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Empirical Essays on
Corporate Finance and Market Microstructure

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Chapter I

Overview

> "[...] the only relevant test of the validity of a hypothesis is comparison of prediction with experience."
>
> Milton Friedman (1953, p. 8–9)

This dissertation comprises three self-contained papers that contribute to the empirical research in the area of Corporate Finance and Financial Market Microstructure. With regard to Corporate Finance such research has a long tradition and is concerned with various corporate financing and investment decisions, e.g., on capital structure and merger & acquisitions. For the field of Financial Market Microstructure, however, consideration of empirical data reflects a more recent development, targeting the trading of financial securities and the mode of operation and design of financial market places.

Before providing a short summary for each of the essays, I briefly outline what they have in common and how they relate to each other, despite the fact that they cover fairly distinct research questions. The first essay "Measuring the Quality of Corporate Governance: Is There a Uniform Standard?" is dedicated to the subject of Corporate Governance that forms a cross-sectional topic in the field of Corporate Finance. In particular, Corporate Governance covers the process of decision making and implementation within large corporations in the tension of separation of ownership (shareholders) and control (managers) and the required alignment of the management's interests with those of the owners. In the second essay "Repurchasing Shares in the Open Stock Market: Beneficial or Harmful to Stock Market Liquidity?", a specific corporate finance decision is examined: the repurchase of own shares by corporations in the open stock market. While contributing to a growing literature that establishes a link between research questions from the field of Financial Market Microstructure and Corporate Finance, this paper specifically covers the impact of firms' repurchase activity on the stocks' market liquidity. Finally, with the third essay "Breaking Up Large Trades: Do Theoretical Trade Execution Models Explain Insider Trading Behavior?", the field of Corporate Finance is left behind to investigate the decision making of individuals in the area of trade execution. I test the predictions of trade execution models with the help of insider trading data. By considering stocks' microstructure characteristics as exogenous factor in rational decision making concerning trade execution strategies, this essay extends the research in the field of Financial Market Microstructure.

Beside the fact that all essays deal with research questions from the field of Corporate Finance or Financial Market Microstructure, they also have in common to provide empirical findings. Empirical analysis and research requires the availability of and access to large-sample data of high quality. At present, these requirements frequently favor the use of US data. Therefore, the two essays dealing with share repurchases and insider trading are based on US data drawn from the Wharton Research Data Services (WRDS), the premier data provider for financial databases. More specifically, I use the NYSE's Trades and Quotes (TAQ) database, Thomson Reuters' Insider Filing Data Feed (IFDF), Thomson Financial's SDC Merger & Acquisitions database, the Center for Research in Security Prices (CRSP) database, as well as Standard & Poor's COMPUSTAT database. In contrast, due to its topic of interest, the essay on corporate governance is a cross-country study with international data coming from Institutional Shareholder Services (ISS) and Thomson Reuters' Worldscope/Datastream database. To analyze the large samples, I make extensive use of statistical and econometrical methods. I conduct my analyses with the help of the statistical software program STATA. In addition, I use SAS software to run computations on TAQ data on the WRDS servers and to run linear optimizations as well as maximum likelihood estimations. Based on this approach, I derive the following results:

The first essay (Chapter II), "Breaking Up Large Trades: Do Theoretical Trade Execution Models Explain Insider Trading Behavior?", examines trade execution models by exploiting the availability of actual trading data for insiders on a daily basis. More specifically, it addresses the optimal break up of large blocks of shares into multiple trades executed over the course of several trading days. Using IFDF insider trading data, I document that trade splitting - which is already a well recognized phenomenon in institutional trading - is also commonly applied by corporate insiders. In general, four distinct trade patterns can be distinguished. While trading a constant volume over all days within a trading sequence accounts for about 10% of all multiple-day trading strategies, increasing, decreasing, and non-monotone trade patterns account for about 30% each. Explaining these observable trade patterns requires trade execution models with diverse assumptions. In this paper, I examine the group of decreasing trade patterns as these are predicted by standard trade execution models. Specifically, I calibrate a discrete-time model which uses an expected utility framework and assumes traders to be risk averse and price impact functions to be linear. Utilizing this model calibrated with high-frequency TAQ data, I explore to which extend the model's predictions are consistent with actually observed trading strategies. With respect to the trade pattern dimension, the model correctly predicts about 28% of the observations in the sample when deviations are measured in revenue terms. For a small number of observations (11%), however, the model fails to yield an admissible solution for the given trading horizon and instead favors immediate execution or execution over shorter trading horizons. Optimizing the trade pattern and trade horizon dimension at the same time reduces the successful prediction rate to about 13%. Optimizing the actual trading strategies according to the predictions of the model yields on average a revenue improvement of 1.74% for sale transactions and 0.55% for purchase transactions. Going beyond this analysis, I use the large cross-sectional sample to empirically assess the overall benefit from splitting up large trades. The overall revenue improvement associated with switching from immediate to optimal execution is positively related to the size of the total asset position. Expressed as multiple of the relative trade size, the median percentage improvement amounts to 1.6-1.7 times the $ trading volume scaled by the average daily $ trading volume. Of this total improvement potential, the median insider realizes about two thirds with his/her their actual trading strategy. Finally, several robustness checks with respect to the risk aversion of the insiders and the price impact functions convey that the convexly decreasing trade patterns of the optimal trading strategies are sensitive to the assumed functional form of the price impact function which even dominates the same effect steaming from a certain risk aversion of the traders. However, so far little research is available on the estimation of price impact functions for individual stocks and their functional form. More research in this area is needed before the endeavor of empirically explaining multiple day trading strategies based on mathematical models can fully succeed.

