Intraday Price Discovery and Volatility: An Examination of the Mexico Futures Market (MexDer) using ultra high frequency data

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October 2006

Abstract

This paper conducts a pilot study on a high frequency dataset of futures prices from an emerging market economy (Mexico) to investigate the price effects of trading intensity. We extend the Ben Sita and Westerholm (2006) model, which divides the intensity effect into liquidity and information components, by including trading volume as an additional measure of intensity. Analyzing ten months of tick by tick data, we find that the time duration between transactions exerts a negative influence on price changes for interest rate futures. Additionally, increases in order flow and trade volume have a positive influence on price changes. This evidence suggests that managing both time and trading volume are important aspects of trading in the Mexican futures market.

Preliminary: This paper conveys the results of a pilot study only, and is not for citation without the permission of the author.

JEL Classification: G15, G14, C32
Keywords: Emerging markets, market microstructure, trading intensity, ultra-high frequency data, Autoregressive conditional duration

* We would like to thank MexDer, Mercardo Mexicano de Derivados, S.A. de C.V. for providing the data.
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1 Introduction

This paper examines the price effects of duration within a microstructure model of price discovery for an emerging market exchange, the Mexican futures market. Duration is defined as the time elapsed between consecutive trades. Previous studies in this area focus upon either the equities, futures or foreign exchange markets of developed economies. The contribution of this paper is twofold. We extend the Ben Sita and Westerholm (2006) trade duration and trade direction indicator decomposition of the bid-ask spread by explicitly including trade volume as a component of the trade direction indicator. The rationale for including volume is threefold. First, following Easley and O’Hara (1987), informed traders may engage in large volume trading or they may choose to segment large volume trades, thereby generating a larger number of informationally based trades. Thus, trade volume conveys information and may have a direct effect upon prices. Second, Engle (2000) and Manganelli (2005) model volume as a stochastic process in estimating the impact on trades. Third, DeJong et al. (1996) provide evidence that transaction size is positively related the price effect.

Our second contribution is to examine the price effects of duration for a developing (or emerging) futures market, where trades tend to be less frequent and the level of liquidity lower than that of a developed futures market. The most relevant prior research on the Mexican futures market, undertaken by Zhong et al. (2004) investigates the hypothesis that the futures market serves an important price discovery function, and that the introduction of futures trading has enhanced volatility in the underlying spot market. In particular, the paper tests both hypotheses simultaneously using daily frequency data from Mexico in the context of an EGARCH model that also incorporates possible cointegration between the futures and spot markets. The evidence supports both hypotheses, suggesting that the futures market in Mexico is a useful price discovery vehicle, although futures trading has also been a source of instability for the spot market.

The paper is structured as follows. In the next section we present an overview of the existing literature. Section three discusses the econometric model and the
methodology employed. Section four presents the empirical analysis and section five concludes providing suggestions for future research.

2 Literature Review

Market microstructure economics focuses on how prices adjust to new information and how the trading mechanism affects asset prices. More importantly, much of modern microstructure theory is driven by the key insight of models of asymmetric information, namely, that trades convey information. The specialist, by observing trading activity, gradually learns the information held by informed traders and adjusts prices so that, at any point in time, prices reflect the expectation of the securities terminal value conditional on all public information, including prior trades. As a consequence, only in the long run will prices fully adjust to incorporate any new information.

In theoretical models, trading in financial markets occurs either for information or for liquidity reasons. Glosten and Milgrom (1985) and Kyle (1985) describe the mechanisms by which prices change to incorporate new information, yet time is never explicitly modeled in either study. However, since informed traders randomize between trading and waiting, the bid-ask spread in these models is a function of the arrival rate of bid and ask prices. In fact each model treats informed traders differently, Glosten and Milgrom (1985) allow informed traders to trade intensively as if it is their sole opportunity to trade, while in Kyle (1985) they trade gradually. While there is no indication in either study that time affects the trading behaviour of traders, it is clear that there is a time dimension, simply because prices converge in these models at different rates for uninformed and informed traders. Comparing the two models, Back and Baruck (2004) demonstrate that informed (uninformed) traders trade with a lower (higher) trading rate that corresponds to one time unit (the square root of that time unit). Despite these differences, they find evidence that the Kyle (1985) and Glosten and Milgrom (1985) models are actually models of the same phenomenon, in that trades move prices because there is a possibility that the trader is better informed than the market at large.
Informed agents are motivated as they possess relevant private information about the real value of the asset which is hidden from the rest of the population. They will act strategically in an attempt to profit from holding this information. As a consequence, both the market maker and the uninformed agents face a learning problem, that is, how to infer the true value of the traded asset by observing the behaviour of the other traders. They can learn by looking at market information, such as prices, volumes or times between trades. Time is also a significant factor in price discovery as demonstrated in Easley and O’Hara (1992). In their model, information flow is not continuous as informed traders abstain from trading on occasions and market makers equate the absence of informed traders as a lack of news. However, this holds only under the assumption that there is sufficient liquidity to allow informed traders to trade at their convenience, and that they are not patient in the sense of Kyle (1985). Additionally, O’Hara (2003) points out that liquidity is also an important factor to price discovery. Consequently, the absence of traders is not a conclusive indication that there is no news, since it may be the absence of liquidity that keeps informed traders out of the market. A further reason offered by Diamond and Verrecchia (1987) is that market regulators might voluntarily suspend informed trading when the new information is expected to have an extreme impact on price. Alternatively, informed traders may elect to stay out of the market for purely strategic reasons. For instance, Back and Baruck (2004) assert that when informed traders realize that their aggregate profits increase more when they trade gradually than when they trade intensively, they will adopt a lower trading rate.

