LOCATION MATTERS:

AN EXAMINATION OF TRADING PROFITS

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Abstract

The electronic trading system Xetra of the German Security Exchange provides a unique data source on the equity trades of 756 professional traders located in 23 different cities and 8 European countries. We explore informational asymmetries across the trader population: Traders located outside Germany in non-German speaking cities show lower proprietary trading profit. Their underperformance is not only statistically significant, it is also of economically significant magnitude and occurs for the 11 largest German blue chip stocks. We also examine if a trader location in Frankfurt as the financial center or local proximity of the trader to the corporate headquarter of the traded stock or affiliation with a large financial institution results in superior trading performance. The data provides no evidence for a 'financial center advantage' or 'increasing institutional scale economies' in proprietary trading. However, we find evidence for an information advantage due to corporate headquarter proximity for high frequency (intra-day) trading.

Information and its presumed asymmetric distribution has become an important aspect of financial market theory. But while information heterogeneity of agents is now a common assumption in microstructure models, direct evidence on the scope of such asymmetry is hard to provide.[1] Existing theories offer little guidance as to who should be the better informed investors. Moreover, it has proven difficult to document the existence of any investor group which consistently outperforms the market. Professional mutual fund managers for example appear unable to 'beat' the market.[2]

This paper uses geographic trader locations as proxies for information asymmetry. We examine the proprietary trading profits of 756 professional traders located in 8 European countries with equal access to the electronic trading platform 'Xetra' of the German Security Exchange. The non-discriminatory nature of the trading system make our data particularly suited for assessing the scope of international information barriers in equity trading. The most important result of our analysis is that foreign traders in non-German speaking financial centers have inferior trading profits in their proprietary trading of German stocks. Their relative trading losses are most pronounced for medium frequency (intra-week) and low frequency (intra-quarter) trading. Foreign underperformance is not only statistically significant, it is also of economically significant magnitude and occurs for large blue chip stocks.

The literature on portfolio allocation has given increasing emphasis to the role of international information asymmetry. Gehrig (1993), Kang and Stulz (1997) and Brennan and Cao (1997) all emphasize informational asymmetry as their preferred explanation for the concentration of portfolio investment in domestic assets known as the home equity bias.[3] It is argued that linguistic and cultural borders often coincide with international borders and represent formidable information barriers. Kang and Stulz document that foreign investment in Japanese equity is concentrated in large and

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[1] Direct evidence for asymmetric information is provided by court cases on insider trading. But this gives little insight with respect to the scope of information asymmetries in the outsider population.

[2] See for example Chevalier and Ellison (1999) and Malkiel (1995).

[3] Initial explanations focused on barriers to international investment such as government restrictions on foreign and domestic capital flows, foreign taxes, and variable transaction costs like transaction tarifs and fees. Tesar and Werner (1995) argue against such variable transaction costs, which should decrease asset turnover. They find evidence that foreign portfolio turnover exceeds the turnover of domestic equity. For a recent overview on the home equity bias, see Lewis (1999).

export oriented firms for which the international information asymmetry is presumably smaller. Coval and Moskowitz (1999) show that even US domestic portfolio funds are geographically biased towards the home of the fund. The latter suggests that information asymmetry may have a strictly geographic dimension. Asset proximity can then provide an information advantage even in the absence of cultural and linguistic information barriers. Grinblatt and Keloharju (1999) confirm the intra-country geographic investment bias for Finnish data. But they also identify a separate language bias in the investment behavior of the Swedish language minority. Evidence on asset flows also assigns a role to geography. Portes and Rey (1999) are able to explain a large proportion of global equity flows with a gravity model, in which distance is interpreted as a proxy for information costs.

Common to all these contributions is that information asymmetry is indirectly inferred from asset allocation decisions. But such allocation decisions may reflect investment preference of a purely psychological nature. To learn more about information asymmetry we have to look directly at investment profitability. Coval and Moskowitz (2000) examine the regional investment bias of US mutual funds and find that their local investment generates a higher average return. International evidence is provided by Shukla and Inwegen (1995) based on US and UK mutual funds. Controlling for differential tax treatment, fund expenses and fund objectives, they find that UK fund managers investing in the US underperform relative to their US colleagues. Bacidore and Sofianos (2000) use inventory data on NYSE specialists to document higher information asymmetry and increased adverse selection risk for their market making in non-US stocks relative to US stocks. Other evidence runs against a simple story of a foreign information disadvantage. Grinblatt and Keloharju (2000) calculate profit measures based on daily positions in large Finnish stocks registered by the depository institution. They find that foreign investors outperform the investments of Finnish households. They interpret this as evidence for higher financial sophistication of the foreign investor group. Similarly, Seasholes (2000) finds information advantages for foreign capital flows into Taiwan and Thailand. However, it is difficult to exclude the possibility that domestic investors use off-shore capital in their domestic investment.

Our paper looks at international information asymmetry revealed in the proprietary trading profits of professional traders. For professional traders we can assume a high and similar degree of financial sophistication. They use the same trading system in a similar European time zone. Most importantly, the location of the investment decision maker is clearly identified. We calculate trading profits based on actual transaction data over a 4 month period. This is a rather short time span relative to the long-run data available for mutual funds. But transaction data presents a number of advantages over mutual fund data. First, we can assure data completeness. We do not have any self-selection or survivorship problems since our data set includes all transactions of all traders participating in the electronic limit order book.[4] Second, the data allows us to calculate market to market trading profits exclusive of fees and transaction costs. Third, we can compare the cross-sectional investment behavior of different investors in the same asset. Transaction data thus avoids the difficult problem of comparing investment strategies with different unknown risk profiles based on beta or other factors.

The empirical work is organized around five important hypothesis concerning the information geography of a stock market:

1. *Financial center hypothesis:* Traders located in the German financial center (Frankfurt) enjoy an information advantage over other traders for trading in German equity. Local interaction between traders and financial intermediaries (mostly situated in Frankfurt) improves trading performance.

2. *Joint cultural and geographic distance hypothesis*: Traders outside Germany in non-German speaking locations face an information disadvantage and trade less profitably. The information barrier may be either linguistic or geographic in nature.[5]

3. *Pure geographic distance hypothesis*: Traders outside Germany in the German speaking financial centers of Austria and Switzerland have less information be-

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[4]By contrast the survivorship bias in mutual fund data is likely to vary across different national fund samples. For a discussion of the selection bias in US mutual fund data, see B. Malkiel (1995).

[5]A financial institution in a non-German speaking country could employ a German speaking trader to eliminate linguistic information barriers. We are not able to verify the distribution of German language skills, but assume here that it is on average lower in the foreign trader community.

cause of geographic distance. We assume that linguistic or cultural information barriers do not matter for Austria and Switzerland.

4. *Headquarter proximity hypothesis*: Traders located in local proximity to the corporate headquarter of the traded corporation enjoy a comparative information advantage and show superior trading performance in the 'local stock'. The information advantage results from local interaction with headquarter staff facilitated by geographic proximity.

5. *Institutional economies of scale hypothesis*: Traders in large financial institutions with many traders enjoy an information advantage over those in smaller institutions. First, traders in large institutions may have access to better information sources like databases or in-house research. Second, they may enjoy private information about a larger client order flow.

The remainder of the paper is organized as follows. Section I discusses the institutional framework and the data. The methodology for calculating trading profits is explained in Section II. To distinguish the profitability of market making at intra-day, intra-week and intra-quarter frequencies, we undertake a spectral profit decomposition inspired by Hasbrouck and Sofianos (1993). In the appendix we provides more details on the technical aspects of such a decomposition. The dependent variables are explained in Section III and the regression results are discussed in Section IV. Section V summarizes the results and concludes.