The second research paper (Chapter III), titled “Repurchasing Shares in the Open Stock Market: Beneficial or Harmful to Stock Market Liquidity?”, deals with open market repurchases which are the most popular repurchase method in the US. The US dollar volume of share repurchases has surpassed cash dividends as dominant payout channel over the last years. Compared to other traders, repurchasing firms usually trade very large volumes and managers who execute the repurchase programs possess non-public information about the firm. The combination of these two facts raises the question whether and how open market share repurchases affect the stock's market liquidity. By answering this question, the paper contributes to the long debate about the liquidity impact of open market repurchases. In December 2003, the Securities and Exchange Commission (SEC) issued a new rule which enhanced the disclosure of firms' actual implementation of share repurchase programs. I use these newly available data for my analysis. The sample covers all firms with a primary listing of common stock at the NYSE between 2004 and 2008. Based on this data set, I test two competing hypotheses on the liquidity effect of open market repurchases. The competing market maker hypothesis predicts a positive liquidity effect, while the information asymmetry hypothesis speaks in favor of a negative liquidity effect. In contrast to the latter hypothesis, the analysis reveals no evidence in support of a harmful liquidity effect of open market stock repurchases. Rather, a beneficial liquidity impact is observable as reflected in narrower bid-ask spreads and larger (bid-side) depths. Put differently, the price and quantity dimension of liquidity is found to improve in the course of open market repurchases. Beside making different predictions about the final liquidity impact of share repurchases, the competing hypotheses also differ with respect to the main transmission channel of the liquidity effect. The information asymmetry hypothesis assumes liquidity to deteriorate due to a change in the firm's information environment. The competing market maker hypothesis assumes the liquidity to improve due to a change in the firm's trading characteristics.

Disentangling informational and real friction effects, however, is difficult. I use two different methods to validate the robustness of my findings. I observe that the favorable liquidity effects are attributable to changes in firms' real trading characteristics rather than to changes in their information environment. In summary, open market repurchases seem not to be associated with previously unrecognized liquidity costs that stem from adverse selection related to an increase in the fraction of informed market participants.

The third essay (Chapter IV) is joint work with Ernst Maug and titled "Measuring the Quality of Corporate Governance: Is There a Uniform Standard?". An emerging literature in corporate governance investigates governance indices and typically follows a "tick-box"-approach, which constructs comprehensive governance indices by simply adding the number of desirable governance provisions in place for each company. Some recent papers show that only a small number of critical corporate governance attributes that are included in these comprehensive indices can be consistently related to firm valuation. However, the critical attributes in these papers relate so far only to the institutional environment in the US and it is unclear whether they have any relevance for firms domiciled outside the US. We investigate the heterogeneity of the critical attributes that determine the quality of corporate governance across institutional environments. Our starting point is the hypothesis that what is a good provision in one country may not at all be also a good provision in another country. To establish which corporate governance attributes are reliably related to firm value within an institutional environment, we group countries according to their legal origin (e.g., Scandinavian law). For each resulting group of countries, we identify between three and six (out of a total of 53) attributes that are consistently related to firm valuation. In a subsequent step, we then use these attributes to construct parsimonious governance indices for each group of countries. The attributes that we include in each of the indices are hardly overlapping, resulting in correspondingly small correlations between indices. Importantly, each index was found to have a statistically and economically significant influence on company valuation for the respective group of countries with the same legal origin, but hardly any association with firm valuation in any of the other groups. These findings indicate that there is no uniform cross-country standard against which firm-level corporate governance can be measured.

Chapter II

Breaking Up Large Trades: Do Theoretical Trade Execution Models Explain Insider Trading Behavior?

1 Introduction

This paper analyzes trade execution strategies of corporate insiders, or, more specifically, the optimal break up of large blocks of shares by insiders into multiple trades executed over the course of several trading days. In doing so, the paper aims to answer two main questions: Do corporate insiders follow a rational model in splitting up their trades into a sequence of several daily transactions? And, do theoretical trade execution models describe trading behavior as it actually occurs in real life? To answer these questions, I develop an empirically implementable model of optimal trade execution and calibrate it to actual firm data to assess observable execution strategies of US insiders. Under the assumptions of constant absolute risk aversion and normally distributed stock prices, I determine optimal trading strategies for a sample of NYSE or AMEX listed companies over the period 2004-2009.

In the relevant literature, breaking up large trades over several trading days is already a well recognized phenomenon for institutional trades. Chan and Lakonishok (1995) as well as Keim and Madhavan (1995) show that a significant dollar volume of institutional trades is completed within two or more trading days. Similar strategies are used by large individual investors such as the management of the company or other large blockholders. An example is the purchase of 1,000,000 shares worth $4.4 million in November 2008 by Steve Creamer, CEO of EnergySolutions Inc. Over 3 subsequent trading days he traded 450,000, 319,200, and 230,800 shares, respectively. Another example is the sale of 410,000 shares worth $3.0 million in July 2004 by Andrea Jung, CEO at Avon Inc. She traded daily amounts of 195,000, 125,000, and 90,000 shares. Whether such execution strategies are an optimal trading approach is the topic of this paper.

