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ABSTRACT

Information and Geography: Evidence from the German Stock Market*

Xetra, the electronic trading system of the German Security Exchange, provides a unique data source on the equity trades of 451 large 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 profits. Their under-performance is not only statistically significant, it is also of economically significant magnitude and occurs for large blue chip stocks. We also examine if a trader location in Frankfurt as the financial centre 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 centre advantage'. But the data show decreasing 'institutional scale economies' and an information advantage due to corporate headquarter proximity for high frequency (intra-day) trading.

JEL Classification: F20, F21, G10, G14, G15
Keywords: trading profits, geography, home bias

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NON-TECHNICAL SUMMARY

Financial markets are trading places for information. Better information is rewarded by trading profits. While in the last 20 years economists have recognised the role of information asymmetries between agents, their scale and scope in financial markets remain an open question. Occasional court verdicts on insider trading point to information advantages (typically for corporate insiders), but give little indication as to how information is distributed in the wider financial community of outsiders.

We investigate empirically how information advantages are related to the geographic location of a trader. Do traders located in foreign countries under-perform relative to domestic traders when it comes to proprietary trading of domestic equity? If yes, are language barriers or their absence (for example between Germany, Austria and Switzerland) key to performance differences? Do traders located at a physical site of the stock market (like Frankfurt) do better for DAX stocks than traders in regional centres (like Munich)? Do traders in Munich outperform traders in Frankfurt when it comes to trading a stock that has its corporate headquarter in Munich? Do larger institutions with many traders outperform small institutions due to scale economies in the production of information?

These are questions of great practical interest as new trading technologies provide non-discriminatory market access from any geographical location. But these questions are also related to what may determine the distribution of equity stakes in the larger investment community. Empirical research has established that the portfolios of domestic equity investors tend to be heavily biased towards domestic equity: a phenomenon known as the ‘home equity bias’. This behaviour implies that investors forgo the benefits of a better risk diversification of a truly international portfolio. Initial explanations for this phenomenon focused on barriers to international investment such as government restrictions on foreign and domestic capital flows, taxes, tariffs and fees. But recent evidence shows that even within the US investors tend to prefer shares in local companies. Local informational advantages emerge therefore as a prime explanation.

But the ultimate test for superior information is superior trading performance, not simply portfolio bias in favour of more familiar stocks. In line with this idea, we use new microeconomic data on more than 1300 traders using the electronic trading system Xetra of the German Security Exchange. We concentrate on the 451 largest traders that do at least 100 transactions in any of the 11 randomly selected stocks over a 4-month period. These large traders are located in 23 different cities and 8 different European countries. In spite of this wide geographic distribution all traders enjoy the same fair access to electronic trading platform. The absence of institutional discrimination makes Xetra data ideal for tracing asymmetric information within the trader community.

We measure risk-adjusted profits at different horizons and distinguish high frequency trading based on intra-day profits, medium-frequency profits based on weekly profits and low-frequency profits based on monthly profits. This distinction is useful since our data spans only 4 months and intra-day profits are observed more frequently than weekly or monthly profits. The high frequency profits are therefore a more powerful statistical measure of information asymmetries than low frequency ones.

A linear regression model is used to explore the role of location for the individual trading profits at the three frequencies. We find that a trader location in Frankfurt does not provide a comparative profit advantage. This is evidence against an informational 'financial centre advantage'. By contrast, a location in a foreign non-German speaking city holds a strongly negative correlation with profitability and this foreign profit shortfall is documented for intraday, weekly and monthly profits. We note that foreign under-performance is not only statistically significant, but also of considerable economic magnitude. The relative quarterly profits loss of a foreign trader averages 1.2 million DM per account with more than 100 proprietary transactions. Foreign traders in the German speaking countries (Austria and Switzerland) do not show significantly lower profits. This suggests that it is linguistic and cultural barriers, rather than geographic distance *per se*, that hold the key to the informational advantage identified in the data.

To test for a local proximity advantage we mark all traders that are at a distance of less than 100 kilometres from one of the 9 corporate headquarters outside Frankfurt (two stock companies are headquartered in Frankfurt) and test if their trading performance in this particular stock is superior. We find that local proximity is positively correlated with intra-day profits, indicating local information advantages. But we cannot find a statistically significant correlation at lower frequencies. The data show no evidence that large financial institutions have a better trading performance than smaller ones. 'Informational scale economies' do not seem to exist in proprietary equity trading. In order to verify that these results are robust we develop various behavioural control variables, like the number of transactions of a trader, the percentage of trade initiations or the risk of the portfolio. Including these additional variables in our regression does not change any of the previous results.

Our research confirms that geography is important in determining how information is distributed across market participants. In particular, the profit difference between domestic and foreign traders appears to be very pronounced. These results suggest that market-making in equity markets might be less of a ‘global business’ than often asserted.

1 Introduction

Financial markets are trading places for information. Better information is rewarded by trading profits. Information and its presumed asymmetric distribution has therefore taken center stage in economic theory of financial markets.[1] But while informational heterogeneity of agents has become a common assumption in our microstructure models, direct evidence on the scope of such asymmetries is much harder to provide.[2] This is the objective of our analysis of equity trades. We examine the proprietary trading profits of 453 large traders located in 8 European countries with equal access to the electronic trading platform of the German Security Exchange. The most important result is that foreign traders in non-German speaking financial centers have inferior trading profits both for high frequency (intra-day) trading as well as for lower frequencies (intra-week and intra-quarter). Their 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 asymmetries. Gehrig (1993), Kang and Stulz (1994) and Brennan and Cao (1997) all emphasize informational asymmetries 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 US foreign investment in Japanese equity is concentrated in large and export oriented firms for which transpacific informational asymmetries are 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 asymmetries may even have a strictly regional geographic dimension. Asset proximity can then provide an informational advantage even in the absence of cultural and linguistic information barriers. In economic geography information aspects have been related to the emergence of financial centers. Gehrig (1998) argues that public information provided by information technology and local interaction in the form

[1] The keywork 'asymmetric information' generates more than 2000 entries in the database Econlit.