I. Institutional Framework and Data

In June 1997 the German Security Exchange introduced a new order driven electronic trading platform named Xetra. Since then the Xetra system has covered an increasing percentage of German security trading. It allows a decentralized and equal access to the German stock market. By October 1998, approximately 1600 stocks could be traded through over 1300 trading terminals in 11 countries. This wide distribution of trader locations makes Xetra an interesting system for testing the microstructure hypothesis of an asymmetric information geography in equity trading.

The Xetra system supports continuous electronic trading through an open limit order book. The trader identity is kept anonymous in the order book. Both the beginning and the end of the trading day is marked by an auction in each security. Additional intra-day auctions can be triggered by large price movements. The system executes trades based on strict price and time priority.[6]

Our data set on Xetra transactions comes from the Trading Surveillance Unit of the Frankfurt Securities Exchange. It contains all electronic Xetra trades for the 11 German blue chip stocks represented in the Stoxx 50 index over the four months period 31.08.98 to 31.12.98. Figure 1 plots the price history for the 11 stocks. The trading platform Xetra accounted for over 90 percent of the turnover in the German blue chips.[7] Parallel floor transactions or transactions in other exchanges with cross listings are not part of the data set. The transaction data include transaction time, price, volume and an identification number for each of the two traders. Moreover, we know the time of the order placement (as opposed to order execution). This enables us to identify which counterpart initiated the trade.[8] Furthermore, Xetra trades distinguish proprietary (own account) trading from client (agent) trading. This distinction allows us to reconstruct the proprietary trading history for each trader.

An additional advantage of our data set is that we can infer the trader location. The data indicate the institutional affiliation of each trader as a partially encrypted 5 letter code. The last two letters (non-encrypted) of this code indicate the location (Example: xxxFR for Frankfurt).[9] The first 3 letters of the institutional code are encrypted to

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[6] A detailed documentation of the Xetra trading system is available online under http://www.exchange.de. See in particular 'Xetra Market Model, Release 3', (1998).

[7] Only Daimler-Chrysler (DCX) and Deutsche Telecom (DTE) have an important trading volume outside Xetra of approximately 20 percent because of cross listings at the NYSE. Our results are not sensitive to the exclusion of these two stocks.

[8] We refer to trade initiating orders (executed against existing limit orders in the order book) as market orders, even though those orders may formally have a limit price attached to them. The strict time preference of the execution mechanism implies that the limit price of the first placed limit order determines the transaction price. The second limit order works like a market order.

[9] We used a public list of Xetra members (1999) to verify if the institutional code correctly indicates the trader location. The member list states the institutional code as well as the name and telephone number of the head trader. We checked the institutional code against the area code of the trader's telephone number. We found only two errors for the 335 listed members: Bankers Trust International PLC (brtFR) and Credit Agricole Indosuez Cheuvreux Deutschland GmbH (chvFR) indicate a Frankfurt location while the head traders are listed with telephone numbers in London and Paris, respectively.

prevent identification of any particular institution. The institutional code is part of our data set, but not revealed through the order book. The identification of the trader location based on institutional code might be incorrect for those institutions which operate trading terminals in more than one location. This is the case only for 9 out of 335 institutions.[10] For these members the code typically indicates Frankfurt as the trading location even if it is undertaken from a terminal in London or Paris.

In order to have a sufficient number of trading events for each trader in each stock, we restrict our sample to traders who undertake at least 10 proprietary transaction in at least one stock. If a trader undertakes less than 10 proprietary transactions in a particular stock we exclude those transactions from our analysis. This reduces the original sample of 1342 traders in 11 countries to 756 traders in 8 countries.[11] Table I provides a summary statistics for the number of traders and their combined transactions for each of the following three groups: all traders, proprietary traders and sample proprietary traders with at least 10 stock transactions in a single stock. For all 11 stocks proprietary transactions account for 62 percent of the Xetra transactions. Our sample (with the cut-off at 10 trades) covers 99.2 percent of all proprietary trades. The remainder of the paper focuses on this subset of trades.

II. Methodology

The following section explains the methodology and the econometric model specification. Let $s = 1, 2, ...T$ denote the sequence of market transaction in a particular stock and let q_s denote the (signed) inventory change (transaction quantity) for a particular trader. We define the inventory position $\widetilde{Q}_t$ of the trader as the deviation of the accumulated quantity $Q_t = \sum_{s=1}^{t} q_s$ from its long-run average inventory level $\overline{Q} = \frac{1}{T} \sum_{s=1}^{T} Q_s$. Formally, $\widetilde{Q}_t = Q_t - \overline{Q}$. The average inventory $\overline{Q}$ is estimated from the data

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[10] The document Xetra members (1999) lists these 9 institutions separately.

[11] In a previous version of the paper, we set a much higher threshold value of 100 transactions for each account. This reduces the number of profit observation to 1653 for 451 large traders. The higher threshold increases the average quality of the profit observations (since more trades enter on average) at the cost of reducing the cross-sectional sample size. In particular, it reduces the number of profit observations for Austrian and Swiss traders to a very small number. The main results of our paper are robust to this trade-off. We also verify that the excluded proprietary transactions do not generate any selection bias for the profit statistics of the four trader types.

as we do not have any information of the initial inventory level at the beginning of the sample period.[12]

The price change following transaction s is given by $\Delta P_{s+1} = P_{s+1} - P_s$. The market to market profit over a period of T market transactions is calculated as $\sum_{s=1}^{T} \widetilde{Q}_s \Delta P_{s+1}$ and the profit per market transaction follows as

$$\Pi = \frac{1}{T} \sum_{s=1}^{T} \widetilde{Q}_s \Delta P_{s+1}. \tag{1}$$

The inventory management of a trader might in general comprise short-run and long-run inventory cycles. Accordingly, profit might come from covariance based on either short-run or long-run comovements of inventory and price change. Given a data span limited to T observations, long-run comovement over T/N periods can be observed only N times and their measurement involves higher standard errors as T/N becomes large. On the other hand information asymmetries might have their most pronounced profit impact in the long run and appear therefore only in the low frequency comovements of inventory and price changes. This trade-off motivates a decomposition of profit in the frequency domain. Since the trading profit defined in (1) is a cross-product, basic spectral techniques may be applied directly. A Fourier analysis is used to extract the sinusoidal components of the inventory level and the price change at particular frequencies. If the inventory level and the price change are in phase (i.e., have peaks and troughs that match), then the contribution to the cross-product and the trading profit is positive. If both move out of phase, the contribution is negative.

A. Spectral Profit Decomposition

For the purpose of your study it is not useful to report the profit contribution of each single frequency. Instead we group frequencies into three frequency bands. [13] These are the high frequency band representing intra-day profit, the medium frequency band corresponding to the intra-week profit and the low frequency band measuring the profit contribution of weekly to quarterly inventory cycles. The spectral decomposition thus

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[12]See Hansch et al. (1998) for a similar approach. They also show that the initial inventory level Q_0 does not enter the term $\widetilde{Q}_t = Q_t - \overline{Q}$.

[13]This approach is suggested by Engle (1974,1978).

produces (frequency domain) profit subsamples. These subsamples are of different sensitivity to the microstructure of the market and the trading characteristics of a trader. High frequency trading profit for example should be most sensitive to limited market depth or the bid-ask spread, whereas medium and low frequency profits are not.