The theoretical literature on optimal trade execution studies the following problem: A trader wants to liquidate (purchase) a large position of shares in a risky stock within a finite time horizon. Thereby, the price of the underlying security is affected by exogenous events as well as by the insider's trades. In particular, the stock price is pushed up (moved down) as the trader buys (sells) a large position of shares. Thus, the trader faces a trade-off situation. The larger the position she immediately trades at once, the larger the unfavorable permanent and temporary price impact caused by her trade. At the same time, the uncertainty about the security's fundamental value is minimized due to immediate execution. However, the longer the period used by the trader to execute the transaction, the larger the uncertainty about exogenous price changes, while the unfavorable price impact is minimized. Several authors develop models to solve this optimization problem.[1] This theoretical literature is limited to formally deriving solutions to models of different complexity. As such, the models are highly stylized with a strong focus on their mathematical tractability. Numerical analyzes are only provided sporadically to illustrate the comparative statics of the models.

So far, no attempt has been made to apply these models to real world settings. Therefore, I develop a discrete-time model in this paper, which can be calibrated empirically and which yields optimal trading strategies that are representative of the corresponding continuous-time models in the theoretical literature. The optimal trading strategies derived with this model are characterized by decreasing daily trade volumes that evolve following a convex curvature. Beside examining the optimality of trade patterns, I apply the model to examine the optimality of the length of the trading horizon by prioritizing optimal trading strategies of

[1] See, e.g., Bertsimas and Lo (1998), Hisata and Yamai (2000), Almgren and Chriss (2001), Subramanian and Jarrow (2001), Almgren (2003), He and Mamaysky (2005), Huberman and Stanzl (2005), Schoeneborn (2008), Schied and Schoeneborn (2009), and Schied, Schoeneborn, and Tehranchi (2010).

different length. In the empirical part of the paper, I parametrize the theoretical model with cross-sectional data. In particular, I use high-frequency trade and quote data to estimate the microstructure parameters that describe the price formation process in the trade execution model. These parameters are the stock price volatility as well as the expected price impact from the insider's own trading. I use the parametrized model to determine optimal trading strategies that are then compared to the trading strategies actually observed for a sample of US insiders. The trading behavior of insiders - these are either members of the management or large shareholders with an equity stake of more than 10%[2] - is particularly well suited for the test of these trade execution models, because insiders usually trade larger asset positions than other shareholders and are more sensible to liquidity- and/or information-related concerns, which drive the price impact.

In a first step, I document that trade splitting is commonly applied by corporate insiders. In general, four distinct trade patterns can be distinguished. While trading a constant volume over all days within a trading sequence accounts for about 10% of all multiple-day trading strategies, increasing, decreasing, and non-monotone trade patterns account for about 30% each. Explaining these observable trade patterns requires trade execution models with diverse assumptions. I examine the group of decreasing trade patterns as these are predicted by standard trade execution models. In a second step, I use a representative standard trade execution model to explore to which extend the model's predictions are consistent with actually observed trading strategies. With respect to the trade pattern dimension, the model correctly predicts about 28% of the observations in the sample when deviations are measured in revenue terms. For a small number of observations (11%), however, the model fails to yield an admissible solution for the given trading horizon and instead favors immediate execution or execution over shorter trading horizons. Optimizing the trade pattern and trade horizon dimension at the same time reduces the successful prediction rate to about 13%. Further optimization of the actual trading strategies, according to the predictions of the model, yields on average a revenue improvement of 1.74% for sale transactions and 0.55% for purchase transactions. Going beyond this analysis, I use the large cross-sectional sample to empirically assess the overall benefit from splitting up large trades. The overall revenue

[2]See the definition in Section 16 of the Securities Exchange Act.

improvement associated with switching from immediate to optimal execution is positively related to the size of the total asset position. Expressed as multiple of the relative trade size, the median percentage improvement amounts to 1.6-1.7 times the $ trading volume scaled by the average daily $ trading volume. Of this total improvement potential, the median insider realizes about two thirds with his/her their actual trading strategy. Finally, several robustness checks with respect to the risk aversion parameters and the price impact coefficients convey that the convexly decreasing trade patterns of the optimal trading strategies are sensitive to the assumed functional form of the price impact function which even dominates the same effect steaming from the trader's level of risk aversion. However, so far little research is available on the estimation of price impact functions for individual stocks and their functional form. More research in this area is needed before the endeavor of empirically explaining multiple day trading strategies based on theoretical models can fully succeed.

This paper contributes the trade execution literature as well as to the literature on insider trading. To the best of my knowledge, this paper offers the first empirical and structural test of a theoretical trade execution model. Thus, it provides empirical evidence on how asset-specific microstructure parameters such as price impact and price volatility influence the execution of trading strategies. By examining the trade execution decision of insiders, the paper also adds an additional aspect to the empirical literature on insider trading. So far, the insider trading literature mainly focuses on assessing short-term and long-term returns following the disclosure of insider trades and examining insider trading activities around firm-specific announcements or events. Only very recently, empirical studies have started to look at sequences of insider trades (Betzer, Gider, Metzger, and Theissen, 2010; Lebedeva, Maug, and Schneider, 2009). However, these papers focus on the relation between insider trades and their public reporting and changes in the disclosure regulation due to the Sarbanes-Oxley Act (SOX). Therefore, the identification of trade sequences in these papers is based on the point in time at which (one or more) trades are disclosed to the public. In contrast to these papers, I use a simpler and more intuitive trade sequence definition that is consistent with the trade execution literature. I consider all trades executed in the same direction on subsequent trading days by the same insider as belonging to one trading sequence or strategy, independent from any disclosure.