[2] 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.

[3] Initial explanation 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).

of 'face to face communication' are complements. A financial center facilitates the latter. Choi et al. (1986,1996) and Jaeger et al. (1992) study the allocation of bank branches in different financial centers. Local branch representation according to their view presents an important information linkage.

Common to all these contributions is that informational asymmetries are indirectly inferred from asset allocation decisions. But such allocation decision may be influenced by persistent investment habits dating from past capital restrictions. Or they may reflect investment preference of a purely psychological nature. The concentration of the home bias in small, nontraded goods-producing firms may reflect a non-financial preference for local investment. Allocation decision may therefore be a poor indicator of information asymmetries.

We argue that a better test for asymmetric information are different returns under equal market access. Some evidence for systematic return variations is provided by Shukla and Inwegen (1995) for the US and UK mutual fund industry. Controlling for differential tax treatment, fund expenses and fund objectives, they find that UK fund managers investing in the US underperformed relative to their US colleagues. In line with Shukla and Inwegen, we infer informational asymmetries from trading profitability. But we use direct transaction data to identify trading profits. This approach presents a number of advantages over the mutual fund data used by Shukla and Inwegen. First, we can assure data completeness. We do not have any adverse selection or survivorship problems since our data set includes all transactions of all system traders in a particular asset. By contrast the survivorship bias in mutual fund data is likely to vary across different national fund samples.[4] Second, the data is net of fees and transaction costs. Third, all market participants have symmetric and equal access to the electronic trading platform and operate in the same European time zone. We can exclude any discrimination based on trading technology within the trader population. Our data is therefore particularly suited for tracing information asymmetries.

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 informational advantage over other traders for trading in German equity. Local interaction between traders and financial intermediaries (mostly situated in Frankfurt) improves trading performance.

[4]For a discussion of the selection bias in US mutual fund data see B. Malkiel (1995).

2. *Joint cultural and geographic distance hypothesis*: Traders outside Germany in non-German speaking locations face informational 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 because 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 advantages 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 2 discusses the institutional framework and the data. The methodology for calculating trading profits is explained in Section 3. To distinguish the profitability of market making at intra-day, intra-week and intra-quarter levels, we undertake a spectral profit decomposition inspired by Hasbrouck and Sofianos (1993). Their paper also provides more detailed discussion of the technical aspects. The dependent variables are explained in Section 4 and the regression results are discussed in Section 5. Section 6 summarizes the results and concludes.

2 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

[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.

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.

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. At any time there is only one Xetra market price.[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 11 DAX blue chip stocks over the four months period 31.08.98 to 31.12.98.[7] During this period Xetra accounted for over 75 percent of the turnover in the DAX blue chips. Parallel floor transactions 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 prevent identification of any particular institution. The identification of the trader location based on institutional

[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]The 11 randomly chosen DAX 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).

[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.

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, we restrict our sample to traders who undertake at least 100 proprietary transaction in a particular stock. This reduces the original sample of 1342 traders in 11 countries to 451 traders in 8 countries. 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 large proprietary traders with at least 100 stock transactions. For all 11 stocks proprietary transactions by large traders account for more than 50 percent of all Xetra transactions. The remainder of the paper focuses on this subset of transactions.

3 Methodology

The following section explains the methodology and the econometric model specification. Let $s = 1, 2, ...T$ denote the sequence of 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 as we do not have any information of the initial inventory level at the beginning of the sample period.[11]

The price change following transaction s is given by $\Delta P_s = P_{s+1} - P_s$ and the price change relative to the long-run average $\Delta\overline{P}$ as $\Delta\widetilde{P}_s = \Delta P_s - \Delta\overline{P}$. Profits from market making over a period of T market transactions are calculated as $\sum_{s=1}^{T} \widetilde{Q}_s \Delta\widetilde{P}_s$ and the profits per market transaction follows as the covariance of inventory and price changes

$$\overline{\Pi} = \frac{1}{T}\sum_{s=1}^{T} \widetilde{Q}_s \Delta\widetilde{P}_s.$$

The inventory management of a trader might in general comprise short-run and long-run inventory cycles. Accordingly, profits 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

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

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

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. This consideration suggest a spectral separation of market making profits into short-run, medium-run and long-run profits. The high frequency profit spectrum can be expected to be the most sensitive measure of information asymmetries.

3.1 Spectral Profit Decomposition

Expected profits as covariance can be decomposed into its different spectral components represented by the function $C_{Q\Delta P}(\omega)$ called cospectrum. Let L, M, H denote a partition of the frequency interval $[0, \pi]$ into low frequencies $L = [0, a)$, medium frequencies $M = [a, b)$ and high frequencies $H = [b, \pi]$. We can then decompose expected profits into three elements

$$\begin{aligned} \Pi &= 2\int_0^{\pi} C_{Q\Delta P}(\omega)d\omega \\ &= 2\int_0^{a} C_{Q\Delta P}(\omega)d\omega + 2\int_a^{b} C_{Q\Delta P}(\omega)d\omega + 2\int_b^{\pi} C_{Q\Delta P}(\omega)d\omega \\ &= \Pi^L + \Pi^M + \Pi^H. \end{aligned}$$

Since the expected profits is given by the covariance of inventory and price changes, scaling the inventory cycle or the price level by a factor k also scales the expected profits by the same factor. To obtain a standardized profit measure across stocks and different inventory cycles, we normalize expected profits with the standard deviation of the inventory value $V_s = \widetilde{Q}_s P_s$ in the respective frequency bands. The variance of the inventory value can be decomposed according to

$$\begin{aligned} Var(V) &= 2\int_0^{\pi} C_{VV}(\omega)d\omega \\ &= 2\int_0^{a} C_{VV}(\omega)d\omega + 2\int_a^{b} C_{VV}(\omega)d\omega + 2\int_b^{\pi} C_{VV}(\omega)d\omega \\ &= Var(V^L) + Var(V^M) + Var(V^H). \end{aligned}$$

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

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

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.