Formally, the cross-product (1) can be decomposed into its different spectral components represented by the function $Co_{Q\Delta P}(\omega_k)$ called cospectrum.[14] The appendix provides more details on technical aspect of the spectral decomposition. Let L, M, H denote a partition of the (positive) Fourier frequencies $\{\omega_1, ..., \omega_N\}$ into a subset L of low frequencies, a subset M of medium frequencies and a subset H of high frequencies. We can then decompose profit into three elements

$$
\begin{aligned}
\Pi &= 2 \sum_{k=1}^{N} Co_{Q\Delta P}(\omega_k) \\
&= 2 \sum_{k \in L} Co_{Q\Delta P}(\omega_k) + 2 \sum_{k \in M} Co_{Q\Delta P}(\omega_k) + 2 \sum_{k \in H} Co_{Q\Delta P}(\omega_k) \\
&= \Pi^L + \Pi^M + \Pi^H.
\end{aligned}
$$

Since profit is given by the cross-product of the inventory level and price change, scaling the inventory cycle also scales the trading profit by the same factor. To obtain a standardized profit measure across stocks and different inventory cycles, we normalize profit with the standard deviation of the inventory value $V_s = \tilde{Q}_s P_s$ in the respective frequency bands. The variance of the inventory value can also be decomposed in the corresponding frequency bands

$$
Var(V) = Var(V^L) + Var(V^M) + Var(V^H).
$$

The standard deviations of the three variance components represent the inventory risk measure, that is $\mathrm{RISK}^f = \sqrt{Var(V^f)}$. Standardized profits for the three frequency bands $f = L, M, H$ are defined as

$$
\tilde{\Pi}^f = \frac{\Pi^f}{\sqrt{Var(V^f)}}.
$$

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[14] A technical condition for the spectral decomposition is stationarity of the price changes and the inventory process. Price changes are stationary. Financial institutions typically impose trading limits on the proprietary positions of traders. We do not formally test for stationary inventories because of the short data span of only 4 months and the notoriously low power of such tests.

In order to allow for a simple interpretation of standardized profits we scale the measure RISK^f to have a unit mean across all traders in the same stock. The term $\widetilde{\Pi}^f$ therefore expresses the profits of a trader with the average (representative) inventory risk in the respective stock and frequency band.

Since the profit calculation is based only on proprietary trades an important measurement issue is the correct self-identification of the trade type. A trader may for example incorrectly declare client trades as proprietary trades.[15] This implies an inventory measurement error $\widetilde{Q}_s^m$. As a consequence profit is mismeasured by $(1/T)$ $\sum_{s=1}^T \widetilde{Q}_s^m \Delta P_{s+1}$, which becomes zero (for a large T) if the inventory measurement error is uncorrelated with the price change ΔP_{s+1}. Only a correlation of the inventory measurement error with the price change distorts the profit statistics.

B. Econometric Specification

We use a linear regression model to explain standardized profit $\widetilde{\Pi}_{ij}^f$ of trader $i = 1, 2, \ldots N_I$ in stock $j = 1, 2, \ldots N_J$ as a linear function of the locational characteristics $\mathbf{X}_{ij}$ and behavioral characteristics $\mathbf{Y}_{ij}$ summarized in the matrix $\mathbf{Z}_{ij} = (\mathbf{X}_{ij}, \mathbf{Y}_{ij})$. The locational characteristics identify a subset of traders through dummy variables. This implies that we can allow only for random effects μ_i^f within the trader population. The stock specific profitability on the other hand can be captured by a fixed effects α_j^f for each stock. The panel specification is of the form

$$\widetilde{\Pi}_{ij}^f = \alpha_j^f + \beta^f \mathbf{Z}_{ij} + \mu_i^f + \epsilon_{ij}^f, \tag{2}$$

where the errors μ_i^f and ϵ_{ij}^f are mean zero, uncorrelated with itself and each other, uncorrelated with $\mathbf{Z}_{ij}$ and homoscedastic. The time series of the market to market profit (in transaction time) is calculated for each stock specific profit accounts of each trader and separated into the profit contributions of the three frequency bands $f = L, M, H$. If there are N_j traders in stock j, the total number of profit observations is $3 \times \sum_{j=1}^{N_J} N_j$.

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[15] The self-declaration of the trades as client or proprietary trades is (to our knowledge) not subject to external controls by the market authorities, but may be subject to internal controls. The scope of the internal controls is hard to evaluate. We highlight that the trade type is not revealed in the open order book. Strategic motivations for an incorrect declaration can therefore be discarded.

An important requirement for the profit decomposition is to preserve the comparability of the profit measures across traders. We therefore apply a uniform definition of the three frequency bands to all traders based on all transactions in the market, not based on a trader's individual transactions. This produces identical and comparable spectral frequency bands for all traders independent of the number of their transactions. The low frequency band comprises the 10 lowest frequencies corresponding to inventory cycles of more than one week (intra-quarter). The medium frequency band is chosen to capture the profitability of intra-week cycles with the frequencies 11 to 100. The high frequency band captures the intra-day cycles with the remaining frequencies 101 to $T/2$.

Table II provides a summary statistics for profit, standardized profit and inventory risk. The average profit (standardized profit) per market transaction in the high, medium and low frequency bands are DM 0.04 (0.29), DM 0.12 (0.35) and DM 1.72 (1.44) per market transaction. The standard deviations are given by DM 3.25 (1.97), DM 7.22 (4.19) and DM 40.09 (15.64), respectively. Scaling the trading profit by the inventory risk (RISK) decreases the standard deviation of the profit distribution and reduces the role of profit outliers in our regression analysis. Our sample group of proprietary traders as a whole earned trading profits relative to other market participants. The high dispersion of profits and losses illustrates the considerable risk involved in proprietary trading. We also note that the standard deviation of the profit per transaction increases considerably as we consider the medium and low frequency bands. This corresponds to a similar increase in the average inventory risk in the medium and low frequency bands.

III. Determinants of Trading Profits

The dependent variables $\mathbf{Z}_{ij} = (\mathbf{X}_{ij}, \mathbf{Y}_{ij})$ require a detailed discussion. We distinguish exogenous locational characteristics $\mathbf{X}_{ij}$ for each trader and behavioral variables $\mathbf{Y}_{ij}$ controlling for heterogeneity of trading behavior across the trader population.

A. Locational Trader Characteristics

The locational characteristics

$$\mathbf{X}_{ij} = (\text{FRANKFURT}_i, \text{FOREIGN}_i, \text{SWISS}_i, \text{PROXIMITY}_{ij}, \text{SIZE}_{ij})$$

are chosen to reflect a potential information asymmetry across the trader population. Each variable corresponds to a test of one of the five hypothesis spelled out in the introduction. The dummy variable FRANKFURT_i takes on the value of one for traders in Frankfurt and zero otherwise. This variable measures the locational advantage for being in Germany's financial center and physical site of the stock market. The role of financial centers in information processing has been emphasized by Gehrig (1998). He argues that local interaction between financial intermediaries in financial centers is crucial for the evaluation of equity [16] (financial center hypothesis). A second consideration for including a Frankfurt dummy is the concentration of foreign bank subsidiaries and their traders in Frankfurt. If foreign bank subsidiaries have an informational disadvantage relative to native institutions, the Frankfurt dummy may capture this opposite effect. Unfortunately, our data does not allow us to distinguish foreign bank subsidiaries from German financial institutions. Table III shows the distribution of profit accounts by stock and trader location. Frankfurt based traders manage 58 percent of all profit accounts. Taking this high percentage of Frankfurt based trading as evidence of the 'financial center hypothesis' would be misleading. It might simply reflect persistence of a geographic pattern which required physical presence (on the floor) prior to the existence of a decentralized trading technology.