The remainder of this paper is organized as follows. In Section 2, I develop and solve the theoretical trade execution model. In Section 3, I describe the construction of the data set and explain the empirical calibration of the model. In Section 4, I present and discuss the obtained empirical findings. In this section, I also include tests validating the robustness of the main results. I conclude in Section 5.

2 Trade execution model

2.1 Related literature

Before I introduce the trade execution model that I calibrate empirically, I give a short overview of the various models available in the trade execution literature. I classify and compare the most relevant models along four crucial dimensions: the framework for the risk-reward trade-off, the exogenously given time parameter, the assumed stock price dynamics, and the chosen time dimension.

First, different frameworks are applied to model the risk-reward trade-off. While He and Mamaysky (2005), Schied and Schoeneborn (2009), as well as Schied, Schoeneborn, and Tehranchi (2010) use an expected utility framework, previous authors optimized mean-variance functions (Almgren and Chriss, 2001; Almgren, 2003) or mean-standard-deviation functions (Hisata and Yamai, 2000; Konishi and Makimoto, 2001; Dubil, 2002; Moench, 2009). Since mean-variance optimization is a second-order approximation, and thus, a special case of an expected utility functional, the resulting objective functions only differ with respect to the weighting of the risk aversion parameter (see Schoeneborn, 2008, p. 27).[3]

Second, the models differ with regard to the exogenous parameter that concerns the time dimension of the optimization problem. Almgren and Chriss (2001), Almgren (2003), He and Mamaysky (2005), and Schied, Schoeneborn, and Tehranchi (2010) assume that the liquidation horizon is exogenously given. These models derive a distribution of trading volumes over the given horizon as solution. They make no assumption on the speed of liquidation, i.e., on how many shares are sold per trading period. Other authors such as Hisata and Yamai (2000), Dubil (2002), and Moench (2009) endogenize the liquidation horizon. In con-

[3]However, the equivalence of mean-variance and expected utility optimization in a static setting disappears in a dynamic setting (Schoeneborn, 2008, p. 27f).

sequence, these authors derive the optimal liquidation horizon as solution in their models. This endogenization comes at the cost of assuming a constant speed of execution which implies that the same number of shares is traded in each period.[4]

Third, the models work with different stock price processes. The building blocks for modeling the stock price process include a Brownian motion and either one or two functions that model the price impact. The Brownian motion is usually arithmetic with zero drift.[5] Concerning the price impact functions, all models are partial equilibrium models which assume that the price impact of large trades is exogenously given. The price impact is not derived from equilibrium considerations as in the prominent model of Kyle (1985). The vast majority of models follows the microstructure literature and incorporates temporary and permanent price impact effects. The permanent price impact affects all subsequent trades, while the temporary price impact only affects the current trade, but vanishes instantly thereafter. It is rather the assumed functional form of the price impact functions in which the models differ. The base case is to assume a linear functional form for both price impact components as done by Almgren and Chriss (2001), Hisata and Yamai (2000), as well as Schied and Schoeneborn (2009). Other papers such as Almgren (2003), Dubil (2002), or Schied, Schoeneborn, and Tehranchi (2010) assume non-linear impact functions. Deviating from the linear functional form implies that the price impact per unit traded is no longer constant irrespective of trade size, but is either increasing (or decreasing) in trade size. Accordingly, rapid trading leads to larger (or lower) price effects. Thus, the optimal solutions derived from the models are directly affected by the modeling choice for the price dynamics. A comparative study on the size of this effect has not yet been conducted. However, the general shape of the optimal trading strategy - which is a decreasing trade volume that follows a convex curvature - is not affected by this modeling choice.

[4]A third group of papers works with an infinite time horizon, but allows daily trade volumes to become zero. See, e.g., Konishi and Makimoto (2001) as well as Schied and Schoeneborn (2009).

[5]A geometric Brownian motion is the more traditional model. However, due to the short trade horizons typically considered in these models, the approximation with an arithmetic Brownian motion causes no major bias, but makes to optimization problem easier to handle. See Forsyth, Kennedy, Tse, and Windcliff (2009) on the (negligible) impact of the approximation on the optimal solution as well as He and Mamaysky (2005) and Moench (2009) for the use of a geometric Brownian motion. The drift term is usually ignored by referring to the same argument of a short time horizon. See Almgren and Chriss (2001) and Schied, Schoeneborn, and Tehranchi (2010) for the analysis of alternative models with non-zero drift. Almgren and Chriss (2001) show that the drift effect on the optimal solution is minimal.

Finally, the trade execution models are either formulated in discrete or continuous time.[6] The vast majority of models adopts continuous-time approaches, e.g., Hisata and Yamai (2000), Konishi and Makimoto (2001), Dubil (2002) Almgren (2003), He and Mamaysky (2005), Schied and Schoeneborn (2009), or Schied, Schoeneborn, and Tehranchi (2010). Compared to discrete-time models, continuous models often have the advantage of providing closed-form solutions and acting as limit of discrete-time models. For empirical applications, however, continuous-time models must be discretized to reflect reality.