3.2 Measurement Issues

Since our profit calculations are 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 a percentage λ of client trades as proprietary trades.[12] Or he may sell a certain proportion of his proprietary trades to clients. Both cases imply a proportional inventory measurement error given by $\varepsilon_s = \lambda\widetilde{Q}_s$, by which the correct inventory $\widetilde{Q}_s^c$ deviates from the inferred inventory $\widetilde{Q}_s$.

Any hidden constant inventory outflow to clients (at current market prices) or any incorrect declaration of (a constant percentage of) client trades as proprietary trades alters the inventory level to $\widetilde{Q}_s^c = (1-\lambda)\widetilde{Q}_s$. It is straightforward to verify that our standardized profit measure $\widetilde{\Pi}^f$ is unchanged in the latter case.

3.3 Econometric Specification

We use a linear regression model to explain standardized profits $\widetilde{\Pi}_{ij}^f$ of trader $i = 1, 2, ...N_I$ in stock $j = 1, 2, ...N_J$ as a function of the locational characteristics $\mathbf{X}_{ij}$ and behavioral characteristics $\mathbf{Y}_{ij}$ summarized in the matrix $\mathbf{Z}_{ij} = (\mathbf{X}_{ij}, \mathbf{Y}_{ij})$.

Given a small number of stocks and a large number of traders N_j in each stock, we choose a model with fixed effects α_j^f for each stock and random effects μ_i^f for each trader. The panel specification takes on the form:

$$\widetilde{\Pi}_{ij}^f = \alpha_j^f + \beta^f \mathbf{Z}_{ij} + \mu_i^f + \epsilon_{ij}^f. \tag{1}$$

The standardized profits are calculated for each 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 $3 \times \sum_{j=1}^{N_J} N_j$. 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 50. The high frequency band captures the intra-day cycles with the remaining frequencies 51 to $T/2$.

[12] 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.

Table II provides a summary statistics for profits, standardized profits and inventory risk. The average profit (standardized profit) per market transaction in the high, medium and low frequency bands are DM 0.09 (0.78), DM 0.16 (0.52) and DM 3.79 (3.68) per market transaction. The standard deviations are given by DM 5.21 (4.48), DM 11.48 (8.43) and DM 64.30 (32.1), respectively. Scaling the trading profits by the inventory risk decreases the standard deviation of the profit distribution and reduces the role of profit outliers in our regression analysis. Our sample group of large 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.

4 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.

The locational characteristics

$$\mathbf{X}_{ij} = (\mathrm{DFRA}_i, \mathrm{DFOR1}_i, \mathrm{DFOR2}_i, \mathrm{DPRO}_{ij}, \mathrm{SIZE}_{ij})$$

are chosen to reflect information asymmetries across the trader population. The dummy variable DFRA_i distinguishes whether the trader location is Frankfurt ($\mathrm{DFRA}_i = 1$) or elsewhere ($\mathrm{DFRA}_i = 0$). 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 (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 native financial institutions. Finally, we note that a small number of financial institutions trade from London and Paris with an institutional code which identifies them (incorrectly) as based in Frankfurt. This may also counterbalance a financial center effect if foreign traders underperform.

Table III provides summary statistics on the locational dummy variables. Frankfurt accounts for more than 50 percent of the large proprietary traders in any stock. 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 $\mathrm{DFOR1}_i$ and $\mathrm{DFOR2}_i$ 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 (1994) to justify the home equity bias. Brennan and Cao (1997) accept the same foreign-home information asymmetry to explain equity flow behavior. The dummy $\mathrm{DFOR1}_i$ marks all trader locations where German is not an important or official language. It therefore captures cultural and linguistic information barriers in addition to a geographic distance effect. The locations include Amsterdam, Copenhagen, London, Paris and Vasa (Finland). This trader group present 8.8 percent of our profit observations. The dummy variable $\mathrm{DFOR2}_i$ includes the German speaking locations in Austria and Switzerland (Lausanne, Linz, Luzern, Vienna, Zug, Zurich). Only 24 profit observations (or 1.3 percent of all observations) concern a trader in this group. The dummy $\mathrm{DFOR2}_i$ measures a 'pure geographic distance effect' under the assumption that a common language eliminates linguistic information barriers.

A fourth locational dummy variable is DPRO_{ij}. It indicates a distance of less than 100 km between the trader location and the headquarters of the company j for corporations located outside Frankfurt.[13] 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 decentralized industrial structure of Germany helps us to distinguish it from the 'financial center hypothesis'. Of the 11 DAX stocks 9 have corporate headquarters outside Frankfurt (Table III). Altogether 6 percent of our 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

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

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 11.29 traders (Table II).

The behavioral trader characteristics

$$\mathbf{Y}_{ij} = (\mathrm{DCLT}_{ij}, \mathrm{TRNU}_{ij}, \mathrm{TRIN}_{ij}, \mathrm{RISK}_{ij})$$

are our control variables. The dummy variable DCLT_{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. These effects are controlled for by the dummy for parallel client trading. Approximately 9 percent of the trader population undertake parallel client trading (Table II).

