*	*0.800*	*0.040*	*0.491*	*0.000*	*0.924*	*0.550*	*0.063*	*0.136*	*0.961*	*0.271*	*0.685*	*0.537*
STT	6.511	0.384	-0.191	0.033	0.220	0.335	0.030	-0.372	-0.294	-0.023	-0.082	0.068	-0.074	-0.079
p-value	*0.000*	*0.001*	*0.011*	*0.392*	*0.001*	*0.000*	*0.547*	*0.633*	*0.077*	*0.837*	*0.130*	*0.521*	*0.181*	*0.283*
UBS	5.246	-0.321	-0.248	-0.185	0.252	0.440	0.054	0.956	0.186	0.329	0.003	-0.273	-0.039	-0.121
p-value	*0.000*	*0.013*	*0.007*	*0.000*	*0.000*	*0.000*	*0.141*	*0.109*	*0.333*	*0.017*	*0.964*	*0.004*	*0.543*	*0.033*
VAL	7.176	-0.130	0.254	-0.146	-0.201	0.433	0.056	-0.326	0.025	0.126	0.123	0.039	0.107	-0.034
p-value	*0.000*	*0.580*	*0.072*	*0.085*	*0.044*	*0.000*	*0.040*	*0.680*	*0.932*	*0.463*	*0.227*	*0.746*	*0.167*	*0.321*
Mean	**6.822**	**0.216**	**-0.01**	**-0.159**	**0.093**	**0.539**	**0.008**	**0.188**	**0.012**	**-0.02**	**0.036**	**0.002**	**-0.021**	**-0.010**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 14. cont'd Individual stock restricted regressions over pooled sample period.

Model is*:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}\end{aligned}$$

Matched Control Stocks														
	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}
WMT	6.974	0.295	-0.313	-0.290	0.315	0.515	0.003	1.729	0.096	0.196	0.237	-0.173	-0.136	-0.009
p-value	*0.000*	*0.053*	*0.000*	*0.000*	*0.000*	*0.000*	*0.920*	*0.041*	*0.632*	*0.028*	*0.004*	*0.045*	*0.010*	*0.803*
CCN	4.637	-0.279	-0.034	0.162	0.039	0.194	0.018	0.199	0.401	0.045	-0.097	0.014	0.100	-0.050
p-value	*0.000*	*0.104*	*0.831*	*0.115*	*0.600*	*0.004*	*0.529*	*0.811*	*0.235*	*0.863*	*0.479*	*0.918*	*0.379*	*0.251*
AOC	6.101	0.211	0.046	-0.090	0.156	0.859	0.028	1.039	0.653	-0.151	-0.017	-0.042	-0.005	0.003
p-value	*0.000*	*0.282*	*0.600*	*0.469*	*0.004*	*0.000*	*0.241*	*0.141*	*0.046*	*0.234*	*0.905*	*0.622*	*0.950*	*0.926*
UNH	5.692	0.411	-0.258	-0.043	0.350	0.355	0.023	1.139	-0.038	0.137	-0.094	-0.161	0.233	0.024
p-value	*0.000*	*0.001*	*0.000*	*0.526*	*0.000*	*0.000*	*0.524*	*0.045*	*0.845*	*0.119*	*0.239*	*0.021*	*0.000*	*0.555*
KO	8.248	0.304	-0.184	-0.010	0.178	0.353	-0.038	0.182	0.758	0.020	-0.141	-0.043	0.163	-0.006
p-value	*0.000*	*0.189*	*0.019*	*0.912*	*0.014*	*0.000*	*0.143*	*0.843*	*0.007*	*0.847*	*0.165*	*0.667*	*0.004*	*0.867*
T	7.701	0.205	-0.078	-0.097	0.263	0.394	-0.012	1.706	0.593	-0.229	0.162	-0.022	-0.055	-0.025
p-value	*0.000*	*0.058*	*0.259*	*0.341*	*0.000*	*0.000*	*0.563*	*0.155*	*0.001*	*0.031*	*0.187*	*0.843*	*0.373*	*0.434*
DOV	7.187	0.179	0.026	-0.210	0.065	0.515	0.011	0.534	0.239	-0.024	0.168	0.002	0.023	0.005
p-value	*0.000*	*0.169*	*0.753*	*0.027*	*0.280*	*0.000*	*0.696*	*0.517*	*0.306*	*0.857*	*0.147*	*0.986*	*0.728*	*0.914*
ALL	8.203	0.253	-0.028	-0.286	0.059	0.576	0.019	-1.030	0.132	-0.158	0.247	0.184	-0.066	-0.030
p-value	*0.000*	*0.083*	*0.728*	*0.002*	*0.378*	*0.000*	*0.505*	*0.248*	*0.630*	*0.204*	*0.021*	*0.075*	*0.300*	*0.510*
GP	6.764	0.001	-0.013	-0.332	0.161	0.463	0.023	-0.114	1.110	-0.172	0.247	0.054	0.312	0.000
p-value	*0.000*	*0.996*	*0.884*	*0.003*	*0.036*	*0.000*	*0.399*	*0.887*	*0.000*	*0.134*	*0.038*	*0.556*	*0.000*	*0.989*
PHM	6.680	0.587	-0.097	-0.196	0.055	0.564	0.012	-1.088	0.384	-0.035	0.114	0.196	-0.116	0.032
p-value	*0.000*	*0.000*	*0.263*	*0.022*	*0.385*	*0.000*	*0.668*	*0.199*	*0.290*	*0.824*	*0.299*	*0.118*	*0.094*	*0.474*
APF	5.218	1.733	0.066	0.272	0.093	0.917	-0.073	-0.443	-1.587	-0.117	-0.275	-0.002	-0.562	0.034
p-value	*0.001*	*0.245*	*0.851*	*0.628*	*0.619*	*0.000*	*0.260*	*0.813*	*0.306*	*0.791*	*0.643*	*0.991*	*0.008*	*0.638*

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 14. cont'd Individual stock restricted regressions over pooled sample period.

Model is*:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}\end{aligned}$$

Matched Control Stocks														
	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}
CLB	6.198	-0.020	0.152	-0.218	-0.119	0.502	0.019	1.369	0.221	0.227	-0.010	-0.156	0.000	0.034
p-value	*0.000*	*0.921*	*0.308*	*0.191*	*0.136*	*0.000*	*0.598*	*0.149*	*0.674*	*0.333*	*0.963*	*0.243*	*0.999*	*0.575*
MRO	6.845	0.412	-0.015	-0.146	0.123	0.752	0.014	-0.099	0.267	-0.066	-0.015	0.060	-0.197	-0.020
p-value	*0.000*	*0.016*	*0.854*	*0.227*	*0.060*	*0.000*	*0.506*	*0.913*	*0.355*	*0.597*	*0.911*	*0.577*	*0.005*	*0.533*
HTN	5.695	-0.341	0.052	-0.031	0.063	0.566	-0.021	1.055	0.563	0.153	-0.108	-0.150	-0.049	0.049
p-value	*0.000*	*0.160*	*0.676*	*0.807*	*0.415*	*0.000*	*0.488*	*0.195*	*0.082*	*0.381*	*0.452*	*0.216*	*0.532*	*0.269*
CNF	6.704	0.101	-0.028	-0.293	0.082	0.550	0.019	0.112	0.705	0.031	0.082	-0.069	0.120	-0.018
p-value	*0.000*	*0.414*	*0.783*	*0.004*	*0.299*	*0.000*	*0.559*	*0.888*	*0.017*	*0.820*	*0.484*	*0.521*	*0.081*	*0.674*
NKE	6.448	-0.013	0.060	-0.336	0.100	0.557	0.014	0.560	0.106	-0.075	0.245	0.026	0.005	0.065
p-value	*0.000*	*0.944*	*0.483*	*0.002*	*0.100*	*0.000*	*0.630*	*0.458*	*0.701*	*0.570*	*0.058*	*0.791*	*0.938*	*0.118*
AMG	6.467	0.308	0.018	-0.238	0.018	0.306	0.039	-1.159	-0.078	-0.143	0.147	0.171	-0.024	-0.038
p-value	*0.000*	*0.091*	*0.847*	*0.012*	*0.796*	*0.000*	*0.325*	*0.071*	*0.728*	*0.250*	*0.179*	*0.069*	*0.661*	*0.447*
PKI	7.621	0.105	0.079	-0.089	-0.014	0.329	-0.045	-0.586	0.504	-0.085	0.029	0.082	0.230	0.008
p-value	*0.000*	*0.478*	*0.355*	*0.125*	*0.847*	*0.000*	*0.668*	*0.403*	*0.022*	*0.488*	*0.690*	*0.432*	*0.000*	*0.941*
HIT	4.326	-0.041	-0.144	0.054	0.096	0.185	-0.033	0.599	-0.119	0.328	-0.127	-0.116	0.012	0.029
p-value	*0.000*	*0.860*	*0.314*	*0.562*	*0.295*	*0.002*	*0.271*	*0.409*	*0.751*	*0.101*	*0.267*	*0.374*	*0.886*	*0.522*
AGX	6.508	-0.665	0.474	0.464	-0.201	0.367	0.139	-2.773	1.080	-0.569	-0.628	0.230	-0.028	-0.168
p-value	*0.000*	*0.189*	*0.044*	*0.054*	*0.106*	*0.003*	*0.002*	*0.015*	*0.072*	*0.068*	*0.022*	*0.143*	*0.867*	*0.001*
Mean	**6.511**	**0.187**	**-0.01**	**-0.10**	**0.094**	**0.491**	**0.008**	**0.147**	**0.299**	**-0.03**	**0.008**	**0.004**	**-0.002**	**-0.004**

