

Positive feedback trading under stress: evidence from the US Treasury securities market

Benjamin H Cohen, Bank for International Settlements
and Hyun Song Shin, London School of Economics¹

Abstract

A vector autoregression is estimated on tick-by-tick data for quote changes and signed trades of two-year, five-year and 10-year on-the-run US Treasury notes. Confirming the results found by Hasbrouck (1991) and others for the stock market, signed order flow tends to exert a strong effect on prices. More interestingly, however, there is often - but not always - a strong effect in the opposite direction, particularly at times of volatile trading. An examination of tick-by-tick trading on an especially volatile day confirms this finding. At least in the US Treasury market, trades and price movements appear likely to exhibit positive feedback at short horizons, particularly during periods of market stress. This suggests that the standard analytical approach to the microstructure of financial markets, which focuses on the ways in which the information possessed by informed traders becomes incorporated into market prices through order flow, should be complemented by an account of how price changes affect trading decisions.

1. Introduction

A principal conclusion of the theoretical literature on market microstructure holds that order flow - the sequential arrival of the buy and sell decisions of active traders - plays a vital role in price discovery. In the most influential papers, such as Glosten and Milgrom (1985) and Kyle (1985), order flow plays this role because of the presence of information asymmetries across traders, resulting in adverse selection effects. In Glosten and Milgrom (1985), for example, market-makers do not know whether an incoming order is from an informed or an uninformed trader, and quoted bid and ask prices reflect a trade-off between losses to trading with informed traders and profits to trading with uninformed traders.

By means of a vector autoregression (VAR) analysis of the time series properties of equity price changes and order flows, Hasbrouck (1991) documents a number of apparently robust empirical findings that support the adverse selection approach. Notably, order flow influences prices in the way predicted by the theory. Buy orders raise prices and sell orders lower prices, and there is a component of the price change that may be regarded as the permanent price impact of a trade that remains even after time has elapsed to smooth away transitory effects.

Another robust finding in Hasbrouck's study, however - and one which is relevant for our paper - is that there is also a strong relationship in the opposite direction: from price changes to order flows. Specifically, Hasbrouck finds a strongly *negative* relationship between current order flow and past price changes. In other words, price increases are followed by sales, and price falls are followed by purchases. Given the strong positive effect of past order flow on prices, this relationship between prices and subsequent order flow therefore has a mildly dampening effect on price behaviour.

One of the goals of the present paper is to examine how well the intuitions and models motivated by the stock market and the associated empirical findings translate into another important class of assets: that of fixed income government securities. The market for government securities is important in its own right given its size and benchmark status in the financial market, but we believe that it may in addition offer some valuable lessons in our understanding of market dynamics that differ from the

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stock market. It is likely that the models motivated by the stock market would fit in less well in those markets, such as for foreign exchange or government bonds, where it is less clear how the theoretical categories can be mapped onto real world variables. The analogue of the “fundamentals” for stocks in the case of Treasury securities corresponds to broadly macroeconomic considerations, and it seems less easy to tell a plausible story of a subset of (private sector) traders having strictly better information about these fundamentals than the others.

To a significantly greater extent than for equities, the fixed income (and foreign exchange) pages of the financial press as well as the commentary from traders themselves abound in strategic trading terms such as overhangs of leveraged positions, short covering and the like. This suggests that these strategic interactions between traders may result in market dynamics that differ from those in markets, such as equities, that conform to the adverse selection-based models of market microstructure.

Our objective in this paper is to investigate whether this intuition can be substantiated from the market data. We take the VAR methods used by Hasbrouck (1991) and apply them to the US Treasury securities market. Our conclusions point to some interesting and revealing differences from Hasbrouck’s original results for the stock market. To anticipate our main findings, we find that:

- Under tranquil market conditions, when trading is orderly and trading frequency is low, most of the qualitative conclusions in Hasbrouck (1991) for the stock market are replicated. The key difference is that, whereas Hasbrouck found that past price changes generally have a negative effect on order flow, we find this only to be the case when price volatility and trading frequency are at their lowest. For most of the sample period, the effect is either zero or slightly positive.
- However, during periods of high price volatility and active trading, there appears to be a structural shift in the market dynamics. In such periods, the positive effects of past order flow on current prices, *and vice versa*, are reinforced. In other words, not only do buy orders elicit higher prices, but price increases in turn elicit more buy orders. As a result, price movements become more positively autocorrelated (or less negatively autocorrelated) at short horizons.

The structural shift in market dynamics to positive feedback trading is detectable even during a single day’s trading, and coincides with bursts of intense trading activity. The onset of frenetic trading is accompanied by rapid price changes and a heavily one-sided order flow. We illustrate this effect by examining in some detail the particularly volatile trading on 3 February 2000, when markets were unsettled following the US Treasury’s announcements on debt management policy and rumours about large losses at certain institutions.

Positive feedback trading is consistent with the market adage that one should not try to “catch a falling knife” - that is, one should not trade against a strong trend in price. Some recent empirical studies are also consistent with such behaviour. Hasbrouck (2000) finds that a flow of new market orders for a stock are accompanied by the withdrawal of limit orders on the opposite side. Danielsson and Payne’s (1999) study of foreign exchange trading on the Reuters 2000 trading system shows how the demand or supply curve disappears from the market when the price is moving against it, only to reappear when the market has regained composure.

The next section describes the data set used and applies the VAR methodology to intraday trading in on-the-run US Treasury notes over the period 1999-2000. Section 3 examines trading on an especially volatile day in some detail, as a way of illustrating how price and transaction behaviour can shift suddenly in volatile trading conditions in ways that cannot be fully explained by an approach based on adverse selection and order flow.

Providing a theoretical basis for an explanation of this kind of positive feedback trading is an important unresolved task. It is not our objective in this paper to tackle this issue, but we will identify the possible ingredients of such a theory in Section 4. We suggest an alternative (and to some degree complementary) theoretical approach that relies on the strategic interactions among traders. Section 5 concludes.

2. Testing for strategic interaction among traders

2.1 The data

The data are provided by GovPX, Inc. GovPX provides subscribers with real-time quotes and transaction data on US Treasury and agency securities and related instruments compiled by a group of inter-dealer brokers, including all but one of the major brokers in this market. For each issue, GovPX records the best bid and offer quotes submitted by primary bond dealers, the associated quote sizes, the price and size of the most recent trade, whether the trade was buyer- or seller-initiated, the aggregate volume traded in a given issue during the day, and a time stamp. Dealers are committed to execute the desired trade at the price and size that they have quoted. However, counterparties can often negotiate a larger trade size than the quoted one through a “work-up” process. Boni and Leach (2001) describe this process. Fleming (2001), who provides an extensive description of this data set, estimates that the trades recorded by GovPX covered about 42% of daily market volume in the first quarter of 2000.

We examine quotes and trades in two-year, five-year and 10-year on-the-run (ie recently issued) Treasury notes over the period January 1999 to December 2000. Although GovPX provides round-the-clock data, we restrict the series to quotes and trades that take place between 07:00 and 17:00, when trading is most frequent. The quotes used are the midpoint of the prevailing bid and ask quotes. When a new issue becomes “on the run”, the GovPX code indicating on-the-run status switches to the new issue starting at 18:00; this means that a given set of *intraday* quotes and trades will always refer to the same issue. Trade volumes are calculated as the difference in the aggregate daily volume recorded for the corresponding security. Because these figures are provided in chronological order, the result is an ordered data set in which each observation is either a quote change, a trade or both.

Table 1a summarises the data used for the three securities. Our observations are in “event time” rather than chronological time. One issue is whether the tick-by-tick returns should be normalised so that they are comparable to calendar returns over a fixed time interval. Our main qualitative results turn out to be insensitive to whether we normalise or not, but for the results to be reported below, returns (r_t) are defined as the difference in the log of the quoted price (more precisely, the midpoint between the prevailing bid and ask quotes) at t and $t-1$, divided by the time difference between t and $t-1$ in minutes.

The number of observations increases with maturity, while the number and size of transactions falls. In other words, the data set includes more quote changes and fewer transactions as maturity rises. As suggested by Fleming (2001), this may reflect differences in coverage by GovPX rather than differences in the actual relative liquidity of two-, five- and 10-year issues, since the excluded broker (Cantor Fitzgerald) is relatively more active in longer-term issues.

The mean absolute value of the return from one observation to the next rises with maturity.² This may suggest that, although bond market price movements are traditionally reported in price terms, the underlying factor driving them is yield changes, since a given yield change produces greater price changes as the duration (the weighted average maturity of the payments underlying the note) rises.

Table 1a also gives the average duration (the time between observations) for the full sample of each bond and for four subsamples. This is about one minute for the two-year note, and about 45 seconds for the five- and 10-year notes. For the 50 trading days where average duration is highest, the time gap was slightly less than two minutes, while for the 50 trading days with the lowest average duration, this gap is about 40 seconds for the two-year note and 30 seconds for the five- and 10-year notes. This suggests that, while there are clearly more active and less active trading days in the sample, divergences in the frequency with which quotes and/or trades are observed are not great.

Average durations are also presented for the 50 days where the difference between the daily high and low price for the specified bond is highest, and for the 50 days where this difference is lowest. We

² In terms of 32nds, which are the usual quote convention for Treasury notes, and assuming a price close to 100, the mean absolute returns shown correspond to price changes of 0.29 32nds for the two-year, 0.67 32nds for the five-year and 1.26 32nds for the 10-year note.

would expect days in the former sample to correspond to relatively volatile trading conditions, while days in the latter are relatively quiet. Again, a clear difference between the two samples in terms of average duration can be observed. Days with wide price swings tended to see more frequent trades and/or quote changes, with observations coming in every 40 to 45 seconds, than quieter days, when the time between observations averaged between 56 and 92 seconds. However, this difference in duration is not great enough to suggest that we should expect to observe differences in the time series properties of the data stemming merely from a substantially longer gap between measured observations.

Confirmation of the relationship between the frequency of trading and various volatility measures is presented in Table 1b for the two-year note. The average duration of a given day tends to be negatively correlated with the range (high-low) of prices observed during the day, the standard deviation of tick-by-tick returns during the day, and the change (open-close) in prices that occurred during the day. The latter three variables tend to be positively correlated with one another.

2.2 Testing for the cross-effects of trades and quote revisions

2.2.1 A two-variable VAR of signed trades and returns

GovPX records the pricing and trading decisions of bond dealers, rather than those of speculative traders or investors. A reasonable assumption is that the dealers participating in the system attempt to minimise their open exposures to bond yields as far as possible, and do not attempt to “take a view” on likely yield movements.³ Under this assumption, when a dealer accepts a bid or offer that has been posted on the system, he could be following one of two possible behavioural rules. One is that, whenever a dealer executes a trade with a customer, either by selling him a bond out of inventory or by buying a bond from him, the dealer immediately submits a countervailing trade to an inter-dealer broker in order to remain balanced. The other is that the dealer only rebalances his exposure periodically. Under the first rule, a transaction observed in the GovPX data closely tracks the transaction decision of a position-taker in the market. Under the second, an observed transaction primarily reflects inventory control operations and not a position-taking decision, except in the sense that position changes lead to inventory adjustments over a relatively long horizon. To the extent that both of these motivations are in action, the dealer-submitted transactions compiled by GovPX are likely to reflect a combination of the speculative strategies of traders and the inventory-control strategies of dealers.

The quotes posted on the system are also likely to reflect a combination of speculative and inventory-control motives. At certain times, a dealer may adjust his posted bid and ask quotes because of the information that he has gleaned from customer order flow. At other times, he may “shade” posted bid and ask quotes in order to induce a sufficient number of buy or sell orders to bring inventory back into line with its desired level. Both categories of motives are likely to influence the posted quotes that we observe on GovPX.

A primary aim of the analysis of intraday financial market data is to understand how the microstructure characteristics of a given market affect the time series characteristics of price quotes, signed transactions, and the interactions between them. If the dealers whose quotes and trades are recorded by GovPX are primarily mimicking customer orders, then this would allow us to test for the informational interaction between prices and trades. Specifically, we could test the result in the theoretical literature on market microstructure noted above, namely that signed order flow should have a measurable impact on price formation. We could also test whether, for reasons that will be discussed in more detail in Section 4, lagged price movements have an impact on trading under certain conditions.

Further, there are reasons to believe that the time series of both order flow and returns themselves exhibit serial dependence. Among the factors that might produce such dependence are inventory

³ Some dealers, however, execute trades on behalf of proprietary trading desks under the umbrella of the same financial institution. For the purposes of this discussion, a proprietary trading desk would be thought of as a “customer” of its affiliated dealer. During the time period covered by this study, January 1999-December 2000, many of the major government bond dealers had either closed or seriously curtailed their proprietary trading operations.

control motives, lagged adjustment to incoming information and minimum tick sizes. Some of these factors would result if dealers followed a customer-driven rule, while others would imply the primacy of inventory adjustment in short-run dealer behaviour.

