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

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Abstract: A vector autoregression is estimated on tick-by-tick data for quote-changes and signed trades of 2-year, 5-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 a strong effect in the opposite direction, particularly at times of volatile trading. Price declines elicit sales and price increases elicit purchases. 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.

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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, 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. 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. Evans and Lyons (2002) document similar findings for the foreign exchange market.

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. Expressed in tabular form, this relationship corresponds to the top right cell of the following matrix of relationships between price changes and signed trades.

		Endogenous variables	
		Return	Signed Trade
Explanatory Variables	Past returns	−	−
	Past signed trades	+	+

Given the strong positive effect of past order flow on prices, the negative relationship between returns and subsequent order flow therefore has a mildly dampening effect on price behaviour.

We take the VAR methods used by Hasbrouck (1991) and apply them to high frequency data on the U.S. treasury securities market. Our conclusions point to some interesting and revealing differences from Hasbrouck's original results for the stock market. We find that under tranquil market conditions, when trading is orderly and trading frequency is low, most of the qualitative conclusions found in Hasbrouck's study are replicated. However, during periods of active trading and high price volatility, there appears to be a structural shift in the market dynamics. In such periods, a price increase elicits more buy orders and a price decrease elicits more sell orders. In tabular form, the relationship between returns and signed order flows take on the following form.

		Endogenous variables	
		Return	Signed Trade
Explanatory Variables	Past returns	−/?	+
	Past signed trades	+	+

Compared with Hasbrouck's study, the top right hand cell changes sign, and becomes positive. The negative autocorrelation of returns also becomes less pronounced. On the face of it, there is some evidence of positive feedback trading in which order flow tends to magnify recent returns.

We illustrate these general findings by examining in some detail the particularly volatile trading on February 3rd 2000, when markets were unsettled following the U.S. Treasury's announcements on debt management policy and rumours about large losses at certain institutions.

Positive feedback trading in low frequency data (weekly or monthly) is often associated with "momentum trading" and other explanations that appeal to boundedly rational traders (De Long et al. (1990), Jagadeesh and Titman (1995), Grinblatt, Titman and Wermers (1995)). Our focus is very different. At the level of tick-by-tick data, such as in our study, positive feedback trading highlights the incentives of sophisticated traders that operate under pressurized trading conditions, in which they are acutely aware of the actions of other traders in the market. For example, positive feedback trading may result if a significant number of market participants are constrained (and know one another to be constrained) in their actions by institutionally mandated loss limits. For a trader who is close to breaching his loss limit, an adverse price move may force him to liquidate his trading position. If there are other traders who have similar trading positions, there will be spillover effects in which the liquidations of one trader pushes prices adversely for other traders. The effect of the loss limit is to shorten the decision horizon of the traders.

Irrespective of what a trader believes about the fundamental value of the asset being traded, the constraints imposed by loss limits, or by similar mechanisms such as margin calls or (in extreme cases) bankruptcy constraints, will dictate a course of action in certain circumstances. Thus, one way of understanding feedback trading at high frequency is in terms of the constraints on traders that shorten their decision horizons and thereby encourage mutually reinforcing behaviour. In particular, if some traders believe that others will be faced by such constraints, they may attempt to anticipate the results of a sharp price move or magnify the trading profit of riding short term price trends by selling into a falling market or buying into a rising one.

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 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 (2001) 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. Evans and Lyons (2003) find that exchange rates do not adjust immediately to the public announcements of macroeconomic news, but rather that there is an interaction between the initial price change and subsequent order flow which pushes prices to its eventual new level.

Theoretical models of such behaviour are still in their infancy, but the recent literature on endogenous liquidity has attempted to address the short term incentives that operate in an active market with strategic traders. Bernardo and Welch (2002) argue that limited liquidity can influence the trading decisions of traders. Brunnermeier and Pedersen (2002) show how the potential distressed selling of small traders can be exploited by a large trader to manipulate the price. In Morris and Shin (2003), traders with short horizons and privately known trading limits interact in a market for a risky asset. Risk-averse, long horizon traders supply a downward sloping residual demand curve that face the short-horizon traders. When the price falls close to the trading limits of the short horizon traders, selling of the risky asset by any trader increases the incentives for others to sell. Sales become strategic complements between the short term traders, and payoffs analogous to a bank run are generated. In the analogue of the "run" outcome in a bank run model, short horizon traders sell because others sell. Using global game techniques, Morris and Shin solve for the unique trigger point at which the liquidity black hole comes into existence.

Recent empirical studies of the impact of liquidity on asset prices such as Kambhu and Mosser (2001), Acharya and Pedersen (2002) and Pastor and Stambaugh (2002) point to the importance of constraints on short term trading strategies and their impact on asset prices.

Providing a theoretical basis for positive feedback trading is an important but (as yet) unresolved task, although the recent literature has made some headway. Our empirical results are not tied to any particular theoretical model, and can be read independently of any presumed story of feedback trading. We intend this study as the first step towards a more systematic investigation of the interaction between market dynamics and trading strategies at the high frequency level.

The next section describes the dataset used and applies a VAR specification 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 the ways in which 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. Section 4 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 to the brokers. However, counterparties can often negotiate a larger trade size than the quoted one through a "work-up" 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 ten-year on-the-run (i.e., recently issued) Treasury notes over the period from January 1999 to December 2000. Although GovPX provides round-the-clock data, we restrict the series to quotes and trades that take place between 7:00 am and 5:00 pm, 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 6:00 pm; 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 dataset 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 normalized 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 normalize or not. 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 event times t and t-1.

The number of observations increases with maturity, while the number and size of transactions falls. In other words, the dataset includes more quote changes and fewer transactions as maturity rises. During the sample period, an average of $4.6 billion of trades are recorded daily on GovPX for the two-year note, more than the five year ($2.5 billion) and ten-year ($1.6 billion) combined, reflecting both more trades and a greater volume per trade. As suggested by Fleming (2001), this may reflect differences in coverage by GovPX rather than differences in the actual relative liquidity of 2, 5 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.[1] The same is true for daily returns.

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 2-year note, and about 45 seconds for the 5- and 10-year notes. For the fifty trading days where average duration is highest, the time gap is slightly less than two minutes for all three notes, while for the fifty trading days with the lowest average duration, this gap is about 40 seconds for the 2-year note and 30 seconds for the 5- and 10- year notes. This suggests that, while there clearly are 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 fifty days where the difference between the daily high and low price (the daily trading range) for the specified bond is highest, and for the fifty days where this difference is lowest. We would expect days in the

[1] 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 0.09 32nds for the 2-year, 0.17 32nds for the 5-year, and 0.32 32nds for the 10-year note.

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 92 seconds for the two-year note and 56 seconds for the ten-year. Duration is also longer for low-volatility days (measured by the standard deviation of the tick-by-tick returns) than for high-volatility days.

Confirmation of the relationship between the frequency of trading and various volatility measures is presented in Table 1b for the 2-year note. The average duration on a given day tends to be negatively correlated with the range (high-low) of prices observed during the day, and the standard deviation of tick-by-tick returns during the day, while the price range and volatility display a strong positive correlation. None of these variables seems to have a strong correlation with the change (open-close) in prices that occurred during the day, suggesting that trading conditions were about as volatile on days when bond prices rose as on days when prices fell.

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

2.2.1 What might the data tell us?

GovPX records the pricing and trading decisions of bond dealers, rather than those of speculative traders or long-term 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.[2]

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 the dealer executes a trade with a customer, either by selling her a bond out of inventory or by buying a bond from her, 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

[2] 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.

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 a series of position changes should eventually (after several minutes or a few hours) lead to a corresponding inventory adjustment transaction. 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 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. Examining prices and trades over very short intervals of time could thus enable 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 behaviour as well.

It should be noted that the security prices studied in this paper – those of on-the-run US Treasury notes – are in fact proxies for the underlying values that are of interest to traders and investors. Thus, a trader who buys a two-year Treasury note may be doing so as part of a strategy to adopt or modify her exposure to some other value, such as the one-year forward rate starting one year from the present, or the spread between Treasury and mortgage-backed securities. Similarly, there are other ways to adopt the same exposure, for example in the futures market. By studying the impact of past returns and trades on present returns and trades, we are thus ignoring many other relevant variables. For example, the return on the on-the-run two-year Treasury note will also reflect returns and trades of other Treasury securities, futures instruments, mortgage bonds, and even equities and foreign exchange instruments. The tests presented here should thus be understood as efforts to measure the strength and direction of the effects being tested, rather than to formulate a fully specified model of the market for US Treasury securities.