The theoretical motivations for the empirical investigations on the price effects of duration are predominantly found in the models of Diamond and Verrecchia (1987) and Easley and O’Hara (1992). Prior to these two contributions, the market microstructure literature did not accord time a prominent information role. In Diamond and Verrecchia (1987), at the beginning of the trading day, one of the two possible events happens either good news or bad news arrives. When good news is received, the informed trader will always buy. When bad news arrives, she will wish to sell or sell short if she does not own the stock. There is no trading in situations where a trader informed of bad news is unable to trade as a short-sale constraint exists. Thus, informed traders will always trade unless
they do not own the stock and/or short-sale constraints exist. Accordingly, long durations are likely to be associated with bad news. In Easley and O’Hara (1992), informed traders trade on either side of their signal (news), but only when there is a signal, and therefore long durations are likely to be associated with no news. These two contributions suggest that time actually conveys information. By definition, an uninformed trader’s decision to trade does not depend on information available at the time of trade. However, informed traders only trade when they have new information available, hence variations in trading rates in Easley and O’Hara (1992) are associated with changing numbers of informed traders. More generally, informed traders would, upon receipt of new information, tend to trade more frequently, and as quickly as possible. However, the analysis of Easley and O’Hara (1987) demonstrates, informed traders may be quickly distinguished by large volume trading and hence their profit opportunities would be lessened. Thus, their incentive to trade quickly is reduced. In response, informed traders may break up large volume trades, thereby generating a larger number of informationally based trades. Thus, according to Dufour and Engle (2000), it is reasonable to assume that variations in the trading intensity are positively related to the behaviour of informed traders. It follows that trading intensity, which results in both short and long durations between trades, as well as trading volumes may provide information to market participants.

In empirical models, customary analysis of the mechanics of the market involves the use of time series data, where the variables of interest are separated by equally spaced fixed time points, in other words, time is non-stochastic. With the availability of high frequency data empirical work on microstructure issues can now investigate the importance of time, that is, time can be modeled as a stochastic process. However, a problem when dealing with ultra-high frequency data is that they are irregularly spaced. Engle and Russell (1998) suggest tackling this issue by modeling directly the duration between trades. High frequency duration models were first introduced in the empirical finance literature by Engle and Russell (1997, 1998) with the autoregressive conditional duration (ACD) model. In these papers, the authors model durations between successive market transactions of a stock, rather than adopting the traditional perspective of examining the volatility of the price process. Zhang et al. (2001) modify the original
Engle and Russell (1998) model by allowing the expected duration to depend non-linearly on past information variables. These authors assert that duration models are particularly suited for applications in a high frequency setting, as one deal with irregularly spaced data. In this framework, the time elapsed between two market events conveys meaningful information. The importance of taking into account the time dimension of the price process is particularly stressed by the market microstructure literature of for example, Easley and O’Hara (1992), O’Hara (1995), and Easley et al. (1997).

Time or explicitly the transaction duration (the time difference between two consecutive transactions) is considered to be a measure of trading intensity, (see for example, Engle and Russell, 1997, 1998; Engle, 2000; Grammig and Wellner, 2002; Renault and Werker, 2002; and Manganelli, 2005). These studies show that duration is inversely proportional to the expected return variance. For example, Engle (2000) provides empirical evidence showing that variations in duration and variations in returns variance are linked to the same news events. Additionally, in some analysis, duration is considered to be a measure of liquidity, see for example, Dufour and Engle (2000), Engle and Lange (2001) and Engle and Lunde (2003). Duration is also documented as a natural measure of the speed by which prices incorporate new information. Dufour and Engle (2000) show that informed traders choose to trade in periods that maximize the number of informed transactions. Duration is also considered as measuring trading risk, see Gouriéoux et al. (1999), Renault and Werker (2002), and Ghysels et al. (2004). In these studies, duration is modeled as a process capturing the risk associated with trading under both price and time uncertainty. For example, in Renault and Werker (2002), duration is split into a deterministic component with transient effects on returns, and a stochastic component with permanent effects on returns variance.

Examining the price effects of trade intensity, Madhavan et al. (1997) provide evidence showing that the trade indicator captures short-term deviations of the observed price from the fundamental price. Proposing a structural model, they show that the transitory price effects account for approximately 60.0 per cent of the total price variance. They hypothesize that a number of variables can be considered to capture these effects.
DeJong et al. (1996) provide evidence showing that the price effect increases with the transaction size, and is estimated to lie between 25.0 per cent and 60.0 per cent of the bid-ask spread. Further, the relation between duration and returns is investigated in Dufour and Engle (2000) extending on the Hasbrouck (1991) vector autoregression (VAR) model. Dufour and Engle (2000) provide evidence showing that prices increase when traders observe short durations. This finding is consistent with the Easley and O’Hara (1992) prediction that market makers revise their prices upward in the presence of informed traders. Considering the Admati and Pfleiderer (1988) prediction that liquidity traders will trade in clusters and accommodate informed traders, assessing the relation between information flow and short durations is not that simple. True, informed traders cannot trade outside the trading framework of liquidity traders, but they will observe short durations. When liquidity is high because of the volatility, informed traders will not trade at market openings and closures as expected.

3 Econometric Methodology

3.1 Foundation for the model

There are two sources of information on which traders rely when conveying their beliefs about an asset’s future value. First, traders rely on public information obtained through news on fundamentals. Second, traders rely on private information that aggregates information from insider traders. In contrast to public information, private information is first known when insider traders transact, buying when prices are below true value, and selling when prices are above true value. Accompanying informed trading, exposed traders learn from past price movements (Glosten and Milgrom, 1985), price duration (Easley and O’Hara, 1992) and price size (Easley and O’Hara, 1987).