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table15. Wald and Chow tests of no structural break at exchange-wide decimalization, Jan. 29, 2001

Model is*:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$$
$$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Decimal Stocks										
Chow Tests						Wald Tests				
AOL	F-stat.	1.40	Prob.	*0.20*		AOL	F-stat.	1.36	Prob.	*0.22*
	LL Ratio	9.80	Prob.	*0.20*			χ^2	9.49	Prob.	*0.22*
ASF	F-stat.	1.38	Prob.	*0.21*		ASF	F-stat.	1.51	Prob.	*0.16*
	LL Ratio	9.70	Prob.	*0.21*			χ^2	10.58	Prob.	*0.16*
BEN	F-stat.	5.17	Prob.	*0.00*		BEN	F-stat.	5.47	Prob.	*0.00*
	LL Ratio	36.12	Prob.	*0.00*			χ^2	38.29	Prob.	*0.00*
CI	F-stat.	3.98	Prob.	*0.00*		CI	F-stat.	3.65	Prob.	*0.00*
	LL Ratio	27.87	Prob.	*0.00*			χ^2	25.58	Prob.	*0.00*
CL	F-stat.	3.11	Prob.	*0.00*		CL	F-stat.	1.85	Prob.	*0.07*
	LL Ratio	21.80	Prob.	*0.00*			χ^2	12.93	Prob.	*0.07*
CPQ	F-stat.	8.58	Prob.	*0.10*		CPQ	F-stat.	1.59	Prob.	*0.13*
	LL Ratio	59.60	Prob.	*0.09*			χ^2	11.11	Prob.	*0.13*
DCX	F-stat.	17.35	Prob.	*0.00*		DCX	F-stat.	1.26	Prob.	*0.27*
	LL Ratio	118.85	Prob.	*0.00*			χ^2	8.82	Prob.	*0.27*
GMH	F-stat.	3.12	Prob.	*0.00*		GMH	F-stat.	3.05	Prob.	*0.00*
	LL Ratio	21.86	Prob.	*0.00*			χ^2	21.37	Prob.	*0.00*
GT	F-stat.	3.23	Prob.	*0.00*		GT	F-stat.	3.23	Prob.	*0.00*
	LL Ratio	22.61	Prob.	*0.00*			χ^2	22.59	Prob.	*0.00*
HAR	F-stat.	1.52	Prob.	*0.16*		HAR	F-stat.	1.52	Prob.	*0.16*
	LL Ratio	10.66	Prob.	*0.15*			χ^2	10.61	Prob.	*0.16*
KF	F-stat.	0.72	Prob.	*0.66*		KF	F-stat.	0.72	Prob.	*0.66*
	LL Ratio	5.07	Prob.	*0.65*			χ^2	5.03	Prob.	*0.66*
LE	F-stat.	2.31	Prob.	*0.02*		LE	F-stat.	2.31	Prob.	*0.02*
	LL Ratio	16.20	Prob.	*0.02*			χ^2	16.15	Prob.	*0.02*
LMT	F-stat.	2.62	Prob.	*0.01*		LMT	F-stat.	2.61	Prob.	*0.01*
	LL Ratio	18.36	Prob.	*0.01*			χ^2	18.29	Prob.	*0.01*
MLM	F-stat.	0.39	Prob.	*0.91*		MLM	F-stat.	0.39	Prob.	*0.91*
	LL Ratio	2.76	Prob.	*0.91*			χ^2	2.75	Prob.	*0.91*
RCL	F-stat.	2.97	Prob.	*0.00*		RCL	F-stat.	2.97	Prob.	*0.00*
	LL Ratio	20.81	Prob.	*0.00*			χ^2	20.78	Prob.	*0.00*
S	F-stat.	2.68	Prob.	*0.01*		S	F-stat.	2.68	Prob.	*0.01*
	LL Ratio	18.79	Prob.	*0.01*			χ^2	18.75	Prob.	*0.01*
SGY	F-stat.	2.55	Prob.	*0.01*		SGY	F-stat.	2.55	Prob.	*0.01*
	LL Ratio	17.86	Prob.	*0.01*			χ^2	17.83	Prob.	*0.01*
STT	F-stat.	8.57	Prob.	*0.00*		STT	F-stat.	8.57	Prob.	*0.00*
	LL Ratio	59.58	Prob.	*0.00*			χ^2	59.99	Prob.	*0.00*
UBS	F-stat.	11.17	Prob.	*0.00*		UBS	F-stat.	11.17	Prob.	*0.00*
	LL Ratio	77.38	Prob.	*0.00*			χ^2	78.16	Prob.	*0.00*
VAL	F-stat.	2.01	Prob.	*0.05*		VAL	F-stat.	2.01	Prob.	*0.05*
	LL Ratio	14.09	Prob.	*0.05*			χ^2	14.05	Prob.	*0.05*

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table15 cont'd Wald and Chow tests of no structural break at exchange-wide decimalization, Jan. 29, 2001