From the variety of models described above, I chose the discrete-time model of Almgren and Chriss (2001) as a starting point for my model. Almgren and Chriss (2001) do not make an assumption on the execution speed, but assume the trading horizon to be exogenously given. This modeling choice offers me the opportunity to draw conclusions on two dimensions of the trading strategies. On the one hand, I can study the optimal distribution of trading volumes over trading periods. On the other hand, I can compare optimal trading strategies for different trading horizons, and thereby determine the optimal length of the trading horizon.[7] In contrast to Almgren and Chriss (2001), however, I use a contemporary expected utility framework for optimization instead of a traditional mean-variance optimization.[8]

2.2 Model set-up

For the sake of simplicity, all explanations in this section refer to a situation in which an insider wants to sell a block of shares. Analogous explanations hold for purchase transactions. The mathematical formulation of the optimization problem, however, covers both directions of trade. Therefore, I define D as an indicator for the direction of the trade being $+1$ for a stock purchase and -1 for a stock sale.

I assume that a trader wants to sell a block of $X > 0$ shares (units) of a risky asset within a fixed time interval $[0, T]$. The time horizon T is divided into N equally spaced intervals with discrete points in time $t = 1, \ldots, T$. The optimal trading strategy is determined in advance of trading, and thus, only depends on the information available at time $t = 0$. A

[6]There are also some models that integrate discrete trading in a continuous-time framework by assuming execution lags for trades (e.g., Subramanian and Jarrow, 2001).

[7]Beyond this, trading strategies with a constant trading volume per trading period account for only 10% of all multiple-day trading strategies. See Section 4.2.

[8]The model of Schied and Schoeneborn (2009) is the continuous-time equivalent to the discrete-time model developed in this paper.

trading strategy n is defined by a sequence of numbers $n_1, \ldots, n_T$, with n_t being the number of shares traded between times $t-1$ and t. I require $n_t > 0$ to ensure that all trading strategies only involve trades of the same sign, i.e., no additional buying of shares is allowed during a sell program. X and $n_1, \ldots, n_T$ are related by

$$X = \sum_{t=1}^{T} n_t. \tag{II.1}$$

Stock price dynamics. Following Almgren and Chriss (2001), I assume that the observable transaction price evolves according to two factors - one exogenous and one endogenous factor. The exogenous factor captures market forces that occur randomly and independently of the trader's own trading, e.g., the public announcement of company news. The endogenous factor is the trader's own trading. The microstructure literature distinguishes between a permanent and a temporary effect of trades on stock prices. The temporary price impact is caused by transitory order imbalances and only affects the current trade. The permanent price impact is due to new information revealed by the trade, and thus, affects the current and all future trades. I follow Glosten and Harris (1988) and assume that both endogenous price impact components are linear in the rate of trading including fixed costs per trade and variable cost per share traded (linear form with intercept). Thus, both price impact functions are specified by two impact parameters, a constant, and a per-share effect.

In particular, the observable transaction price in period t, p_t, can be decomposed into the temporary price impact of a large trade n_t and the "fundamental" asset price m_t that would have occurred in the absence of a large trade:

$$p_t = m_t + D\left(\tau_1 + \tau_2 n_t\right). \tag{II.2}$$

τ_1 and τ_2 are the price impact coefficients that determine the temporary price impact function. By definition, the temporary price impact affects only the current transaction price p_t, but not future transaction prices. The trade direction indicator D implies that the price impact is positive (negative) in case of a purchase (sale).[9]

[9]Note that the price impact formulation differs from Almgren and Chriss (2001) who calculate the transaction price p_t by adding the temporary price impact to the fundamental asset price at time $t-1$, i.e., $p_t = m_{t-1} + D\left(\tau_1 + \tau_2 n_t\right)$. However, Almgren and Chriss (2001)'s price impact formulation is not consistent with standard price impact models such as Glosten and Harris (1988).

The "fundamental" asset price m_t is the expected value of the security, conditional on the information available at time t. Thus, the "fundamental" value is assumed to be randomly affected by overall market fluctuations, e.g., changes in the information about the company or other traders' actions. However, new information also reaches the market through information-based trades that reveal private information and cause a permanent price impact. Hence, the "fundamental" value in period t consists of the following components:

$$m_t = m_{t-1} + D\left(\gamma_1 + \gamma_2 n_t\right) + \epsilon_t \tag{II.3}$$

with ϵ_t being a normal random variable with 0 mean and variance σ^2. σ^2 is the variance of changes in the "fundamental" asset value over the period of a single time period (here a single trading day). γ_1 and γ_2 are the fixed and variable permanent price impact coefficients, respectively.[10] They affect the current and all future transaction prices via m_t.

Replacing m_{t-1} recursively yields:

$$m_t = m_0 + \sum_{j=1}^{t} \left[D\left(\gamma_1 + \gamma_2 n_j\right) + \epsilon_j\right]. \tag{II.4}$$

With respect to the price process, I assume that the permanent and temporary price effects are known in advance and constant over time.[11]

Trading revenues (costs). The total trading revenues (costs) are the sum of the product of the number of shares n_t that the insider sells (buys) in each time interval t times the effective transaction price per share p_t received on that sale (purchase):[12]

$$R = -D \sum_{t=1}^{T} n_t p_t. \tag{II.5}$$

Recursively replacing p_t and m_t with equations (II.2) and (II.4), the actual trading revenues (costs) become:

[10] Note that this permanent price impact function differs from the linear function without intercept used by Almgren and Chriss (2001).

[11] Note that time-dependent price impact coefficients can be easily integrated into the model. See Section 4.7 for a discussion.