The variables FOREIGN_i and SWISS_i are dummies for two groups of traders located outside Germany. Foreign traders might face reduced access to the relevant information sources on German stocks. This argument has been made by Kang and Stulz (1997) to justify the home equity bias. Brennan and Cao (1997) accept the same foreign-home information asymmetry to explain equity flow behavior. The dummy FOREIGN_i marks all trader locations where German is not an important or official language. It therefore captures cultural and linguistic information barriers in addition

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[16]See also Choi et al. (1986,1996) and Jaeger et al. (1992) who study the allocation of bank branches in different financial centers. Local branch representation according to their view presents an important information linkage.

to a geographic distance effect. The locations include Amsterdam, Copenhagen, London, Paris and Vasa (Finland). This trader group present 5.9 percent of the profit observations. The dummy variable $SWISS_i$ includes the German speaking locations in Austria and Switzerland (Lausanne, Linz, Vienna, Zug, Zurich). Only 62 profit observations (or 1.4 percent of all observations) concern a trader in this group. The dummy $SWISS_i$ measures a 'pure geographic distance effect' under the assumption that a common language eliminates linguistic information barriers.

The fourth locational dummy variable is $PROXIMITY_{ij}$. It indicates a distance of less than 100 kilometers between the trader location and the headquarters of the company j for corporations located outside Frankfurt.[17] Proximity to the corporate headquarter might provide an advantage if information diffusion has a local geographic dimension and if inside information of corporate headquarters is important as opposed to information produced outside by financial intermediaries. We call this the 'headquarter proximity hypothesis'. The regional dispersion of the corporate headquarters helps us to distinguish it from the 'financial center hypothesis'. Of the 11 stocks in our sample 9 have corporate headquarters outside Frankfurt (Table III). Altogether 7 percent of the profit observations involve traders dealing from a corporate headquarter location other than Frankfurt.

The variable $SIZE_{ij}$ measures the number of active traders in stock j which work for the same financial institution as trader i. This variable captures possible economies of scale in market making within a financial institution. A trader in a large bank with numerous other traders might have access to better information either about the fundamental value of the asset or the client order flow. Institutional size varies from 1 to 48 active traders within the same institution with an average of 11.8 traders (Table II). Foreign traders have on average fewer colleagues in the same institution who trade the same asset. This can be inferred from Table IV, which provides summary statistics for the different locational subsamples. A foreign trader in a non-German speaking location has on average only 2.9 colleagues trading the same asset.

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[17]Traders in proximity to a one of the two Frankfurt headquarters (DBK, LHA) are not counted as proximity traders in order to avoid any colinearity problem with the Frankfurt dummy.

B. Behavioral Trader Characteristics

The behavioral trader characteristics

$$\mathbf{Y}_{ij} = (\text{CLIENT}_{ij}, \text{INTENSITY}_{ij}, \text{INITIATION}_{ij}, \text{RISK}_{ij}^T)$$

are our control variables. The dummy variable CLIENT_{ij} marks traders who do additional client trading parallel to their proprietary trading. Parallel client trading might create moral hazard problems for the trader. Kampovsky and Trautmann (1999) have argued that frontrunning of client orders exists in the Xetra market. Hillion and Suominen (1998) find evidence that traders in the Paris stock market sacrifice proprietary trading profits in price manipulation in order to give client the impression of a better client account execution. We control for any effect of parallel client trading on proprietary trading profits by introducing a dummy. Approximately 15 percent of the trader population undertake parallel client trading. For the subsample of Austrian and Swiss traders this percentage is higher with 31 percent (Table IV).

The variable INTENSITY_{ij} denotes the number of trades undertaken by the trader i in stock j over the sample period. It captures a potential linkage between market making profit and trading intensity. A trader might specialize in trading a single stock (or a group of stocks) and thereby concentrate his trading profit in the respective account. Our trader sample shows considerable variation in trading intensity. The most active trader registered 9129 trades relative to an average of 199 trades. The number of trades per profit account averages 388 for the foreign traders in non-German speaking locations and only 158 for the Austrian and Swiss traders. Traders with little transaction activity are less frequent in the subsample of traders in non-German speaking locations. But their volume per trade does not exceed the average of the trader population.

The average trade direction is measured by INITIATION_{ij}. It indicates the percentage of transactions in stock j initiated by trader i. We refer to initiated trades as market orders. A high percentage of market orders implies a more active inventory management as opposed to a passive liquidity provision through bid-ask spread adjustment. The average trade initiation rate is 49 percent. Its standard deviation is large

at 20 percent indicating large heterogeneity in the trading behavior. The Swiss and Austrian traders stand out as liquidity providers with a trade initiation rate of only 27 percent (Table IV). However, this subsample is based on only 11 traders.

Although our profit measure is scaled by inventory risk, we include RISK_{ij}^T as an additional control variable. The justification is straightforward. Given a limited supply elasticity, large inventory cycles are likely to have a price impact. Therefore, trading profits cannot (ceteris paribus) increase linearly in trade size. The standardized profit measure neglects this non-linearity. Including the variable RISK_{ij} controls for the profit loss due to limited market depth encountered by traders with large inventory cycles. Table IV shows that foreign traders in non-German speaking locations manage profit accounts with a higher standard deviation for the account value.

The three variables SIZE_{ij},INTENSITY_{ij},RISK_{ij}^T are characterized by loptokurtosis. This suggests the logarithmic transformation given by $X_{ij}^{\nabla} = \log(X_{ij}/\overline{X}_j)$ relative to the sample mean $\overline{X}_j$ as a more suitable regressor. We also demean the trade initiation rate and denote it $\text{INITIATION}_{ij}^{\nabla}$. The intercept term α_j^f has now an economic interpretation. It states the average profit in stock j per market transaction of a representative proprietary trader located in Germany but outside Frankfurt and without proximity advantage.

IV. Estimation Results

The following section presents the regression results. We use a GLS random effect estimator for unbalanced data (Baltagi, 1995). The profit equation (2) is estimated separately for the three frequency bands. Tables V provides the parameter estimates for high, medium and low frequency profits. We also repeat the regression for total profits (over all frequency bands). These results do not require any frequency decomposition. The panel data could have a more complex error structure than assumed in our regression model. We therefore report ordinary standard errors (in brackets) and the bootstraped standard errors (in parentheses).[18] Generally, bootstraping does not result in very different standard errors on the coefficients.

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[18]Bootstraped standard erros were obtained from 1000 draws of 756 traders with replacement.

Each profit equation is estimated with and without the behavioral control variables. Including control variables increases the overall R-square from 0.021 to 0.142 (high frequency band), 0.013 to 0.017 (medium frequency band) and 0.011 to 0.014 (low frequency band). The explanatory power of our independent variables is therefore very modest. This should be expected if the return expectations of the traders have a very low correlation with realized returns irrespective of location. We start our discussion with the results on intra-day trading.