The variable TRNU_{ij} denotes the number of trades undertaken by the trader i in stock j over the sample period. TRNU_{ij} captures a potential linkage between market making profits and trading intensity. A trader might specialize in trading a single stock (or group of stocks) and thereby concentrate his trading profits in a few accounts. Our trader sample shows considerable variation in trading intensity. The most active trader registered 9129 trades relative to an average of 473 trades.

The average trade direction is measured by TRIN_{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 49.6 percent. Its standard deviation is large at 17 percent indicating large heterogeneity in the trading behavior.

Although our profit measure is scaled by inventory risk, we include RISK_{ij}^{f} 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}^{f} controls for the profit loss due to limited market depth encountered by traders with large inventory cycles.

The three variables SIZE_{ij},TRNU_{ij},RISK^f_{ij} are characterized by kurtosis with long right tails. This suggests the logarithmic transformation $X'_{ij} = \log(X_{ij}/\overline{X}_j)$ relative to the sample mean $\overline{X}_j = \sum_{i \in N_j} X_{ij}$ as a more suitable regressor. We also adjust the mean for the initiation rate and define $\mathrm{TRIN}'_{ij} = \mathrm{TRIN}_{ij} - \overline{\mathrm{TRIN}}_j$. The intercept term α^f_j has now an economic interpretation. It is the average profit in stock j per market transaction of a representative large proprietary trader located in Germany but outside Frankfurt and without proximity advantage to the company j headquarter.

5 Estimation Results

The following section presents the regression results. We use a maximum likelihood procedure for the iterative estimation of the error components.[14] The three equations are estimated separately for the three frequency bands. The separate estimation is suggested by the fact that we did not find any evidence for significant cross-equation correlation in the residuals. Tables IV, V and VI provide the parameter estimates for the high, medium and low frequency profits, respectively. For completeness we also provide results for total profits (over all frequency bands) in Table VII.

Each equation is estimated with and without the behavioral control variables. Including control variables increases the adjusted R^2 from 0.055 to 0.222 (high frequency band), 0.016 to 0.030 (medium frequency band) and 0.032 to 0.034 (low frequency band). The explanatory power of our variables is therefore very modest below the intra-day frequencies. We start our discussion with the results on intra-day trading.

5.1 Short-Run Trading Profits

For the baseline specification without controls, the statistically significant variables are the fixed effects and most importantly the foreign trader dummy DFOR1 and the proximity dummy DPRO. The fixed effect coefficients denote the profit per market transaction in German marks (DM) of a German benchmark trader outside Frankfurt and without proximity advantage. They are significantly positive for 6 of the 11 stocks. A coefficient estimate of 0.75 on a stock with approximately 50,000 quarterly market transaction implies a quarterly profit

[14] A Gauss algorithm for unbalanced panel data developed by Parke Wilde was used for the estimation. Trading activity with at least 100 transactions ranged from 1 to 11 sample stocks per trader with an average of 3.7 stocks.

from intra-day trading of DM 37,500. The coefficient for the dummy DFOR1 indicates a substantially lower profit for foreign traders. A coefficient estimate of -1.48 translates into an average quarterly trading loss of DM 74,000 in each stock with 50,000 quarterly transactions. If we assume that a foreign trader is active (with more than 100 transactions) in 15 stocks we calculate an average relative quarterly loss of 1.1 million German marks. We consider this a surprisingly high locational disadvantage for foreign-based traders in non-German speaking locations. A second important result is the positive correlation between high frequency profits and headquarter proximity. The local proximity advantage is of similar economic magnitude. The baseline regression shows insignificant coefficients for the locational dummies for Frankfurt (DFRA) and foreign German speaking locations (DFOR2).

We augment the baseline specification to include behavioral controls. The adjusted R^2 increases substantially. Again we find no evidence of a 'financial center advantage' for traders located in Frankfurt. The baseline result of lower intra-day trading profits for foreign traders in non-German speaking locations is robust to the inclusion of the behavioral controls. The same conclusion also hold with respect to the local proximity effect, which remains significant at a 1 percent level. However, the dummy for Austrian and Swiss traders is now negatively correlated with profits with a p-value of 0.034. This is evidence for the 'pure geographic distance hypothesis'. The (negative) institutional size effect disappears if we introduce behavioral controls. Trader affiliation with a large institution does not seem to provide a competitive advantage in high frequency trading.

Inspection of the coefficients of our behavioral control variables gives further insightful results. Parallel client trading (DCLT) is not significantly correlated with high frequency profits. Parallel client trading does not seem to provide any advantage for the trader's proprietary trading. The control variables for the number of trades (TRNU'), the average trade direction (TRIN') and the inventory risk (RISK') are all highly significant with t-values around 10. An increase (by one standard deviation) of the number of trades in a stock from the average 473 trades to 1076 trades is associated with an increased intra-day trading profit of DM $1.58 \times \log(2.28) = 0.56$ per market transaction. This correlation has different plausible interpretations. First, it may measure trading specialization. The market making profits are concentrated in fewer stocks. Second, the number of trades may be a proxy for private information flows to a trader. The variable with the highest statistical significance level is TRIN'. A high trade initiation rate is related to lower intra-day trading profits.

Note also that this effect is economically significant. A trader initiation rate 17 percent (1 standard deviation) higher than the average corresponds to a DM $8.55 \times 0.17 = 1.45$ loss per transaction in the market. Figure 1 provides a graphical illustration of this correlation. Traders relying on market orders in their inventory management have lower intra-day profits. The coefficient on inventory risk (RISK*) is negative. Higher inventory risk correlates with lower risk adjusted profits. This effect most likely captures trading costs due to limited market dept. If we increase the inventory volume and risk by one standard deviation relative to representative trader, the high frequency profit per transaction in the market falls by DM $1.48 \times \log(2.55) = 0.60$.