[12] I follow Schoeneborn (2008) and ignore discounting or the accumulation of interest since I assume that the trading horizon is short (usually not longer than a few days).

$$R = -Dm_0X - D\sum_{t=1}^{T}\left[\left(\sum_{j=t}^{T} n_j\right)\epsilon_t\right] \\ -\sum_{t=1}^{T}\left[\left(\sum_{j=t}^{T} n_j\right)(\gamma_1+\gamma_2 n_t)\right] - \sum_{t=1}^{T} n_t(\tau_1+\tau_2 n_t) \tag{II.6}$$

For a sale transaction, $D=-1$, equation (II.6) readily yields:

$$R^S = m_0X + \underbrace{\sum_{t=1}^{T}\left[\left(\sum_{j=t}^{T} n_j\right)\epsilon_t\right]}_{\text{term 1}} - \underbrace{\sum_{t=1}^{T}\left[\left(\sum_{j=t}^{T} n_j\right)(\gamma_1+\gamma_2 n_t)\right]}_{\text{term 2}} - \underbrace{\sum_{t=1}^{T} n_t(\tau_1+\tau_2 n_t)}_{\text{term 3}}. \tag{II.7}$$

The terms in equation (II.7) have the following economic interpretation: m_0X is the "paper" value of the asset position based on the current "fundamental" value m_0. The three other terms add up to the total "implementation shortfall" (Perold, 1988). The first term captures the revenue effect due to the volatility of the stock price over the trading interval $[0,T]$ caused by information flow and/or trading of other market participants. The second and third term represent the decrease in revenues due to permanent and temporary price effects, respectively, caused by the trader's own trades.

In equation (II.6), ϵ_t is a random variable following a normal distribution. Thus, the trading revenues (costs), which incorporate the sum of ϵ_t as a term, are also a random variable following a normal distribution.

Optimization problem. I assume that the trader wants to maximize the expected utility of the time T trading revenues by optimally selling off the asset position. This expected utility maximization leads to the following optimization problem:

$$\max \mathbb{E}\left[u(R)\right] \tag{II.8}$$

subject to the constraints

$$\sum_{t=1}^{T} n_t = X \tag{II.9}$$

$$0 \leq n_t \leq X \text{ for } t = 1, \ldots, T \tag{II.10}$$

with (II.9) representing the stock holding constraint and (II.10) defining admissible strategies. $u(R)$ denotes the trader's utility function of the trading revenues (costs).

In the above optimization problem, T, the number of trading periods, is an exogenous variable. To extend the analyzes beyond an exogenously given T, I endogenize T by applying the following algorithm: I solve the optimization problem for $T = 1, \ldots, T^{max}$ where T^{max} is a large number. I then determine the optimal time horizon, T^{opt}, as the value of T that maximizes the expected utility and identify $n_1^*, \ldots, n_{T^{opt}}^*$ as the optimal trading strategy.

Preferences. The trader has a (negative) exponential utility function defined over the time T trading revenues R with $\alpha > 0$ representing the risk tolerance (risk-aversion coefficient) of the trader:

$$u(R) = -\exp(-\alpha R). \tag{II.11}$$

This utility function exhibits constant absolute risk aversion (CARA). The greater the value of the parameter α, the more risk-averse the trader in question. Together with the normally distributed trading revenues (costs), this functional form of the trader's preferences is particularly convenient for expected utility calculations and is consistent with the mean-variance optimization frequently used in the theoretical trade execution literature (e.g., Almgren and Chriss, 2001).

2.3 Model solution

The explicit functional form for the expected utility of the normally distributed trading revenues R is a linear function of the mean and variance of the trading revenues:

$$\mathbb{E}[u(R)] = -\exp\left(-\alpha\left(\mathbb{E}(R) - \frac{\alpha}{2}\mathbb{V}(R)\right)\right). \tag{II.12}$$

Hence, by monotonicity, maximizing the expected utility, $\mathbb{E}[u(R)]$, is equivalent to maximizing the following function:

$$M\left[\mathbb{E}\left(R\right),\mathbb{V}\left(R\right)\right]=\mathbb{E}\left(R\right)-\frac{\alpha}{2}\mathbb{V}\left(R\right). \tag{II.13}$$

Thus, the objective function is no longer the expected utility $\mathbb{E}\left[u(R)\right]$, but the function $M\left[\mathbb{E}(R),\mathbb{V}(R)\right]$ that characterizes the distribution (expectation and risk) of the trading revenues (costs). It is negative for stock purchases (= trading costs / cash outflow for the trader) and positive for stock sales (= trading revenues / cash inflow for the trader). The function reflects the expected revenues (costs) to the trader from optimally liquidating (purchasing) an asset position as well as the disutility associated with the uncertainty of the liquidation (execution) process. It can be interpreted as the individual-specific certainty equivalent or shadow price for the position of X shares that is the result of the uncertainty of price movements and the price impact involved in trading the asset position (He and Mamaysky, 2005).