The three price dimensions are important in the characterization of the price process in financial markets. Earlier studies have investigated the three price dimensions using solely either the direction of trade (Glosten and Harris, 1988) or both the size and the direction of trade (Hasbrouck, 1991). Related to this study is the Dufour and Engle (2000) study, where they investigate the hypothesis that informed trading is associated
with short trade durations (Easley and O’Hara, 1992). Contrasting with this proposition is
the view that short durations are associated with liquidity traders who prefer to trade
when the market is thick (Admati and Pfleiderer, 1988). Therefore, when examining the
role of time in price discovery, we utilize normalized duration measures with
expectations about 1. We extend the Dufour and Engle (2000) empirical model by
separating the component of duration associated with liquidity from the component of
duration associated with information. Motivated by the study of Renault and Werker
(2002) that durations can be split into transient and permanent effects, we model the
returns as a function of the order flow, the expected duration, duration innovations and
the trade volume.

3.2 The Structural Model

In this section, we present a simple model that decomposes the bid-ask spread into
order-handling, liquidity and adverse selection costs on the basis of the trade direction
indicator, volume and the duration variable. There are at least three statistical approaches
to decomposing the bid-ask spread. The first, following Roll (1984), is to infer the
components of the bid-ask spread from the serial covariance properties of observed trade
prices. The second, due to Glosten and Harris (1988), is to infer the components of the
bid-ask spread from the trade indicator variable. The third, stems from Huang and Stoll
(1997) and infers the components of the bid-ask spread from the trading indicator and the
trading volume. This paper provides a decomposition based on the trade indicator, trade
time and trade volume, expressed in equation (1).

This model modifies Ben Sita and Westerholm (2006) in that we also include
trade volume mediated by the trade direction indicator. The rationale for including
trading volume is that, following Easley and O’Hara (1987), informed traders may be
quickly distinguished by their large volume trading or they may rationally choose to
segment large volume trades, thereby generating a larger number of informationally
based trades. Thus, trade volume conveys information and may have a direct effect of
prices. Also, Engle (2000) and Manganelli (2005) model volume as a stochastic process
in estimating the impact on trades. Further, DeJong et al. (1996) provide evidence that
transaction size is positively related to the price effect. The empirical model is thus given as:

\[ m_t = m_{t-1} + [\phi_1 + (\phi_2 + \rho_q \theta_1)T_t + \phi_3 v_t]q_t + e_t \]  

(1)

where \( m_t \) is the unobservable price, such that \( m_t = E[p^*_t | \Phi_t] \), where \( p^*_t \) is the log fundamental value and \( m_t \) is the expected value of \( p^*_t \). \( T_t \) is the transaction time, \( v_t \) is the trade volume, \( q_t \) is the buy-sell trade direction indicator variable (taking -1 for seller-initiated trades, +1 for buyer-initiated trades, and 0 for trades occurring within the bid-ask spread), and \( e_t \) is a serially uncorrelated public information shock. Equation (1) decomposes the effects on \( m_t \) into five trading parameters: \( \phi_1 \) captures the cost of processing a trade, \( \phi_2 \) the speed by which transactions occur, \( \theta_1 \) reflects private information revealed by the order flow and the trading intensity, \( \theta_2 \) reflects private information revealed by the trading volume and \( \rho_q \) is the temporal dependence in the order flow that results from either informed traders in their efforts to take advantage of incipient liquidity or noise traders unable to change the direction of trade. Although \( m_t \) is unobservable, the trade price, \( p_t \), is observed albeit measured with error. Following decomposition of the duration variable into temporal and permanent effects, the first difference of equation (1) can be obtained as follows:

\[ m_{t-1} = m_{t-2} + [\phi_1 + (\phi_2 + \rho_q \theta_1)T_{t-1} + \phi_3 v_{t-1}]q_{t-1} + e_{t-1} \]

\[ \Delta m_t = m_t - m_{t-1} \\
= m_{t-1} + [\phi_1 + (\phi_2 + \rho_q \theta_1)T_t + \phi_3 v_t]q_t - \{m_{t-2} + [\phi_1 + (\phi_2 + \rho_q \theta_1)T_{t-1} + \phi_3 v_{t-1}]q_{t-1} + e_{t-1}\} \\
= m_{t-1} - m_{t-2} + \phi_1 q_t - \phi_1 q_{t-1} + \phi_2 T_t q_t - \phi_2 T_{t-1} q_{t-1} + \rho_q \theta_1 T_t q_t - \rho_q \theta_1 T_{t-1} q_{t-1} + \phi_3 v_t q_t - \phi_3 v_{t-1} q_{t-1} + e_t - e_{t-1} \]

Let \( \varepsilon_t = m_{t-1} - m_{t-2} \) the serially uncorrelated public information shocks and since \( m_t \) is unobservable, we substitute trade price, \( p_t \), as a proxy for the efficient price, \( m_t \):

\footnote{It is assumed that informed traders observe short durations when present in the market (Easley and O’Hara, 1992).}
\[ r_i = \phi_1 \Delta q_i + \phi_2 (T_i q_i - T_{i-1} q_{i-1}) + \rho_q \theta_1 (T_i q_i - T_{i-1} q_{i-1}) + \phi_3 (v_i q_i - v_{i-1} q_{i-1}) + \varepsilon_i + n_i - n_{i-1} \]

where \( e_i - e_{i-1} \) is translated into \( n_i - n_{i-1} \) which are serially correlated rounding errors (proxying trade price for the efficient price, where \( n_i \) summarizes the effects of noise trading). Gathering like terms gives:

\[ r_i = [\phi_1 \Delta q_i + (\phi_2 \psi_i + \rho_q \theta_1 C_i + \phi_3 z_i) q_i] + (\varepsilon_i + (n_i - n_{i-1})) \quad (2) \]