Finally, we report the estimates for the error components. Including controls, the random effect for the trader has a variance of $\sigma_\mu^2 = 3.22$ relative to the individual effect for each observation of $\sigma_\epsilon^2 = 10.23$. Residual trading profits in different stocks are correlated if the trading is undertaken by the same trader. But the variance effect for individual stocks is three times larger than the variance of the trader random effect. This suggests important diversification benefits for the trader who spreads his market making activity over many securities.

5.2 Long-Run Trading Profits

Tables V and VI provide the respective parameter estimates for the medium and low frequency bands. Highly significant are the fixed effects and the dummy for foreign traders in non-German speaking locations (DFOR1).

The coefficient estimates for the fixed effects are considerably higher compared to the intra-day profit regression. Higher average market making profits in the lower spectrum are not surprising given the considerable inventory risk associated with long-run inventory cycles. The evidence for the financial center hypothesis is again negative. In fact we find weak evidence of underperformance of traders located in Frankfurt.[15] The 'joint cultural and geographic distance hypothesis' measured by the dummy DFOR1 is confirmed for both intra-week and intra-quarter profit measures with t-values of 4.37 and 3.28, respectively. This

[15] 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). They find that foreign managed mutual funds underperform in the US equity market relative to their US counterparts. A second explanation is the incorrect measurement of some foreign trading from London and Paris as Frankfurt-based trading. Foreign underperformance is therefore showing up as a negative Frankfurt dummy. Unfortunately, our data does not allow further disaggregation of Frankfurt-based traders.

result is again robust to the inclusion of the behavioral controls. The measured locational disadvantage for foreign traders increases by a factor 3 for intra-week and by a factor 8 for intra-quarter profits. Information asymmetries are of particular economic relevance for low frequency inventory cycles. This makes information asymmetries a more plausible explanation for the home equity bias. The group of traders located in Austria and Switzerland (DFOR2) shows lower medium frequency profits, but only at 10 percent significance level after inclusion of behavioral control. Low frequency profits show no evidence for a 'pure geographic distance hypothesis'. But we should be careful here because of the limited sample size of only 24 profit observations in this group. Considerably more observations enter into the proximity dummy. However, the regressions in Tables V and VI show no role for local proximity as a determinant of long-run trading profits. This contrasts with our finding for the intra-day trading profits. Institutional size (SIZE$'$) is negatively correlated with long-run profitability and significantly so for the medium frequency band. Controlling for behavioral trader characteristics does not affect the result. This suggest decreasing returns to scale and presents evidence against the 'institutional scale economy hypothesis'.

Examination of the coefficients of our control variables also provides interesting insights. The number of trades (TRNU$'$) is uncorrelated with medium and low frequency profits. The coefficient for the inventory risk variable (RISK$'$) is less significant for the medium and insignificant for the low frequency profits. This is intuitive because longer inventory cycles imply lower losses on the bid-ask spread and market depth is larger in the long run. Finally, the trade initiation rate (TRIN$'$) is correlated with lower profits in the medium frequency band but higher profits in the low frequency band. This implies that traders relying on market orders recover some of their high and medium frequency losses by low frequency profits. This evidence corresponds to classical microstructure models (Copeland and Galai (1993) and Glosten and Milgrom (1985)), in which some market orders come from agents with better fundamental information. These agents lose on the spread in the short-run, but gain in the long-run.

5.3 Limit versus Market Order Profitability

The profitability of limit orders is essential to the viability of an order driven system like Xetra which depends on limit order submission for its liquidity supply. Previous studies by Harris and Hasbrouck (1993) and Handa and Schwartz (1996) document the profitability of limit orders for individual transactions. The comparison of limit order profitability with market order profitability is evaluated based on the hypothetical delayed execution as a market order in case a limit order remained unfilled.[16] Our inventory reconstructions allows us to study the actual account profitability of limit order versus market order strategies without strong auxiliary assumptions.

Limit order submission can earn the bid-ask while facing an adverse selection risk from better informed traders. The positive short-term profit contribution of a passive limit order strategy is evident in the negative correlation between the percentage of market orders ($TRIN'$) and high and medium frequency profits in Tables IV and V. Better informed traders on the other hand may prefer to submit market orders if their information advantage may be short-lived or the limit order submission risks non-execution. Their information advantage about fundamentals is reflected in the positive correlation of the percentage of market orders and low frequency profits (Table VI).

In a competitive market equilibrium we expect the bid-ask spread to adjust so that expected (risk adjusted) total profits from posting limit orders should be equal to the profit of traders relying on market orders. To examine this proposition we repeat the regression analysis with a standardized measure of total profits comprising all three frequency bands. The regression results are presented in Table VII. The coefficient for the percentage of market orders ($TRIN'$) is insignificant even at the 10 percent level. We therefore cannot reject the hypothesis that market order and limit order strategies provide identical overall profitability.

6 Conclusions

We examine the proprietary trading profits of 451 large 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 in 11 DAX blue chip stocks 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.

[16] Such a methology is obviously problematic since the limit order trader may not need to replace the unfilled limit order with the hypothetical market order.

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 DM 20 per market transaction and stock. This implies a quarterly underperformance of approximately 1.2 million German marks per actively traded blue chip stock.

3. We find weak evidence for an underperformance of Austrian and Swiss traders in high frequency (intra-day) trading. We cannot confirm the 'pure geographic distance hypothesis' for low frequency trading profits.