2.2.2 A two-variable VAR of signed trades and returns

The following vector auto-regression (VAR) should capture many of these short-horizon effects:

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

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, for example through the workup process.[3] Although the estimate of β_0 is positive and significant in all versions of the VAR that we examine, excluding the contemporaneous $trade_t$ 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 eleventh 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 contemporaneous and lagged $trade_t$ 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 (2-year, 5-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. Although we use quote midpoints to

[3] In January 2000, the average length of the workup 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 ten-year. These are all less

calculate r_t, even for observations where the new line of data represents a new transaction (that is, we use the prevailing quotes rather than the transaction price), it is possible that the negative autocorrelation reflects a "bid-ask bounce" effect as described by Roll (1984). Engle and Patton's (2000) study for NYSE stocks show that the price impact of an order falls asymmetrically on the bid and ask quotes. Buyer initiated trades primarily move the ask price while seller-initiated trades move the bid price. When one side of the quote is updated more quickly than the other in response to an order, the mid quote would exhibit behaviour similar to the bid-ask bounce.

- 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 (2002).
- 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 positions in a series of trades, rather than all at once, or that some traders respond to new information with a lag.

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. For the 2-year and 5-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. Only for ten-year notes in the VARs using x_t are the coefficients generally negative, corresponding to Hasbrouck's results for the equity market. This set of effects will be the focus of Sections 3 and 4 of the paper.

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 interested not in the usual impulse-response

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than the average tick lengths, which were 59, 46 and 44 seconds respectively. Boni and Leach (2001) describe and analyse the workup process in the US Treasury market.

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 happens 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 1 to 4 show the cumulative effects of a one-unit increase in returns and buys (the x_t variable) on the cumulative return and number of net buys over the following twenty periods for the two-, five- and ten-year Treasury notes.

The graphs largely confirm the results identified in our earlier review of the signs of the respective raw coefficients. Roughly 77% of a given shock to the return of the five-year note is still contained in the price level 20 periods later; this proportion falls to 69% for the two-year and 68% for the ten-year note (Graph 1). A buy order has a strong positive effect on returns in the short term; a buy causes a cumulative positive return of about 0.27 hundredth of a percent for the two-year note, 0.63 hundredths of a percent for the 5-year note, and 1.05 hundredths of a percent for the 10-year note (Graph 2). In the twenty observations after a net buy order is recorded, a further 0.74 net buys result for the 2-year note, 0.60 net buys for the 5-year, and 0.38 for the 10-year (Graph 4).

As maturity increases, there seems to be a greater impact of trades on returns and less positive autocorrelation of trades. One possible explanation of this is the relatively lower fraction of the market covered by the data at higher maturities. It is likely that returns are influenced not only by the trades executed by the brokers participating in GovPX, but also by those executed by the excluded broker; hence the impact of a trade on the observed return is overestimated when one looks only at GovPX trades. Similarly, the autocorrelation of trades is underestimated, because one is looking only at a fraction of the actual trades in any given period of time. There do not appear to be strong differences across maturities in the pattern of autocorrelation in returns.

The cumulative impact of returns on trades, which as already noted differs strikingly from Hasbrouck's results, is illustrated in Graph 3. The graph shows 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 4.46×10^{-5} from one tick to the next, or about 0.4 hundredths of a percentage point) leads to the occurrence of 3.7% more net buys than would otherwise take place over the subsequent twenty periods, or roughly 19.6 minutes.[4] For the five-year note, there are 3.5% more net buys when the return rises by one standard deviation. However, the fact that the coefficients from the underlying VARs are significant suggests that this is more than a statistical artefact. For the ten year note, the cumulative effect on x_t is negative, with net buys falling by 1.5%.

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 Table 4 labelled "Low duration" show the effects estimated from a VAR similar to that in equation (1) for the days on which the average adjusted duration is unusually low. These should be the days of relatively hectic 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 "High duration" lines show the estimated cumulative effects on days when average adjusted duration was unusually high. These should be days when trading and changes in quotes are relatively slow, suggesting quiet trading conditions.

More precisely, the tables show the sums of different combinations of coefficients from the following VAR[5]:

[4] More precisely, the fraction of total transactions in the next twenty periods that are buys is 0.037 higher than it otherwise would have been.

[5] To save space, the coefficients from this and the other VARs in the remainder of the paper are not given. Coefficients from these VARs are available from the authors.

$$
\begin{aligned}
r_t &= \sum_{i=1}^{10} (\alpha_i + \alpha_i^L d_{t-i}^L + \alpha_i^H d_{t-i}^H) r_{t-i} + \sum_{i=0}^{10} (\beta_i + \beta_i^L d_{t-i}^L + \beta_i^H d_{t-i}^H) x_{t-i} + \varepsilon_{1,t} \\
x_t &= \sum_{i=1}^{10} (\gamma_i + \gamma_i^L d_{t-i}^L + \gamma_i^H d_{t-i}^H) r_{t-i} + \sum_{i=1}^{10} (\delta_i + \delta_i^L d_{t-i}^L + \delta_i^H d_{t-i}^H) x_{t-i} + \varepsilon_{2,t}
\end{aligned}
\tag{2}
$$

The dummy variable ${d^L}_t$ takes the value of one when an observation occurred on one of the fifty days (10% of the sample) when duration, adjusted for time-of-day, seasonal, and time trend factors, was at its lowest, while ${d^H}_t$ is one for observations on the fifty days when adjusted duration was highest. Table 4 also gives the significance levels for different combinations of variables, using a Wald test for the hypothesis that this sum is different from zero.

The duration-based subsamples are determined using an adjusted measure of duration. This adjusted duration equals the ratio of the actual duration to the fitted values from a model that estimates duration using time-of-day, time-of-year, and trend effects. The model closely resembles the linear spline model with “nodes” at the top of each hour developed in Engle (2000). We include a time trend in the estimation in order to account for the fact that the number of observations tends to decline throughout the sample period, reflecting the steadily declining share of US Treasury market trading that is covered by the data. We also add dummy variables for observations in November and December, two months when these markets are less active. The result is a series of fitted duration estimates for each Treasury note studied. The values of these fitted estimates, when graphed over the trading day, exhibit a distinct “U”-shape (Graph 5). Activity is very slow between 7:00 and 8:00 am, then speeds up dramatically between 8:00 and 9:00, when the most closely watched economic statistics tend to be released. The market then slows somewhat, but remains active until 3:00 pm, after which transactions and quote changes dwindle. Adjusting duration by dividing it by these fitted values results in a time series of duration “surprises”.

For all three maturities, the effects of trades on returns tend to be higher on the low-duration days than on the high-duration days or on the days when duration was neither unusually high nor unusually low. These effects do not change in a significant way, however, when one compares unusually high-duration days to “normal” days. This suggests the structural change may be non-linear: low-duration days stand out but high-duration days do not.

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. For the 2-year note, these effects are more strongly positive on low-duration days than in normal times (that is, they lead to more net buys), though the Wald test does not support the hypothesis that this change in the variables is significant. On high-duration days, however, the effects become insignificant in a statistical sense, and a Wald test supports structural change at an 8% significance level. For the 5-year note, the results are qualitatively similar: there is no statistical difference between effects on low-duration and "normal" days, while the effects become insignificant on high-duration days. For the 10-year note, it will be recalled that positive price movements cause an increase in net selling in the sample as a whole. These effects, as well, become insignificant on high-duration days.

Impulse response functions for the different subsamples are illustrated for the two-year note in Graphs 6a-6d. For the cross-effects of signed trades on returns and returns on signed trades, these confirm what was observed from looking at the raw coefficients in Table 4. Whereas a new buy leads to an increase of 0.27 hundredths of a percent in the cumulative return after twenty periods in the sample as a whole, on low-duration days the impact rises to 0.40 hundredths of a percent, while on high-duration days it falls to 0.23 hundredths of a percent (Graph 6b). Effects in the opposite direction grow stronger as well. For the sample as a whole, it will be recalled that an additional standard deviation return results in an increase of 3.7% in the number of buy orders in the next twenty periods. On low-duration days, this rises to 5.3%, while on high-duration days net buys decline by 0.7% (Graph 6c).