At a short enough time horizon - data observed in intervals of minutes and seconds, rather than days or months - one might expect these factors to exert an impact on observed quotes and trades that can be measured statistically, even if at longer time horizons price changes are thought of as being driven more or less exclusively by the arrival of new information. This would allow us to determine which rules are being followed by the dealers in the market and, if we think the mimicking of customer orders is important, to learn more about customer behaviours as well.

The following VAR should capture many of these short-horizon effects:

$$\begin{aligned} r_t &= \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{i=0}^{10} \beta_i trade_{t-i} + \varepsilon_{1,t} \\ trade_t &= \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{i=1}^{10} \delta_i trade_{t-i} + \varepsilon_{2,t} \end{aligned} \quad (1)$$

Here r_t is the return variable cited above, while $trade_t$ is a signed trade variable. Two variables are used for $trade_t$:

x_t , an indicator variable equalling 1 for a buyer-initiated transaction, -1 for a seller-initiated transaction, and zero where there is a change in the price quote without a transaction; and

v_t , the size of the trade in millions of dollars, multiplied by 1 for a buyer-initiated transaction and -1 for a seller-initiated transaction.

The version using x_t is essentially identical to the VAR computed by Hasbrouck (1991). Like Hasbrouck we estimate the contemporaneous impact of trades on prices. That is, we include a term $\beta_0 trade_t$ on the right-hand side of the first equation. This allows for the possibility that trades are "observed" slightly before quote revisions through the work-up process.⁴ Although the estimate of β_0 is positive and significant in all versions of the VAR that we examine, excluding $trade_t$ from the estimation of the first equation produces qualitatively similar results.

Results from the estimation of equation (1) on the full two-year sample are presented in Table 2 for $trade_t = x_t$, and in Table 3 for $trade_t = v_t$. For each trading day, the calculation of the VAR starts with the 11th observation of the day as the dependent variable. This eliminates the above-mentioned effect of the switch from one on-the-run issue to the next, the influence of overnight price changes and the inclusion of the effects of the last few observations in one day on the first few observations in the next.

For three of the four "quadrants" of coefficients - the effects of lags of r_t on r_t ; the effects of lags of $trade_t$ on r_t ; and the effects of lags of $trade_t$ on $trade_t$ - there is a remarkable degree of consistency across the three maturities (two-year, five-year and 10-year) and across the two trade variables (x_t and v_t). The results for all three quadrants conform to those found by Hasbrouck (1991) for the US equity market:

- Lagged returns tend to exert a negative effect on present returns, though this effect is partially reversed in later lags. In other words, returns are negatively autocorrelated at very short time intervals.
- Current and lagged trades tend to exert a positive effect on present returns. In other words, price movements follow order flow. Besides Hasbrouck's findings for the equity market, similar effects have been found for the Treasury market by Fleming (2001) and for the foreign exchange market by Evans and Lyons (forthcoming).
- Lagged trades tend to exert a small but significantly positive effect on current trades. In other words, trades are positively autocorrelated. This may suggest that traders tend to adjust their

⁴ In January 2000, the average length of the work-up process was 20.97 seconds for the on-the-run two-year note, 16.12 seconds for the five-year note and 17.86 seconds for the 10-year. These are all less than the average tick lengths, which were 59, 46 and 44 seconds respectively. Boni and Leach (2001) describe and analyse the work-up process in the US Treasury market.

positions in a series of trades, rather than all at once. It may also imply that inventory adjustment effects (which might suggest negative autocorrelation in signed trades) are weak or absent. Within the very short time horizon covered by the VARs, dealers are apparently content to accommodate these sequential adjustments in traders' positions by running inventory imbalances rather than aggressively moving to restore desired inventory levels.

It is in the "upper right" quadrant - the effect of lagged returns on current signed trades - where the consistency breaks down somewhat across maturities, and where the results are generally different from Hasbrouck's. This set of effects will be the focus of Sections 3 and 4 of the paper.

For the two-year and five-year notes in the VARs using x_t , and for all three maturities in the VARs using v_t , the coefficients on lagged returns (sometimes with the exception of the first lag) tend to be *positive* for current trades. In other words, price increases tend to be followed by buy orders, at short horizons, while price decreases are followed by sell orders. For 10-year notes in the VARs using x_t , the coefficients are negative. This corresponds more closely to Hasbrouck's results for the equity market.

2.2.2 *Estimating cumulative effects*

A standard tool for analysing the results of VARs is the impulse-response function. In the present case, however, we are not interested in the usual impulse-response function - the effect on the level of one of the variables at some future point from a shock to a variable in the system - but in the *cumulative* effects of shocks to the included variables. Thus, for example, we want to know the impact of a new buy order on the overall return over the next several minutes, rather than on the level of the observed return at a specific point in the future. Similarly, we want to know the total number of net buys or sells that happen in the aftermath of a new buy or sell.

To do this, we can cumulate the output of the usual impulse-response function, taking account of the presence of the contemporaneous signed trade as an explanatory variable in the return equation. To construct the orthogonalised shocks to signed trades and returns, we need to make a prior assumption about the direction of causality between the variables. In this case, we assume that signed trades "cause" returns.

Graphs 1a to 4c show the cumulative effects of a one-unit increase in returns and buys on the cumulative return and number of net buys over the following 20 periods for active two-, five- and 10-year Treasury notes. The results using the coefficients estimated over the full two-year sample are given by the line indicated as "Full sample" in each graph.

The graphs largely confirm the results identified in our earlier review of the signs of the respective raw coefficients. Roughly 82% of a given shock to the return of the two-year note is still contained in the price level 20 periods later; this proportion falls to 76% for the five-year and 67% for the 10-year (Graphs 1a-1c). A buy order has a strong positive effect on returns in the short term; a buy causes a cumulative positive return of about 1.1 hundredths of a percentage point for the two-year note, 2.7 hundredths of a percentage point for the five-year note and 4.5 hundredths of a percentage point for the 10-year note (Graphs 2a-2c). In the 20 observations after a net buy order is recorded, a further 0.74 net buys result for the two-year note, 0.60 net buys for the five-year, and 0.37 for the 10-year (Graphs 4a-4c). As maturity increases, there seems to be a greater reversal of shocks to returns, a greater impact of trades on returns and less positive autocorrelation of trades.

The cumulative impact of returns on trades, which as already noted differs strikingly from Hasbrouck's results, is illustrated in Graphs 3a-3c. The graphs show the impact of a one-unit increase in the return. When one considers the typical size of these returns, it becomes clear that the magnitude of the effect is not large. For the two-year note, for example, an increase of one standard deviation in the return (a return of 2.05×10^4 from one tick to the next, or about 2 hundredths of a percentage point) leads to the occurrence of 1.2% more net buys than would otherwise take place over the subsequent 20 periods, or roughly 19.6 minutes.⁵ For the five-year note, there are 3.4% more net buys. However, the

⁵ More precisely, the fraction of total transactions in the next 20 periods that are buys is 0.012 higher than it otherwise would have been.

coefficients are significant, suggesting that this is more than a statistical artefact. For the 10-year note, the cumulative effect on x_t is negative, with net sells rising by 1.3%.

2.3 Estimation results for duration-based subsamples

More interesting than the size of these effects is the way they change over different subsamples. The lines in Graphs 1-4 labelled “High duration” show the cumulative effects when the VAR in equation (1) is estimated using the 50 days (10% of the sample) for which the average time between new observations (trades and/or quote change is highest).⁶ These should be the days of relatively “quiet” trading (and indeed, as already noted, price volatility and the differential between the daily high and low tend to be highest on these days). Similarly, the “Low duration” lines show the estimated cumulative effects on the 50 days when the time between observations is lowest. These should be days when trading and changes in quotes are relatively rapid, suggesting volatile trading conditions.

For all three maturities, the cross-effects between trades and returns on the low-duration days tend to be higher than the effects estimated over the full sample, and are substantially higher than the effects estimated for the high-duration days (Graphs 2a-3c). For the two-year note, the autocorrelations of both trades and returns are higher on low-duration days than on high-duration days, while for the five- and 10-year notes the difference is small or absent (Graphs 1a-c and 4a-c).

The effects of trades on subsequent returns increase strongly and consistently for all three maturities when trading ranges are high, and decline (but remain positive) when trading ranges are low (Graphs 2a-2c). For the two-year note, for example, the impact of a trade on the cumulative return over 20 periods rises from 1.1 hundredths of a percentage point in normal times to 1.4 hundredths on low-duration days, while falling to 0.9 hundredths on high-duration days. The economic significance of this effect can be gauged by comparing these figures to the standard deviation of the tick-by-tick returns, which is 2.1 hundredths of a percentage point.

Effects in the opposite direction - from returns to subsequent trading behaviour - also shift on high- and low-duration days relative to the rest of the sample (Graphs 3a to 3c). For the two-year note, these effects are more strongly positive on low-duration days than in normal times (that is, they lead to more net buys), and become strongly negative on high-duration days (that is, rather than leading to net buys, they lead to net sells). The net number of new buys following on a one standard deviation rise in the return rises from 1.2% to 4.1% on low-duration days, while on high-duration days net sells increase by 8.2%. For the five-year note, the effects are similar. For the 10-year note, positive price movements cause an increase in net selling in the sample as a whole, but cause increased buying on low-duration days, with net buys rising by 1.1%. On high-duration days, net sells are relatively higher.

Given that, as was shown above, order flow tends to have a strong positive effect on returns in this market, that returns have a positive effect on order flow (at least for the two- and five-year notes) and that these effects tend to be stronger on low-duration days, an important consequence of this finding should be that price movements exhibit stronger positive autocorrelation on such days. This prediction is confirmed by Graphs 1a-1c, which show the cumulative effect on r_t of a one standard deviation increase in r_t . For the two-year note, over the full sample period 82% of a positive return is still incorporated into the price quote after 20 observation periods - ie, negative autocorrelation results in 18% of a given return having been reversed 20 minutes later. During high-duration days, however, the proportion that remains in subsequent prices is only 68%. During low-duration days, the return is virtually not eliminated at all, with 98% of a shock to the return still evident after 20 observations. Similar, if weaker, results hold for the five- and 10-year notes.

Trades also become more positively autocorrelated on low-duration days (Graphs 4a-4c). It was noted above that, for the two-year note, a net buy tends to be followed by an additional 0.74 of a net buy over the next 20 observations during the sample period. For the low-duration days, however, 0.83 of a net buy results, while for the high-duration days this figure falls to 0.49. The same pattern can be seen for the five-year note, though the shift is less strong. For the 10-year note, no change in the autocorrelation pattern of signed trades is observed.

⁶ To save space, the coefficients from this and the other VARs based on subsamples are not given. Coefficients from these VARs are available from the authors.

3. A case study: 3 February 2000

The results in Section 2 suggest that, on days of relatively volatile trading activity, traders tend to reinforce price movements (at least at short time horizons) rather than dampening them. This section explores the dynamics of this shift on a particular, very volatile trading day that occurred during the sample period.

3.1 Events of 3 February

3 February 2000 witnessed the sixth highest daily trading range for the on-the-run two-year note in the sample period (Graph 5). The price quoted on GovPX (using the average of the prevailing bid and ask quotes) opened at 99.551 at 07:04, reached a low of 99.523 at 10:03, rose to a high of nearly 99.977 at 12:36, and finished at 99.727 at 17:00. The range of the price from its lowest to its highest point, 0.45% of par, is very large in comparison with the sample median daily price range of 0.12%, the mean absolute value of the daily price change (open to close), 0.07%, and the standard deviation of the daily price change, 0.09%. This price range corresponds to 85 basis points in yield, in comparison with a median daily yield range of 23 basis points.

News accounts of the trading on 3 February, a Thursday, do not point to a specific new piece of public information digested by the market. The market was reported to be unsettled by the US Treasury's plans to change its auction practices and repurchase selected issues as part of a broader policy of using budget surpluses to reduce the debt held by the public. A key piece of public information relevant to that policy had been released on 2 February when the Treasury outlined plans to reduce the amounts of specific maturities to be issued in future auctions, including the popular 30-year bond. This announcement came during trading hours on the 2nd, so it was no longer fresh news to the market on the 3rd. Nevertheless, market commentary focused on the uncertain environment created by the announcement. In its daily report on the US Treasury market, The Associated Press emphasised the uncertain implications of the new Treasury programme for the liquidity of the 30-year bond, and the effects this uncertainty had had on market trading. According to one fund manager:

Folks are kind of shocked. Treasuries have become a scarce commodity. ... It's 'wild, wild stuff', as Johnny Carson used to say. It's definitely a new environment for everybody. We're all trying to figure out what this means for the future (AP Online (2000)).