4. Traders located near corporate headquarters of the traded company outperform other traders in high frequency trading of the respective stock. Again low frequency trading shows no effect of geographic distance on the profit account.

5. We find 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.

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. We underline that this result is obtained for all three spectral dimensions and robust to various controls for behavioral trader heterogeneity. Geographic distance effects measured by corporate headquarter proximity or a trader location in Austria or Switzerland matter only for high frequency (intra-day) trading. This suggests that the linguistic and cultural divide presents a more important information barrier for equity trading than the 'pure geographic distance' effect. Finally, we emphasize that our evidence concerns information asymmetries among large professional traders with at least 100 transactions in one of the selected blue-chip stocks. The revealed information asymmetries are likely to present only a lower bound on similar effects for non-professional investor groups in smaller stocks.

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Table I:
Trader Population

Summary statistics for the number of traders and their combined trades for 11 randomly chosen DAX blue chip stocks for the period 31.08.98 to 31.12.98. Proprietary traders trade on their own account and large proprietary traders undertake at least 100 proprietary trades in the respective stock. The 11 DAX 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).

Stock	All Traders		Proprietary Traders		Large Prop. Traders	
	Number	Trades	Number	Trades	Number	Trades
ALV	930	116984	540	74736	154	65856
BAY	995	119472	569	70028	133	58197
DBK	1102	198050	653	130827	217	118613
DCX	1126	223954	669	132212	221	118554
DTE	923	118792	538	73263	156	63829
LHA	920	90190	498	49158	110	40080
MEO	870	82526	487	48811	103	39102
MNN	947	139132	542	85801	162	75706
RWE	817	68228	467	43143	92	35102
SIE	1012	150480	589	96676	181	86464
VEB	927	95888	532	59906	124	50630
Total	1342	1403696	882	864561	451	752952

Table II:
Summary Statistics

Locational dummy variable are introduced for traders in Frankfurt (DFRA), for foreign traders in non-German speaking locations (DFOR1), for foreign traders in German speaking locations of Austria and Switzerland (DFOR2) and for traders located within a 100 km distance of the corporate headquarter (DPRO) in case the corporation is headquartered outside Frankfurt. SIZE indicates the number of traders within the same institution trading the same stock. DCLT indicates if a trader undertakes client trading parallel to his proprietary trading. TRNU gives the number of proprietary trades in the same stock. TRIN indicates the percentage of initiated trades (market orders). Trading profits per market transaction ($\overline{\Pi}$), standardized profits per transaction ($\widetilde{\Pi}$) and the standart deviation of the inventory value (RISK) are stated for the high frequency (H), medium frequency (M) and low frequency (L) band.

Variable	Symbol	Minimum	Maximum	Mean	STD
Dummy Frankfurt	DFRA	0	1	0.65	0.48
Dummy Foreign 1	DFOR1	0	1	0.09	0.28
Dummy Foreign 2	DFOR2	0	1	0.01	0.11
Dummy Proximity	DPRO	0	1	0.06	0.23
Number of Traders	SIZE	1	48	11.29	12.27
Dummy Client Trans.	DCLT	0	1	0.09	0.28
Number of Trades	TRNU	100	9129	473	603
Initiation Rate	TRIN	0.003	0.983	0.496	0.168
Profits (H)	$\overline{\Pi}^H$	−71.92	57.13	0.09	5.21
Profits (M)	$\overline{\Pi}^M$	−93.48	139.86	0.16	11.48
Profits (L)	$\overline{\Pi}^L$	−375.61	1475.24	3.79	64.30
Standard Profits (H)	$\widetilde{\Pi}^H$	−24.13	32.22	0.78	4.48
Standard Profits (M)	$\widetilde{\Pi}^M$	−34.59	45.37	0.52	8.43
Standard Profits (L)	$\widetilde{\Pi}^L$	−120.29	105.27	3.68	32.10
STD inventory (H)	$\text{RISK}^H \times 10^{-3}$	5.2	18078	552	855
STD inventory (M)	$\text{RISK}^M \times 10^{-3}$	2.7	51285	1808	2663
STD inventory (L)	$\text{RISK}^L \times 10^{-3}$	0.8	31338	7433	14273

Table III:
Large Proprietary Traders by Location

Distinguished are large proprietary traders located in Frankfurt (DFRA), foreign traders outside Germany in an non-German speaking location (DFOR1), foreign traders outside Germany in a German speaking location of Austria and Switzerland (DFOR2) and traders located within a 100 km distance to the corporate headquarter of the stock company (DPRO) in case it is different from Frankfurt.

Stocks	Corporate Headquarter	Trader by Location				All
		DFRA	DFOR1	DFOR2	DPRO	
ALV	Munich	99	11	1	11	154
BAY	Leverkusen	84	13	3	12	133
DBK	Frankfurt	131	19	2	0	217
DCX	Stutgart	139	16	4	8	221
DTE	Bonn	101	13	3	11	156
LHA	Frankfurt	76	9	1	0	110
MEO	Cologne	64	10	1	10	103
MNN	Duesseldorf	114	11	2	11	162
RWE	Essen	62	8	1	6	92
SIE	Munich	109	23	2	14	181
VEB	Düsseldorf	88	12	2	8	124
Total		259	31	6	59	451

Table IV:
High Frequency Trading Profits

Intra-day (high frequency) trading profits in 11 DAX stocks and 451 large proprietary traders are pooled to obtain 1653 individual profit accounts with at least 100 transactions each. The (risk adjusted) trading profits are regressed on fixed effects for each stock, locational dummies for Frankfurt based traders (DFRA), for foreign traders in non-German speaking locations (DFOR1) and traders in Austria and Switzerland (DFOR2), for traders in local proximity (up to 100 km) to the respective corporate headquarter (DPRO) and a variable for the number of traders in the same financial institution as the trader under consideration (SIZE′). The behavioral control variables are a dummy for parallel client trading (DCLT), the trader's total number of trades (in logs) in the respective stock (TRNU′), the percentage of market orders (trade initiations) among these trades (TRIN′), and a measure of the standard deviation of the inventory value in the respective stock (RISK′). The iterative maximum likelihood estimation allows for random effects for each trader. We indicate significance at a 1 percent (**) and 5 percent (*) level.