This increase in the mutual impact of trades and returns on one another results in an increase in the persistence of shocks to returns. For the full sample, 69% of a shock to the quote midpoint remains in the price after twenty periods. On low duration days, this proportion rises to 86%, while on high-duration days it falls to 62% (Graph 6a). However, the impact of a new trade on the direction of trading does not change appreciably across the different subsamples (Graph 6d).

3. A case study: February 3, 2000

The results in Section 2 suggest that, on days of relatively rapid 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 very volatile trading day that occurred during the sample period.

3.1 Events of February 3

February 3, 2000, witnessed the sixth highest daily trading range for the on-the-run two-year note in the sample period (Graph 7). The price quoted on GovPX (using the average of the prevailing bid and ask quotes) for the two year note opened at 99.551 at 7:04 am, reached a low of 99.523 at 10:03 am, rose to a high of nearly 99.977 at 12:36 pm, and finished at 99.727 at 5:00 pm. 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 February 3, a Thursday, do not point to a specific new piece of macroeconomic information being 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 February 2, 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 relating to trading on the 3rd focused on the uncertain environment created by the previous day's announcement. In its daily report on the US Treasury market, the Associated Press emphasised the uncertain implications of the new Treasury program on 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 February 3:

> Adding to Thursday's mayhem was a widespread rumor 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 rumor 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 pm on 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.[6]

February 3 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 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.

[6] We are grateful to Michael Fleming for calling our attention to this news story.

Examination of Graph 7 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 5. From 7:00 am to 11:00 am, prices were flat or slightly higher, bid-ask spreads were wider than usual but steady, duration was somewhat shorter than usual, and there was a roughly even balance between buys and sells. From 11:00 am to 12:15 pm, prices rise sharply, accompanied by an imbalance of buys over sells and a shortening of duration. This is presumably the time when rumours about a troubled institution dominate market trading, with prices at first bid up on the expectation that the institution would have to close out a large short position. From 12:15 pm to 2:00 pm prices fall about as sharply, with sells outnumbering buys and duration remaining very low. This followed the New York Fed announcement. In both the second and third periods, quoted bid-ask spreads are wide and volatile, and occasionally negative.[7] Finally, from 2:00 pm to 5:00 pm, prices rise gradually amid relatively calm conditions, with duration close to normal levels, though bid-ask spreads remain elevated.

Two points are worth noting with regard to Table 5, both of which suggest that the bond market on February 3 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 2:00 and 5:00.

Second, the bid-ask spread was at its highest between 12:15 and 2:00 - 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.

[7] 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.

3.2 Price movements and order arrival: A closer look

A closer examination of trading patterns throughout the day presents further puzzles (Graphs 8a - 8d). 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 buildup of purchases to be followed more or less immediately by information-driven price increases, and a buildup of sales to be followed by price declines.

During the 7-11:30 period (Graph 8a), 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 (e.g. just after 10:04) and declines with sells (e.g. just before 8:18). But the order flows and price movements appear to be simultaneous; the price graph does not wait for a buildup of orders before it starts moving. And periods of persistent one-sidedness in the market (e.g. 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 downward - and only then (around 10:44) do we see clusters of sales.

As the rumours of a troubled institution begin to take hold (Graph 8b), the price rises amid heavy buying. But sometimes the price rises 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 appear 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 8c) 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 fall without any order flows, other times associated with heavy selling. Prices seem to stabilise around 1:05 pm, even though traders continue to sell. A cluster of buys eventually emerges just before 1:16, but the market seems happy with its new level - even when the buys are followed by further sales.

During the last three hours of the trading day, the market rises slowly and without much volatility (Graph 8d). A heavy series of buy orders does not do much to move the price. These may derive 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 an alternative kind of price volatility, consider the trading pattern for the 2-year note on the morning of January 28, 2000 (Graph 9). 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 8:30. 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 tend to have little or no impact on the price, perhaps because participants understand that this represented the squaring of speculative positions and the rebalancing of portfolios. Trading volume is 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 (1999a) and Huang et al (2001).[8]

3.3 VAR analysis

Graphs 10a-10d illustrate estimations of the cumulative effects of returns and signed trades on one another, and of returns on subsequent returns, when the VAR in model (1) is applied to prices and trades recorded for the 2-year note on February 3, 2000. Because there are fewer data points, five lags are used in each equation instead of ten. As before, the impulse-response graphs assume that causation runs from trades to

[8] Green (forthcoming), however, finds that the adverse-selection component of effective Treasury bid-ask spreads rises after information announcements. He interprets this result as showing an increase in the informational role of trading.

returns. Sums of coefficients for the different time periods for the two, five and ten year notes are provided in Table 6. In what follows we will focus on the results for the two-year note.

Cross effects between trades and returns seem to have been stronger on February 3 than they were during the full two-year sample period. The impact of trades on returns is about twice as strong on February 3 as during the full sample, with a new buy order leading, on average, to an increase of 0.53 hundredths of a percentage point in the return (Graph 10b). The effect of returns on trades is also substantially higher than normal on February 3: a one standard deviation positive return now leads to a 5.2% increase in the likelihood of a purchase after ten periods, more than 50% higher than the effect estimated for the sample as a whole (Graph 10c). The persistence of shocks to returns is also stronger. Ten periods after a positive shock to the return, 77% of the increase remains in the bond price, compared with 69% for the sample as a whole (Graph 10a). The autocorrelation of trading behaviour is weaker, however. A new buy order is followed by an additional 0.56 of a net buy over the subsequent ten periods, in contrast to the effect in the broad sample, which was estimated to be 0.72 (Graph 10d).

These patterns shifted in the course of the day, in ways analogous to the shifts across the different subsamples studied in model (2). During the most turbulent period, 11 am-2 pm, when duration was at its shortest, trades had a relatively stronger effect on returns and were relatively more autocorrelated than was the case either before 7 am or after 2 pm. In the 7-11 am and 11 am-2 pm periods, returns had strong positive effects on the direction of trades, while after 2 pm this relationship became negative. The persistence of shocks to returns was much higher between 11 am and 2 pm, while before and after this time it was about the same as that estimated for the full sample.

3.4 Trading in volatile conditions: A summary

Combining the evidence from the duration-based subsamples and from February 3, 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 February 3 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.

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 rapid and volatile. We examine trading in the 2-year, 5-year, and 10-year on-the-run treasury notes over the period January 1999 - December 2000. 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 positively (or less negatively) autocorrelated on days when conditions are more volatile. This pattern is evident when one compares unusually turbulent days with normal days or unusually quiet days. It also emerges from a close analysis of quotes and trades from February 3, 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.

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

	Two-year	Five-year	Ten-year
Number of observations	358,361	494,437	506,880
Of which:			
% trades only	39.7	22.5	18.9
% quote-changes only	49.5	64.7	70.9
% trades & quote-chges	10.8	12.8	10.2
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
Tick-by-tick returns[1]			
Mean	5.28×10^{-9}	5.64×10^{-10}	-7.02×10^{-9}
Mean abs value	2.76×10^{-5}	5.38×10^{-5}	0.000101
Std Deviation	4.46×10^{-5}	8.31×10^{-5}	0.000156
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

[1]Log change in midpoint between bid and ask quotes.

Table 1a (cont.)

	Two-year	Five-year	Ten-year
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

Table 1b. Correlations among daily price range, price change, volatility and average duration: 2-year note.

	Price range	Volatility	Price change [4]
Duration [1]	-0.502	-0.359	-0.031
Price range [2]		0.552	0.093
Volatility [3]			0.129

[1] Daily average time between observations, in minutes, detrended and adjusted for time-of-day and time-of-year effects.

[2] Difference between daily high and low prices.

[3] Daily standard deviation of tick-by-tick returns.

[4] Difference between daily close and open prices.

Table 2. Vector autoregression results: signed trades.

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

$$r_t = \sum_{i=1}^{10} a_i r_{t-i} + \sum_{i=0}^{10} b_i x_{t-i} + e_{1,t}$$

$$x_t = \sum_{i=1}^{10} g_i r_{t-i} + \sum_{i=1}^{10} d_i x_{t-i} + e_{2,t}$$

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 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 January 4, 1999, through December 29, 2000, and includes only the transactions and quote-changes taking place between 7:00 am and 5:00 pm. On each day, the estimation starts with the eleventh observation after 7:00 am.