Given the nature of the price dynamics, I compute the expected value and variance of the trading revenues (costs) as:

$$\mathbb{E}\left(R\right)=-Dm_0X-\gamma_1\sum_{t=1}^{T}\left(\sum_{j=t}^{T}n_j\right)-\gamma_2\sum_{t=1}^{T}n_t\left(\sum_{j=t}^{T}n_j\right)-\tau_1\sum_{t=1}^{T}n_t-\tau_2\sum_{t=1}^{T}n_t^2, \tag{II.14}$$

$$\mathbb{V}\left(R\right)=\mathbb{E}\left[\left(R-\mathbb{E}\left(\mathbb{R}\right)\right)^2\right]=\sigma^2\sum_{t=1}^{T}\left(\sum_{j=t}^{T}n_j\right)^2. \tag{II.15}$$

Thus, I obtain the final program:

$$\begin{aligned} \max M\left[\mathbb{E}\left(R\right),\mathbb{V}\left(R\right)\right] \quad &= \quad \mathbb{E}\left(R\right)-\frac{\alpha}{2}\mathbb{V}\left(R\right) \\ &s.t. \quad \sum_{t=1}^{T}n_t=X \\ &\qquad 0\leq n_t\leq X\ for\ t=1,\ldots,T \end{aligned} \tag{II.16}$$

with $\sum_{t=1}^{T}n_t=X$ representing the stock holding constraint and $0\leq n_t\leq X$ defining admissible trading strategies.

To solve the constrained optimization problem (II.16), I introduce a Lagrange multiplier

λ, yielding the following unconstrained problem:

$$\max L(n_t, \lambda) = \mathbb{E}(R) - \frac{\alpha}{2}\mathbb{V}(R) - \lambda\left(X - \sum_{t=1}^{T} n_t\right). \tag{II.17}$$

The parameters λ and $n_1, ..., n_T$ are the unknowns. I determine the unique global maximum by setting the partial derivatives of $L(n_t, \lambda)$ with each of the unknown variables equal to zero. Taking the partial derivatives yields:

$$\frac{\partial L}{\partial \lambda} = X - \sum_{t=1}^{T} n_t \tag{II.18}$$

$$\begin{aligned} \frac{\partial L}{\partial n_k} &= -\gamma_1 k - 2\gamma_2 n_k - \gamma_2 \left[\sum_{t=1}^{k-1} n_t + \sum_{t=k+1}^{T} n_t\right] \\ &\quad -\tau_1 - 2\tau_2 n_k - \alpha\sigma^2 \left[\sum_{t=1}^{k-1} t n_t + k n_k + k \sum_{t=k+1}^{T} n_t\right] - \lambda. \end{aligned} \tag{II.19}$$

Setting the partial derivatives (II.18) and (II.19) equal to zero and rearranging terms yields the general form of a system of $T+1$ equations with the same number of unknowns.

Proposition. *The solution to the optimization problem (II.17) corresponds to the solution* $n = \begin{bmatrix} n_1 & n_2 & \dots & n_T & \lambda \end{bmatrix}^T$ *to the matrix equation*

$$A \cdot n = b \tag{II.20}$$

with the coefficient matrix

$$A = \begin{bmatrix} -\left(2\gamma_2 + 2\tau_2 + \alpha\sigma^2\right) & -\left(\gamma_2 + \alpha\sigma^2\right) & \dots & -\left(\boldsymbol{\gamma_2} + \alpha\sigma^2\right) & -1 \\ -\left(\gamma_2 + \alpha\sigma^2\right) & -\left(2\gamma_2 + 2\tau_2 + 2\alpha\sigma^2\right) & \dots & -\left(\gamma_2 + 2\alpha\sigma^2\right) & -1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -\left(\gamma_2 + \alpha\sigma^2\right) & -\left(\gamma_2 + 2\alpha\sigma^2\right) & \dots & -\left(2\gamma_2 + 2\tau_2 + T\alpha\sigma^2\right) & -1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{II.21}$$

and the constant vector

$$b = \begin{bmatrix} \gamma_1 + \tau_1 \\ 2\gamma_1 + \tau_1 \\ \vdots \\ T\gamma_1 + \tau_1 \\ X \end{bmatrix}. \tag{II.22}$$

Some numerical analyses are most suitable to illustrate the shape of the solution to equations (II.20)-(II.22) given in the above proposition.[13] At this point, however, I postpone a numerical example and comparative statics analysis to Section 4 to first empirically calibrate the model in Section 3.

3 Data and empirical calibration

My empirical analysis requires data on insider trades as well as stock price and stock trading data. Therefore, I merge data from three different sources: Thomson Reuters' Insider Filing Data Feed (IFDF), the Center for Research in Security Prices (CRSP)'s historical stock database, and the NYSE's Trade and Quote (TAQ) database. Before I explain how I calibrate the model of optimal trade execution, I describe the construction of the sample of insider transactions and provide some descriptive information on actual insider trading sequences.

3.1 Construction of the insider data set

My data source for insider transactions is the IFDF database. I include all

- □ open market or private purchases (transaction code "P") and sales (transaction code "S") of non-derivative securities,
- □ between the 31st of December 2003 and the 4th of January 2010,[14]

[13] I solve the system of linear equations by using the SOLVE function in SAS Proc IML.

[14] Two arguments speak in favor of not extending the time period before 2004. First, disclosure regulation on insider trades changed in August 2002 due to the Sarbanes-Oxley Act (SOX). The disclosure period for insider trades was shortened from up to 40 days to 2 business days. The insider trading literature has shown that there exist significant disclosure day returns for insider purchases. Thus, the change in disclosure regulation might be associated with a change in price impact effects relevant for deriving optimal trading

- with complete data on CUSIP ("cusip6" and "cusip2"), person identifier ("personid"), and transaction date ("trandate"),
- which have not been amended (amendment indicator "blank"),
- which have been verified by Thomson Reuter's (cleanse indicator "R", "H", "L", or "I"),
- which have been traded in the insider's own interest (ownership code "D")[15].