	No Behavioral Controls		With Behavioral Controls	
	Coefficient	STD Error	Coefficient	STD Error
Dummy ALV	1.195	**0.445	1.173	**0.409
Dummy BAY	0.749	0.465	0.907	*0.430
Dummy DBK	0.579	0.410	0.776	*0.377
Dummy DCX	−0.075	0.417	−0.146	0.385
Dummy DTE	0.990	*0.449	1.028	*0.415
Dummy LHA	1.262	**0.480	1.008	*0.446
Dummy MEO	0.455	0.494	0.568	0.458
Dummy MNN	1.325	**0.446	1.556	**0.411
Dummy RWE	0.557	0.510	0.683	0.475
Dummy SIE	1.004	*0.432	1.184	**0.397
Dummy VEB	0.998	*0.474	1.201	**0.439
DFRA	−0.273	0.391	−0.110	0.409
DFOR1	−1.482	*0.638	−1.629	**0.556
DFOR2	0.648	1.413	−2.652	*1.251
DPRO	2.007	**0.508	1.747	**0.474
SIZE′	−0.302	*0.147	−0.042	0.130
DCLT	-	-	−0.084	0.456
TRNU′	-	-	1.582	**0.163
TRIN′	-	-	−8.550	**0.721
RISK′	-	-	−1.478	**0.141
Observations		1653		1653
Adjusted $\overline{R}^2$		0.055		0.222
Variance σ_μ^2		4.70		3.22
Variance σ_ϵ^2		11.22		10.23

Table V:
Medium Frequency Trading Profits

Intra-week (medium frequency) trading profits in 11 DAX stocks and 451 large proprietary traders are pooled to obtain 1653 individual profit accounts with at least 100 transactions each. The (risk adjusted) trading profits are regressed on fixed effects for each stock, locational dummies for Frankfurt based traders (DFRA), for foreign traders in non-German speaking locations (DFOR1) and traders in German speaking locations (DFOR2), for traders in local proximity to the respective corporate headquarter (DPRO) and a variable for the number of traders in the same financial institution as the trader under consideration (SIZE′). The behavioral control variables are a dummy for parallel client trading (DCLT), the trader's total number of trades (in logs) in the respective stock (TRNU′), the percentage of market orders (trade initiations) among these trades (TRIN′), and a measure of the standard deviation of the inventory value in the respective stock (RISK′). The iterative maximum likelihood estimation allows for random effects for each trader. We indicate significance at a 1 percent (**) and 5 percent (*) level.

	No Behavioral Controls		With Behavioral Controls	
	Coefficient	STD Error	Coefficient	STD Error
Dummy ALV	2.089	*0.820	2.213	**0.827
Dummy BAY	1.897	*0.875	2.133	*0.885
Dummy DBK	0.772	0.719	0.943	0.737
Dummy DCX	1.776	*0.732	1.983	**0.747
Dummy DTE	0.678	0.825	0.908	0.839
Dummy LHA	1.584	0.916	1.661	0.922
Dummy MEO	1.611	0.948	1.755	0.951
Dummy MNN	2.771	**0.823	3.051	**0.833
Dummy RWE	1.802	0.990	1.896	0.995
Dummy SIE	1.172	0.786	1.352	0.798
Dummy VEB	2.301	*0.903	2.486	**0.909
DFRA	−1.399	*0.591	−1.438	*0.587
DFOR1	−4.132	**0.946	−3.912	**0.939
DFOR2	−2.787	2.070	−3.769	2.084
DPRO	−0.727	1.029	−1.085	1.022
SIZE′	−0.402	0.217	−0.238	0.219
DCLT	-	-	−2.208	**0.804
TRNU′	-	-	0.226	0.308
TRIN′	-	-	−5.398	**1.345
RISK′	-	-	−0.451	0.234
Observations		1653		1653
Adjusted $\overline{R}^2$		0.0159		0.030
Variance σ_μ^2		3.84		3.37
Variance σ_ϵ^2		62.90		62.53

Table VI:
Low Frequency Trading Profits

Intra-quarter (low frequency) trading profits in 11 DAX stocks and 451 large proprietary traders are pooled to obtain 1653 individual profit accounts with at least 100 transactions each. The (risk adjusted) trading profits are regressed on fixed effects for each stock, locational dummies for Frankfurt based traders (DFRA), for foreign traders in non-German speaking locations (DFOR1) and traders in German speaking locations (DFOR2), for traders in local proximity to the respective corporate headquarter (DPRO) and a variable for the number of traders in the same financial institution as the trader under consideration (SIZE′). The behavioral control variables are a dummy for parallel client trading (DCLT), the trader's total number of trades (in logs) in the respective stock (TRNU′), the percentage of market orders (trade initiations) among these trades (TRIN′), and a measure of the standard deviation of the inventory value in the respective stock (RISK′). The iterative maximum likelihood estimation allows for random effects for each trader. We indicate significance at a 1 percent (**) and 5 percent (*) level.