2-year, full sample

	Dept variable: r_t		Dept variable: x_t	
	Coef.	t-stat.	Coef.	t-stat.
Lags of r_t				
1	-0.256	-151.86	-130.075	-4.80
2	-0.146	-83.96	267.373	9.57
3	-0.063	-35.66	219.595	7.78
4	-0.022	-12.74	122.318	4.33
5	-0.005	-2.99	74.322	2.63
6	0.002	0.87	34.122	1.21
7	0.006	3.56	13.347	0.47
8	0.010	5.79	37.079	1.32
9	0.003	1.89	12.744	0.46
10	0.001	0.90	50.216	1.88
Lags of x_t [a]				
0	0.665	63.59		
1	0.989	90.95	0.260	153.80
2	0.531	47.98	0.114	64.41
3	0.155	13.96	0.024	13.47
4	0.061	5.49	0.005	2.59
5	-0.014	-1.29	-0.003	-1.50
6	-0.049	-4.45	0.001	0.48
7	-0.041	-3.71	0.003	1.41
8	-0.044	-3.98	0.005	2.60
9	-0.002	-0.19	0.003	1.74
10	-0.010	-0.90	0.003	1.46
$\overline{R}^2$	0.11		0.10	

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

Table 2 (cont). 5-year, full sample

	Dept variable: r_t		Dept variable: x_t	
	Coef.	t-stat.	Coef.	t-stat.
Lags of r_t				
1	-0.257	-179.89	155.093	14.67
2	-0.091	-61.85	41.131	3.77
3	-0.035	-23.82	71.799	6.55
4	0.002	1.04	49.575	4.52
5	0.005	3.16	22.074	2.02
6	0.015	10.25	22.190	2.03
7	0.008	5.60	-5.441	-0.50
8	0.014	9.17	-11.409	-1.04
9	0.013	8.79	-5.459	-0.50
10	0.008	5.43	6.509	0.62
Lags of x_t[a]				
0	2.289	118.35		
1	1.728	86.97	0.164	112.78
2	0.998	49.59	0.105	71.22
3	0.328	16.23	0.048	31.90
4	0.065	3.22	0.021	14.12
5	-0.015	-0.76	0.009	6.18
6	-0.065	-3.20	0.002	1.29
7	-0.048	-2.35	0.003	2.15
8	-0.063	-3.14	0.004	2.41
9	0.011	0.57	0.003	1.90
10	-0.018	-0.92	0.003	2.37
$\overline{R}^2$	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	-0.268	-190.03	38.188	7.47
2	-0.117	-80.15	-38.226	-7.22
3	-0.063	-43.17	-17.908	-3.36
4	-0.019	-12.81	-17.048	-3.19
5	-0.004	-2.95	-19.238	-3.60
6	0.006	4.12	-12.031	-2.26
7	0.003	2.16	-13.565	-2.54
8	0.006	4.10	-10.258	-1.93
9	0.004	3.02	-5.363	-1.02
10	0.007	4.69	-2.859	-0.57
Lags of x_t[a]				
0	3.964	101.70		
1	3.490	87.91	0.129	90.40
2	2.135	53.23	0.079	54.30
3	1.037	25.75	0.035	23.75
4	0.426	10.57	0.014	9.72
5	0.078	1.94	0.006	4.11
6	0.009	0.21	0.004	2.85
7	-0.062	-1.54	0.004	2.68
8	-0.023	-0.56	0.005	3.46
9	-0.087	-2.16	0.005	3.21
10	-0.038	-0.96	0.004	2.88
$\overline{R}^2$	0.10		0.03	

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

Table 3. Vector autoregression results: signed order flow.

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

$$r_t = \sum_{i=1}^{10} a_i r_{t-i} + \sum_{i=0}^{10} b_i v_{t-i} + e_{1,t}$$

$$v_t = \sum_{i=1}^{10} g_i r_{t-i} + \sum_{i=1}^{10} d_i v_{t-i} + e_{2,t}$$

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 January 4, 1999, through December 29, 2000, and includes only the transactions and quote-changes taking place between 7:00 am and 5:00 pm. On each day, the estimation starts with the eleventh observation after 7:00 am.

2-year, full sample

	Dept variable: r_t		Dept variable: v_t	
	Coef.	t-stat.	Coef.	t-stat.
Lags of r_t				
1	-0.212	-126.04	3129.254	4.36
2	-0.109	-63.42	5927.097	8.09
3	-0.034	-19.61	3312.052	4.49
4	-0.003	-1.58	465.159	0.63
5	0.006	3.42	2078.347	2.82
6	0.007	4.08	967.235	1.31
7	0.009	4.95	794.467	1.08
8	0.012	6.68	722.322	0.98
9	0.004	2.36	1098.867	1.51
10	0.002	1.23	1001.097	1.41
Lags of v_t [a]				
0	0.019	48.08		
1	0.018	44.73	0.052	31.05
2	0.012	30.13	0.074	43.52
3	0.005	11.42	0.042	24.89
4	0.001	1.33	0.074	43.67
5	-0.002	-4.11	0.002	1.02
6	-0.003	-7.64	0.016	9.47
7	-0.002	-3.78	0.009	5.17
8	-0.002	-5.54	0.015	8.87
9	-0.001	-3.62	0.007	3.84
10	-0.001	-1.75	-0.006	-3.77
$\overline{R}^2$	0.06		0.02	

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

Table 3 (cont). 5-year, full sample

	Dept variable: r_t		Dept variable: v_t	
	Coef.	t-stat.	Coef.	t-stat.
Lags of r_t				
1	-0.223	-156.24	2642.990	21.52
2	-0.063	-42.95	2382.348	18.93
3	-0.017	-11.72	2043.797	16.20
4	0.012	8.11	1391.112	11.03
5	0.009	6.47	844.571	6.70
6	0.017	11.66	544.473	4.32
7	0.008	5.72	261.360	2.08
8	0.013	8.82	193.415	1.54
9	0.012	8.17	205.151	1.64
10	0.007	4.83	83.945	0.69
Lags of v_t[a]				
0	0.125	75.12		
1	0.091	54.11	0.080	55.47
2	0.056	33.34	0.053	36.71
3	0.023	13.57	0.032	22.37
4	0.006	3.34	0.017	12.02
5	0.002	1.31	0.008	5.46
6	-0.003	-1.54	0.004	2.73
7	-0.002	-1.26	0.007	5.01
8	-0.005	-2.94	0.003	1.76
9	0.000	0.12	0.005	3.44
10	0.001	0.50	0.001	0.63
$\overline{R}^2$	0.06		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 Coef.	t-stat.	Dept variable: v_t Coef.	t-stat.
Lags of r_t				
1	-0.237	-167.74	515.908	11.04
2	-0.091	-62.69	283.281	5.90
3	-0.047	-32.04	316.900	6.58
4	-0.009	-6.48	219.174	4.54
5	-0.001	-0.37	163.829	3.40
6	0.007	4.58	107.184	2.22
7	0.002	1.48	56.687	1.18
8	0.004	2.92	66.828	1.39
9	0.003	1.79	57.360	1.20
10	0.005	3.55	105.165	2.26
Lags of v_t[a]				
0	0.296	69.32		
1	0.183	42.73	0.053	37.34
2	0.130	30.21	0.044	30.84
3	0.065	15.02	0.029	20.08
4	0.021	4.97	0.015	10.50
5	-0.004	-1.00	0.009	6.36
6	0.001	0.16	0.005	3.19
7	-0.013	-2.92	0.006	4.30
8	0.000	0.07	0.007	5.01
9	-0.007	-1.68	0.004	2.91
10	0.008	1.76	0.007	5.01
$\bar{R}^2$	0.07		0.01	

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

Table 4. VAR coefficients for different subsamples.