A. Short-Run Trading Profits

For the baseline specification (Table V, column (1)) shows highly significant point estimates for the constant term and the PROXIMITY dummy. The constant term measures the average profit per market transaction in German marks (DM) for a German benchmark trader. A point estimate of 0.605 for a representative stock with approximately 30,000 quarterly market transactions implies a quarterly profit from intra-day trading of DM 18,000 per profit account with at least 10 transactions. Not reported are the fixed effects, which capture excess profit in a particular stock. They are small and generally insignificant. The sum of the constant term and any stock specific fixed effect is always positive. Proprietary intra-day trading is therefore profitable for the representative trader in all 11 stocks.[19] The point estimate for the PROXIMITY dummy is 0.322 and significant on a 1 percent level. This implies that geographic proximity to the corporate headquarter increases the quarterly trading profits from intra-day trading in the respective stock by approximately DM 10,000. The negative coefficients for the FRANKFURT and FOREIGN dummies indicate a lower average profit for Frankfurt traders and foreign traders in non-German speaking locations. However, their losses relative to the representative German benchmark trader are not statistically significant.

We augment the baseline specification to include behavioral controls (Table V, column (2)). The overall R-square increases substantially to 0.142. The point estimate for the foreign underperformance increases to −0.486 and is now statistically significant on a 5 percent level. It implies a quarterly relative loss from intra-day trading of

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[19] We employ the term profitability here in the sense of gross profitability of the propriatory trading activity only. Ignored are all costs which support the trading activity.

approximately DM $15,000$ per account. If a representative foreign trader deals in 20 different stocks, his relative quarterly loss from intra-day trading alone amount to DM $300,000$. The proximity dummy is again significant at a 1 percent level. This indicates a role for geography if distance to corporate headquarters is very small. For the Swiss and Austrian traders we do not find a statistically significant underperformance for intra-day trading. We interpret this as evidence against the 'pure geographic distance hypothesis'. The (negative) institutional size effect from the benchmark regression disappears if we introduce behavioral controls. High frequency trading profits indicate no competitive advantage or disadvantage for traders in large financial institutions. Neither do intra-day profits reveal any 'financial center advantage' for traders located in Frankfurt.

Inspection of the point estimates of the behavioral control variables gives further insights. Parallel client trading is not significantly correlated with intra-day profits. But the control variables for the number of trades (INTENSITY$^\nabla$), the average trade direction (INITIATION$^\nabla$) and the inventory risk (RISK$^\nabla$) are all highly significant with t-values above 10. More frequent trading in a stock is positively correlated with the profitability of the respective account. A large number of trades might indicate trading specialization in a particular stock. The variable with the highest statistical significance level is INITIATION$^\nabla$. Traders relying on market orders in their inventory management have lower intra-day profits since trade initiation implies a short-run loss of the bid-ask spread. The coefficient on inventory risk (RISK$^\nabla$) is also negative. Higher inventory variation correlates with lower standardized profits. The control variable RISK$^\nabla$ captures trading costs due to limited market depth.

In order to check the robustness of our estimation results, we eliminate the one percent profit outliers. The same qualitative results are obtain. In particular the underperformance of traders in non-German speaking locations and the overperformance of proximity traders is confirmed at similar significance levels for the reduced sample. The results were also robust to the inclusion of volume (turnover) per trade or total volume as additional control variables.

Finally, we highlight the estimates for the error components. Including controls, the

random effect for the trader has a standard deviation of $\sigma(\text{Trader}) = 0.901$ relative to the individual effect for each observation of $\sigma(\text{Obs.}) = 1.547$. Residual trading profits in different stocks are correlated if trading is undertaken by the same trader. But the variance effect for individual stocks is much larger than the variance of the trader random effect. This suggests important diversification benefits for a trader who spreads his market making activity over many securities.

A. Medium and Long-Run Trading Profits

We now turn to the medium and long-run trading profits. Columns (3)(4) and (5)(6) in Tables V report the respective estimation results. Highly significant for the medium frequency profit are the constant term and the dummy coefficient for traders in non-German speaking locations (FOREIGN). Intra-week proprietary trading is again profitable for the representative German trader. But it is on average loss making for the foreign traders. The relative profit shortfall for traders in non-German speaking locations is statistically significant with a t-statistics of 4.9. Medium frequency profits therefore show clearer evidence for foreign underperformance than is evident in high frequency trading. The point estimate of -1.432 indicates that the average relative loss of foreign traders increases by a factor 3 as we move from intra-day profits to intra-week profits. We conclude that information disadvantage of foreign traders has a larger impact on their intra-week trading results than on their intra-day trading results. For Austrian and Swiss traders (SWISS) we obtain a profit shortfall with a 3 percent significance level, but only if we include the behavioral control variables. This underperformance of the Austrian and Swiss traders is weak evidence for the pure geographic distance hypothesis. Institutional size shows a weak negative correlation with profitability even after inclusion of the control variables. There is no evidence for increasing institutional scale economies in proprietary trading. Neither do we find any support for the financial center hypothesis. The data indicates in fact a moderate underperformance of traders located in Frankfurt.[20]

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[20]One explanation for this result is the strong representation of foreign banks branches in Frankfurt. They might have an informational disadvantage relative to native institutions and bias the Frankfurt coefficient downwards. This interpretation correspond to evidence by Shukla and Inwegen (1995).

For the low frequency profit, the constant term is again positive, but not statistically significant. The low sampling rate for low frequency covariances implies a very noisy profit statistics illustrated by the large error component estimates. The estimated overall standard deviation of the residual errors is 7 times higher than for the high frequency profit. Nevertheless, the point estimate for traders in non-German speaking locations (FOREIGN) is negative at a 1 percent significance level under both inclusion and exclusion of the control variables.[21] All other locational characteristics show no statistically significant correlation with low frequency profit. In particular the headquarter proximity dummy is insignificant for both intra-week or intra-quarter profits. Hence, local proximity seems to provide only very short-lived information advantages. An example for such a short-lived advantage might be insider information immediately prior to a public announcement.

The coefficient estimates for the control variables provide additional insights. The number of trades (INTENSITY$^\nabla$) is uncorrelated with medium and low frequency profits. Similarly, the coefficient for the inventory risk variable (RISK$^\nabla$) is insignificant for medium and low frequency profits. This is intuitive because longer inventory cycles moderate losses on the bid-ask spread because market depth is larger in the long run. Finally, the trade initiation rate (INITIATION$^\nabla$) is negatively correlated with high and medium frequency profits, but positively correlated with low frequency profits. This implies that traders relying on market orders recover some of their high and medium frequency losses by low frequency profits. The evidence reveals a market microstructure in which traders with better information submit market order. These traders lose on the spread in the short-run, but gain in the long-run.

In order to measure overall performance of the trader types we also look at the regression for total profit provided in columns (7) and (8) of Table V. The point estimates for the constant term and the FOREIGN dummy are again highly significant. Total

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They find that foreign managed mutual funds underperform in the US equity market relative to their US counterparts. Unfortunately, our data does not allow further disaggregation of Frankfurt-based traders.

[21]The results are again not generated by observational outliers. Again we eliminate the 1 percent highest and lowest profit observation and find that the results are qualitatively robust. Inclusion of volume per trade or total volume as additional control variables did not qualitatively alter the regression outcome either.

foreign underperformance (over all 3 frequency bands) amounts to almost DM 8 per market transaction. For a stock with 30,000 quarterly transactions we obtain a quarterly relative proprietary trading loss of approximately DM 240,000 per account. This is a surprisingly high locational disadvantage for foreign based traders. We can only speculate on the exact source of the information disadvantage for the foreign trader community. The major commercial information networks Reuters and Bloomberg transmit messages in both German and English. Multilingual networks should therefore tend to eliminate information asymmetry. Instead, some traders cite oral communication networks, while others mention private newsletters circulating among traders. More comprehensive microdata on individual traders is need to distinguish between different explanations.