	No Behavioral Controls		With Behavioral Controls	
	Coefficient	STD Error	Coefficient	STD Error
Dummy ALV	5.413	3.137	5.643	3.199
Dummy BAY	5.203	3.336	5.406	3.412
Dummy DBK	2.219	2.769	2.446	2.877
Dummy DCX	14.404	**2.818	14.706	**2.915
Dummy DTE	6.725	*3.157	7.000	*3.244
Dummy LHA	4.432	3.487	4.631	3.546
Dummy MEO	11.757	**3.608	11.784	**3.657
Dummy MNN	9.920	**3.145	10.081	**3.217
Dummy RWE	4.008	3.762	4.035	3.824
Dummy SIE	4.453	3.013	4.703	3.089
Dummy VEB	3.940	3.438	4.088	3.501
DFRA	−4.542	2.328	−4.671	*2.342
DFOR1	−12.250	**3.734	−11.837	**3.759
DFOR2	1.089	8.190	5.763	8.352
DPRO	−5.130	3.922	−4.760	3.924
SIZE′	−2.010	*0.858	−2.085	*0.878
DCLT	-	-	−3.336	3.199
TRNU′	-	-	−0.932	1.175
TRIN′	-	-	11.650	*5.320
RISK′	-	-	0.505	0.732
Observations		1653		1653
Adjusted $\overline{R}^2$		0.032		0.034
Variance σ_μ^2		79.07		76.78
Variance σ_ϵ^2		866.21		865.09

Table VII:
Total Trading Profits

Total trading profits in 11 DAX stocks and 451 large proprietary traders are pooled to obtain 1653 individual profit accounts with at least 100 transactions each. The (risk-adjusted) trading profits are regressed on fixed effects for each stock, locational dummies for Frankfurt based traders (DFRA), for foreign traders in non-German speaking locations (DFOR1) and foreign traders in German speaking locations (DFOR2), for traders in local proximity to the respective corporate headquarter (DPRO) and a variable for the number of traders in the same financial institution as the trader under consideration (SIZE′). The behavioral control variables are a dummy for parallel client trading (DCLT), the trader's total number of trades (in logs) in the respective stock (TRNU′), the percentage of market orders (trade initiations) among these trades (TRIN′), and a measure of the standard deviation of the inventory value in the respective stock (RISK′). The iterative maximum likelihood estimation allows for random effects for each trader. We indicate significance at a 1 percent (**) and 5 percent (*) level.

	No Behavioral Controls		With Behavioral Controls	
	Coefficient	STD Error	Coefficient	STD Error
Dummy ALV	11.121	**3.374	10.216	**3.423
Dummy BAY	9.678	**3.589	9.122	*3.650
Dummy DBK	5.219	2.979	4.334	3.074
Dummy DCX	17.642	**3.032	16.691	**3.118
Dummy DTE	9.544	**3.396	8.731	*3.470
Dummy LHA	8.390	*3.752	7.153	3.797
Dummy MEO	13.524	**3.882	12.952	**3.916
Dummy MNN	16.041	**3.383	15.907	**3.441
Dummy RWE	7.359	4.047	6.339	4.092
Dummy SIE	8.538	**3.241	7.882	*3.302
Dummy VEB	8.879	*3.698	8.232	*3.745
DFRA	−7.699	**2.505	−6.881	**2.500
DFOR1	−21.298	**4.017	−19.506	**4.013
DFOR2	−4.607	8.811	−6.587	8.928
DPRO	0.031	4.219	−1.237	4.203
SIZE*	−3.298	**0.923	−2.438	**0.938
DCLT	-	-	−6.125	3.419
TRNU′	-	-	2.361	1.282
TRIN′	-	-	−8.101	5.681
RISK′	-	-	−3.371	**0.897
Observations		1653		1653
Adjusted $\overline{R}^2$		0.063		0.072
Variance σ_μ^2		91.57		86.07
Variance σ_ϵ^2		1002.21		997.17

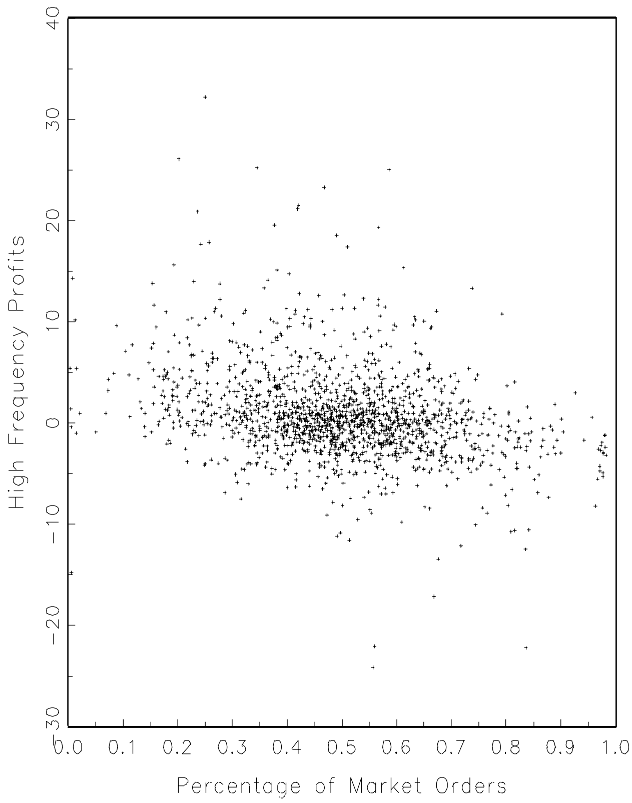

Figure 1: Intra-day (high frequency) trading profits in 11 DAX stocks and 451 large proprietary traders are pooled to obtain 1653 individual profit accounts. The profits are plotted as a function of the percentage of market order in each account.