The table shows the sums of different combinations of coefficients from the following VAR:

$$r_t = \sum_{i=1}^{10}(a_i + a_i^L d_{t-i}^L + a_i^H d_{t-i}^H) r_{t-i} + \sum_{i=0}^{10}(b_i + b_i^L d_{t-i}^L + b_i^H d_{t-i}^H) x_{t-i} + e_{1,t}$$

$$x_t = \sum_{i=1}^{10}(g_i + g_i^L d_{t-i}^L + g_i^H d_{t-i}^H) r_{t-i} + \sum_{i=1}^{10}(d_i + d_i^L d_{t-i}^L + d_i^H d_{t-i}^H) x_{t-i} + e_{2,t}$$

where d_{t-i}^L is a dummy variable taking the value one during the fifty days when average adjusted duration is lowest during the sample, and d_{t-i}^H equals one during the fifty days when average adjusted duration is highest. The 401 days on which both dummies equal zero are referred to as "normal" days. The values in the column "Sum of coefs" are the total of the effects estimated for that subsample. Thus, the first figure in the first column is $\sum_{i=1}^{10} a_i$, the second figure is $\sum_{i=1}^{10}(a_i + a_i^L)$, and so on. The values under the column "Vs. normal" are the *additional* effects for that subsample, relative to the effects estimated for the 401 days that are not in either the high-duration or the low duration subsample. Thus, the first figure in the second column is $\sum_{i=1}^{10} a_i^L$, the second is $\sum_{i=1}^{10} a_i^H$, and so on. The asterisks indicate the significance level for the F-statistic of a Wald test of the hypothesis that the corresponding sum of coefficients is different from zero. Two asterisks indicate rejection at the 5% level or better, while one asterisk indicates rejection at a level between 5% and 10%.

Two year note				
	Return equation		Signed trade equation	
	Sum of coefs	Vs normal	Sum of coefs	Vs normal
Coefficients on returns				
"Normal" days	-0.563 **		767.5 **	
Low duration	-0.210 **	0.353 **	912.8 **	145.3
High duration	-0.599 **	-0.036	-134.5	-902.1 *
Coefficients on signed trades [1]				
"Normal" days	2.277 **		0.421 **	
Low duration	3.026 **	0.749 **	0.348 **	-0.073 **
High duration	2.173 **	-0.104	0.404 **	-0.018

[1] Coefficient estimates for return equation multiplied by 100,000.

Table 4 (cont).

Five year note				
	Return equation		Signed trade equation	
	Sum of coefs	Vs normal	Sum of coefs	Vs normal
Coefficients on returns				
"Normal" days	-0.288 **		395.4 **	
Low duration	-0.707 **	-0.419 **	229.1 *	-166.3
High duration	-0.325 **	-0.036	-83.5	-478.8 **
Coefficients on signed trades [1]				
"Normal" days	5.066 **		0.364 **	
Low duration	6.876 **	1.809 **	0.293 **	-0.071 **
High duration	5.297 **	0.231	0.381 **	0.018

Ten year note				
	Return equation		Signed trade equation	
	Sum of coefs	Vs normal	Sum of coefs	Vs normal
Coefficients on returns				
"Normal" days	-0.424 **		-99.7 **	
Low duration	-0.855 **	-0.430 **	-133.0 *	-33.3
High duration	-0.355 **	0.069	-67.7	32.1
Coefficients on signed trades [1]				
"Normal" days	10.759 **		0.286 **	
Low duration	13.443 **	2.684 **	0.241 **	-0.045 **
High duration	10.477 **	-0.282	0.300 **	0.014

[1] Coefficient estimates for return equation multiplied by 100,000.

Table 5. Trading epochs for the 2-year note on February 3, 2000.

	Return [1]	% buys	Mean duration	Mean bid-ask spread [2]
7:00 am - 11:00 am	0.00063	52.6	0.61	0.0097
11:00 am - 12:15 pm	0.00340	65.9	0.53	0.0102
12:15 pm - 2:00 pm	-0.00317	40.9	0.48	0.0181
2:00 pm - 5:00 pm	0.00090	66.7	0.96	0.0120
Memo item: Full sample (1/99-12/00)	*0.00067* [3]	*52.9*	*0.98*	*0.0065*

Notes: [1] Log change in quote midpoint.

[2] Difference between prevailing ask and bid quotes.

[3] Mean absolute value of daily log quote-midpoint changes.

Table 6. VAR Coefficients for February 3, 2000.

This table gives the sums of the estimated coefficients from the following vector autoregression for three time periods on February 3 2000:

$$r_t = \sum_{i=1}^{5} a_i r_{t-i} + \sum_{i=0}^{5} b_i x_{t-i} + e_{1,t}$$

$$v_t = \sum_{i=1}^{5} g_i r_{t-i} + \sum_{i=1}^{5} d_i v_{t-i} + e_{2,t}$$

In each quadrant, the table shows the sum of the coefficients on the corresponding variable (e.g. $\sum_{i=1}^{5} a_i$). The asterisks indicate the significance level for the F-statistic of a Wald test of the hypothesis that the corresponding sum of coefficients is different from zero. Two asterisks indicate rejection at the 5% level or better, while one asterisk indicates rejection at a level between 5% and 10%.

Two year note		
	Return equation	Signed trade equation
Coefficients on return		
7 am - 11 am	-0.588 **	1393.2
11 am - 2 pm	-0.288 *	1224.4 *
2 pm - 5 pm	-0.477 *	-836.9
Coefficients on signed trade		
7 am - 11 am	5.506 [a] **	0.164 *
11 am - 2 pm	4.475 [a] **	0.444 **
2 pm - 5 pm	4.291 [a] **	0.376 **

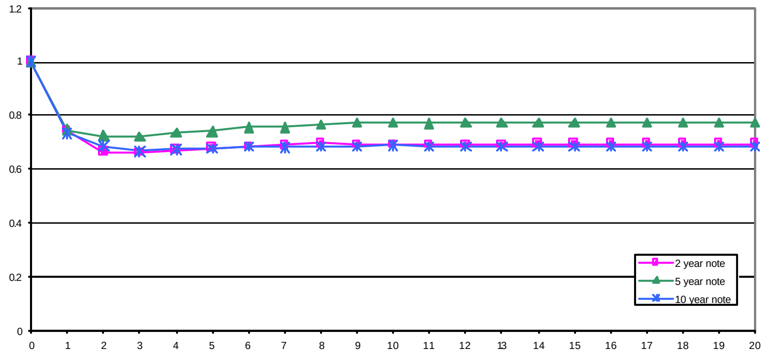
Five year note		
	Return equation	Signed trade equation
Coefficients on return		
7 am - 11 am	-0.331 **	501.5
11 am - 2 pm	0.020	50.2
2 pm - 5 pm	-0.100	-166.2
Coefficients on signed trade		
7 am - 11 am	7.221 [a] **	0.321 **
11 am - 2 pm	10.893 [a] **	0.383 **
2 pm - 5 pm	12.850 [a] **	0.101

[a] Coefficient estimates multiplied by 100,000.

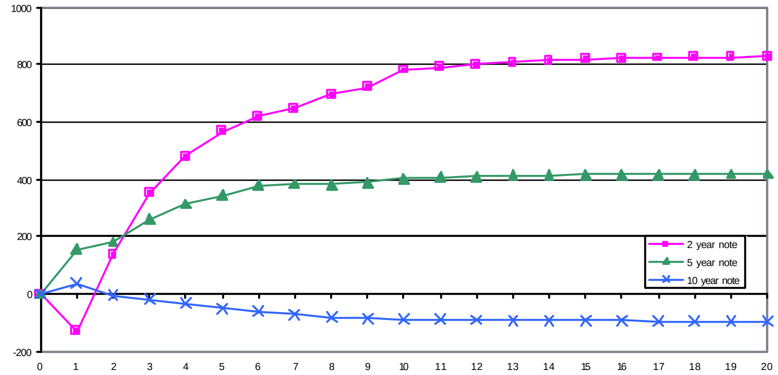
Ten year note				
	Return equation		Signed trade equation	
Coefficients on return				
7 am - 11 am	-0.071		-282.5	**
11 am - 2 pm	0.381	**	50.6	
2 pm - 5 pm	-0.004		-767.9	**
Coefficients on signed trade				
7 am - 11 am	26.435 [a]	**	0.205	**
11 am - 2 pm	10.803 [a]	**	0.344	**
2 pm - 5 pm	7.865 [a]		0.228	**

[a] Coefficient estimates multiplied by 100,000.

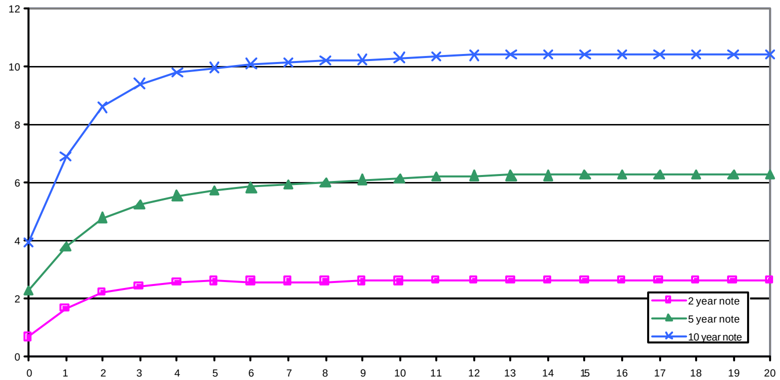
Graph 1. Cumulative effect on return of an additional one unit return.