In the same article, The Associated Press noted another series of events which may have influenced trading on 3 February:

Adding to Thursday's mayhem was a widespread rumour that the dramatic decline in bond yields had wiped out a large unnamed financial institution and that a rescue meeting was being held at the Federal Reserve Bank of New York. The rumour prompted a statement from the New York Fed denying there was a meeting to discuss market volatility (AP Online (2000)).

An item released on the Market News International Wire at 12:14 that day reads in its entirety:

NEW YORK (MktNews) - A spokesman for the Federal Reserve Bank of New York Thursday declined all comment on a rumor widespread in financial markets that there would be an emergency meeting at the Fed to address big losses at a financial firm.

The spokesman said it is Fed policy not to comment on such rumors.

The completely unsubstantiated rumor circulated all morning Thursday, and appeared related to the market dislocations triggered by the Treasury's plans to cut back on supply of long-term securities. That has resulted in an inversion in the Treasury yield curve in recent days and a huge rally in Treasury long bonds Wednesday and Thursday.⁷

3 February thus seems to offer an excellent opportunity for a case study of patterns of trading in the US Treasury market under conditions of uncertainty. With the exception of the Fed's announcement denying the rumour, there was no occasion when a piece of price-relevant information simultaneously

⁷ We are grateful to Michael Fleming for calling our attention to this news story.

became known to all participants. Instead, there was uncertainty as to how markets themselves would be expected to behave in the new environment of shrinking supply. The rumours of an institution in trouble added to the uncertainty, but undoubtedly, as tends to happen in these situations, the main area of uncertainty for market participants was the nature and extent of the knowledge possessed by *other* participants.

Examination of Graph 5 suggests that the day can be divided into four periods in terms of trading behaviour. Characteristics of these periods, and comparable figures for the full two-year sample, are presented in Table 4. From 07:00 to 11:00, prices were flat or slightly higher, bid-ask spreads were wider than usual but steady, and there was a roughly even balance between buys and sells. From 11:00 to 12:15, prices rose sharply, accompanied by an imbalance of buys over sells. This is presumably the time when rumours about a troubled institution dominated market trading, with prices at first bid up on the expectation that the institution would have to liquidate a large short position. From 12:15 to 14:00 prices fell about as sharply, with sells outnumbering buys. This followed the New York Fed announcement. In both the second and third periods, quoted bid-ask spreads were wide and volatile, and occasionally negative.⁸ Finally, from 14:00 to 17:00, prices rose gradually amid relatively calm conditions, though bid-ask spreads remained elevated.

Two points are worth noting with regard to Table 4, both of which suggest that the bond market on 3 February behaved in a more complex way than would be implied by a simple adverse selection model in which information is incorporated in order flow.

First, while it is clear that an imbalance of buy orders over sell orders was associated with rising prices and vice versa, it is interesting that a virtually identical share of buys (66%) led to a sharp price increase between 11:00 and 12:15, but to only a relatively mild price increase between 14:00 and 17:00.

Second, the bid-ask spread was at its highest between 12:15 and 14:00 - even though, as noted above, the Fed announcement was probably the day's most influential piece of *public* information. If wide bid-ask spreads indicate a high degree of information asymmetry, as the adverse selection model would predict, one would expect that when an important item of news, with a direct and immediate bearing on market prices, becomes known simultaneously to all market participants, this would contribute to a significant *narrowing* of bid-ask spreads.

3.2 Comparing price movements and order arrival

A closer examination of trading patterns throughout the day presents further puzzles (Graphs 6a-6d). It is worthwhile, first, to consider what the different theoretical frameworks used in market microstructure would predict about the patterns of price movements and orders. A pure neoclassical view would suggest that the price moves automatically to adjust to new information, and that buys and sells should be essentially balanced whatever the price level is and in whatever direction it is moving. If orders primarily reflect inventory adjustment, then groups of buys and sells should alternate, with a large number of buys leading to price increases (as dealers rebuild inventory) and sells leading to price decreases (as they lay off inventory) in an essentially predictable rhythm. According to an adverse selection-based view, we would expect to see an exogenous build-up of purchases to be followed more or less immediately by information-driven price increases, and a build-up of sales to be followed by price declines.

During the 07:00-11:30 period (Graph 6a), buys and sells appear to be balanced over the period as a whole, but do not seem to follow any of these predictions closely. Rising prices are associated with buys (eg just after 10:04) and declines with sells (eg just before 8:18). But the order flows and price movements appear to be simultaneous; the price graph does not wait for a build-up of orders before it starts moving. And periods of persistent one-sidedness in the market (eg the buying activity from 10:17 until around 10:40) are not followed by price movements that would be sustained enough to return inventories to balance; instead, on this occasion, the price hovers for a while, then turns downwards - and only then (around 10:44) do we see clusters of sales.

⁸ Both the very wide and the negative bid-ask spreads are probably the result of "stale" quotes that dealers did not have time to update.

As the rumours of a troubled institution begin to take hold (Graph 6b), the price rose amid heavy buying. But sometimes the price rose with little or no buying, as in the phase just after 11:46, and again around 12:12. At the very top of the market, from around 12:15 onward, traders appeared to be buying at peaks, and selling at valleys. Again, neither the neoclassical, nor the inventory adjustment, nor the adverse selection view appears to explain the interaction between price and order behaviour.

The period after the Fed announcement (Graph 6c) is virtually the mirror image of the hour or so that preceded it - this despite the very different nature of the information that was driving the market in the two periods, with rumours replaced by credibly stated facts. Prices sometimes fell without any order flows, at other times accompanied by heavy selling. Prices seemed to stabilise around 13:05, even though traders continued to sell. A cluster of buys eventually emerged just before 13:16, but the market seemed happy with its new level - even when the buys were followed by further sales.

During the last three hours of the trading day, the market rose slowly and without much volatility (Graph 6d). A heavy series of buy orders did little to move the price. These may have derived from traders covering short positions entered into during the previous phase, or they may represent the rebuilding of inventory by dealers (though an examination of *cumulative* order flow, not shown here, would cast doubt on this).

For an example of a distinct kind of price volatility, consider the trading pattern for the two-year note on the morning of 28 January 2000 (Graph 7). In this case new information - an unexpectedly strong non-farm payroll figure - became instantaneously available to virtually all market participants when the data were released at 08:30. Trading appears to have reflected first the anticipation of, then the accommodation to, this new information, while virtually no trades took place when the announcement was being made. While some position-taking in anticipation of the announcement moved the price somewhat, in the aftermath of the announcement trades tended to have little or no impact on the price, perhaps because participants understood that this represented the squaring of speculative positions and the rebalancing of portfolios. Trading volume was much higher after the announcement than before, as can be seen in the shorter time intervals between the times indicated on the x-axis (which are spaced 50 ticks apart). This pattern of the adjustment of Treasury prices to information releases conforms to similar findings by Fleming and Remolona (1999) and Huang et al (2001).

3.3 VAR analysis

Graphs 8a-8d illustrate estimations of the cumulative effects of returns and signed trades on one another, and of returns on subsequent returns, when the VAR in equation (1) is applied to prices and trades recorded for the two-year note on 3 February 2000. Because there are fewer data points, five lags are used in each equation instead of 10. Cross-effects between trades and returns seem to have been stronger on 3 February than they were during the full two-year sample period. The impact of trades on returns was about twice as strong on 3 February as it was during the full sample, with a new buy order leading, on average, to an increase of 2.23 hundredths of a percentage point return (Graph 8b). The effect of returns on trades is also substantially higher than normal on 3 February: a one standard deviation positive return now leads to a 3.8% increase in the likelihood of a purchase after 10 periods, more than three times the effect estimated for the sample as a whole (Graph 8c). However, the effects of the variables on themselves - the persistence of shocks to returns and the positive feedback of trades - were weaker. Only 69% of an increase in the return remains in the bond price 10 periods later, compared with 81% for the sample as a whole (Graph 8a). A new buy order is followed by an additional 0.57 of a net buy over subsequent periods, in contrast to the usual effect of 0.74 (Graph 8d).

These patterns shifted in the course of the day. During the most turbulent period, 11:00-14:00, trades had a relatively stronger effect on returns and were relatively more persistent than was the case either before 07:00 or after 14:00. In the 07:00-11:00 and 11:00-14:00 periods, returns had strong positive effects on the direction of trades, while after 14:00 this relationship became negative. The effects of returns on subsequent returns were more or less the same as for the full sample, and did not change much during the day. The persistence of returns did not alter very much throughout 3 February.

3.4 Trading in volatile conditions: a summary

Combining the evidence from the duration-based subsamples and from 3 February 2000, it appears that the interactions between price movements and trade behaviour change in at least two ways at

times when trading is volatile and uncertainty is high. First, the impact of trades on price movements (the conventional adverse selection effect) is stronger. Second, however, effects in the other direction - from price movements to trades - become stronger as well. It is also clear that markets can sometimes shift suddenly from one regime to another in terms of the absolute and relative strengths of these different effects. In the case of 3 February 2000, for example, it appears that positive feedback effects diminished substantially as price movements stabilised in the afternoon, and information-driven price dynamics were replaced with a greater role for inventory adjustments.

4. Discussion

The results presented in Sections 2 and 3 suggest that the traditional approach to market microstructure, which is focused on the ways in which information gets incorporated into market prices through order flow, needs to be augmented by a deeper understanding of the strategic interactions among market participants.

When market participants pursue their individual goals in the face of uncertainty in the market, there are several ways in which they may affect each others' interests. As well as the direct interaction between the two counterparties to a transaction, there are other indirect interactions that occur through the impact of trades on price and other characteristics of the market. These interactions affect the incentives of market participants, and may also have a direct bearing on their payoffs, and hence their conduct in the market.

Take the example of a market in which two traders face a market-maker who attempts to smooth his inventory position across trades. When the market-maker receives a sell order from one of the traders, he may subsequently set a price that is relatively low in order to attract a buy order from the other trader. The trader who then purchases at this low price has benefited from the sell order from the first trader, even though the interaction is indirect, through the market-maker. This example is one where the actions of the two traders are *offsetting* in the sense that a sale by the first leads to a purchase by the second. The larger the sale, the greater is the incentive to buy, and vice versa. When viewed over the two trading periods, the actions of the two traders can be seen as *strategic substitutes*, in which the greater incidence of one action leads to a greater incentive (via prices) to adopt the reverse action. In terms of price dynamics, the payoff interactions between the two traders have a stabilising effect in which any deviation of price from its fair value elicits a trade that dampens this deviation.

We may contrast this with modes of interaction where traders' actions are mutually reinforcing and short-term fluctuations are amplified. For instance, let us modify the above example so that both traders are portfolio managers whose respective mandates dictate that they engage in portfolio insurance by using trading techniques that replicate a synthetic call option through delta-hedging. This entails selling the asset when its price falls and buying it when its price rises. In this scenario, when the price of the asset falls because of an exogenous shock, both traders will attempt to sell it to the market-maker. But if the market-maker then marks down the price for inventory reasons, the rigid trading rule of both traders dictates a further round of selling, which may feed into even lower prices. This is an instance where the strategic interaction between the traders is *mutually reinforcing*, rather than offsetting. The greater the sale by one trader, the greater is the sale by the other trader. In other words, the actions of the traders are *strategic complements*.

The example of strict portfolio insurance is admittedly extreme, although accounts of the 1987 stock market crash attribute some blame to such practices (see Genotte and Leland (1990)). More generally, however, mutually reinforcing interactions are characteristic of markets where traders have short decision horizons, or where they operate under external constraints on their decisions. The short horizon may be due to internally imposed trading limits that arise as a response to agency problems within an organisation, or when traders operate under a risk management system which circumscribes their actions. In those markets where traders are highly leveraged, the short horizon can be attributed to bankruptcy constraints, which may require positions to be sold for cash when net asset values are low or when a margin call dictates liquidation of trading positions.

The distinction between stabilising and amplifying interactions between traders suggests an important dimension along which we can classify the interaction between market participants. Mutually reinforcing actions are a distinctive characteristic of markets under stress. We have witnessed its disruptive effects on several occasions in the recent episodes of market distress following the Asian

crisis of 1997 and the Russian/LTCM crisis of 1998. Financial commentators, central bankers and other regulators have consequently devoted a great deal of attention to understanding the nature of positive feedback trading and its implications for supervision and policy execution.

In contrast to the concerns expressed by central bankers and other regulators about the effects of feedback trading, the literature on market microstructure has placed relatively little weight on the possible payoff interaction between traders through mutually reinforcing actions.⁹ In part, this is explained by the prevailing theoretical approach to microstructure issues, which emphasises the adverse selection problem faced by a market-maker who faces possibly better informed traders. The task of the market-maker is to anticipate his losses to better informed insiders. This is typically done by quoting prices that incorporate an actuarially fair safety margin so that losses to insiders are compensated by gains from uninformed traders. The direction of causality runs from order flows to price changes.