Model is*:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$$
$$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Matched Control Stocks											
Chow Tests						Wald Tests					
WMT	F-stat.	2.90	Prob.	*0.01*		WMT	F-stat.	2.93	Prob.	*0.00*
	LL Ratio	20.36	Prob.	*0.00*			χ^2	20.50	Prob.	*0.00*
CCN	F-stat.	2.24	Prob.	*0.03*		CCN	F-stat.	2.24	Prob.	*0.03*
	LL Ratio	15.75	Prob.	*0.03*			χ^2	15.65	Prob.	*0.03*
AOC	F-stat.	3.06	Prob.	*0.00*		AOC	F-stat.	3.31	Prob.	*0.00*
	LL Ratio	21.47	Prob.	*0.00*			χ^2	23.20	Prob.	*0.00*
UNH	F-stat.	4.63	Prob.	*0.00*		UNH	F-stat.	4.63	Prob.	*0.00*
	LL Ratio	32.37	Prob.	*0.00*			χ^2	32.39	Prob.	*0.00*
KO	F-stat.	3.49	Prob.	*0.00*		KO	F-stat.	3.49	Prob.	*0.00*
	LL Ratio	24.43	Prob.	*0.00*			χ^2	24.41	Prob.	*0.00*
T	F-stat.	3.46	Prob.	*0.00*		T	F-stat.	3.46	Prob.	*0.00*
	LL Ratio	24.25	Prob.	*0.00*			χ^2	24.23	Prob.	*0.00*
DOV	F-stat.	0.89	Prob.	*0.51*		DOV	F-stat.	0.58	Prob.	*0.78*
	LL Ratio	6.25	Prob.	*0.51*			χ^2	4.04	Prob.	*0.78*
ALL	F-stat.	0.87	Prob.	*0.10*		ALL	F-stat.	1.82	Prob.	*0.08*
	LL Ratio	1142.57	Prob.	*0.08*			χ^2	12.72	Prob.	*0.08*
GP	F-stat.	26.00	Prob.	*0.00*		GP	F-stat.	26.00	Prob.	*0.00*
	LL Ratio	177.84	Prob.	*0.00*			χ^2	181.97	Prob.	*0.00*
PHM	F-stat.	5.21	Prob.	*0.00*		PHM	F-stat.	5.21	Prob.	*0.00*
	LL Ratio	36.38	Prob.	*0.00*			χ^2	36.44	Prob.	*0.00*
APF	F-stat.	1.95	Prob.	*0.06*		APF	F-stat.	1.95	Prob.	*0.06*
	LL Ratio	13.77	Prob.	*0.06*			χ^2	13.68	Prob.	*0.06*
CLB	F-stat.	1.79	Prob.	*0.08*		CLB	F-stat.	1.83	Prob.	*0.08*
	LL Ratio	12.62	Prob.	*0.08*			χ^2	12.81	Prob.	*0.08*
MRO	F-stat.	5.45	Prob.	*0.00*		MRO	F-stat.	5.45	Prob.	*0.00*
	LL Ratio	38.07	Prob.	*0.00*			χ^2	38.14	Prob.	*0.00*
HTN	F-stat.	3.15	Prob.	*0.00*		HTN	F-stat.	3.15	Prob.	*0.00*
	LL Ratio	22.08	Prob.	*0.00*			χ^2	22.05	Prob.	*0.00*
CNF	F-stat.	10.93	Prob.	*0.00*		CNF	F-stat.	10.99	Prob.	*0.00*
	LL Ratio	75.65	Prob.	*0.00*			χ^2	76.95	Prob.	*0.00*
NKE	F-stat.	1.29	Prob.	*0.25*		NKE	F-stat.	1.29	Prob.	*0.25*
	LL Ratio	9.10	Prob.	*0.25*			χ^2	9.06	Prob.	*0.25*
AMG	F-stat.	3.53	Prob.	*0.00*		AMG	F-stat.	3.53	Prob.	*0.00*
	LL Ratio	24.75	Prob.	*0.00*			χ^2	24.73	Prob.	*0.00*
PKI	F-stat.	5.59	Prob.	*0.00*		PKI	F-stat.	5.90	Prob.	*0.00*
	LL Ratio	39.07	Prob.	*0.00*			χ^2	41.32	Prob.	*0.00*
HIT	F-stat.	1.92	Prob.	*0.06*		HIT	F-stat.	1.92	Prob.	*0.06*
	LL Ratio	13.48	Prob.	*0.06*			χ^2	13.44	Prob.	*0.06*
AGX	F-stat.	3.04	Prob.	*0.00*		AGX	F-stat.	3.00	Prob.	*0.00*
	LL Ratio	21.37	Prob.	*0.00*			χ^2	21.00	Prob.	*0.00*

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 16a. . Results of pooled estimation.
Sample period Oct. 2, 2000 till Jan. 26, 2001.

Model is*:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID\,1_{t-1}}$$

All Stocks Pool		
	Coefficient	p-value
AOL	9.445	*0.000*
ASF	6.218	*0.000*
BEN	6.707	*0.000*
CI	6.506	*0.000*
CL	7.666	*0.000*
CPQ	9.233	*0.000*
DCX	7.153	*0.000*
GMH	8.129	*0.000*
GT	6.747	*0.000*
HAR	5.987	*0.000*
KF	4.994	*0.000*
LE	6.394	*0.000*
LMT	7.470	*0.000*
MLM	5.730	*0.000*
RCL	6.772	*0.000*
S	7.837	*0.000*
SGY	6.232	*0.000*
STT	6.927	*0.000*
UBS	6.272	*0.000*
VAL	5.328	*0.000*
WMT	8.723	*0.000*
CCN	3.971	*0.000*
AOC	6.482	*0.000*
UNH	7.378	*0.000*
KO	8.314	*0.000*
T	9.570	*0.000*
DOV	7.107	*0.000*
ALL	8.000	*0.000*
GP	7.896	*0.000*
PHM	6.173	*0.000*
APF	4.035	*0.000*
CLB	4.878	*0.000*
MRO	6.970	*0.000*
HTN	5.301	*0.000*
CNF	6.804	*0.000*
NKE	7.025	*0.000*
AMG	6.165	*0.000*
PKI	6.896	*0.000*
HIT	4.176	*0.000*
AGX	3.751	*0.000*
β_0	0.191	*0.000*
β_1	-0.014	*0.335*
β_2	-0.149	*0.000*
β_3	0.096	*0.000*
β_4	0.511	*0.000*
β_5	0.009	*0.040*

R-squared	0.422726
Adjusted R-sq.	0.422222
S.E. of regr.	1.892327
Sum sq. resid	184405.6
Log likelihood	-105987.8
Mean dep. var	7.735439
S.D. dep. var	2.48952
AIC	4.114384
SIC	4.122282
Durbin-Watson	2.000205

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 16a. Cont'd Results of pooled estimation.
Sample period Oct. 2, 2000 till Jan. 26, 2001.

Model is*:

$$\log\left(VNET_t\right) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$$
$$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID} 1_{t-1}$$

Decimal Stocks Pool		
	Coefficient	p-value
AOL	9.396	*0.000*
ASF	6.189	*0.000*
BEN	6.664	*0.000*
CI	6.474	*0.000*
CL	7.618	*0.000*
CPQ	9.182	*0.000*
DCX	7.111	*0.000*
GMH	8.079	*0.000*
GT	6.701	*0.000*
HAR	5.955	*0.000*
KF	4.944	*0.000*
LE	6.357	*0.000*
LMT	7.427	*0.000*
MLM	5.692	*0.000*
RCL	6.732	*0.000*
S	7.790	*0.000*
SGY	6.202	*0.000*
STT	6.895	*0.000*
UBS	6.242	*0.000*
VAL	5.287	*0.000*
β_0	0.211	*0.000*
β_1	-0.019	*0.334*
β_2	-0.160	*0.000*
β_3	0.100	*0.000*
β_4	0.534	*0.000*
β_5	0.011	*0.093*

Control Stocks Pool		
	Coefficient	p-value
WMT	8.834	*0.000*
CCN	4.051	*0.000*
AOC	6.587	*0.000*
UNH	7.468	*0.000*
KO	8.432	*0.000*
T	9.693	*0.000*
DOV	7.203	*0.000*
ALL	8.108	*0.000*
GP	8.005	*0.000*
PHM	6.262	*0.000*
APF	4.160	*0.000*
CLB	4.964	*0.000*
MRO	7.087	*0.000*
HTN	5.396	*0.000*
CNF	6.899	*0.000*
NKE	7.124	*0.000*
AMG	6.241	*0.000*
PKI	6.955	*0.000*
HIT	4.228	*0.000*
AGX	3.847	*0.000*
β_0	0.188	*0.000*
β_1	-0.010	*0.642*
β_2	-0.106	*0.000*
β_3	0.092	*0.000*
β_4	0.486	*0.000*
β_5	0.008	*0.234*

R-squared	0.380207
Adjusted R-squared	0.379627
S.E. of regression	1.830739
Sum squared resid	89417.46
Log likelihood	-54028.8
Mean dependent var	7.919973
S.D. dependent var	2.324341
Akaike info criterion	4.048289
Schwarz criterion	4.056266
Durbin-Watson stat	2.000593

R-squared	0.452141
Adjusted R-squared	0.451589
S.E. of regression	1.956058
Sum squared resid	94930.96
Log likelihood	-51893.09
Mean dependent var	7.536912
S.D. dependent var	2.641366
Akaike info criterion	4.180786
Schwarz criterion	4.189286
Durbin-Watson stat	2.001634

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 16b. Results of pooled estimation
Sample period Feb. 8, 2001 till May 31, 2001.