where \( r_i = 100 \times \ln \left( \frac{p_i}{p_{i-1}} \right) \) is the logarithmic return in percent. \( \psi_i = a_0 + a_1 x_{i-1} + a_2 \psi_{i-1} \) is the expected duration process truncated at the first lag, \( x_i = T_i - T_{i-1} \) is the duration. \( C_i = \left( \psi_i \right) \left( \psi_{i-1} \right) - 1 \) is the innovation in trading intensity which is defined as the covariance of the standardized residual of duration. \( \Delta q_i = q_i - q_{i-1} \) is the residual in the orderflow, \( z_i = b_0 + b_1 w_{i-1} + b_2 z_{i-1} \) is the expected change in the volume process, truncated at the first lag, \( w_i = v_i - v_{i-1} \). \( \varepsilon_i \) is the serially uncorrelated public information shock which is equivalent to the change in the unobservable fundamental value (price), \( m_i - m_{i-1} \). \( n_i - n_{i-1} \) is the serially correlated rounding error term which arises since the observable trade price, \( p_i \), measures the unobservable price, \( m_i \), with error. Equation (2) shows that the return, \( r_i \), reflects both the public information shock (through \( \varepsilon_i \)) and the trading friction effects (through \( n_i \)) associated with \( p_i \).

In Dufour and Engle (2000) the relationship between \( r_i \) and \( x_i \) is assumed to be significant for short durations, but not for long durations as a result of the long absence of informed traders from the market (Easley and O’Hara, 1992). Equation (2) differs from that of Dufour and Engle (2000) in that \( x_i \) is spilt into a temporal and a permanent component consistent with Renault and Werker (2002). The temporal component is estimated by the expected duration, \( \psi_i \), and the permanent component by the duration.
innovation component, \( C_t \). The former term captures liquidity and the latter information effects. The two terms are obtained from estimating the ACD(1,1) model. Further, equation (2) differs from the model in Ben Sita and Westerholm (2006) in that transaction size is incorporated consistent with DeJong et al. (1996). By analogy to the ACD(1,1) model, the expected change in volume \( z_t \) is obtained by estimating the ACV(1,1) model.

Upon examining equation (2), it is clear that the error term has two components; a fundamental component \( \epsilon_t \) and a transitory component \( (n_t - n_{t-1}) \). The fundamental error induces permanent price changes, and is related to the fundamental volatility that consists of random price changes that do not revert. The transitory component is related to the transitory volatility that is taken as an implicit transaction cost and a measure of the market quality, (Hasbrouck, 1993). Thus, it is relevant for market regulators to be able to distinguish between the fundamental and the transitory volatility when addressing issues related to excess volatility.

The standardized measure of market quality, which can be derived from equation (2) is:

\[
\rho = \frac{-\sigma_n^2 + (2(\phi_1 + \phi_2 + \phi_3 ) + \phi_1^2 )\rho_q}{(\phi_1 + \phi_2 + \phi_3)^2 + \rho_q \theta_1^2 + \sigma_\epsilon^2 + 2\sigma_n^2}
\]

(3)

where \( \rho \) is the ratio of the first order covariance to the variance. This ratio measures the first order autocorrelation process of the governing returns. According to Ben Sita and Westerholm (2006) the first order autocorrelation can be interpreted as a measure of institutional trading environment quality and it puts into contribution the entire price process. The smaller the absolute value of the ratio, ignoring intensity effects on the price process, the better the quality of trading in that marketplace, since a lower coefficient is an indication that the duration variables either decrease the covariance bias or increase the variance in the trade process.
3.3 The ACD Model

Two different approaches have been proposed to model irregularly spaced data: *Time Deformation* (TD) models (see, for example, Clark (1973), Stock (1988), and Ghysels and Jasiak (1998); and *Autoregressive Conditional Duration* (ACD) models (see Engle, 1996; and Engle and Russell, 1998). The TD approach uses auxiliary transformations to relate observational/economic time to calendar time. The preferred approach in the context of this paper is the ACD approach that directly models the time between events, such as trades. The ACD is a type of dependent point process particularly suited for modeling characteristics of duration series such as clustering and overdispersion. This parameterization is most easily expressed in terms of the waiting times between events.

Let \( x_i = T_i - T_{i-1} \) be the interval of time between event arrivals, called the duration. The distribution of the duration is specified directly on the past duration. According to Engle and Russell (2004), the ACD model is specified by the expectation of the duration given the past arrival times, \( \psi_j \), such that

\[
E(x_i | x_{i-1}, x_{i-2}, \ldots, x_1) = \psi_i(x_{i-1}, x_{i-2}, \ldots, x_1) = \psi_i
\]

and,

\[
x_i = \psi_i \epsilon_i
\]

where \( \epsilon_i \sim \text{i.i.d. with density } p(\epsilon; \varphi). \)

Engle and Russell (1998) suggest and apply linear parameterizations for the expectation given by

\[
\psi_i = \omega + \sum_{j=1}^{p} \alpha_j x_{i-j} + \sum_{j=1}^{q} \beta_j \psi_{i-j}
\]
since the conditional expectation of the duration depends on $p$ lags of the duration and $q$ lags of the expected duration this is termed an ACD$(p,q)$ model.

Accordingly, the Autoregressive Conditional Volume (ACV) model ACV$(p,q)$ is given by

$$z_t = \tau + \sum_{j=1}^{p} \alpha_j w_{t-j} + \sum_{j=1}^{q} \beta_j z_{t-j}$$  \hspace{1cm} (7)

The ACD$(p,q)$ model of (6) and the ACV$(p,q)$ model of (7) appear very similar to the ARCH$(p,q)$ models of Engle(1982) and Bollerslev (1986). Engle and Russell (2004) note that the two models share many of the same properties. Thus both the ACD$(p,q)$ and ACV$(p,q)$ models can be modeled as GARCH processes.