V. Conclusions

We examine the proprietary trading profits of 756 traders located in 8 European countries with equal access to the electronic trading system Xetra of the German Security Exchange. We examine their trading profits of the 11 German blue chip stocks in the Stoxx 50 index and undertake a spectral profit decomposition into intra-day, intra-week and intra-quarter profits. The results can be summarized as follows:

1. Traders located in the financial center Frankfurt do not outperform traders in other German locations. This suggests that local interaction between traders is not crucial to trading performance.

2. Traders in non-German speaking locations show a statistically significant underperformance for intra-day, intra-week and intra-quarter trading profits. Their total underperformance is economically large and averages approximately DM 8 per market transaction and stock for all proprietary profit accounts with at least 10 trades per trimester. This implies an average quarterly underperformance of approximately DM 240,000 per actively traded blue chip stock. Most of this average underperformance can be attributed to the lower trading frequencies and is therefore very hard to detect given the large overall dispersion of individual

19

trading profits and the small number of trader observations within any financial institution.

3. We find some evidence for an underperformance of Austrian and Swiss traders in medium frequency (intra-week) trading. Overall the evidence for their underperformance is weak. But this might be explained by a lack of statistical power due to the small number of Austrian and Swiss traders. Hence, we hesitate to discard the 'pure geographic distance hypothesis' in a favor of exclusively linguistic and cultural information barriers.

4. Traders located near corporate headquarters of the traded company outperform other traders in high frequency trading of the respective stock. Medium and low frequency trading shows no effect of local proximity on trading profits. A plausible explanation is that local traders find it easier to establish and maintain a privileged relationship with a company insider who might communicate information shortly before it becomes public. However, this proximity advantage is quantitatively small and by definition restricted to the subset of stocks with local headquarters.

5. We find weak evidence for decreasing economies of scale on the institutional level if size is measured by the number of traders actively trading for the same financial institution. We exclude increasing informational scale economies in proprietary trading. In other words, large financial institutions do not have more profitable proprietary traders.

Of these results the most important contribution of our paper is the evidence for a large profit differences for the proprietary trading of domestic versus foreign traders in non-German speaking locations. This result is obtained for all three spectral dimensions and robust to various controls for behavioral trader heterogeneity. The presented evidence concerns the information asymmetry among professional traders dealing in very large and liquid blue-chip stocks. The revealed information asymmetry is likely to present only a lower bound on similar effects for smaller stocks. Exploring this

information asymmetry and its source with more comprehensive data is an interesting task for future research.

Appendix: Spectral Decomposition

This appendix provides a brief technical overview of the spectral decomposition for the profit time series into high, medium and low frequency profits. Let X_t and Y_t represent two time series of length T and assume X_t has a zero mean. We develope the case in which T is an odd integer and define positive Fourier frequencies $\omega_k = 2\pi k/T$ for $k = 1, ...N$ and $N = (T-1)/2$. The Fourier transform of X_t is given by

$$J_x(\omega_k) = \frac{1}{T}\sum_{t=1}^{T} X_t e^{-i\omega_k t},$$

where $i = \sqrt{-1}$ and $J_x(\omega_k)$ represents Fourier components of the series X_t at frequency ω_k. Furthermore, we defined coefficients α_k^x and β_k^x for the series X_t as

$$\alpha_k^x = \frac{1}{T}\sum_{t=1}^{T} X_t \cos(\omega_k t) \text{ and } \beta_k^x = \frac{1}{T}\sum_{t=1}^{T} X_t \sin(\omega_k t)$$

to express the Fourier components as $J_x(\omega_k) = \alpha_k^x - i\beta_k^x$. Similarly, we obtain the Fourier components of Y_t as $J_y(\omega_k) = \alpha_k^y - i\beta_k^y$. We can recover the time series representation using the inverse transform

$$X_t = 2\sum_{k=1}^{N} \alpha_k^x \cos(\omega_k t) + \beta_k^x \sin(\omega_k t),$$

which expresses each data point in terms of the N frequency components. The cross-product of X_t and Y_t can be restated as

$$\Pi = \frac{1}{T}\sum_{t=1}^{T} X_t Y_t = 2\sum_{k=1}^{N}(\alpha_k^x \alpha_k^y + \beta_k^x \beta_k^y) = 2\sum_{k=1}^{N} J_x(\omega_k)\overline{J_y(\omega_k)},$$

where the overbar denotes the complex conjugation (see H Hamilton, 1994, page 272). This equivalent representation reveals the contribution of the various frequency components to the cross-product. These frequency components are the sample equivalent

of the so-called cospectrum at frequency ω_k,

$$Co_{XY}(\omega_k) = J_x(\omega_k)\overline{J_y(\omega_k)}.$$

We can now partition the set of frequencies $\{\omega_1, ..., \omega_N\}$ into different frequency bands to capture their respective contribution to the cross-product. For a partition into a

low frequency band L, a medium frequency band M and a high frequency band H, we obtain the decomposition

$$\Pi = 2 \sum_{k \in L} Co_{XY}(\omega_k) + 2 \sum_{k \in M} Co_{XY}(\omega_k) + 2 \sum_{k \in H} Co_{XY}(\omega_k) = \Pi_L + \Pi_M + \Pi_H.$$

The market to market profit definition (1) has a cross-product with one lagged variable. Shifting the original sequence for the price change by one observation allows a simple computation.

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Table I:
Trader Population

Summary statistics for the number of traders and their combined trades for 11 German stocks in the Stoxx 50 index for the period 31.08.98 to 31.12.98. Proprietary traders trade on their own account and sample proprietary traders undertake at least 10 proprietary trades in the respective stock. The 11 German stocks in the Stoxx 50 index are Allianz (ALV), Bayer (BAY), Deutsche Bank (DBK), Daimler-Chrysler (DCX), Deutsche Telecom (DTE), Lufthansa (LHA), Mannesmann (MNN), Metro (MEO), RWE (RWE), Siemens (SIE) and Veba (VEB).

Stock	All Traders		Proprietary Traders		Sample Prop. Traders	
	Number	Trades	Number	Trades	Number	Trades
ALV	930	116984	540	74736	374	74112
BAY	995	119472	569	70028	414	69404
DBK	1102	198050	653	130827	499	130180
DCX	1126	223954	669	132212	515	131574
DTE	925	125508	546	77626	405	77082
LHA	920	90190	498	49158	326	48470
MEO	870	82526	487	48811	326	48183
MNN	947	139132	542	85801	395	85137
RWE	817	68228	467	43143	285	42358
SIE	1012	150480	589	96676	428	96066
VEB	927	95888	532	59906	359	59147
Total	1342	1410412	883	868924	756	861713

Table II:
Summary Statistics

Locational dummy variable are introduced for traders in Frankfurt (FRANKFURT), for foreign traders in non-German speaking locations (FOREIGN), for foreign traders in German speaking locations of Austria and Switzerland (SWISS) and for traders located within a 100 kilometer distance of the corporate headquarter (PROXIMITY) in case the corporation is headquartered outside Frankfurt. SIZE indicates the number of traders within the same institution trading the same stock. CLIENT indicates if a trader undertakes client trading parallel to his proprietary trading. INTENSITY gives the number of proprietary trades in the same stock. INITIATION indicates the percentage of initiated trades (market orders). Trading profits per market transaction, standardized profits per market transaction and the standard deviation of the inventory value (RISK) are stated for the high frequency (H), medium frequency (M) and low frequency (L) band as well as for total profits in all frequency bands (T).