Model is*: $$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID1_{t-1}}$$

All Stocks Pool		
	Coefficient	p-value
WMT	8.844	*0.000*
CCN	4.340	*0.000*
AOC	6.966	*0.000*
UNH	7.576	*0.000*
KO	8.493	*0.000*
T	9.637	*0.000*
DOV	7.375	*0.000*
ALL	8.044	*0.000*
GP	7.264	*0.000*
PHM	6.740	*0.000*
APF	4.491	*0.000*
CLB	5.513	*0.000*
MRO	7.638	*0.000*
HTN	5.813	*0.000*
CNF	6.336	*0.000*
NKE	7.317	*0.000*
AMG	6.025	*0.000*
PKI	6.746	*0.000*
HIT	4.514	*0.000*
AGX	3.504	*0.000*
AOL	9.755	*0.000*
ASF	6.674	*0.000*
BEN	6.974	*0.000*
CI	6.936	*0.000*
CL	7.981	*0.000*
CPQ	9.320	*0.000*
DCX	7.326	*0.000*
GMH	8.607	*0.000*
GT	6.712	*0.000*
HAR	6.122	*0.000*
KF	5.266	*0.000*
LE	6.305	*0.000*
LMT	7.889	*0.000*
MLM	5.840	*0.000*
RCL	7.373	*0.000*
S	8.075	*0.000*
SGY	6.223	*0.000*
STT	7.468	*0.000*
UBS	5.733	*0.000*
VAL	5.319	*0.000*
β_0	0.290	*0.000*
β_1	-0.028	*0.060*
β_2	-0.114	*0.000*
β_3	0.092	*0.000*
β_4	0.526	*0.000*
β_5	0.002	*0.707*

R-squared	0.422008
Adjusted R-sq.	0.421436
S.E. of regr.	1.842248
Sum sq. resid	154577.6
Log likelihood	-92525.34
Mean dep. var	7.712487
S.D. dep. var	2.421991
AIC	4.060859
SIC	4.069664
Durbin-Watson	1.972806

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 16b. cont'd Results of pooled estimation
Sample period Feb. 8, 2001 till May 31, 2001.

Model is*:
$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID1_{t-1}}$$

Decimal Stocks Pool		
	Coefficient	p-value
AOL	9.718	*0.000*
ASF	6.642	*0.000*
BEN	6.944	*0.000*
CI	6.913	*0.000*
CL	7.949	*0.000*
CPQ	9.281	*0.000*
DCX	7.301	*0.000*
GMH	8.575	*0.000*
GT	6.683	*0.000*
HAR	6.105	*0.000*
KF	5.249	*0.000*
LE	6.276	*0.000*
LMT	7.861	*0.000*
MLM	5.819	*0.000*
RCL	7.350	*0.000*
S	8.041	*0.000*
SGY	6.206	*0.000*
STT	7.438	*0.000*
UBS	5.719	*0.000*
VAL	5.299	*0.000*
β_0	0.181	*0.000*
β_1	-0.020	*0.327*
β_2	-0.122	*0.000*
β_3	0.090	*0.000*
β_4	0.538	*0.000*
β_5	0.002	*0.759*

Control Stocks Pool		
	Coefficient	p-value
WMT	8.814	*0.000*
CCN	4.359	*0.000*
AOC	6.987	*0.000*
UNH	7.599	*0.000*
KO	8.522	*0.000*
T	9.671	*0.000*
DOV	7.402	*0.000*
ALL	8.072	*0.000*
GP	7.285	*0.000*
PHM	6.759	*0.000*
APF	4.515	*0.000*
CLB	5.529	*0.000*
MRO	7.663	*0.000*
HTN	5.833	*0.000*
CNF	6.355	*0.000*
NKE	7.341	*0.000*
AMG	6.050	*0.000*
PKI	6.767	*0.000*
HIT	4.524	*0.000*
AGX	3.528	*0.000*
β_0	0.441	*0.000*
β_1	-0.030	*0.191*
β_2	-0.110	*0.000*
β_3	0.091	*0.000*
β_4	0.518	*0.000*
β_5	0.000	*0.941*

R-squared	0.396909
Adjusted R-sq.	0.396266
S.E. of regr.	1.793783
Sum sq. resid	75405.78
Log likelihood	-46985.6
Mean dep. var	7.804998
S.D. dep. var	2.308591
AIC	4.007638
SIC	4.016574
Durbin-Watson	1.990328

R-squared	0.42445
Adjusted R-sq.	0.42377
S.E. of regr.	1.91599
Sum sq. resid	77473.04
Log likelihood	-43708.60
Mean dep. var	7.50405
S.D. dep. var	2.52404
AIC	4.13957
SIC	4.14937
Durbin-Watson	1.95614

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 17a. Time sample pooled estimation of decimal stocks and control stocks, allowing for a change in coefficients after decimalization.

Model is:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID\ 1_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID\ 1_{t-1}} I^{CP}\end{aligned}$$

	Decimal pool comb. time sample	Coeff.	p-value		Control Pool comb. time sample	Coeff.	p-value
β_0	AOL	9.399	*0.000*	β_0	WMT	8.834	*0.000*
β_0	ASF	6.190	*0.000*	β_0	CCN	4.052	*0.000*
β_0	BEN	6.665	*0.000*	β_0	AOC	6.587	*0.000*
β_0	CI	6.475	*0.000*	β_0	UNH	7.467	*0.000*
β_0	CL	7.619	*0.000*	β_0	KO	8.432	*0.000*
β_0	CPQ	9.184	*0.000*	β_0	T	9.694	*0.000*
β_0	DCX	7.112	*0.000*	β_0	DOV	7.204	*0.000*
β_0	GMH	8.081	*0.000*	β_0	ALL	8.108	*0.000*
β_0	GT	6.702	*0.000*	β_0	GP	8.005	*0.000*
β_0	HAR	5.956	*0.000*	β_0	PHM	6.262	*0.000*
β_0	KF	4.945	*0.000*	β_0	APF	4.160	*0.000*
β_0	LE	6.359	*0.000*	β_0	CLB	4.965	*0.000*
β_0	LMT	7.428	*0.000*	β_0	MRO	7.088	*0.000*
β_0	MLM	5.693	*0.000*	β_0	HTN	5.397	*0.000*
β_0	RCL	6.733	*0.000*	β_0	CNF	6.899	*0.000*
β_0	S	7.792	*0.000*	β_0	NKE	7.124	*0.000*
β_0	SGY	6.203	*0.000*	β_0	AMG	6.241	*0.000*
β_0	STT	6.898	*0.000*	β_0	PKI	6.955	*0.000*
β_0	UBS	6.243	*0.000*	β_0	HIT	4.229	*0.000*
β_0	VAL	5.288	*0.000*	β_0	AGX	3.848	*0.000*
β_1	PSIWL_1	0.211	*0.000*	β_1	PSIWL_1	0.187	*0.000*
β_2	LOG(NUMBE	-0.019	*0.321*	β_2	LOG(NUMBE	-0.010	*0.657*
β_3	LOG(SPREAI	-0.160	*0.000*	β_3	LOG(SPREAI	-0.106	*0.000*
β_4	LOG(VOLUM	0.100	*0.000*	β_4	LOG(VOLUM	0.092	*0.000*
β_5	LOG(NPTIME	0.534	*0.000*	β_5	LOG(NPTIME	0.486	*0.000*
β_6	LOG(APRESI	0.010	*0.096*	β_6	LOG(APRESI	0.008	*0.218*
β_7	CP*AOL	0.315	*0.151*	β_7	CP*WMT	0.023	*0.918*
β_7	CP*ASF	0.449	*0.009*	β_7	CP*CCN	0.287	*0.092*
β_7	CP*BEN	0.276	*0.107*	β_7	CP*AOC	0.382	*0.053*
β_7	CP*CI	0.434	*0.009*	β_7	CP*UNH	0.116	*0.555*
β_7	CP*CL	0.326	*0.087*	β_7	CP*KO	0.075	*0.736*
β_7	CP*CPQ	0.093	*0.678*	β_7	CP*T	-0.037	*0.882*
β_7	CP*DCX	0.186	*0.316*	β_7	CP*DOV	0.185	*0.359*
β_7	CP*GMH	0.489	*0.018*	β_7	CP*ALL	-0.048	*0.826*
β_7	CP*GT	-0.022	*0.902*	β_7	CP*GP	-0.738	*0.000*
β_7	CP*HAR	0.146	*0.381*	β_7	CP*PHM	0.483	*0.011*
β_7	CP*KF	0.300	*0.122*	β_7	CP*APF	0.334	*0.133*
β_7	CP*LE	-0.085	*0.626*	β_7	CP*CLB	0.543	*0.004*
β_7	CP*LMT	0.429	*0.023*	β_7	CP*MRO	0.561	*0.008*
β_7	CP*MLM	0.124	*0.454*	β_7	CP*HTN	0.419	*0.021*
β_7	CP*RCL	0.613	*0.001*	β_7	CP*CNF	-0.560	*0.004*
β_7	CP*S	0.245	*0.212*	β_7	CP*NKE	0.201	*0.320*
β_7	CP*SGY	-0.001	*0.996*	β_7	CP*AMG	-0.209	*0.230*
β_7	CP*STT	0.536	*0.002*	β_7	CP*PKI	-0.203	*0.266*
β_7	CP*UBS	-0.528	*0.001*	β_7	CP*HIT	0.275	*0.078*
β_7	CP*VAL	0.008	*0.962*	β_7	CP*AGX	-0.336	*0.077*
β_8	CP*PSIWL_1	-0.028	*0.593*	β_8	CP*PSIWL_1	0.253	*0.000*
β_9	CP*LOG(NUM	-0.002	*0.944*	β_9	CP*LOG(NUI	-0.029	*0.350*
β_{10}	CP*LOG(SPR	0.039	*0.037*	β_{10}	CP*LOG(SPR	-0.001	*0.984*
β_{11}	CP*LOG(VOL	-0.009	*0.688*	β_{11}	CP*LOG(VOL	0.004	*0.859*
β_{12}	CP*LOG(NPT	0.004	*0.794*	β_{12}	CP*LOG(NPT	0.026	*0.121*
β_{13}	CP*LOG(APR	-0.009	*0.331*	β_{13}	CP*LOG(APR	-0.008	*0.371*