In such an environment, the intensity of trading is related to the arrival rate of new information, although the theory admits a wide variety of empirical manifestations of this process. Easley and O'Hara (1992) propose a framework in which trading activity is positively related to the arrival rate of new information. When information flow is slow, trading activity itself is slow, while when information flow is fast, this is reflected in high trading activity. In this view, a burst of market activity is due to the exogenous arrival of new information. Easley and O'Hara coined the term "event uncertainty" to describe the fluctuations in the arrival rate of new information. The term refers to the uncertainty concerning this exogenous process. In contrast, Lyons (1996) proposes an alternative "hot potato" hypothesis for the foreign exchange market in which dealer inventory adjustment takes centre stage, and hence higher levels of trading activity are associated with lower arrival rates of new information. In both cases, however, the direction of causality runs from order flows to price changes.

The results presented in Sections 2 and 3 above suggest that, while the order flow effect on prices is undoubtedly present and important in the US government securities market, under certain circumstances the direction of causality is reversed, so that price changes influence order flow. The effect seems particularly strong in situations where trading is rapid and volatile.

These features are reminiscent of economic models where agents' actions are mutually reinforcing, such as during currency attacks or bank runs. Such contexts are usually fertile territory for multiple equilibria, where there is more than one set of self-fulfilling beliefs. For instance, in the currency attack context, when the agents believe that a currency peg will fail, their actions in anticipation of this precipitate the crisis itself, while if they believe that a currency is not in danger of imminent attack, their inaction spares the currency from attack, thereby vindicating their initial beliefs. The global game method advocated by Morris and Shin (2000) may be one way to introduce elements of concerted shifts in trading positions as a function of the underlying fundamental. Consider the following sketch of a model of short-term traders who operate in a market with limited liquidity. Traders face the choice of taking a long position in an asset, or taking a short position (both up to some fixed bound). They are assumed to have short horizons, so that their payoffs are determined by the price of the asset at the next date. The traders operate in a market with limited liquidity, in the following sense. When the net demand for the asset among the traders is non-zero, the market clears by means of a residual demand/supply function which is imperfectly elastic. The greater the net demand from the set of traders, the higher is the market-clearing price. Conversely, the greater the net supply, the lower is the market-clearing price.

This framework gives rise to strategic complementarities in which the actions of the traders are mutually reinforcing. If a large proportion of the traders decide to switch from being short to taking a long position, the market-clearing price is raised accordingly, and hence the incentive for any individual trader to take a long position is increased. Conversely, the larger the proportion of the traders who switch to a short position, the lower will be the market-clearing price, and hence the greater is the incentive for an individual trader to take a short position. Notice the importance of the short horizon assumption here, and the absence of players with deep pockets that stand ready to provide an infinitely elastic demand/supply function. The uncertainty in the return from date $t-1$ to date t thus has two components. As well as any exogenous uncertainty in the fundamental value of the

⁹ Among the few exceptions is the literature on momentum trading in the stock market. See DeLong et al (1990), Grinblatt et al (1995) and Jegadeesh and Titman (1993).

asset, there is the endogenous price response arising from the trading decisions of the traders themselves and the imperfectly elastic residual demand/supply function. When each trader has a noisy signal concerning the exogenous uncertainty, the traders follow a switching strategy around a threshold point for the signal realisation in which a trader goes long if his signal lies above this threshold, but goes short if it lies below it.

One consequence of this equilibrium is that the short-run demand curve for the asset is upward-sloping. The traders buy the asset when the fundamentals are good, which is precisely when the fundamental value of the asset is high. But the traders' actions exacerbate the price response, sending the price higher. This price response validates the action to buy. In terms of the observables, this equilibrium entails that the traders tend to buy the asset (or keep to a long position) precisely when the price of the asset is high. Conversely, if the fundamentals are bad, the traders as a group tend to sell the asset, which brings about a low price for the asset. The demand curve for the group as a whole is therefore upward-sloping.

Since the degree of strategic interaction depends on the initial holdings of the traders, so will the return density. The price response seen for 3 February 2000 may be better understood by reference to the fact that many active traders had short positions on US Treasury securities before the Federal Reserve's announcement.

The "Duke of York" price pattern for the trading on 3 February 2000 is suggestive of the following scenario. An initial frenzy of buying is triggered when the traders are caught short in a rising market. The exaggerated price response pushes the price up to a sharp peak at around 12:30, by which time we may conjecture that some of the net short positions of the traders had been unwound, and some may have taken on long positions. The unwinding of the net short positions reduces the probability of continued upward movement in prices. The actual price response in the afternoon of 3 February is sharply downwards, reversing much of the price increase seen in the morning. The market recovers some of its composure by 14:00, from which time the market trades in relatively tranquil mode until the close.

We believe this line of investigation may yield theoretical models that do a better job of capturing strategic notions such as overhangs of leveraged positions, short-covering and the like.

5. Conclusions

We have found that the interactions between trades and quote changes in the US Treasury securities market tend to change in important ways when trading conditions are volatile. The impact of trades on prices tends to become stronger, confirming a common theoretical result in the market microstructure literature. The impact of prices on trades tends to change as well on more volatile days, generally in a positive direction. As a consequence of these two effects, price changes tend to be more highly autocorrelated on days when conditions are more volatile. This pattern can be seen for the two-year, five-year and 10-year on-the-run Treasury notes over the period January 1999-December 2000. It also emerges from a close analysis of quotes and trades from 3 February 2000, which was a particularly volatile trading day during this period.

The models commonly used in the analysis of market microstructure emphasise adverse selection effects resulting from the presence of informed and uninformed traders in the market. This helps to explain the impact of trades on prices, but a richer theoretical approach is necessary to capture the impact of prices on trades. Such effects might come out of a model where traders face uncertainty, not just about the fundamental value of an asset, but also about the precision of the signals observed by them and by other traders. In such an environment, a price movement in a given direction could lead a trader to revalue the asset in the same direction, at least for a short period of time. This would lead to positive feedback in trading behaviour and, as a result, in returns over short horizons.

Tables

Table 1a
Statistics on returns, trades and trading volumes (1999-2000)

	Two-year	Five-year	10-year
Number of observations	358,361	494,437	506,880
<i>of which:</i>			
% trades only	39.7	22.5	18.9
% quote changes only	49.5	64.7	70.9
% trades and quote changes	10.8	12.8	10.2
Tick-by-tick returns ¹			
Mean	-1.29×10^{-6}	-1.50×10^{-6}	-2.19×10^{-6}
Mean abs value	0.000090	0.000209	0.000394
Std deviation	0.000205	0.000436	0.000824
Daily returns			
Mean	3.68×10^{-6}	7.07×10^{-7}	-7.20×10^{-6}
Mean abs value	0.000667	0.001750	0.003065
Std deviation	0.000882	0.002325	0.004017
Trades			
Number of trades	180,967	174,406	147,546
% buys	52.9	51.1	50.6
Volume per trade (\$m)			
Mean	12.96	7.28	5.45
Std deviation	22.65	9.03	7.41
Trading days	501	501	501
Transactions per day	361.21	348.12	294.50
Volume per day (\$m)	4,622	2,534	1,604
Time between ticks (minutes)			
Full sample	0.98	0.76	0.74
High duration days (top 50)	1.96	1.93	1.81
Low duration days (bottom 50)	0.67	0.48	0.51
Low trading range days (bottom 50)	1.53	1.00	0.93
High trading range days (top 50)	0.73	0.59	0.61
Low volatility days (bottom 50)	1.18	1.15	1.06
High volatility days (top 50)	0.78	0.62	0.62

¹ Log change in midpoint between bid and ask quotes.

Table 1b
**Correlations among daily price range, price change, volatility and
average duration: two-year note**

	Price range	Volatility	Price change¹
Duration ²	– 0.443	– 0.211	– 0.257
Price range ³		0.654	0.717
Volatility ⁴			0.323

¹ Difference between daily closing and opening prices. ² Daily average time between observations, in minutes.
³ Difference between daily high and low prices. ⁴ Daily standard deviation of tick-by-tick returns.

Table 2
Vector autoregression results: signed trades
Two-year, full sample

This table gives the estimated coefficients from the following vector autoregression:

$$r_t = \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{i=0}^{10} \beta_i x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{i=1}^{10} \delta_i x_{t-i} + \varepsilon_{2,t}$$

r_t is defined as the change from $t-1$ to t in the log of the midpoint between the prevailing bid and ask quotes, divided by the time (in minutes) between observations. The variable x_t takes the value one for a buyer-initiated trade, minus one for a seller-initiated trade and zero for a quote revision without a trade. The VAR is estimated over the period from 4 January 1999 to 29 December 2000, and includes only the transactions and quote changes taking place between 07:00 and 17:00. On each day, the estimation starts with the eleventh observation after 07:00.

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

	Dept variable: r_t		Dept variable: x_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.228	- 8.85	- 10.692	- 2.34
2	- 0.070	- 5.93	24.111	4.52
3	- 0.019	- 2.29	16.445	3.15
4	0.024	2.65	5.173	1.01
5	0.016	2.24	- 0.828	- 0.15
6	0.011	1.61	- 4.384	- 0.80
7	0.011	1.64	- 1.658	- 0.31
8	0.022	1.49	3.178	0.59
9	0.007	0.97	1.814	0.32
10	0.001	0.17	7.368	1.33
Lags of x_t^a				
0	1.355	45.00		
1	4.029	70.58	0.260	164.32
2	2.190	19.23	0.115	64.16
3	0.625	7.86	0.026	14.64
4	0.196	3.00	0.007	3.86
5	- 0.130	- 2.04	- 0.001	- 0.67
6	- 0.244	- 4.00	0.002	1.03
7	- 0.195	- 3.38	0.003	1.72
8	- 0.157	- 2.58	0.005	2.78
9	0.023	0.29	0.003	1.80
10	- 0.039	- 0.55	0.003	1.55
\bar{R}^2	0.08			

Table 2 (cont)
Five-year, full sample

	Dept variable: r_t		Dept variable: x_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.283	- 24.66	17.078	10.30
2	- 0.087	- 8.95	5.797	3.11
3	- 0.029	- 3.45	13.028	6.98
4	0.007	0.72	10.600	5.56
5	0.005	0.91	8.084	4.15
6	0.021	4.13	8.309	4.33
7	0.008	1.98	0.111	0.06
8	0.016	4.25	1.525	0.79
9	0.012	3.68	- 0.529	- 0.27
10	0.008	2.40	1.162	0.63
Lags of x_t^a				
0	7.452	110.26		
1	7.866	61.82	0.166	124.66
2	4.918	32.95	0.107	71.08
3	1.944	13.08	0.049	31.68
4	0.652	4.24	0.021	13.93
5	0.198	1.41	0.009	5.84
6	- 0.192	- 1.52	0.001	0.95
7	- 0.141	- 1.23	0.003	1.69
8	- 0.254	- 2.30	0.003	1.93
9	- 0.037	- 0.35	0.002	1.58
10	- 0.101	- 0.97	0.003	2.28
\bar{R}^2	0.10		0.06	

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

Table 2 (cont)
10-year, full sample

	Dept variable: r_t		Dept variable: x_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.279	- 23.95	2.232	2.92
2	- 0.107	- 10.64	- 7.714	- 9.34
3	- 0.069	- 9.62	- 3.833	- 4.44
4	- 0.027	- 4.89	- 1.992	- 2.22
5	- 0.012	- 2.37	- 1.724	- 1.94
6	- 0.003	- 0.56	- 1.494	- 1.64
7	- 0.001	- 0.24	- 0.942	- 1.04
8	0.002	0.60	- 0.311	- 0.34
9	0.004	0.84	- 0.514	- 0.56
10	0.009	2.46	- 0.238	- 0.27
Lags of x_t^a				
0	13.003	104.39		
1	15.125	61.18	0.130	100.35
2	9.359	34.68	0.079	53.03
3	5.382	19.70	0.035	22.57
4	2.812	11.19	0.014	8.91
5	1.109	4.61	0.005	3.48
6	0.758	3.32	0.004	2.33
7	0.076	0.34	0.003	2.14
8	0.001	0.00	0.004	2.89
9	- 0.016	- 0.07	0.004	2.78
10	0.088	0.40	0.004	2.57
\bar{R}^2	0.09		0.03	

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

Table 3
Vector autoregression results: signed order flow
Two-year, full sample

This table gives the estimated coefficients from the following vector autoregression:

$$r_t = \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{i=0}^{10} \beta_i v_{t-i} + \varepsilon_{1,t}$$

$$v_t = \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{i=1}^{10} \delta_i v_{t-i} + \varepsilon_{2,t}$$

r_t is defined as the change from $t-1$ to t in the log of the midpoint between the prevailing bid and ask quotes. The variable v_t is the size of the trade in millions of dollars, multiplied by the directional indicator x_t defined above. The VAR is estimated over the period from 4 January 1999 to 29 December 2000, and includes only the transactions and quote changes taking place between 07:00 and 17:00. On each day, the estimation starts with the eleventh observation after 07:00.