### 3.4 Alternative Empirical Models

As a robustness check we examine a set of alternative models for the estimation of the implied bid-ask spread. Madhavan et al. (1997) using data from the New York Stock Exchange find that about 60.0 per cent of the total variance is attributable to the transitory variance. This model is the base upon which our model and the Ben Sita and Westerholm (2006) model is derived. In terms of its information content, the Dufour and Engle (2000) VAR model provides interesting guidelines on the direction of the relationship between duration and price change. The DeJong et al. (1996) model estimated on data from the Paris Bourse provides yet another perspective on the role of trading intensity in measuring the price effects. We cross validate our results based on equation (2) by estimating the following empirical models,

$$r_t = \theta(q_t - \rho_q q_{t-1}) + \phi(q_t - q_{t-1}) + u_{1t} \hspace{1cm} (8a)$$

$$r_t = (\gamma_0 q_t + \gamma_1 q_{t-1}) + [\delta_0 \ln(x_t)q_t + \delta_1 \ln(x_{t-1})q_{t-1}] + u_{2t} \hspace{1cm} (8b)$$

$$r_t = a_0 + (R_0 \Delta q_t + R_1 \Delta q_{t-1}) + (e_0 q_{t-1} + e_1 q_t z_{t-1}) + u_{3t} \hspace{1cm} (8c)$$
where $u_{t1}$, $u_{t2}$, and $u_{t3}$ are random error terms. The Madhavan et al. (1997) model is produced in equation (8a). Here, order processing cost is captured by $\phi$ and the adverse selection cost by $\theta$. In the Dufour and Engle (2000) model (equation 8b) the order processing costs are given by $(\gamma_0 - \gamma_1)q$ and the adverse selection costs by $(\delta_0 - \delta_1)\ln(x)q$. The DeJong et al. (1996) model (equation 8c) is interpreted differently. Here, the order processing cost component is $R_0 - e_0 - e_1\alpha + (R_1 - 0.5e_1)z$, where $\alpha$ is the median of trade size divided by the natural logarithm of 2, and the adverse selection component is given by $e_0 + e_1\alpha - 0.5e_1z$. This model differs from the two other models since in this model, price revisions are associated with changes in the expectations of the true value of the stock given the size of the transaction. We estimate equation (8a) using the maximum likelihood estimator, and equations (8b) and (8c) by the OLS estimator with robust errors.

4 Empirical Analysis

4.1 Data

The Mexican Derivatives Exchange (MexDer) began operations on December 15, 1998, trading US Dollar futures contracts. Trading on the stock index (IPC) commenced on April, 15 1999 and trading on interest rate futures commenced one month later. The market operated via open outcry until May 8, 2000 when electronic trading was established. Trading on the MexDer is conducted through a completely automated system, such that prices are revealed to the general public both domestically and globally. Market makers trade in a limit order book market and maintain bid and ask quotes for futures contracts for which they are registered, in order to promote their trading.

This pilot study captures the infancy of electronic trading on the MexDer using futures data spanning the period August 28, 2000 to June 29, 2001. Specifically, we use tick by tick data for the 28 day interest rate futures contract (TIIE28) and the US dollar futures contract (DEUA), the two most actively traded futures listed on the Mexican derivatives exchange (MexDer). The trading session runs from 7:30am to 2:00pm (local
time) in the case of the US dollar future and 7:30am to 2:15pm for the interest rate future. The data includes information relating to transactions, maturity, trade price, opening price and trade volume.

The data sample comprises 178 trading days for interest rate futures and 203 trading days for US dollar futures, giving rise to 1,721 recorded transactions for the interest rate futures and 2,033 recorded transactions for the US dollar futures. Unfortunately, these transactions do not equal the respective 1,721 and 2,033 information ticks. The reason is that some transactions are redundant in the neighbourhood of each other. To prepare the data for the analysis, we drop any transaction that occurred before the opening time, 7:30am, and after the closing time 2:00pm, (2:15pm in the case of the interest rate future). To obtain active price movements, we thin the trade price process, similar to that of Ben Sita and Westerholm (2006). This consists of ignoring a price at time $t-1$ if this price equals the price at time $t$ and in such a case adding the trading volume of the price at time $t-1$ to the trading volume at time $t$. We then compute the duration between trades, treating the overnight period as if it did not exist, so that, for example, the time elapsing between 13:59:30 and 7:30:10 of the following day is only 40 seconds. We adopt this strategy because of the infrequent trading nature of the futures contracts. According to Manganelli (2005), eliminating the duration of the overnight period would cause the loss of important information for futures trading. The underlying assumption here is that information flow is continuous. Eliminating the duration of the overnight period when there is no trade, would remove the suggestion that there is no news, which is implied by long (overnight) duration. Additionally, we eliminate all transaction data with zero duration. We treat these transactions as one single transaction, summing up all volumes. Taking these adjustments into consideration, the sample is reduced to 1,219 information ticks for interest rate futures and 1,896 for the US dollar futures.

Further, we also adjust for the time of day effects of durations and volume. There is a consensus in the literature that both duration and volatilities exhibit a typical pattern over the course of the trading day, with very high trading activity both at the beginning
and at the end of the day. In order to remove this feature from the data, the duration and volume series were diurnally adjusted as in Engle (2000). To accomplish this, we regressed durations and volumes on a piecewise linear function of the times of day to adjust both the trade duration and the trading volume for the time of day effects,

\[
\tilde{x}_i = \frac{x_i}{E[x_i|f(t)]} \quad (9)
\]

\[
\tilde{z}_i = \frac{z_i}{E[z_i|f(t)]} \quad (10)
\]

where

\[
f(t) = \beta_0 + \sum_{j=1}^{4} \beta_j (t - k_j)
\]

for \( k_j \) fixed at 27000 (7:30am), 34200 (9:30am), 41400 (11:30am) and 48600 (1:30pm) seconds, and \( \beta_k \) are consistent (but inefficient) OLS estimates as we regress the respective trade duration and trade volumes on \( f(t) \).