	Decimal pool	Control pool
R-squared	0.388	0.448
Adjusted R-squared	0.388	0.448
S.E. of regression	1.814	1.926
Durbin-Watson stat	1.996	1.981

	Wald	P-value
F-statistic	9.436	0.000
Chi-square	245.329	0.000

	Wald	Chow	P-value
F-statistic	16.434	16.43134	0.000
Chi-square	427.275	425.756	0.000

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 17b. cont'd. Pooled estimation over each sample period, allowing for differences in control stock coefficients. Model is*:

$$
\begin{aligned}
\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\
& + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID\ 1_{t-1}} \\
& + \beta_7 \log(ENPTIME_t) I^C + \beta_8 \log(NUMBER_{t-1}) I^C + \beta_9 \log(SPREAD_{t-1}) I^C \\
& + \beta_{10} \log(VOLUME_{t-1}) I^C + \beta_{11} \log(NPTIME\_ERR_t) I^C \\
& + \beta_{12} \log(APRESID_{t-1}) I^{+/-}_{PRESID\ 1_{t-1}} I^C
\end{aligned}
$$

Fractional Trading Period

		Coeff.	p-value
β_0	WMT	8.829	*0.000*
β_0	CCN	4.048	*0.000*
β_0	AOC	6.583	*0.000*
β_0	UNH	7.463	*0.000*
β_0	KO	8.426	*0.000*
β_0	T	9.688	*0.000*
β_0	DOV	7.199	*0.000*
β_0	ALL	8.103	*0.000*
β_0	GP	8.000	*0.000*
β_0	PHM	6.258	*0.000*
β_0	APF	4.154	*0.000*
β_0	CLB	4.960	*0.000*
β_0	MRO	7.083	*0.000*
β_0	HTN	5.393	*0.000*
β_0	CNF	6.895	*0.000*
β_0	NKE	7.119	*0.000*
β_0	AMG	6.237	*0.000*
β_0	PKI	6.951	*0.000*
β_0	HIT	4.226	*0.000*
β_0	AGX	3.844	*0.000*
β_0	AOL	9.395	*0.000*
β_0	ASF	6.187	*0.000*
β_0	BEN	6.663	*0.000*
β_0	CI	6.473	*0.000*
β_0	CL	7.617	*0.000*
β_0	CPQ	9.181	*0.000*
β_0	DCX	7.110	*0.000*
β_0	GMH	8.078	*0.000*
β_0	GT	6.699	*0.000*
β_0	HAR	5.953	*0.000*
β_0	KF	4.942	*0.000*
β_0	LE	6.356	*0.000*
β_0	LMT	7.426	*0.000*
β_0	MLM	5.690	*0.000*
β_0	RCL	6.730	*0.000*
β_0	S	7.789	*0.000*
β_0	SGY	6.200	*0.000*
β_0	STT	6.895	*0.000*
β_0	UBS	6.241	*0.000*
β_0	VAL	5.285	*0.000*
β_1	PSIWL_1	0.212	*0.000*
β_2	LOG(NUMBE	-0.020	*0.327*
β_3	LOG(SPREAI	-0.160	*0.000*
β_4	LOG(VOLUM	0.100	*0.000*
β_5	LOG(NPTIME	0.534	*0.000*
β_6	LOG(APRESI	0.011	*0.104*
β_7	CONTROL*P	-0.024	*0.646*
β_8	CONTROL*L	0.009	*0.747*
β_9	CONTROL*L	0.054	*0.044*
β_{10}	CONTROL*L	-0.008	*0.712*
β_{11}	CONTROL*L	-0.048	*0.002*
β_{12}	CONTROL*L	-0.002	*0.794*

R-squared	0.423
Adjusted R-squared	0.422
Durbin-Watson stat	2.001

	Wald	p-value
F-statistic	2.736	0.012
Chi-square	16.416	0.012

Fully-Decimal Trading Period

		Coeff.	p-value
β_0	WMT	8.876	*0.000*
β_0	CCN	4.350	*0.000*
β_0	AOC	6.985	*0.000*
β_0	UNH	7.601	*0.000*
β_0	KO	8.525	*0.000*
β_0	T	9.677	*0.000*
β_0	DOV	7.405	*0.000*
β_0	ALL	8.078	*0.000*
β_0	GP	7.284	*0.000*
β_0	PHM	6.760	*0.000*
β_0	APF	4.507	*0.000*
β_0	CLB	5.520	*0.000*
β_0	MRO	7.666	*0.000*
β_0	HTN	5.830	*0.000*
β_0	CNF	6.353	*0.000*
β_0	NKE	7.340	*0.000*
β_0	AMG	6.045	*0.000*
β_0	PKI	6.767	*0.000*
β_0	HIT	4.516	*0.000*
β_0	AGX	3.522	*0.000*
β_0	AOL	9.728	*0.000*
β_0	ASF	6.649	*0.000*
β_0	BEN	6.952	*0.000*
β_0	CI	6.920	*0.000*
β_0	CL	7.957	*0.000*
β_0	CPQ	9.291	*0.000*
β_0	DCX	7.309	*0.000*
β_0	GMH	8.584	*0.000*
β_0	GT	6.691	*0.000*
β_0	HAR	6.111	*0.000*
β_0	KF	5.256	*0.000*
β_0	LE	6.283	*0.000*
β_0	LMT	7.869	*0.000*
β_0	MLM	5.826	*0.000*
β_0	RCL	7.357	*0.000*
β_0	S	8.049	*0.000*
β_0	SGY	6.212	*0.000*
β_0	STT	7.445	*0.000*
β_0	UBS	5.723	*0.000*
β_0	VAL	5.305	*0.000*
β_1	PSIWL_1	0.183	*0.000*
β_2	LOG(NUMBE	-0.020	*0.336*
β_3	LOG(SPREAI	-0.121	*0.000*
β_4	LOG(VOLUM	0.090	*0.000*
β_5	LOG(NPTIME	0.538	*0.000*
β_6	LOG(APRESI	0.002	*0.735*
β_7	CONTROL*P	0.257	*0.000*
β_8	CONTROL*L	-0.017	*0.557*
β_9	CONTROL*L	0.015	*0.437*
β_{10}	CONTROL*L	0.004	*0.855*
β_{11}	CONTROL*L	-0.026	*0.110*
β_{12}	CONTROL*L	-0.002	*0.844*

R-squared	0.422
Adjusted R-squared	0.422
Durbin-Watson stat	1.973

	Wald	p-value
F-statistic	3.686	0.001
Chi-square	22.113	0.001

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 18a. Tests for differences in coefficients of matched decimal and control stocks in individual stock uninteracted regressions over Oct. 2, 2000 till Jan. 26, 2001.