Graph 3. Cumulative effect on net buys of an additional one unit return.

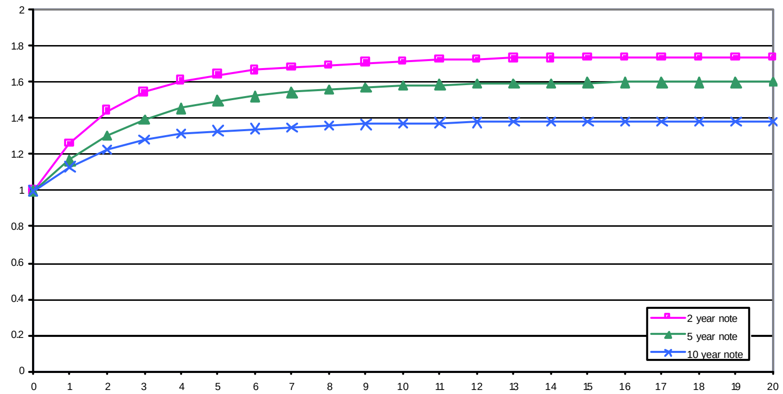


Graph 2. Cumulative effect on return of an additional net buy.

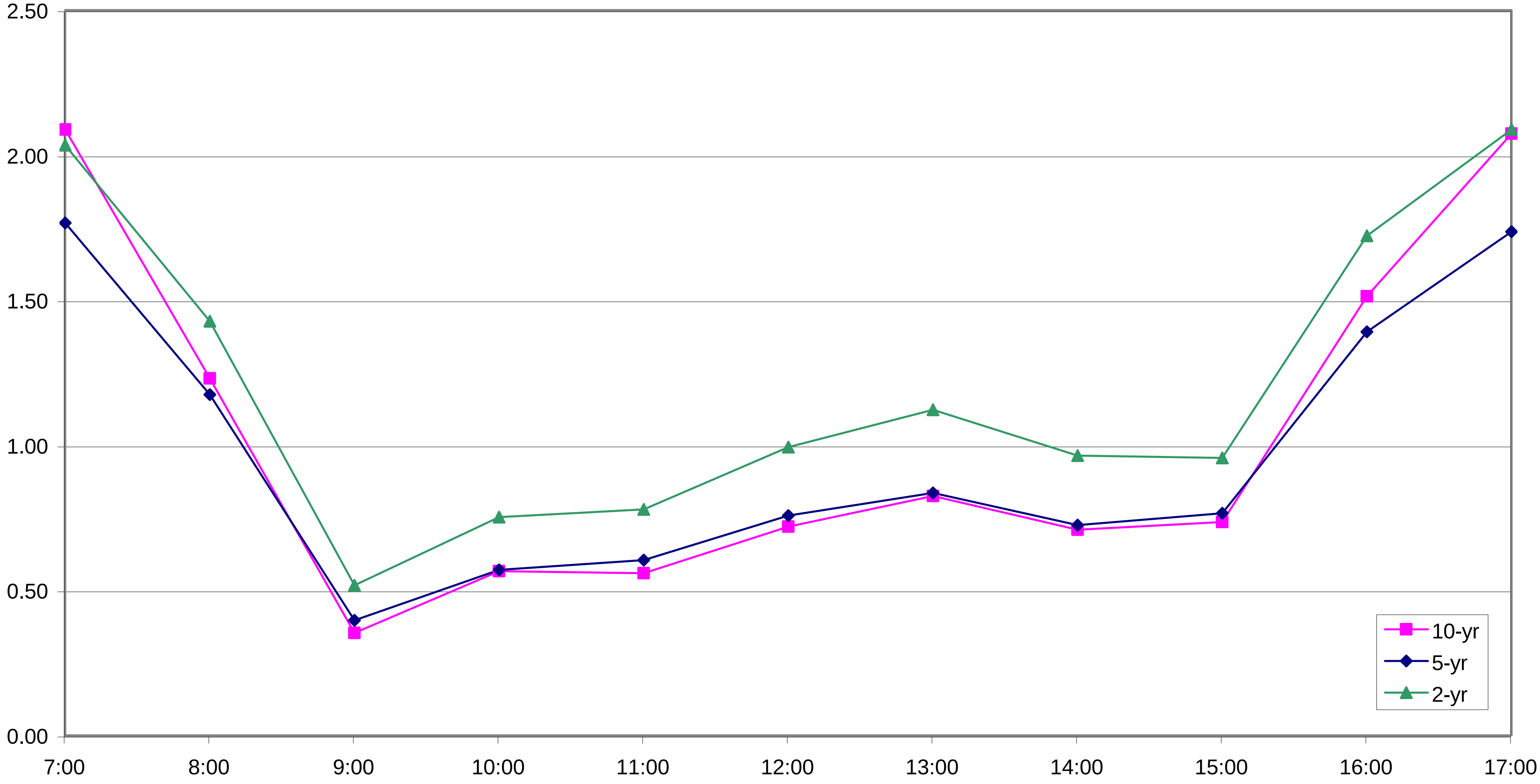


Note: Return figures multiplied by 100,000.

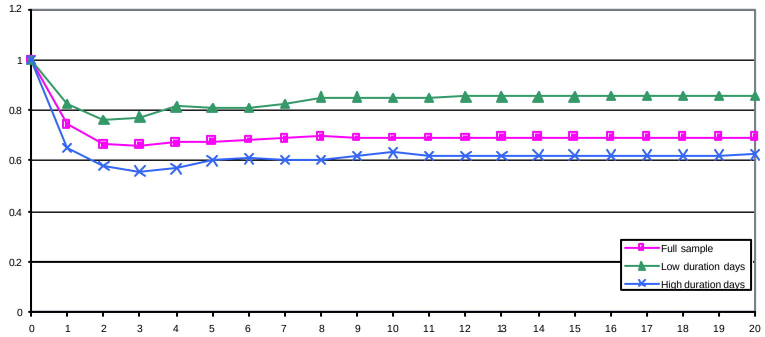
Graph 4. Cumulative effect on net buys of an additional net buy.



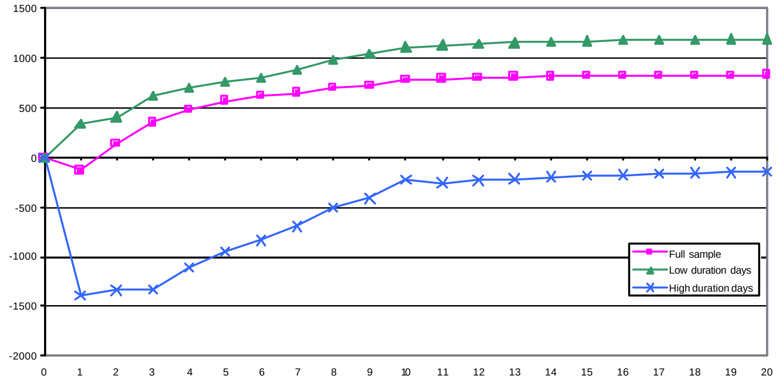
Graph 5. Fitted duration at different times of the day.