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

	Dept variable: r_t		Dept variable: v_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.202	- 7.93	793.723	4.89
2	- 0.050	- 4.52	877.265	4.49
3	- 0.006	- 0.76	306.628	1.39
4	0.031	3.65	- 102.586	- 0.51
5	0.018	2.72	107.892	0.59
6	0.011	1.72	- 108.072	- 0.58
7	0.010	1.61	36.596	0.19
8	0.021	1.57	90.123	0.56
9	0.007	1.00	245.149	1.44
10	0.001	0.12	211.914	1.40
Lags of v_t^a				
0	0.050	15.18		
1	0.068	15.56	0.053	2.43
2	0.048	12.87	0.075	5.71
3	0.020	7.43	0.043	2.51
4	0.004	1.93	0.075	3.64
5	- 0.004	- 1.08	0.002	0.13
6	- 0.012	- 3.32	0.017	1.05
7	- 0.006	- 2.13	0.009	0.52
8	- 0.007	- 3.28	0.015	0.82
9	- 0.005	- 1.64	0.007	0.41
10	- 0.001	- 0.33	- 0.006	- 0.50
\bar{R}^2	0.05		0.02	

Table 3 (cont)
Five-year, full sample

	Dept variable: r_t		Dept variable: v_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.261	- 23.06	370.143	18.32
2	- 0.068	- 7.18	355.989	16.75
3	- 0.016	- 2.00	324.818	15.09
4	0.015	1.71	231.494	10.67
5	0.010	1.78	161.104	7.19
6	0.023	4.91	120.218	5.66
7	0.008	2.30	62.606	2.83
8	0.016	4.50	60.668	2.89
9	0.012	3.62	50.043	1.75
10	0.007	2.26	24.166	1.16
Lags of v_t^a				
0	0.410	41.53		
1	0.410	34.24	0.082	32.69
2	0.279	23.88	0.055	26.23
3	0.138	13.46	0.034	17.98
4	0.051	5.19	0.019	9.04
5	0.027	2.83	0.009	4.76
6	- 0.008	- 0.79	0.004	2.32
7	0.003	0.31	0.007	4.43
8	- 0.024	- 2.78	0.002	1.43
9	- 0.002	- 0.26	0.005	2.77
10	0.002	0.26	0.001	0.47
\bar{R}^2	0.07		0.02	

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

Table 3 (cont)
10-year, full sample

	Dept variable: r_t		Dept variable: v_t	
	Coef	t-stat	Coef	t-stat
Lags of r_t				
1	- 0.260	- 22.61	61.921	10.12
2	- 0.090	- 9.13	32.092	4.85
3	- 0.057	- 8.35	40.767	5.51
4	- 0.020	- 3.73	38.354	5.41
5	- 0.008	- 1.63	28.502	4.08
6	- 0.001	- 0.15	19.427	2.17
7	0.000	- 0.09	13.393	1.80
8	0.003	0.63	17.261	2.30
9	0.003	0.80	17.918	2.43
10	0.009	2.38	20.015	2.80
Lags of v_t^a				
0	0.937	28.82		
1	0.792	22.82	0.054	18.76
2	0.575	19.10	0.045	18.74
3	0.367	14.52	0.030	13.05
4	0.177	8.28	0.016	6.10
5	0.036	1.72	0.009	5.06
6	0.053	2.56	0.005	2.17
7	- 0.033	- 1.64	0.006	3.25
8	0.014	0.68	0.007	3.48
9	- 0.004	- 0.22	0.004	2.18
10	0.031	1.58	0.007	2.61
\bar{R}^2	0.07		0.01	

^a Coefficient estimates for the r_t equation are multiplied by 100,000.

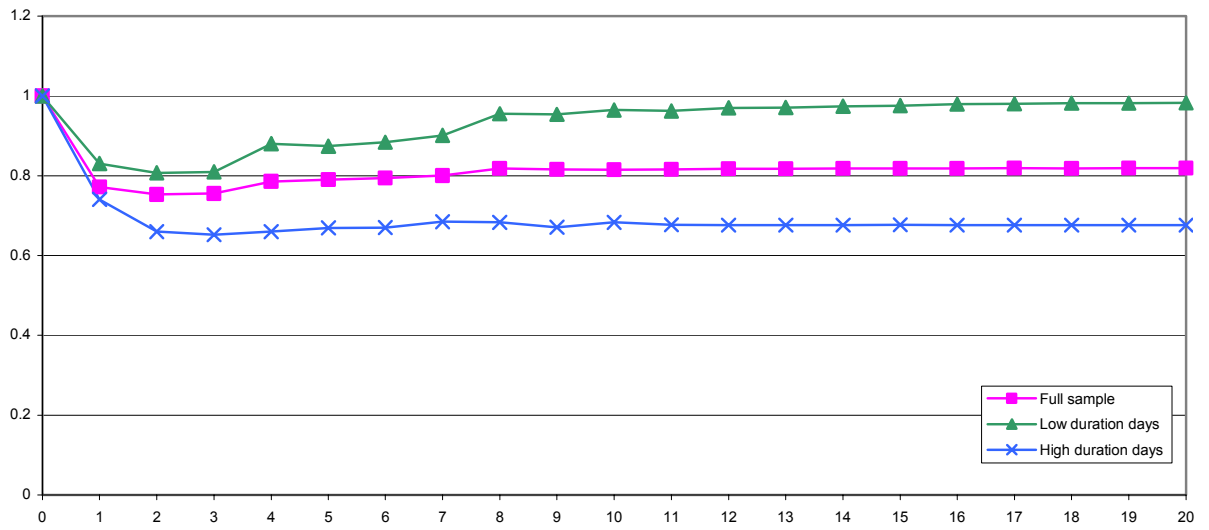
Table 4
Trading epochs for the two-year note on 3 February 2000

	Price change	% buys	Mean bid-ask spread ¹
07:00-11:00	0.063	52.6	0.0097
11:00-12:15	0.340	65.9	0.0102
12:15-14:00	- 0.316	40.9	0.0181
14:00-17:00	0.090	66.7	0.0120
<i>Memo item:</i> Full sample (1/99-12/00)	0.067 ²	52.9	0.0065

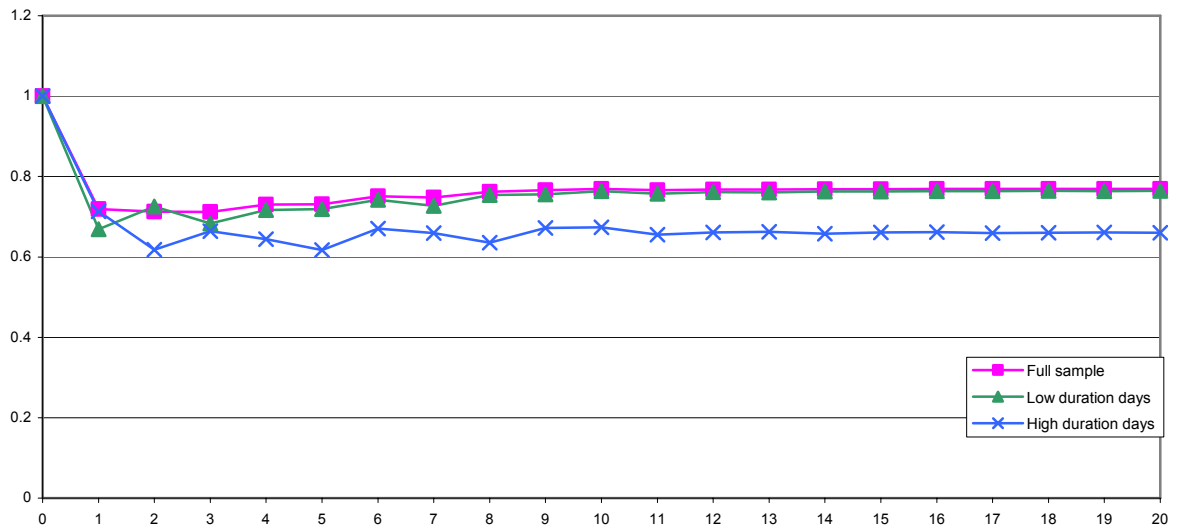
¹ Difference between prevailing ask and bid prices. ² Average of absolute values of daily price changes.

Graphs

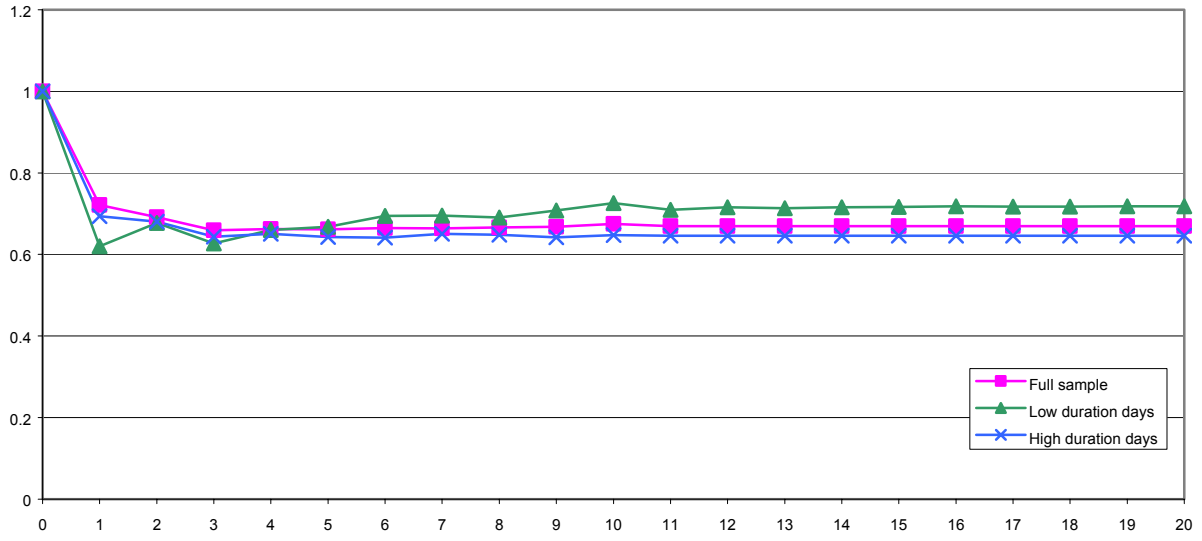
Graph 1a
 Cumulative effect on net returns of an additional one unit return:
 two-year note



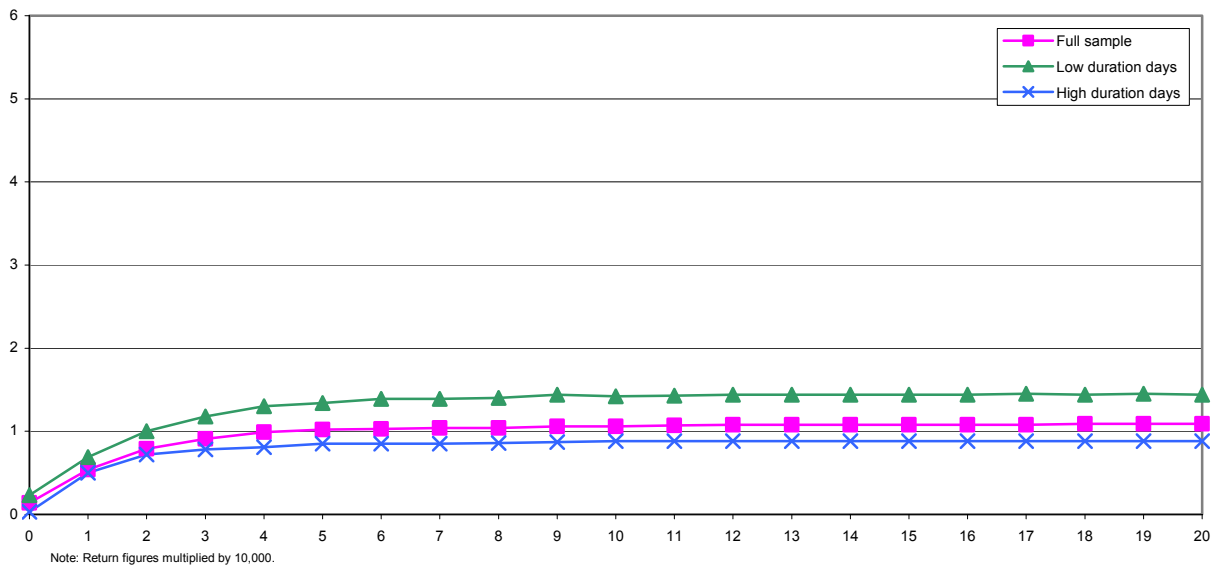
Graph 1b
 Cumulative effect on net returns of an additional one unit return:
 five-year note