Model is*: $$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

t-Test: Two-Sample Assuming Equal Variances

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	6.825	0.215	-0.008	-0.159	0.092	0.539	0.008
Variance	0.921	0.151	0.021	0.008	0.020	0.020	0.001
Observations	20.000	20.000	20.000	20.000	20.000	20.000	20.000
Pooled Variance	1.000	0.210	0.023	0.028	0.018	0.029	0.002
Hyp. Mean Dif.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
df	38.000	38.000	38.000	38.000	38.000	38.000	38.000
t Stat	1.010	0.103	0.111	-1.219	-0.093	0.890	-0.046
P(T<=t) one-tail	0.159	0.459	0.456	0.115	0.463	0.190	0.482
t Crit.one-tail	1.686	1.686	1.686	1.686	1.686	1.686	1.686
P(T<=t) two-tail	0.319	0.918	0.912	0.231	0.927	0.379	0.964
t Crit. two-tail	2.024	2.024	2.024	2.024	2.024	2.024	2.024

t-Test: Two-Sample Assuming Unequal Variances

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	6.825	0.215	-0.008	-0.159	0.092	0.539	0.008
Variance	0.921	0.151	0.021	0.008	0.020	0.020	0.001
Observations	20.000	20.000	20.000	20.000	20.000	20.000	20.000
Hyp. Mean Dif.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
df	38.000	35.000	38.000	25.000	38.000	35.000	37.000
t Stat	1.010	0.103	0.111	-1.219	-0.093	0.890	-0.046
P(T<=t) one-tail	0.159	0.459	0.456	0.117	0.463	0.190	0.482
t Crit.one-tail	1.686	1.690	1.686	1.708	1.686	1.690	1.687
P(T<=t) two-tail	0.319	0.918	0.912	0.234	0.927	0.380	0.964
t Crit. two-tail	2.024	2.030	2.024	2.060	2.024	2.030	2.026

t-Test: Paired Two Sample for Means

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	6.825	0.215	-0.008	-0.159	0.092	0.539	0.008
Variance	0.921	0.151	0.021	0.008	0.020	0.020	0.001
Observations	20.000	20.000	20.000	20.000	20.000	20.000	20.000
Pooled Variance	0.651	-0.099	0.537	-0.114	0.459	0.448	0.230
Hyp. Mean Dif.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
df	19.000	19.000	19.000	19.000	19.000	19.000	19.000
t Stat	1.705	0.099	0.163	-1.174	-0.126	1.176	-0.052
P(T<=t) one-tail	0.052	0.461	0.436	0.128	0.451	0.127	0.479
t Crit.one-tail	1.729	1.729	1.729	1.729	1.729	1.729	1.729
P(T<=t) two-tail	0.105	0.922	0.872	0.255	0.901	0.254	0.959
t Crit. two-tail	2.093	2.093	2.093	2.093	2.093	2.093	2.093

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 18a. cont'd

Anova: Single Factor

Tests for differences in coefficients of matched decimal and control stocks in individual stock uninteracted regressions over Oct. 2, 2000 till Jan. 26, 2001.

Model is*:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
β_0	20	6.38819	0.31941	0.7023
β_1	20	0.2992	0.01496	0.45904
β_2	20	0.10716	0.00536	0.02165
β_3	20	-1.27839	-0.06392	0.05933
β_4	20	-0.07917	-0.00396	0.01977
β_5	20	0.95983	0.04799	0.0333
β_6	20	-0.01126	-0.00056	0.00233

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.88234	6	0.31372	1.69227	0.12762	2.167425
Within Groups	24.6564	133	0.18539			
Total	26.5388	139				

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 18b.
Tests for differences in coefficients of matched decimal and control stocks in individual stock uninteracted regressions over Feb. 8, 2001 till May 31, 2001.

Model is*: $\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1})$
$+ \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$

t-Test: Two-Sample Assuming Equal Variances

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	7.01063	0.23292	-0.033	-0.1225	0.09468	0.5164	-0.0014
Variance	1.31787	0.12233	0.04862	0.00822	0.02373	0.01927	0.0008
Observations	20	20	20	20	20	20	20
Pooled Variance	1.69368	0.12565	0.03655	0.00722	0.02016	0.02358	0.00103
Hyp. Mean Dif.	0	0	0	0	0	0	0
df	38	38	38	38	38	38	38
t Stat	0.87695	-2.3202	0.22391	-1.2466	-0.1088	0.57871	-0.5292
P(T<=t) one-tail	0.19301	0.0129	0.41201	0.1101	0.45695	0.2831	0.29988
t Crit.one-tail	1.68595	1.68595	1.68595	1.68595	1.68595	1.68595	1.68595
P(T<=t) two-tail	0.38602	0.0258	0.82403	0.22019	0.91391	0.5662	0.59975
t Crit. two-tail	2.02439	2.02439	2.02439	2.02439	2.02439	2.02439	2.02439

t-Test: Two-Sample Assuming Unequal Variances

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	7.01063	0.23292	-0.033	-0.1225	0.09468	0.5164	-0.0014
Variance	1.31787	0.12233	0.04862	0.00822	0.02373	0.01927	0.0008
Observations	20	20	20	20	20	20	20
Hypothesized Mean D	0	0	0	0	0	0	0
df	36	38	34	37	37	37	36
t Stat	0.87695	-2.3202	0.22391	-1.2466	-0.1088	0.57871	-0.5292
P(T<=t) one-tail	0.19316	0.0129	0.41208	0.1102	0.45696	0.28315	0.29996
t Critical one-tail	1.6883	1.68595	1.69092	1.68709	1.68709	1.68709	1.6883
P(T<=t) two-tail	0.38633	0.0258	0.82417	0.2204	0.91392	0.56629	0.59992
t Critical two-tail	2.02809	2.02439	2.03224	2.02619	2.02619	2.02619	2.02809

t-Test: Paired Two Sample for Means

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Mean	7.01063	0.23292	-0.033	-0.1225	0.09468	0.5164	-0.0014
Variance	1.31787	0.12233	0.04862	0.00822	0.02373	0.01927	0.0008
Observations	20	20	20	20	20	20	20
Pooled Variance	0.60074	0.13626	0.33035	-0.3423	0.28501	0.43542	0.13451
Hyp. Mean Dif.	0	0	0	0	0	0	0
df	19	19	19	19	19	19	19
t Stat	1.36255	-2.4964	0.26991	-1.0773	-0.1283	0.76524	-0.5677
P(T<=t) one-tail	0.09448	0.01095	0.39507	0.14742	0.44963	0.22677	0.28845
t Crit.one-tail	1.72913	1.72913	1.72913	1.72913	1.72913	1.72913	1.72913
P(T<=t) two-tail	0.18896	0.0219	0.79014	0.29484	0.89926	0.45353	0.5769
t Crit. two-tail	2.09302	2.09302	2.09302	2.09302	2.09302	2.09302	2.09302

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 18b. cont'd

Anova: Single Factor
Tests for differences in coefficients of matched decimal and control stocks
in individual stock uninteracted regressions over Feb. 8, 2001 till May 31, 2001.

Model is*: $$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

SUMMARY

Groups	Count	Sum	Average	Variance
β_0	20	7.2181	0.3609	1.40316
β_1	20	-5.2016	-0.2601	0.21708
β_2	20	0.27074	0.01354	0.05031
β_3	20	-0.6697	-0.0335	0.01932
β_4	20	-0.0977	-0.0049	0.02901
β_5	20	0.56203	0.0281	0.02697
β_6	20	-0.1074	-0.0054	0.00179

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3.97299	6	0.66216	2.65224	0.01837	2.16743
Within Groups	33.2051	133	0.24966			
Total	37.1781	139				

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume,
NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 19.
Anova tests of same stock coefficient changes from test to control sample period.