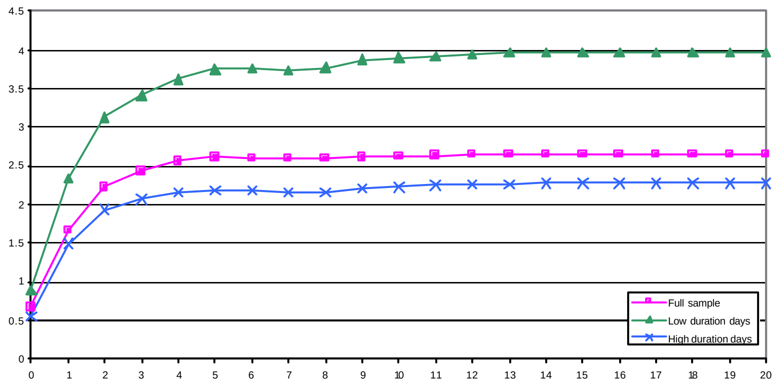
Graph 6a. Cumulative effect on net returns of an additional one unit return: 2 year note



Graph 6c. Cumulative effect on net buys of an additional one unit return: 2 year note

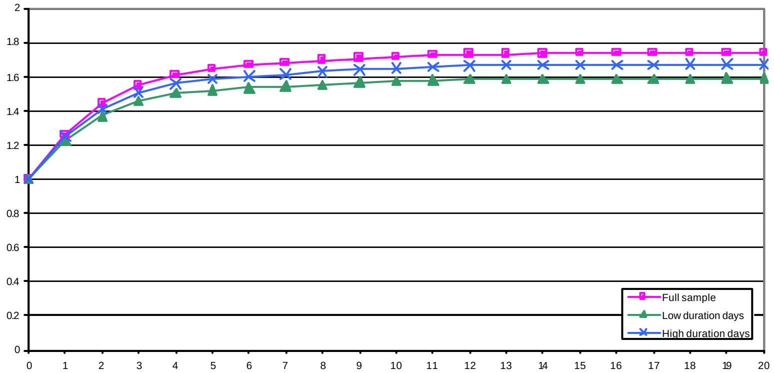


Graph 6b. Cumulative effect on return of an additional net buy: 2 year note

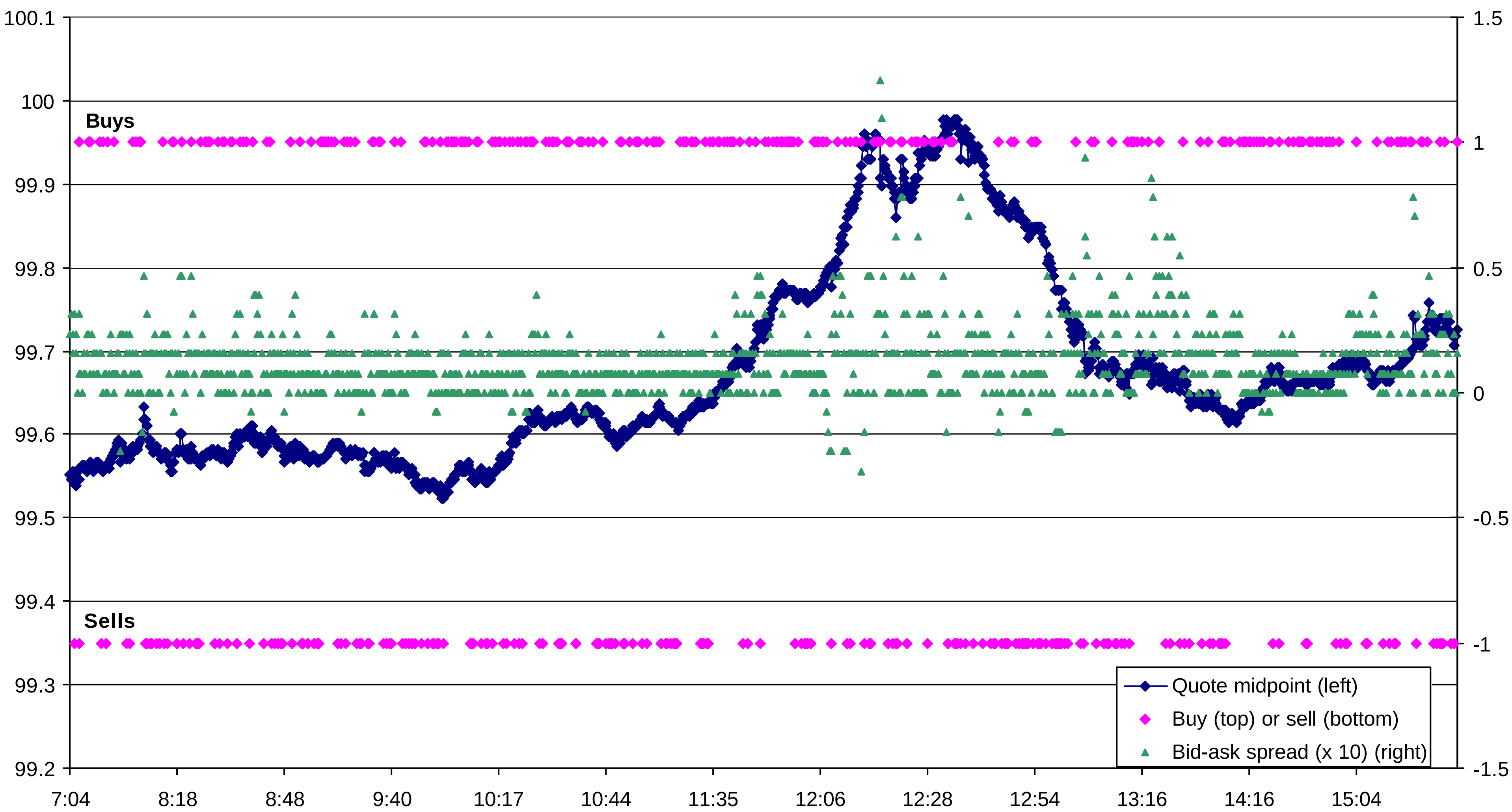


Note: Return figures multiplied by 100000.

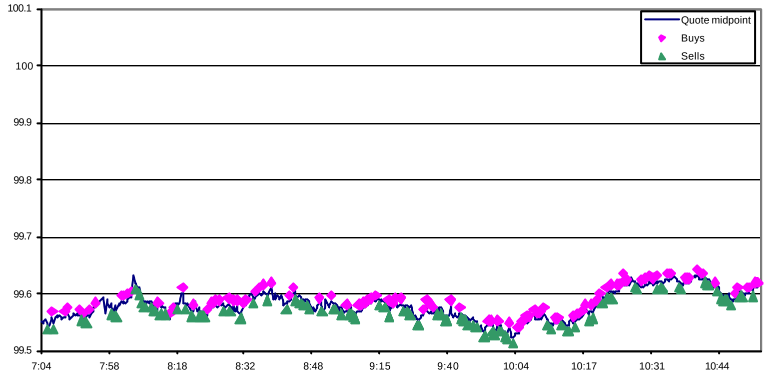
Graph 6d. Cumulative effect on net buys of an additional net buy: 2-year note



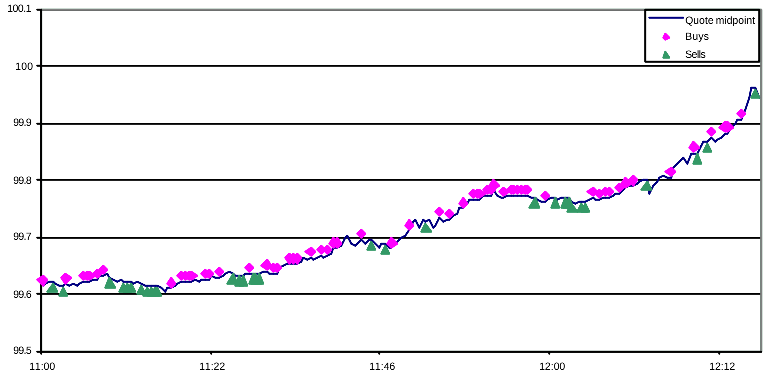
Graph 7. Quotes, trades and bid-ask spreads for the two-year Treasury note: Feb 3, 2000



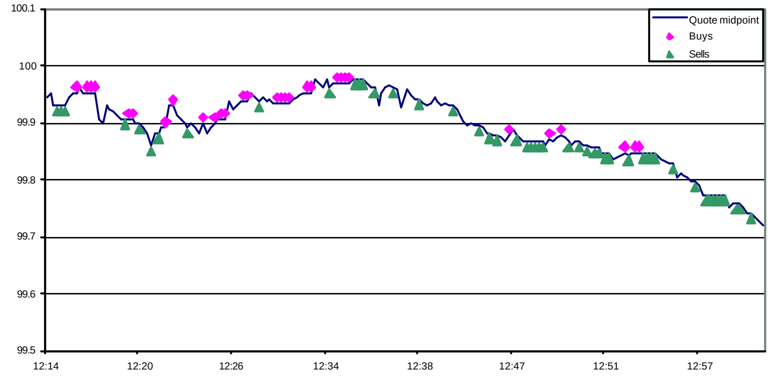
Graph 8a. Quotes and transactions in the 2-year note:
Feb 3, 7 am - 11 am