Variable	Minimum	Maximum	Mean	Std. Dev.
FRANKFURT	0	1	0.58	0.49
FOREIGN	0	1	0.06	0.23
SWISS	0	1	0.01	0.12
PROXIMITY	0	1	0.07	0.25
SIZE	1	48	11.8	12.3
CLIENT	0	1	0.15	0.36
INTENSITY	10	9129	199	415
INITIATION	0	1	0.49	0.19
RISK (H) $\times 10^{-3}$	0.40	18079	266	578
RISK (M) $\times 10^{-3}$	0.14	51286	859	1816
RISK (L) $\times 10^{-3}$	0.05	313338	3423	9415
RISK (T) $\times 10^{-3}$	0.66	318022	3565	9597
Profit (H)	-71.91	57.13	0.04	3.25
Profit (M)	-93.48	139.86	0.12	7.22
Profit (L)	-375.61	1475.24	1.72	40.09
Profit (T)	-411.77	1503.52	1.89	41.79
Stand. Profit (H)	-11.29	21.53	0.29	1.97
Stand. Profit (M)	-23.15	24.51	0.35	4.19
Stand. Profit (L)	-56.48	61.20	1.44	15.64
Stand. Profit (T)	-80.75	145.12	2.64	18.20

Table III:
Profit Accounts by Stock and Traders Location

We report the number of proprietary profit accounts with at least 10 transactions by stock and trader location. Distinguished are traders located in Frankfurt (FRANKFURT), foreign traders outside Germany in an non-German speaking location (FOREIGN), foreign traders outside Germany in a German speaking location of Austria and Switzerland (SWISS) and traders located within a 100 kilometer distance to the corporate headquarter of the stock company (PROXIMITY) in case it is different from Frankfurt. The proximity dummy is always set to zero for traders in Frankfurt to avoid any colinearity problem with the Frankfurt dummy.

Stocks	Corporate Headquarter	Trader by Location				All Accounts
		FRANKFURT	FOREIGN	SWISS	PROXIMITY	
ALV	Munich	215	22	5	32	374
BAY	Leverkusen	238	22	6	44	414
DBK	Frankfurt	274	32	8	0	499
DCX	Stutgart	282	30	10	20	515
DTE	Bonn	244	24	5	33	405
LHA	Frankfurt	199	17	5	0	326
MEO	Cologne	197	18	3	36	326
MNN	Düsseldorf	233	19	6	40	395
RWE	Essen	188	15	2	24	285
SIE	Munich	236	32	7	36	428
VEB	Düsseldorf	209	22	5	36	359
Obs.		2515	253	62	301	4326

Table IV:
Subsample Statistics

Summary statistics for the profit accounts of 4 distinct trader groups are provided. We distinguish traders located in Frankfurt (FRANKFURT), foreign traders outside Germany in an non-German speaking location (FOREIGN), traders outside Germany in a German speaking location of Austria and Switzerland (SWISS) and traders located within a 100 kilometer distance to the corporate headquarter of the stock company (PROXIMITY) in case it is different from Frankfurt. The sample mean, median and standard deviation are reported for the following variables: SIZE indicates the number of traders within the same institution trading the same stock. CLIENT is a dummy which marks a trader undertakes client trading parallel to his proprietary trading. INTENSITY measure the number of proprietary trades in the same stock. INITIATION indicates the percentage of initiated trades (market orders). RISK (T) measures the standard deviation of the account value over all three frequency bands. We also report volume per trade, total profits and standardized total profits.

| Variable	Traders by Location				All Traders
	FRANKFURT	FOREIGN	SWISS	PROXIMITY	
SIZE					
Mean	14.4	2.9	2.2	8.3	11.8
Median	8.0	2.0	2.0	4.0	7.0
Std. Dev.	13.9	2.0	0.8	8.8	12.3
CLIENT					
Mean	0.09	0.13	0.31	0.18	0.15
Median	0.00	0.00	0.00	0.00	0.00
Std. Dev	0.29	0.33	0.46	0.39	0.36
INTENSITY					
Mean	197	388	158	175	199
Median	76	183	51	43	66
Std. Dev.	404	529	222	392	415
INITIATION					
Mean	0.50	0.50	0.27	0.47	0.49
Median	0.50	0.50	0.24	0.47	0.49
Std. Dev.	0.19	0.16	0.25	0.20	0.20
RISK (T) $\times 10^{-3}$					
Mean	3767	5566	1578	3168	3565
Median	1420	2204	341	669	1138
Std. Dev.	8048	11251	4448	18600	9597
Volume per Trade					
Mean	200	171	117	191	195
Median	183	157	88	170	177
Std. Dev.	103	90	98	98	102
Profit (T)					
Mean	0.08	−1.88	3.17	6.40	1.89
Median	0.51	−0.32	0.09	0.24	0.32
Std. Dev	33.06	46.43	15.72	89.44	41.79
Stand. Profit (T)					
Mean	2.37	−3.32	2.74	3.82	2.64
Median	2.85	−2.17	3.22	3.44	2.89
Std. Dev.	18.09	18.48	17.83	18.23	18.20
Obs. per Trader	5.82	5.85	5.61	6.34	5.77
Obs.	2515	253	62	302	4326

Table V:
Determinants of Trading Profit

The propriatory trading profits of 756 traders in 11 German stocks in the Stoxx 50 index are pooled to obtain 4326 individual profit accounts with at least 10 transactions each. A spectral decompostion is used to separate total profits of each account to intra-day (high frequency) profit, intra-week (medium frequency) profit and intra-quarter (low frequency) profit. We scale (standardize) profits by the standard deviation of the account value in the respective frequency band. Standardized trading profits are regressed on fixed effects for individual stocks (not reported) and locational dummies for various subsets of traders. We distinguish Frankfurt based traders (FRANKFURT), foreign traders in non-German speaking locations (FOREIGN), traders in the German speaking locations of Switzerland and Austria (SWISS) and traders in local proximity to the respective corporate headquarter (PROXIMITY). The variable SIZE measures the number of traders in the same financial institution as the trader under consideration. The behavioral control variables are a dummy for parallel client trading (CLIENT), the trader's total number of trades in the respective stock (INTENSITY), the percentage of market orders among these trades (INITIATION), and a measure of the standard deviation of the inventory value in the respective stock (RISK). Variables marked ($^{\triangledown}$) are in logs and/or demeaned. We use a GLS random effect estimator for unbalanced panels with random effects for each trader. Reported are ordinary standard errors (in brackets) and bootstraped standard errors (in parentheses). Significance on a 5 percent (*) and 1 percent level (**) is indicated.