Model is*: $$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) * I^{+/-}_{PRESID_{t-1}}$$

Anova of Decimal stocks coefficient changes.

Groups	*Count*	*Sum*	*Average*	*Variance*
β_0	20	-3.711241	-0.185562	0.589668
β_1	20	-0.367061	-0.018353	0.22265
β_2	20	0.498848	0.024942	0.045285
β_3	20	-0.724558	-0.036228	0.009095
β_4	20	-0.056315	-0.002816	0.018999
β_5	20	0.454096	0.022705	0.003339
β_6	20	0.1806	0.00903	0.001662

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.647048	6	0.107841	0.847525	0.535532	2.167425
Within Groups	16.92328	133	0.127243			
Total	17.57033	139				

Anova of Control stocks coefficient changes.

Groups	*Count*	*Sum*	*Average*	*Variance*
β_0	20	-2.88133	-0.144067	1.259989
β_1	20	-5.867889	-0.293394	0.372576
β_2	20	0.662429	0.033121	0.038038
β_3	20	-0.115852	-0.005793	0.049328
β_4	20	-0.074875	-0.003744	0.015527
β_5	20	0.056295	0.002815	0.035443
β_6	20	0.084482	0.004224	0.002434

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.687213	6	0.281202	1.110007	0.359879	2.167425
Within Groups	33.69337	133	0.253334			
Total	35.38059	139				

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 20. Pooled estimation over the combined time sample periods, with a 40-element intercept.
Interacted variable allow for a shift in individual stock intercept and all pooled coefficients at
the time of the exchange-wide decimaization (Jan. 29, 2001.)

Model is*:

$$\begin{aligned}\log(VNET_t) = {} & \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) \\ & + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID_{t-1}} \\ & + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} \\ & + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} \\ & + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID_{t-1}} I^{CP}\end{aligned}$$

All stocks both sample periods pool				
Variable	Coeff.	Std. Error	t-Statistic	p-value
WMT	8.723	0.109	80.376	*0.000*
CCN	3.971	0.085	46.939	*0.000*
AOC	6.482	0.096	67.653	*0.000*
UNH	7.378	0.095	77.898	*0.000*
KO	8.315	0.107	77.628	*0.000*
T	9.570	0.121	79.277	*0.000*
DOV	7.107	0.098	72.793	*0.000*
ALL	8.000	0.108	74.293	*0.000*
GP	7.896	0.106	74.741	*0.000*
PHM	6.172	0.091	67.776	*0.000*
APF	4.036	0.130	31.152	*0.000*
CLB	4.878	0.094	51.988	*0.000*
MRO	6.970	0.100	69.694	*0.000*
HTN	5.302	0.092	57.877	*0.000*
CNF	6.803	0.099	68.958	*0.000*
NKE	7.025	0.099	71.210	*0.000*
AMG	6.165	0.088	69.670	*0.000*
PKI	6.896	0.091	75.878	*0.000*
HIT	4.176	0.081	51.757	*0.000*
AGX	3.751	0.104	35.956	*0.000*
AOL	9.445	0.114	82.996	*0.000*
ASF	6.218	0.090	69.315	*0.000*
BEN	6.707	0.092	72.728	*0.000*
CI	6.506	0.091	71.322	*0.000*
CL	7.666	0.103	74.374	*0.000*
CPQ	9.234	0.116	79.377	*0.000*
DCX	7.153	0.100	71.716	*0.000*
GMH	8.129	0.109	74.653	*0.000*
GT	6.747	0.102	66.426	*0.000*
HAR	5.987	0.090	66.228	*0.000*
KF	4.994	0.108	46.039	*0.000*
LE	6.394	0.097	65.901	*0.000*
LMT	7.470	0.101	73.724	*0.000*
MLM	5.730	0.091	62.974	*0.000*
RCL	6.772	0.100	67.927	*0.000*
S	7.837	0.107	73.432	*0.000*
SGY	6.233	0.090	69.301	*0.000*
STT	6.927	0.093	74.420	*0.000*
UBS	6.272	0.090	69.747	*0.000*
VAL	5.327	0.094	56.971	*0.000*
β_1	0.191	0.026	7.300	*0.000*
β_2	-0.014	0.014	-0.957	*0.338*
β_3	-0.149	0.011	-13.165	*0.000*
β_4	0.096	0.011	8.885	*0.000*
β_5	0.511	0.008	66.225	*0.000*
β_6	0.010	0.005	2.106	*0.035*
CP*WMT	0.105	0.158	0.662	*0.508*
CP*CCN	0.359	0.128	2.799	*0.005*
CP*AOC	0.471	0.140	3.358	*0.001*
CP*UNH	0.184	0.140	1.313	*0.189*

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy,
APRESID = |price change|.

Table 20. cont'd
Pooled estimation over the combined time sample periods, with a 40-element intercept.
Interacted variable allow for a shift in individual stock intercept and all pooled coefficients at the time of the exchange-wide decimaization (Jan. 29, 2001.)
Model is*:

$$\log(VNET_t) = \beta_0 + \beta_1 \log(ENPTIME_t) + \beta_2 \log(NUMBER_{t-1}) + \beta_3 \log(SPREAD_{t-1}) + \beta_4 \log(VOLUME_{t-1}) + \beta_5 \log(NPTIME\_ERR_t) + \beta_6 \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} + \beta_7 I^{CP} + \beta_8 \log(ENPTIME_t) I^{CP} + \beta_9 \log(NUMBER_{t-1}) I^{CP} + \beta_{10} \log(SPREAD_{t-1}) I^{CP} + \beta_{11} \log(VOLUME_{t-1}) I^{CP} + \beta_{12} \log(NPTIME\_ERR_t) I^{CP} + \beta_{13} \log(APRESID_{t-1}) I^{+/-}_{PRESID1_{t-1}} I^{CP}$$

All stocks both sample periods pool				
Variable	Coeff.	Std. Error	t-Statistic	p-value
CP*KO	0.163	0.159	1.021	*0.307*
CP*T	0.050	0.179	0.277	*0.782*
CP*DOV	0.254	0.147	1.723	*0.085*
CP*ALL	0.030	0.157	0.188	*0.851*
CP*GP	-0.646	0.148	-4.360	*0.000*
CP*PHM	0.555	0.139	3.997	*0.000*
CP*APF	0.444	0.174	2.558	*0.011*
CP*CLB	0.625	0.142	4.400	*0.000*
CP*MRO	0.653	0.150	4.358	*0.000*
CP*HTN	0.499	0.133	3.764	*0.000*
CP*CNF	-0.480	0.140	-3.423	*0.001*
CP*NKE	0.279	0.147	1.895	*0.058*
CP*AMG	-0.151	0.127	-1.186	*0.236*
CP*PKI	-0.162	0.135	-1.201	*0.230*
CP*HIT	0.329	0.119	2.767	*0.006*
CP*AGX	-0.255	0.147	-1.733	*0.083*
CP*AOL	0.293	0.169	1.733	*0.083*
CP*ASF	0.444	0.140	3.170	*0.002*
CP*BEN	0.254	0.134	1.889	*0.059*
CP*CI	0.418	0.131	3.182	*0.002*
CP*CL	0.301	0.150	2.003	*0.045*
CP*CPQ	0.069	0.176	0.391	*0.696*
CP*DCX	0.159	0.149	1.071	*0.284*
CP*GMH	0.462	0.162	2.850	*0.004*
CP*GT	-0.048	0.141	-0.341	*0.733*
CP*HAR	0.124	0.136	0.913	*0.361*
CP*KF	0.259	0.160	1.616	*0.106*
CP*LE	-0.101	0.143	-0.706	*0.480*
CP*LMT	0.405	0.150	2.695	*0.007*
CP*MLM	0.099	0.134	0.739	*0.460*
CP*RCL	0.587	0.150	3.924	*0.000*
CP*S	0.223	0.157	1.419	*0.156*
CP*SGY	-0.022	0.130	-0.166	*0.868*
CP*STT	0.528	0.139	3.786	*0.000*
CP*UBS	-0.549	0.129	-4.262	*0.000*
CP*VAL	-0.019	0.129	-0.146	*0.884*
β_8	0.100	0.040	2.492	*0.013*
β_9	-0.015	0.021	-0.725	*0.468*
β_{10}	0.035	0.015	2.324	*0.020*
β_{11}	-0.002	0.016	-0.144	*0.885*
β_{12}	0.015	0.011	1.364	*0.173*
β_{13}	-0.008	0.006	-1.315	*0.188*