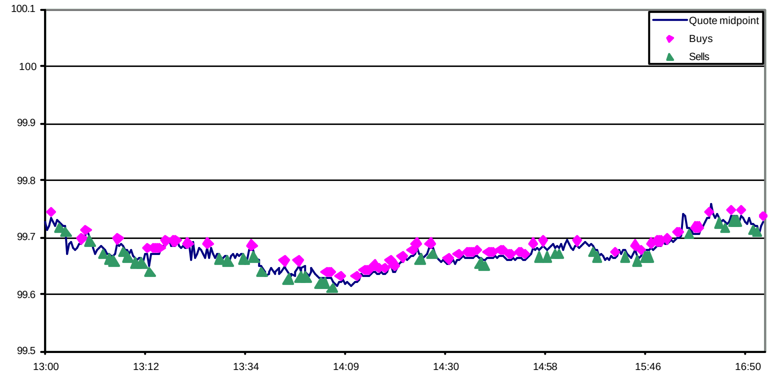
Graph 8b. Quotes and transactions in the 2-year note:
Feb 3, 2000, 11 am - 12:15 pm



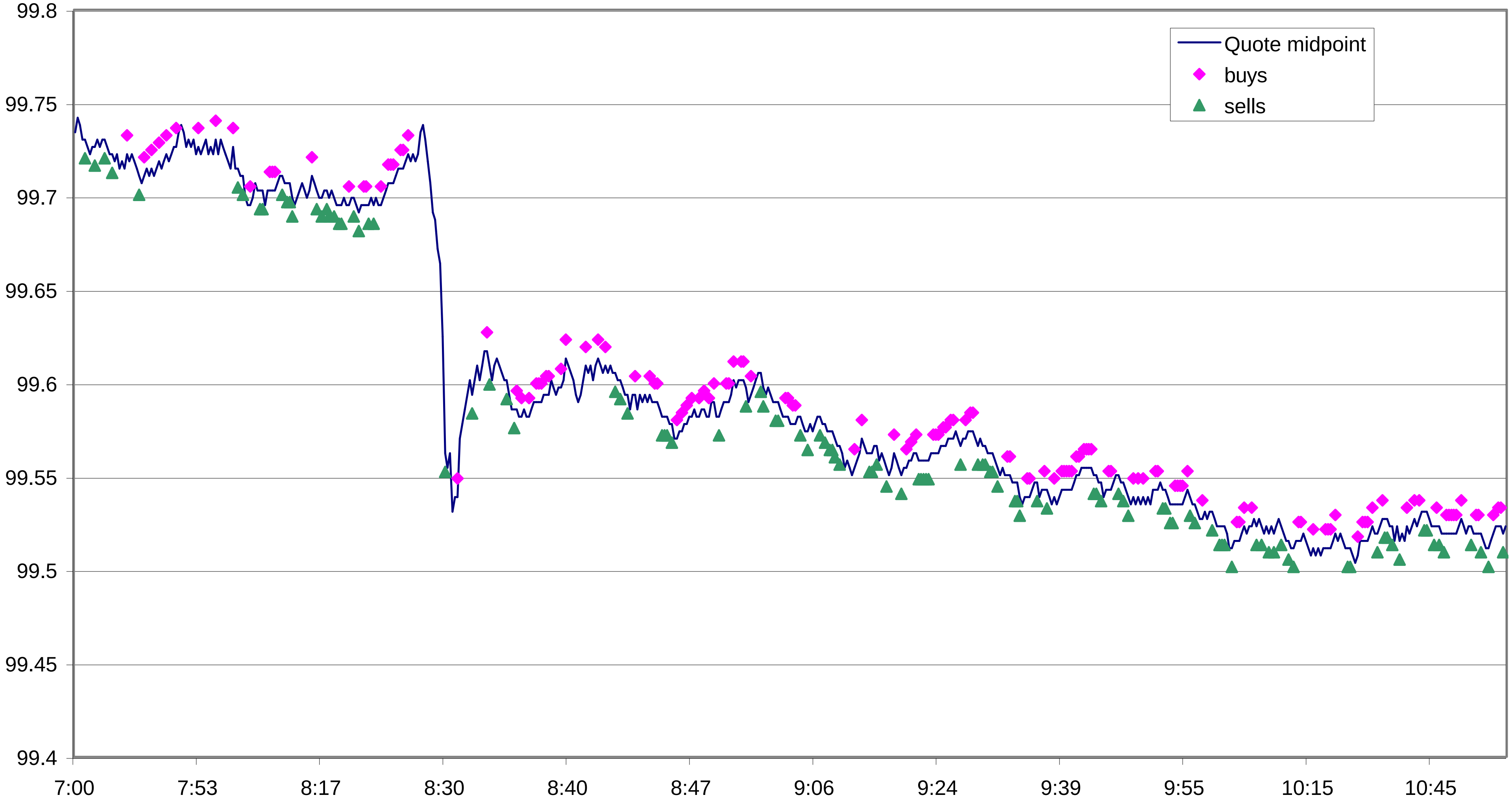
Graph 8c. Quotes and transactions in the 2-year note:
Feb 3, 2000, 12:15 pm -1 pm



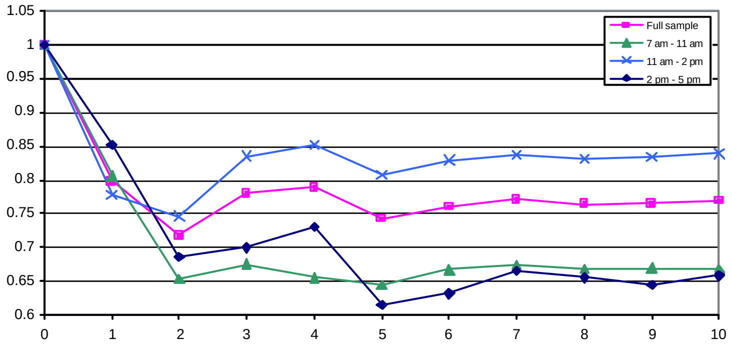
Graph 8d. Quotes and transactions in the 2-year note:
Feb 3, 2000, 1 pm - 5 pm



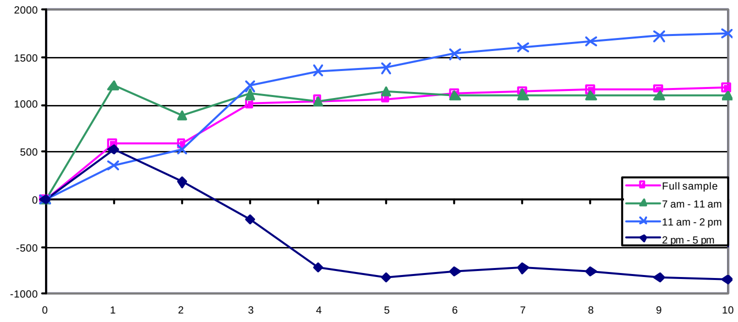
Graph 9. Quotes and transactions in the two-year note:
Jan 28, 2000, 7:00-11:00 am



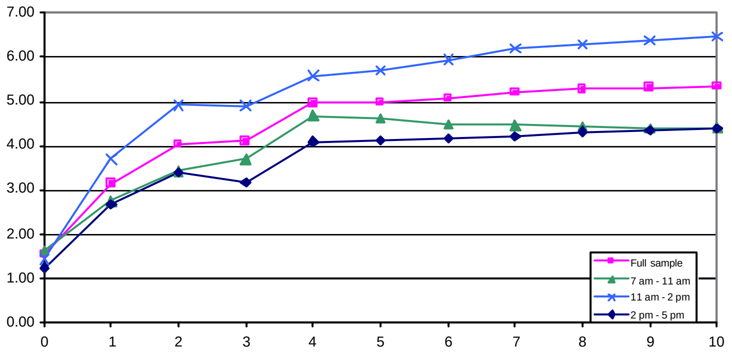
Graph 10a. Cumulative effect on net returns of an additional one unit return: 2 year note, February 3, 2000



Graph 10c. Cumulative effect on net buys of an additional one unit return: 2 year note, February 3, 2000



Graph 10b. Cumulative effect on return of an additional net buy: 2 year note, February 3, 2000



Note: Return figures multiplied by 100000.

Graph 10d. Cumulative effect on net buys of an additional net buy: 2 year note, February 3, 2000