### 4.2 Descriptive Statistics

In Table 1 we report summary statistics for the variables used in the analysis. We note that the returns \( (r_i) \) for both interest rate and US dollar futures exhibit negative skewness and leptokurtosis, typical characteristics of financial returns data. Negative skewness is an indication that the probability of observing a large negative jump on both futures contracts is greater during the sample period. The returns for both futures indicate that there is clustering and overdispersion in the data (the standard deviation is larger than the mean). The adjusted variables \( (\tilde{x}_i; \tilde{w}_i) \) are close to their expected values of unity. Dealing with adjusted variables allows us to investigate the effects of excess dispersion on the return. So we can investigate to what extent incorporating adjusted duration and volume might improve Madhavan et al. (1997) that implicitly assume duration and volume effects equal 1. Neither the mean nor the median of the trade indicator variable, \( (q_i) \), give any indication that this variable is zero as expected under the null hypothesis, that a trade at buy (ask) is immediately followed by a trade at ask (buy). The derived
variable \( (C_i) \) is meant to capture the forces that drive away prices from their fundamental values.

### 4.3 Estimation Results

Table 2a reports the coefficients for the ACD(1,1) model. The coefficients for the ACD(1,1) model for the interest rate futures contract shows that the model captures trading momentum. However, this momentum is not captured for the US dollar futures contract. In essence, there appears to be a far greater persistence in the duration process for interest rate future than there is for US dollar futures. However, we cannot argue strongly that this is an actual fact, as the autocorrelation coefficient for the US dollar future is not significantly different from zero. The results provide evidence that last period’s trade duration lowers the expected duration of the current period trade for US dollar futures contract. In contrast, for the interest rate futures contract, the duration of last period’s trade increases the expected duration of the current period trade. These results may be indicating the prominence of informed traders in the respective products.

The estimated autoregressive coefficients of the ACV(1,1) model are reported in table 2b. All the coefficients are highly significant. Admati and Pfleiderer (1988) demonstrate that, in equilibrium, all discretionary liquidity traders choose to trade together. Therefore, according to their model, we should observe a clustering of trading volume at some point during the day. Our results show that volume is persistent for both interest rate and US dollar futures, which provide evidence for trading volume clustering. However, volume is a more persistent process for the US dollar futures, indicating that US dollar futures are more frequently traded than interest rate futures. The underlying intuition for more clustering in the trading volume for US dollar futures could relate to the fact that more discretionary liquidity traders buy and sell US dollar futures. The decision of discretionary liquidity traders to postpone their trading until an announcement has been released will make it easier for the market maker to infer the informed agent’s reasons for trading. It is important to note that the coefficients of the ACV(1,1) model are all positive and significant, indicating that large transaction size increases the expected transaction size of the next trade. Tables 2a and 2b show that both duration and volume
are able to capture traditional volatility regularities. Though duration and volume do not explicitly predict variance, they are able to forecast future trading intensities. In essence, the ACD and ACV estimates of Table 2 represent the volatility path from a time and a volume perspective, respectively.

We report the coefficients of the maximum likelihood estimates of the model in equation (2) in table 3. The results of our model indicate that only the change in the order flow coefficient is significant for both the interest rate and US dollar futures. Nevertheless, we recognize that expected duration and duration innovation coefficients, \( \phi_2 \) and \( \theta_1 \), respectively, are negatively related to returns for interest rate futures and positively related to returns in the case of the US dollar futures. Since both the liquidity \( (\phi_2) \) and information \( (\theta_1) \) coefficients have positive effects on the returns for US dollar futures trading, it means that liquidity traders are the ones who appear to dictate the time to trade. This is consistent with the results of the ACV model.

Another noteworthy result is that the coefficient for the order flow variable, \( \phi_1 \) is negatively related to returns for US dollar futures. This particular coefficient implies that the price of US dollar futures fall over the sample period, showing evidence of the Mexican peso appreciating vis à vis the US dollar. The order flow coefficient in the interest rate futures model shows evidence of an increase, indicating a higher interest rate environment. The autocorrelations of the order flow for the interest rate futures and US dollar futures are 0.24 and 0.08, respectively. Since by definition, \( (1 - 2\lambda = \rho_q) \), where \( \lambda \) is the probability that a trade at bid (ask) is immediately followed by another trade at bid (ask), the conditional probability of a trade continuing on the same side is given by \( 1 - \lambda \), and is 0.38 for interest rate futures and 0.46 for US dollar futures. The results of this model allow us to conclude that price effects in both interest rate and US dollar futures contracts originate mostly from order handling cost. It is also important to note that short duration initiates greater price changes than long duration. This result is in accordance with the hypothesis that long duration is associated with no information. Thus, informed traders will not trade. In contrast, short duration is associated with
information where more trades will be executed and effect price changes. Since informed traders tend to trade more frequently than their uninformed counterpart, with the arrival of information. The estimated first order autocorrelation \((\rho)\) for interest rate futures is 0.0051, relative to an estimate of 0.00012 for the US dollar futures. These estimates measure the ratio of the first order covariance bias to the variance bias. The fact that the interest rate futures estimate is higher than that for the US dollar estimate is a possible indication that the duration coefficients \((\phi_i)\) and \(( \theta_i)\) either increased the covariance bias in the trade process, or decrease the variance bias in the trade process of the interest rate futures. Further, the lower estimate of \(\rho\) in the US dollar futures suggest a better quality of trading in this product.