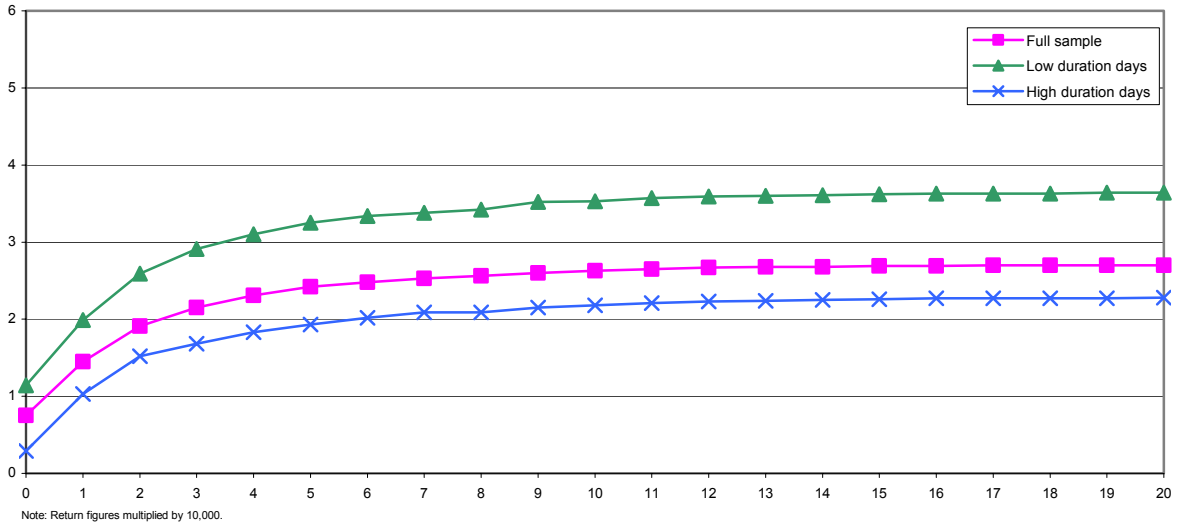
Graph 1c
**Cumulative effect on net returns of an additional one unit return:
 10-year note**



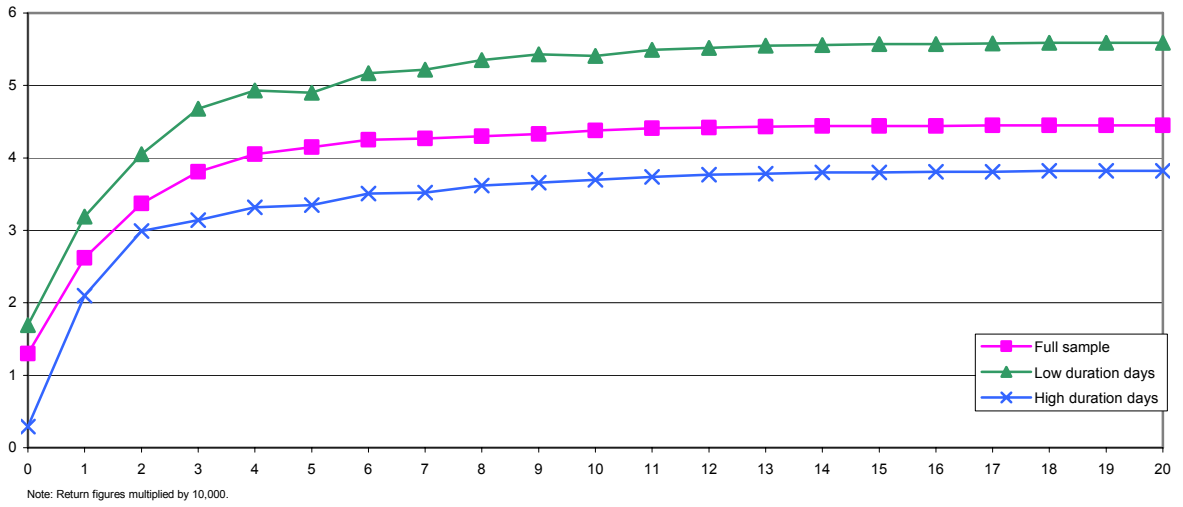
Graph 2a
**Cumulative effect on return of an additional net buy:
 two-year note**



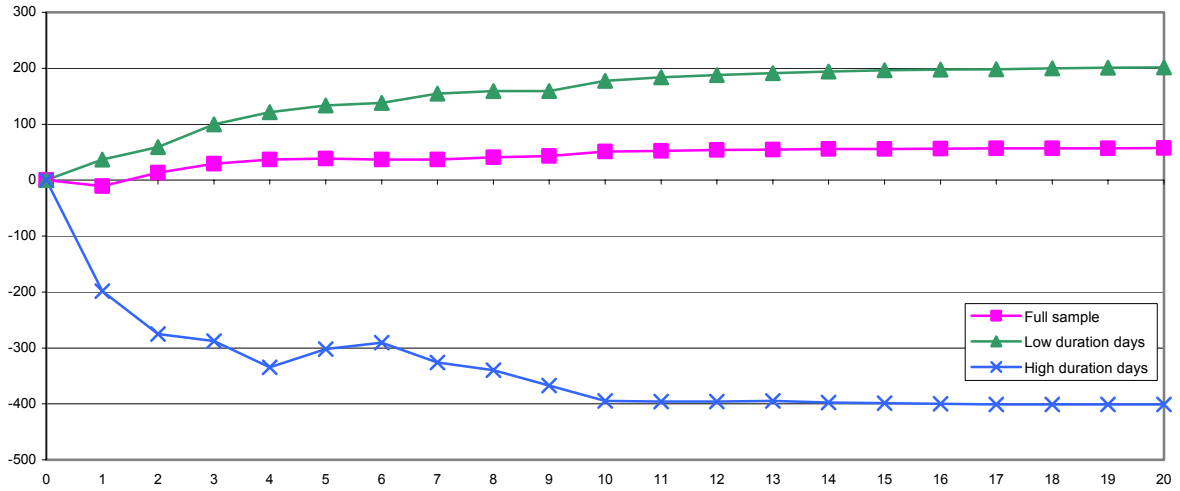
Graph 2b
**Cumulative effect on return of an additional net buy:
 five-year note**



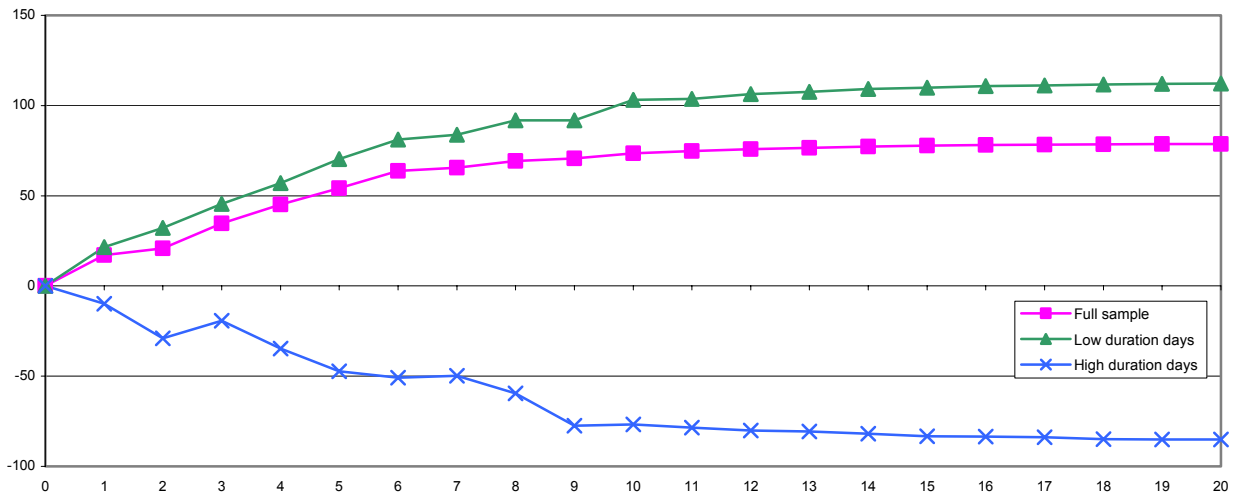
Graph 2c
**Cumulative effect on return of an additional net buy:
 10-year note**



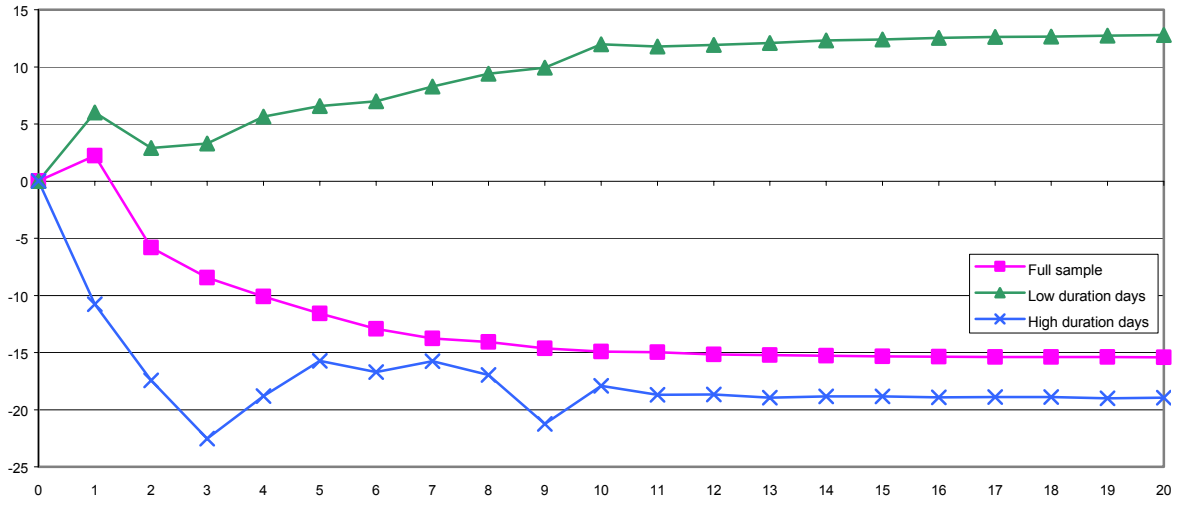
Graph 3a
 Cumulative effect on net buys of an additional one unit return:
 two-year note



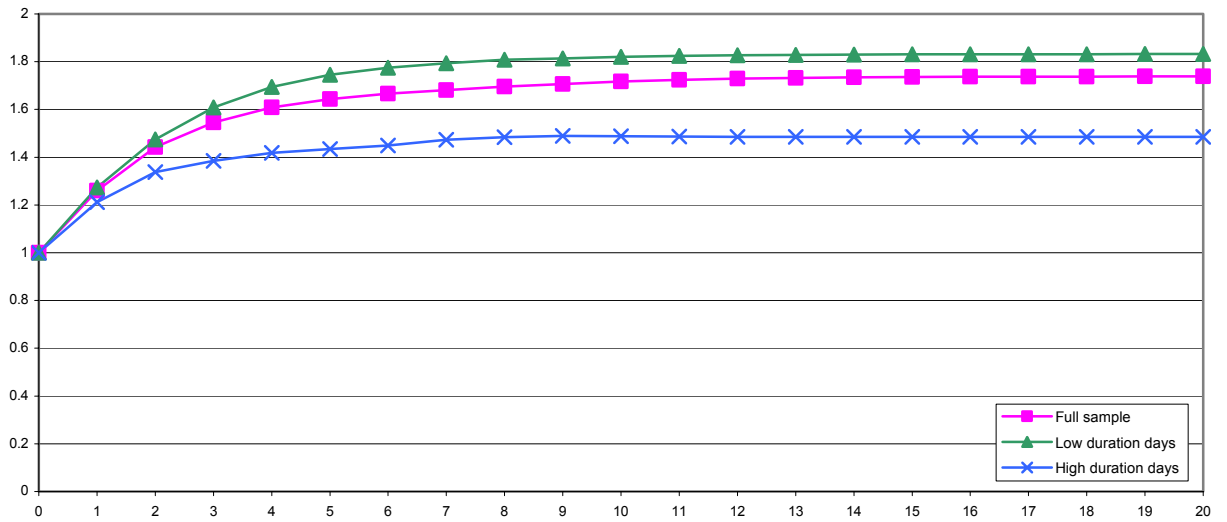
Graph 3b
 Cumulative effect on net buys of an additional one unit return:
 five-year note