R-squared	0.422
Adjusted R-squared	0.422
S.E. of regression	1.869
Sum squared resid	338975.5
Log likelihood	-198531.1
Mean dependent var	7.725
S.D. dependent var	2.458
Akaike info criterion	4.090
Schwarz criterion	4.099
Durbin-Watson stat	1.988

	Chow test	**p-value**	**Wald Test**	**p-value**
F-statistic	14.552	0.000	5.267	0.000
Log likelihood ratio	667.749	0.000	31.601	0.000

* VNET = net dir. volume,
ENPTIME = exp. duration, NUMBER = # of transactions, SPREAD = nominal spread, VOLUME = tr. volume, NPTIME_ERR = impatience proxy, APRESID = |price change|.

Table 21. Common Factor Analysis
Principal component analysis on the 40 element correlation matrix of liquidiy and residuals series.Daily series are generated by aggregating the results from indivudual event time duration-based regressions. Respective eigenvalues can be obtained by multiplying the % by 40, the number of series (i.e. .11387*40=4.555)

Oct. 2, 2000 till Jan. 26, 2001.

	Principal Components			ML Factor Analysis		
	% Explained b y Factor			% Explained b y Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	11.387	6.794	5.982	11.387	6.794	5.982
NNET	8.499	6.679	5.916	8.499	6.679	5.916
RES	7.312	6.574	6.141	7.312	6.574	6.141
EXRES	6.765	6.327	6.075	6.765	6.327	6.075

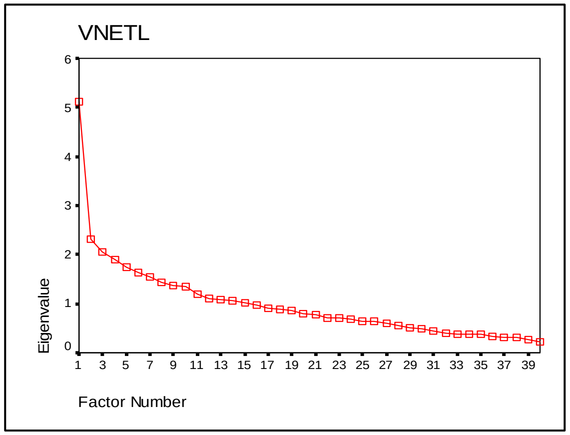
Feb. 8, 2001 till May 31, 2001.

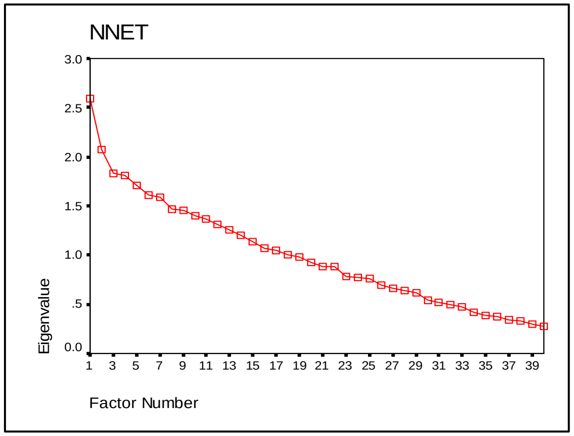
	Principal Components			ML Factor Analysis		
	% Explained b y Factor			% Explained b y Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	15.811	6.927	6.037	15.811	6.927	6.037
NNET	8.218	6.877	6.135	8.218	6.877	6.135
RES	6.993	6.138	5.972	6.993	6.138	5.972
EXRES	8.033	6.291	5.759	8.033	6.291	5.759

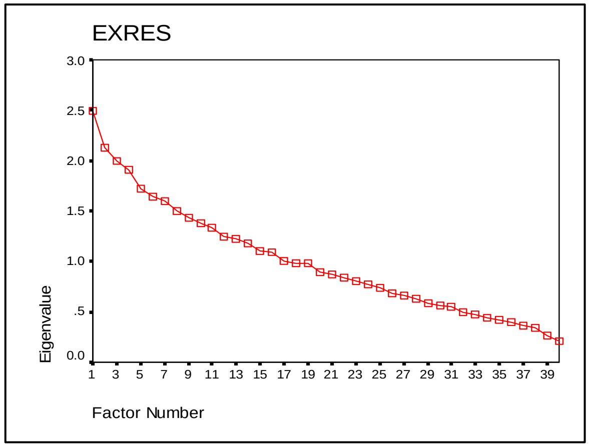
Oct. 2, 2000 till May 31, 2001.

	Principal Components			ML Factor Analysis		
	% Explained b y Factor			% Explained b y Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	12.793	5.814	5.111	12.793	5.814	5.111
NNET	6.483	5.171	4.575	6.483	5.171	4.575
RES	5.593	5.191	4.823	5.593	5.191	4.823
EXRES	6.225	5.332	4.996	6.225	5.332	4.996

Table 22
Scree plots of factor eigenvalues from the estimation period Oct. 2, 2000 till May 31, 2001.







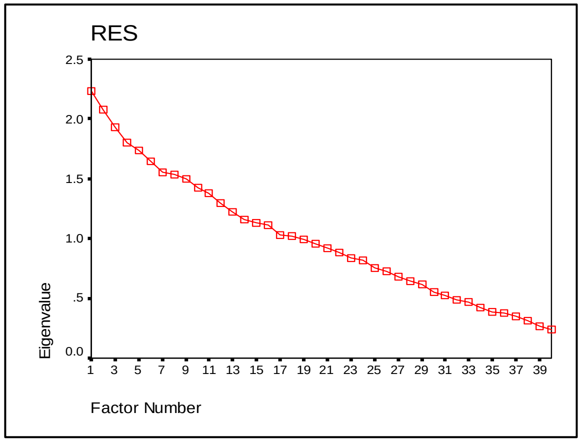


Table 23. Decimal vs Control Stock Common Factor Analysis
Principal component analysis on the 20 element correlation matrix of decimal and control stock liquidiy and residuals series. Daily series are generated by aggregating the results from indivudual event time duration-based regressions. Respective eigenvalues can be obtained by multiplying the % by 20, the number of series (i.e. .13953*20=2.79)

Oct. 2, 2000 till Jan. 26, 2001.

	Decimal Stocks			Control Stocks		
	% Explained by Factor			% Explained by Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	13.953	9.586	8.507	14.649	9.261	7.696
NNET	11.621	9.133	8.405	10.315	9.097	8.591
RES	11.265	9.593	8.389	11.449	9.765	9.048
EXRES	10.652	9.653	8.704	10.345	9.085	8.99

Feb. 8, 2001 till May 31, 2001.

	Decimal Stocks			Control Stocks		
	% Explained by Factor			% Explained by Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	19.976	9.376	8.188	16.881	10.553	9.236
NNET	12.723	9.946	7.88	10.187	9.384	8.442
RES	10.882	9.516	8.238	9.936	9.661	8.898
EXRES	12.535	9.807	8.765	9.504	9.184	7.949

Oct. 2, 2000 till May 31, 2001.

	Decimal Stocks			Control Stocks		
	% Explained by Factor			% Explained by Factor		
Series	**First**	**Second**	**Third**	**First**	**Second**	**Third**
VNETL	16.305	9.268	7.759	14.467	8.51	7.161
NNET	10.13	7.918	7.338	8.54	7.654	7.216
RES	9.465	7.769	7.495	8.839	7.555	7.527
EXRES	9.773	8.54	7.669	8.521	7.969	7.638