Table 4 presents the empirical results of the alternative models. More specifically, Panel A reports the results of the Madhavan et al. (1997) model which uses only the trade indicator variable to split the price effects into transitory and permanent effects. In Panel B we present the results of the Dufour and Engle (2000) model which use the duration variable to investigate its relevance in capturing trading behaviour. Panel C reports the results of the DeJong et al. (1996) model which includes trading size in their structural model. Overall, the results appear to provide similar results to our structural model particularly in terms of direction, but not necessarily in terms of the size effect on returns. Perhaps the most salient point regarding the results of all models is that the price effects of trading in both interest rate and US dollar futures originate mostly from order-handling costs, though the sign effects are contrasting.

5 Conclusions

In this paper we examine the price effects of duration in the context of a microstructure model of price discovery, for the emerging futures market of Mexico, MexDer. Extending the Ben Sita and Westerholm (2006) model, we incorporate both time and volume in a structural model in order to investigate their effects on price changes. In their empirical study, Dufour and Engle (2000) document that long duration has a lower impact on price than does a short duration. Building upon Dufour and Engle (2000) by splitting the duration effect into liquidity and information effects, Ben Sita and
Westerholm (2006) find evidence that both components exert a positive influence on price changes.

Using ten months of tick by tick data on the interest rate futures and the U.S. dollar futures from the Mexican derivatives exchange our pilot study finds mixed results in relation to theory and previous empirical evidence. First, our investigation involving transaction duration for the US dollar futures contract shows that the transient and permanent components of duration exerts positive influence on price changes, these effects are however insignificant. This is similar to the evidence provided by Ben Sita and Westerholm (2006). Conversely, our investigation of transaction duration for the interest rate futures contract indicates that both the transient and the permanent components of duration exert a negative influence on price changes. Also, consistent with Dufour and Engle (2000), we find that in the interest rate futures contract, long duration has a lower impact on price changes than short duration. Second, our investigations involving trade volume suggests that price changes tend to increase when there is an increase in trade volume in both contracts. Additionally, increases in order flow exert a positive influence on price changes for interest rate futures, but a negative influence for US dollar futures. This evidence suggests that managing time and trading volume are important aspects of optimum trading in the Mexican futures market.

Regarding directions for future research, an interesting extension of the econometric framework is to model the interaction between expected duration, expected volume and variance of returns. The underlying intuition of this is that market activity and volatility change over time because new information becomes available to traders at a varying rate. When not much information is available, trading is slow and there are few price changes. In contrast, when new unexpected information hits the market, trades become more frequent, volumes increase and prices move much faster. The implication is that volumes and time between trades influence prices because they are correlated with private information about a stock’s true value.
References


Table 1

Panel A: Summary Statistics on tick by tick data and the ACD Model - Interest Rate Futures
Number of observations: 1218

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_i$</td>
<td>0.004557</td>
<td>0.118360</td>
<td>0.419012</td>
<td>8.482541</td>
<td>-0.120148</td>
<td>-2.847601</td>
<td>2.859945</td>
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<td>$\tilde{x}_i$</td>
<td>0.999928</td>
<td>1.052534</td>
<td>0.355595</td>
<td>2.371193</td>
<td>-0.344877</td>
<td>0.102774</td>
<td>1.845838</td>
</tr>
<tr>
<td>$x_i$</td>
<td>6.253252</td>
<td>6.570182</td>
<td>2.233619</td>
<td>2.273147</td>
<td>-0.390926</td>
<td>1.693149</td>
<td>10.14898</td>
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<tr>
<td>$\tilde{w}_i$</td>
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<td>0.311893</td>
<td>5.058646</td>
<td>31.44518</td>
<td>4.859114</td>
<td>-24.92141</td>
<td>50.73148</td>
</tr>
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<td>$w_i$</td>
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<td>13.81551</td>
<td>1.143301</td>
<td>8.360153</td>
<td>-1.388081</td>
<td>9.210340</td>
<td>17.50439</td>
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<tr>
<td>$\psi_i$</td>
<td>1.413645</td>
<td>4.144019</td>
<td>6.631158</td>
<td>8.027016</td>
<td>-2.071434</td>
<td>-35.92424</td>
<td>7.091163</td>
</tr>
<tr>
<td>$z_i$</td>
<td>-1.267956</td>
<td>-0.131449</td>
<td>4.173118</td>
<td>29.09202</td>
<td>-4.801173</td>
<td>-35.97797</td>
<td>4.369610</td>
</tr>
<tr>
<td>$q_i$</td>
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<td>1.000000</td>
<td>0.994155</td>
<td>1.050500</td>
<td>-0.224722</td>
<td>-1.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>$C_i$</td>
<td>23.38736</td>
<td>-0.140695</td>
<td>550.6397</td>
<td>1143.303</td>
<td>33.38663</td>
<td>-0.249981</td>
<td>18925.35</td>
</tr>
</tbody>
</table>

$r_i$ is the mean return in percent, $x_i$ is the duration mean, $w_i$ is the trading volume mean and $q_i$ is the trade indicator mean. $\psi_i$ is the expected duration mean from an ACD(1,1) model of Engle and Russell (1998). $C_i$ is the signed duration innovation mean. $\tilde{x}_i$ is the adjusted duration mean, $\tilde{w}_i$ is the adjusted volume mean and $z_i$ is the expected volume mean from an ACV(1,1) model.