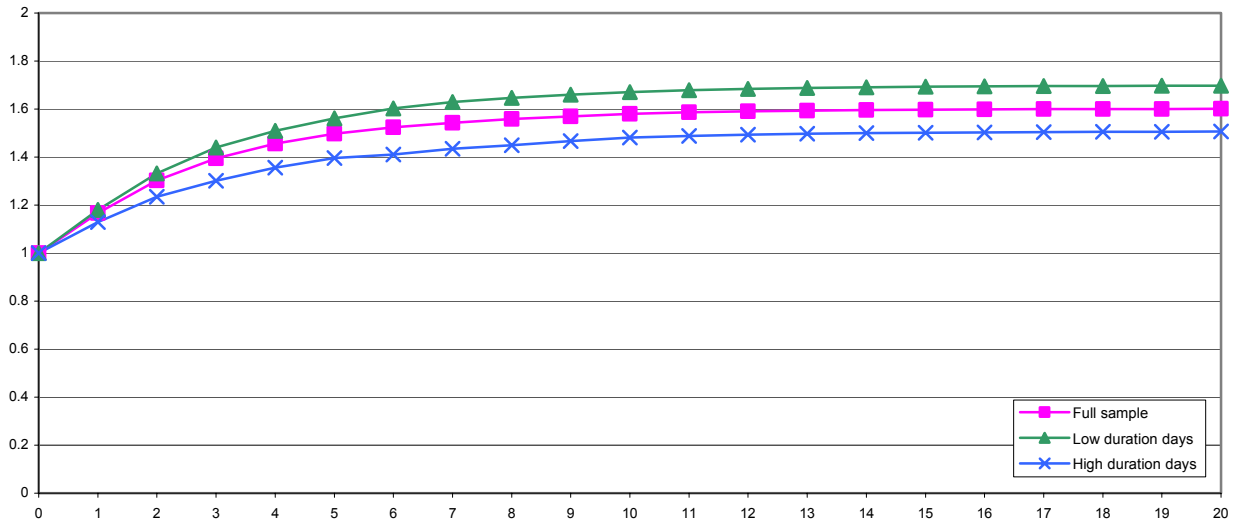
Graph 3c
 Cumulative effect on net buys of an additional one unit return:
 10-year note



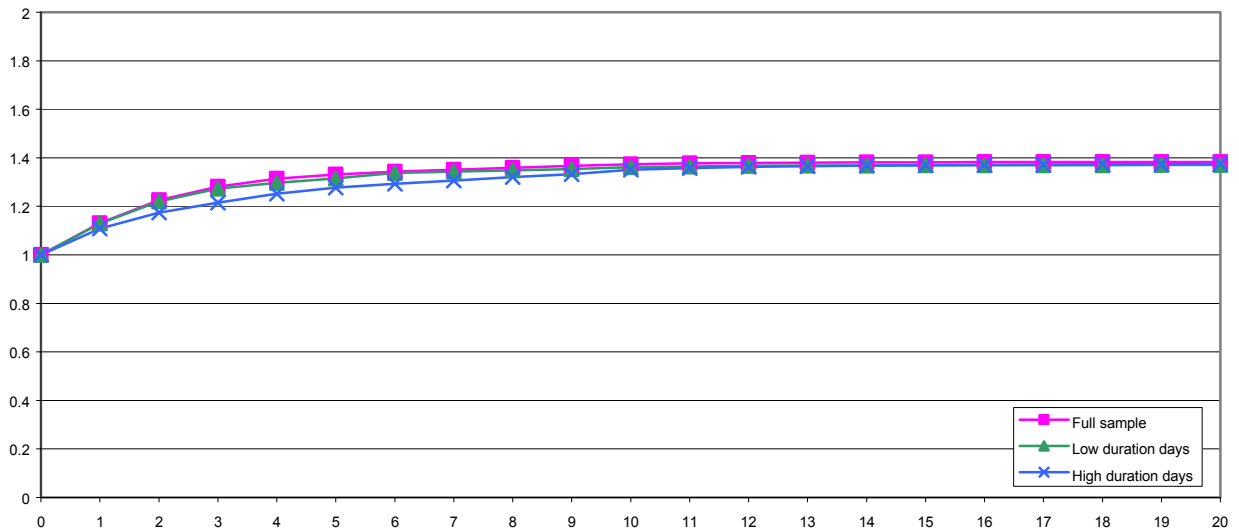
Graph 4a
 Cumulative effect on net buys of an additional net buy:
 two-year note



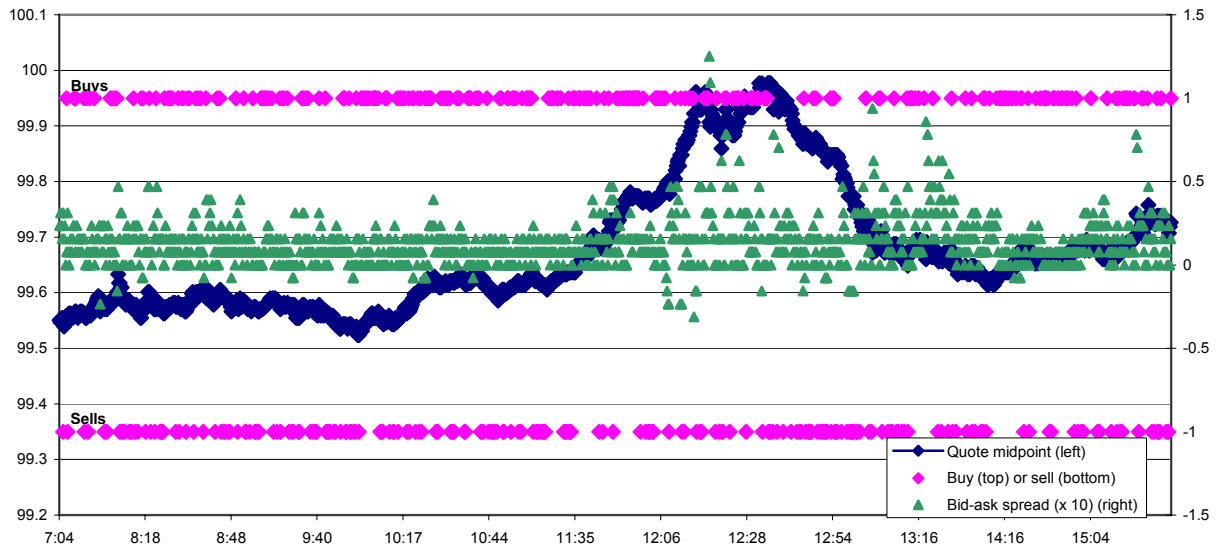
Graph 4b
**Cumulative effect on net buys of an additional net buy:
 five-year note**



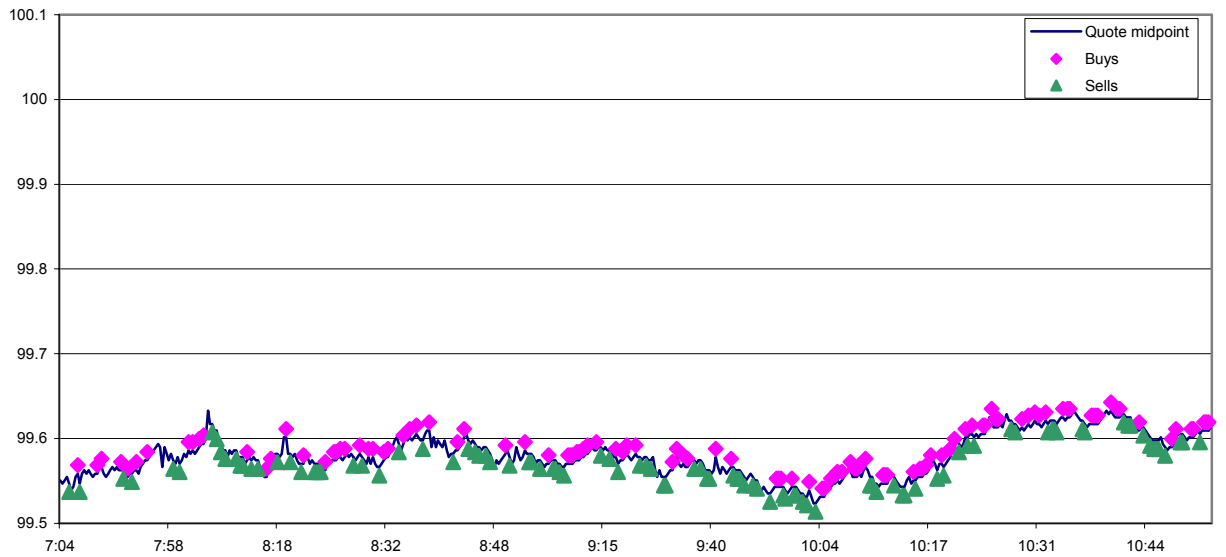
Graph 4c
**Cumulative effect on net buys of an additional net buy:
 10-year note**



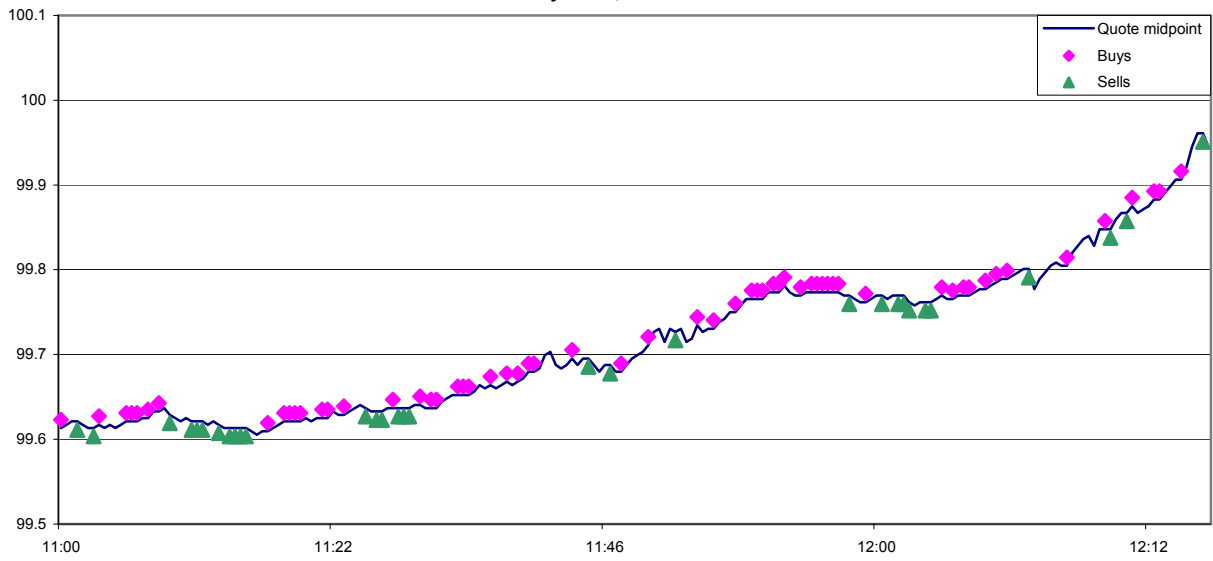
Graph 5
 Quotes, trades and bid-ask spreads for the two-year Treasury note
 3 February 2000



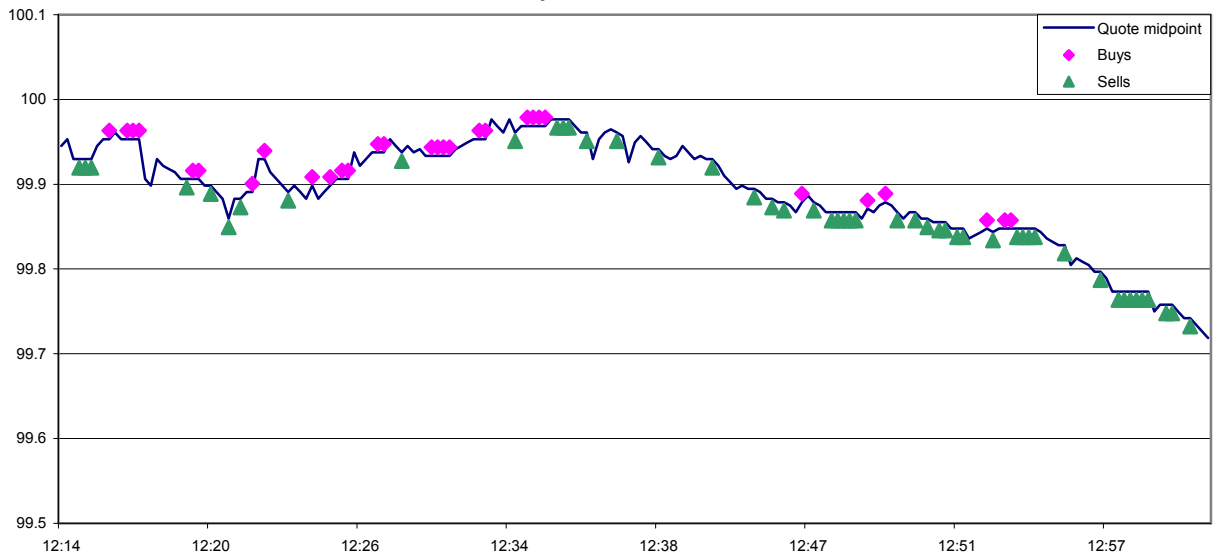
Graph 6a
 Quotes and transactions in the two-year note:
 3 February 2000, 07:00-11:00