	High Freq. Profit		Med. Freq. Profit		Low Freq. Profit		Total Profit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.605**	0.601**	1.064**	1.136**	0.797	0.973	3.908**	4.341**
	(0.120)	(0.115)	(0.240)	(0.245)	(0.905)	(0.923)	(1.049)	(1.069)
	[0.107]	[0.108]	[0.218]	[0.219]	[0.795]	[0.840]	[0.889]	[0.917]
FRANKFURT	−0.169	−0.025	−0.402**	−0.400*	0.164	−0.067	−1.354	−1.076
	(0.112)	(0.100)	(0.154)	(0.160)	(0.614)	(0.634)	(0.732)	(0.749)
	[0.091]	[0.864]	[0.149]	[0.153]	[0.568]	[0.599]	[0.682]	[0.684]
FOREIGN	−0.292	−0.486*	−1.486**	−1.432**	−3.664**	−3.858**	−7.970**	−7.786**
	(0.232)	(0.202)	(0.305)	(0.309)	(1.230)	(1.240)	(1.472)	(1.471)
	[0.276]	[0.256]	[0.355]	[0.344]	[1.242]	[1.282]	[1.598]	[1.616]
SWISS	0.318	−0.142	−1.070	−1.298*	−1.433	−0.552	−2.602	−3.896
	(0.422)	(0.366)	(0.564)	(0.569)	(2.261)	(2.266)	(2.699)	(2.682)
	[0.306]	[0.300]	[0.491]	[0.533]	[1.162]	[1.213]	[1.673]	[1.702]
PROXIMITY	0.322**	0.312**	−0.183	−0.212	−1.595	−1.602	−0.474	−0.651
	(0.122)	(0.116)	(0.274)	(0.274)	(1.030)	(1.030)	(1.193)	(1.189)
	[0.133]	[0.121]	[0.231]	[0.231]	[0.937]	[0.930]	[1.114]	[1.090]
SIZE$^{\nabla}$	−0.118*	−0.017	−0.170**	−0.143*	−0.346	−0.351	−0.998**	−0.618*
	(0.047)	(0.041)	(0.064)	(0.066)	(0.256)	(0.261)	(0.305)	(0.309)
	[0.040]	[0.0358]	[0.067]	[0.070]	[0.234]	[0.251]	[0.291]	[0.296]
CLIENT		−0.060		−0.425*		−0.140		−1.112
		(0.107)		(0.189)		(0.744)		(0.875)
		[0.099]		[0.187]		[0.749]		[0.805]
INTENSITY$^{\nabla}$		0.567**		0.028		−0.090		1.320**
		(0.033)		(0.070)		(0.270)		(0.314)
		[0.053]		[0.087]		[0.289]		[0.364]
INITIATION$^{\nabla}$		−2.332**		−1.076**		4.307**		−2.225
		(0.160)		(0.330)		(1.270)		(1.480)
		[0.165]		[0.375]		[1.339]		[1.656]
RISK$^{\nabla}$		−0.387**		−0.082		0.125		−1.483**
		(0.029)		(0.060)		(0.232)		(0.270)
		[0.031]		[0.073]		[0.265]		[0.331]
Observations	4326	4326	4326	4326	4326	4326	4326	4326
Traders	756	756	756	756	756	756	756	756
$\overline{R}^2$ Within	0.015	0.088	0.005	0.008	0.009	0.012	0.010	0.014
$\overline{R}^2$ Between	0.033	0.256	0.020	0.021	0.022	0.029	0.032	0.047
$\overline{R}^2$ Overall	0.021	0.142	0.013	0.017	0.011	0.014	0.020	0.029
σ(Trader)	1.113	0.901	0.412	0.420	2.978	2.888	4.020	3.824
σ(Obs.)	1.610	1.547	3.986	3.983	14.928	14.907	17.050	17.023
σ(Total)	1.957	1.790	4.008	4.005	15.223	15.184	17.518	17.447

Figure 1. The price history of 11 German blue chip stocks in the Stoxx 50 index over the four months period 31.08.98 to 31.12.98. These stocks are Allianz (ALV), Bayer (BAY), Deutsche Bank (DBK), Daimler-Chrysler (DCX), Deutsche Telecom (DTE), Lufthansa (LHA), Mannesmann (MNN), Metro (MEO), RWE (RWE), Siemens (SIE) and Veba (VEB).
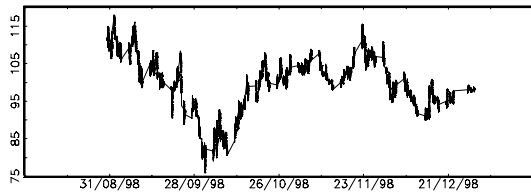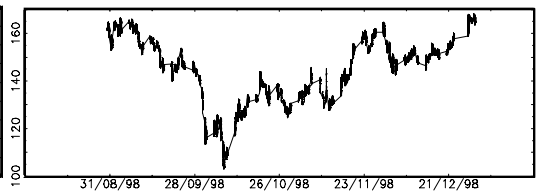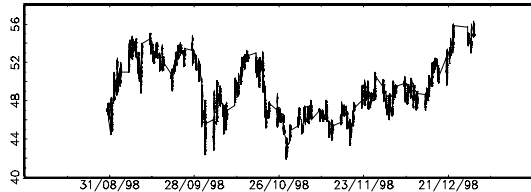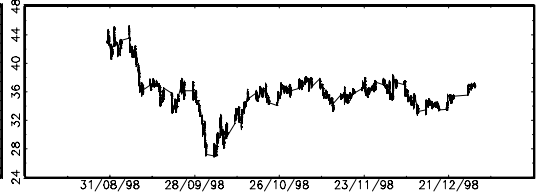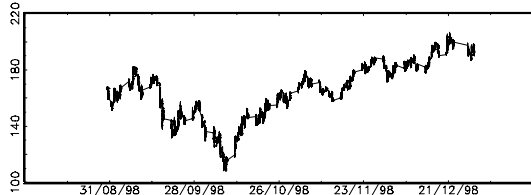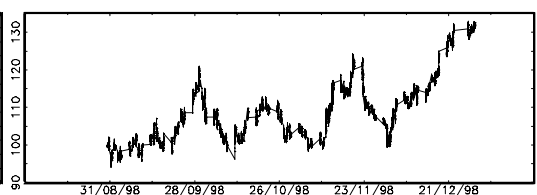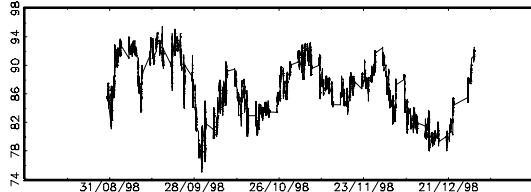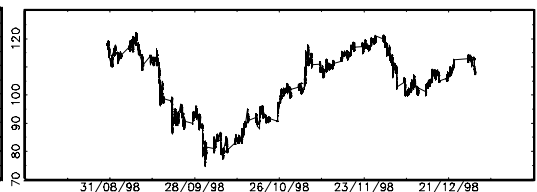
Allianz (ALZ)
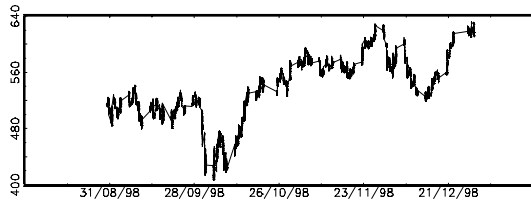
Bayer (BAY)
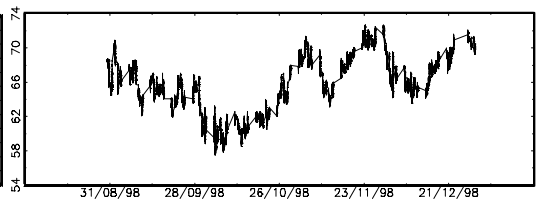
Deutsche Bank (DBK)

Daimler−Chrysler (DCX)

Deutsche Telecom (DTE)

Lufhansa (LHA)

Mannesmann (MNN)

Metro (MEO)

RWE (RWE)

Siemens (SIE)

Veba (VEB)