Panel B: Summary Statistics on tick by tick data and the ACD Model - US Dollar Futures
Number of observations: 1896

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Minimum</th>
<th>Maximum</th>
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</thead>
<tbody>
<tr>
<td>$r_i$</td>
<td>-0.001648</td>
<td>0.009857</td>
<td>3.042923</td>
<td>3.805884</td>
<td>-0.060163</td>
<td>-9.479133</td>
<td>9.352417</td>
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<tr>
<td>$\tilde{x}_i$</td>
<td>1.283929</td>
<td>1.092831</td>
<td>24.28725</td>
<td>446.4881</td>
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<td>3.288653</td>
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<tr>
<td>$x_i$</td>
<td>6.627624</td>
<td>6.921656</td>
<td>2.021960</td>
<td>2.732516</td>
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<td>$\tilde{w}_i$</td>
<td>1.266414</td>
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<td>$w_i$</td>
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<td>3.465796</td>
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<td>-6.907755</td>
<td>6.907755</td>
</tr>
<tr>
<td>$\psi_i$</td>
<td>2.556926</td>
<td>5.333730</td>
<td>6.473017</td>
<td>9.760787</td>
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<td>-36.53481</td>
<td>7.077071</td>
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<tr>
<td>$z_i$</td>
<td>-4.724724</td>
<td>-1.606650</td>
<td>7.667093</td>
<td>9.956660</td>
<td>-2.449200</td>
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<td>3.288653</td>
</tr>
<tr>
<td>$q_i$</td>
<td>-0.092827</td>
<td>-1.000000</td>
<td>0.995945</td>
<td>1.034767</td>
<td>0.186459</td>
<td>-1.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>$C_i$</td>
<td>1241.970</td>
<td>0.400585</td>
<td>4793.97</td>
<td>1879.489</td>
<td>43.26962</td>
<td>0.000556</td>
<td>2083298</td>
</tr>
</tbody>
</table>

$r_i$ is the mean return in percent, $x_i$ is the duration mean, $w_i$ is the trading volume mean and $q_i$ is the trade indicator mean. $\psi_i$ is the expected duration mean from an ACD(1,1) model of Engle and Russell (1998). $C_i$ is the signed duration innovation mean. $\tilde{x}_i$ is the adjusted duration mean, $\tilde{w}_i$ is the adjusted volume mean and $z_i$ is the expected volume mean from an ACV(1,1) model.
Table 2a. Coefficients of the ACD(1,1) model

\[ \psi_t = \omega + \alpha_1 x_{t-1} + \beta_1 \psi_{t-1} \]

<table>
<thead>
<tr>
<th></th>
<th>Interest rate futures</th>
<th>US Dollar futures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>z-statistic</td>
</tr>
<tr>
<td>( \omega )</td>
<td>7.482207</td>
<td>2.384042</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.037686</td>
<td>2.725469</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.786761</td>
<td>9.593276</td>
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</tbody>
</table>

Table 2b. Coefficients of the ACV(1,1) model

\[ z_t = \tau + \alpha_1 w_{t-1} + \beta_1 z_{t-1} \]

<table>
<thead>
<tr>
<th></th>
<th>Interest rate futures</th>
<th>US Dollar futures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>z-statistic</td>
</tr>
<tr>
<td>( \tau )</td>
<td>6.787218</td>
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<td>( \alpha_1 )</td>
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<tr>
<td>( \beta_1 )</td>
<td>0.567152</td>
<td>10.02072</td>
</tr>
</tbody>
</table>
Table 3. Estimation Results of the Trade equation

\[ r_i = \left[ \phi_1 \Delta q_i + (\phi_2 \psi_i + \rho \theta_i C_i + \phi_3 z_i) q_i \right] + (\varepsilon_i + n_i - n_{i-1}) \]

<table>
<thead>
<tr>
<th>Interest rate futures</th>
<th>US dollar futures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>z-statistic</td>
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<tr>
<td>( \phi_1 )</td>
<td>0.058089</td>
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<tr>
<td>( \phi_2 )</td>
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<tr>
<td>( \theta_1 )</td>
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<tr>
<td>( \phi_3 )</td>
<td>0.003559</td>
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</tbody>
</table>
Table 4. Estimation Results of the alternative empirical models

### Panel A: Madahavan et al. (1997) model
\[ r_t = \theta (q_t - \rho q_{t-1}) + \phi (q_t - q_{t-1}) + u_{1,t} \]

<table>
<thead>
<tr>
<th>Interest rate futures</th>
<th>Coefficient</th>
<th>z-statistic</th>
<th>US dollar futures</th>
<th>Coefficient</th>
<th>z-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\phi)</td>
<td>0.03833</td>
<td>2.371277</td>
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<td></td>
</tr>
<tr>
<td>(\theta)</td>
<td>0.02637</td>
<td>1.188277</td>
<td>-6.46E-02</td>
<td>-0.612643</td>
<td></td>
</tr>
</tbody>
</table>

### Panel B: Dufour and Engle (2000) model
\[ r_t = (\gamma_0 q_t + \gamma_1 q_{t-1}) + [\delta_0 \ln(x_t)q_t + \delta_1 \ln(x_{t-1})q_{t-1}] + u_{2,t} \]

<table>
<thead>
<tr>
<th>Interest rate futures</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>US dollar futures</th>
<th>Coefficient</th>
<th>t-statistic</th>
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<tbody>
<tr>
<td>(\gamma_0)</td>
<td>0.045495</td>
<td>1.223413</td>
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<td>-0.835496</td>
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<tr>
<td>(\gamma_1)</td>
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<td>0.185102</td>
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<td>(\delta_0)</td>
<td>0.003005</td>
<td>0.545698</td>
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<td>(\delta_1)</td>
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<td>-0.107873</td>
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<td>-0.313049</td>
<td></td>
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</table>

### Panel C: DeJong et al. (1996) model
\[ r_t = a_0 + (R_0 \Delta q_t + R_1 \Delta q_{t-1} z_t) + (e_0 q_{t-1} + e_1 q_{t-1}) + u_{3,t} \]

<table>
<thead>
<tr>
<th>Interest rate futures</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>US dollar futures</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
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<td>(R_0)</td>
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<td>(R_1)</td>
<td>0.000772</td>
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<tr>
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<tr>
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<td>1.624157</td>
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