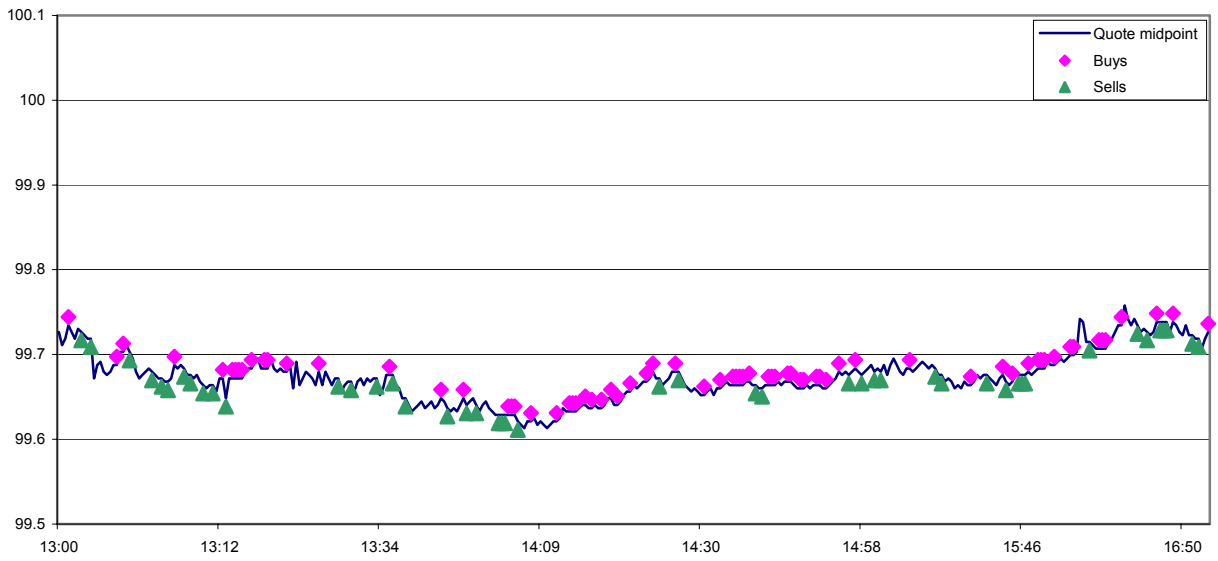
Graph 6b
Quotes and transactions in the two-year note:
3 February 2000, 11:00-12:15



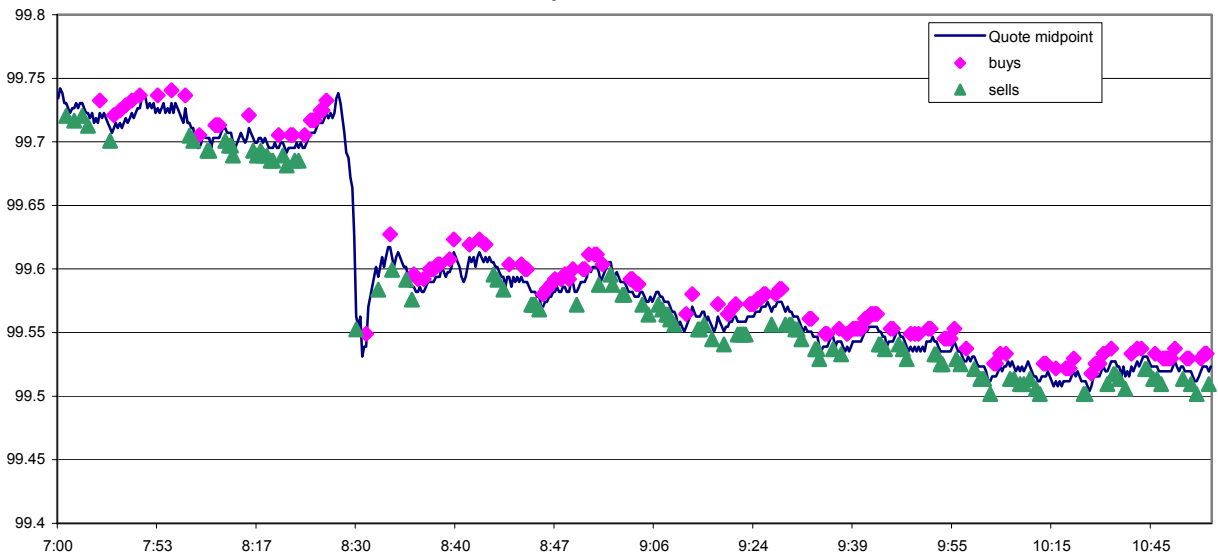
Graph 6c
Quotes and transactions in the two-year note:
3 February 2000, 12:15-13:00



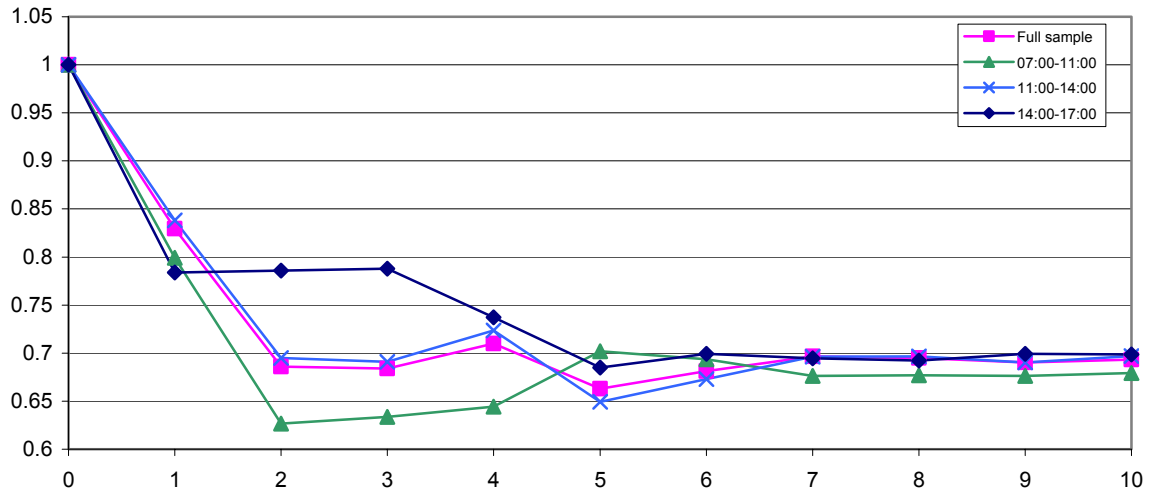
Graph 6d
 Quotes and transactions in the two-year note:
 3 February 2000, 13:00-17:00



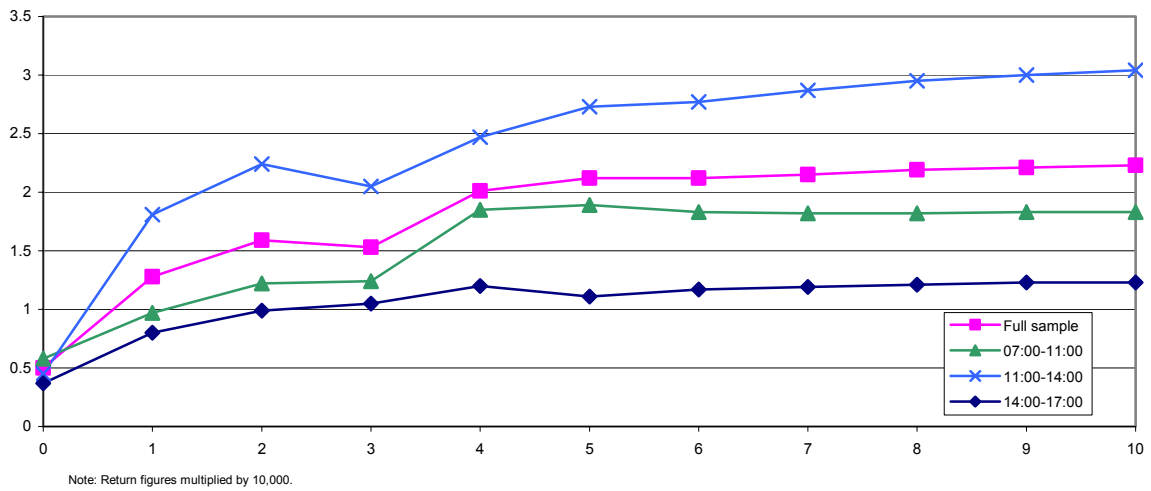
Graph 7
 Quotes and transactions in the two-year note:
 28 January 2000, 07:00-11:00



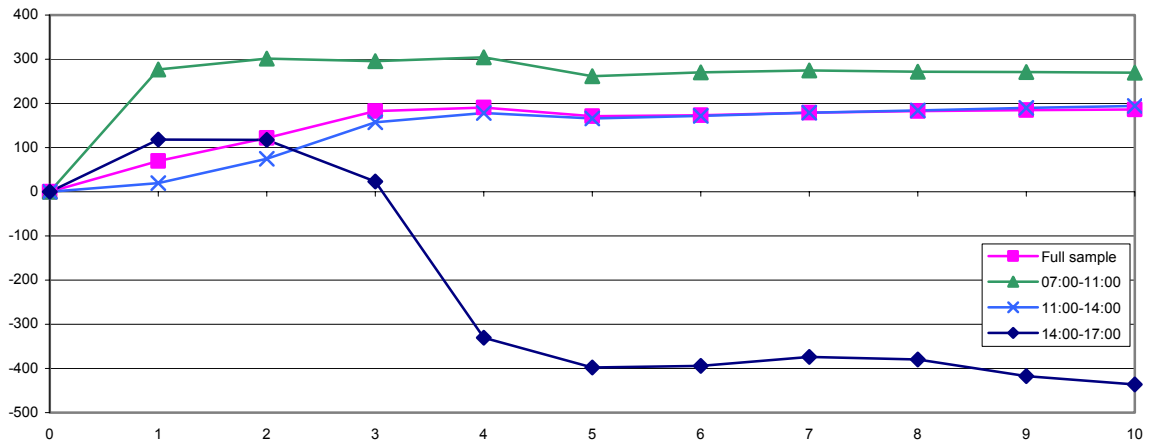
Graph 8a
 Cumulative effect on net returns of an additional one unit return:
 two-year note, 3 February 2000



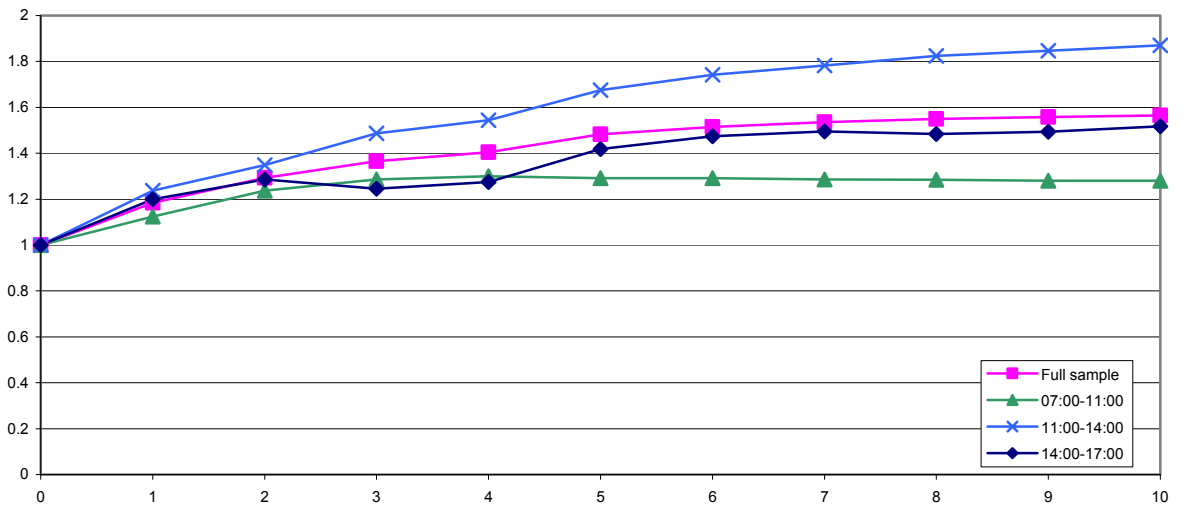
Graph 8b
 Cumulative effect on return of an additional net buy:
 two-year note, 3 February 2000



Graph 8c
 Cumulative effect on net buys of an additional one unit return:
 two-year note, 3 February 2000



Graph 8d
 Cumulative effect on net buys of an additional net buy:
 two-year note, 3 February 2000



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