Dropping all transactions where an insider trades an identical amount of shares in opposite directions on the same trading day leaves me with 1,390,742 records. For the time being, I keep all records with missing data on the transaction price ("tprice") and/or the number of shares traded ("shares") to consider all transactions for the identification of consecutive trades ("trading strategies").

After excluding all observations of firms not covered by CRSP, I have 1,245,549 records in the data set.[16] I use CRSP data to remove problematic records. I follow Marin and Olivier (2008) and Betzer, Gider, Metzger, and Theissen (2010) and delete all records for which the reported transaction price is not within 20% of the CRSP closing price on that day or records that involve more than 20% of the number of outstanding shares reported in CRSP. Furthermore, as Lebedeva, Maug, and Schneider (2009), I delete all transactions where the reported number of shares traded is larger than the CRSP trading volume on that day. Since these transactions were probably privately negotiated, they are not of interest for my analysis. After this filtering process, the sample contains 1,239,786 records.

I then sum up all orders/transactions executed on the same day grouped by the identity of the firm and the insider as well as the trade direction (sale and purchase). This data compression is necessary to use the date-stamped insider data for the calibration of a trade execution model that assumes the individual trading rounds to correspond to trading days.

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strategies. Second, the data availability for the data item "ownership" from the IFDF database improves significantly with the beginning of 2004. This variable denotes the type of the insider's ownership position in the shares traded by him. Besides trading shares directly owned by the insiders, insiders frequently trade shares on behalf of trusts or close family members. These transactions are denoted by "indirect" ownership and excluded from the sample.

[15] I impute 186 missing values on the data item "ownership". This procedure consists of two steps: First, I check for every insider with missing values whether the ownership position of the trades with nonmissing data is consistent over the complete sample period. For 127 insiders this is the case. Thus, I use the unique ownership value also for the missing ownership values. Second, I duplicate the remaining 59 observations with missing values and assign to each one the values "D" (for direct) and "I" (indirect).

[16] The CRSP match is based on the CRSP universe of all common shares (share code "10", "11", or "12").

At the same time, this data compression makes the insider data comparable across firms as some insiders only report the total number of shares traded per day and the volume-weighted average price while other insiders report the number of shares and the transaction price on a per-order basis. This compression results in 332,006 daily transaction records in the data set.[17] I continue to refer to these records as "transactions" or "trades" even if they consist of a number of single orders, while I denote a sequence of transactions or trades executed on consecutive trading days as a "trading strategy" or "trade package". I regard transactions as belonging to a "trading strategy" if transactions (1) are executed on consecutive trading days, (2) by the same insider, and (3) with the same direction of trade (sale or purchase).[18]

After grouping all trades according to the above definition into single-day or multiple-day trading strategies, I use the following six filters to finalize the sample: First, I exclude all single-day trades executed in 2003 or 2010 and all trading strategies starting in 2003 or ending in 2010. Second, I drop all single-day and multiple-day trades with missing IFDF data ("tprice", "shares") and/or missing CRSP data ("prc", "shrout", "vol", "cfacpr", "cfacshr", "exchcd") over the trading period and the 20 trading days before. Third, I exclude all observations with capital measures (e.g., stock split or equity offering) or dividend payments within the trading period and the 20 trading days before.[19] Fourth, I exclude problematic records. I follow Lebedeva, Maug, and Schneider (2009) and exclude all trades and/or trading strategies with a daily trade volume that is larger than the trade volume reported in CRSP. Furthermore, I follow Keim and Madhavan (1995, 1997) and exclude all observations for "penny stocks" (median CRSP price over trading period below $1). Fifth, I drop all trades and/or trading strategies with a change in the exchange at which the stock is listed within the trading period and the 20 trading days before. Finally, I follow Marin and Olivier (2008) and exclude small transactions (single-day trades and trading strategies) where less than 100 shares were traded. This six-step procedure leaves me with a universe of 289,437 records.

My analyses, however, are based on a subset of this IFDF universe. Due to different trading mechanisms and microstructure properties, I limit the sample to stocks listed at

[17] This step also includes dropping 19 observations from the data set because the trading day as reported by the insider is a non-trading holiday.

[18] To correctly identify subsequent trading days, I derive a list of all trading holidays for the sample period from http://www.chronos-st.org/NYSE_Observed_Holidays-1885-Present.html. This list corresponds to all missing weekdays, i.e., all weekdays with no trading activity, in daily CRSP files.

[19] I identify these observations from changes in the cumulative adjustment factors reported in CRSP.

NYSE and AMEX.[20] Further, I focus on the transactions of the top management (CEOs and Chairmen) and large shareholders (more than 10% ownership). These insiders own and trade on average significantly higher share volumes than other insiders such as Directors and Officers which makes trade execution models more relevant for them.

Panel A in Table II.1 provides summary statistics for this IFDF subsample including all stocks listed at NYSE and AMEX. This sample covers 2,822 insiders from 1,434 firms listed at NYSE and 397 firms listed at AMEX. The 31,354 records are clustered into 18,780 trading strategies. The summary statistics are grouped by the direction of trade (sales and purchases) and the length of the trading strategy (five length categories).

– Insert Table II.1 approximately here –

Panel A in Table II.1 shows that the sample consists of 14,782 sell transactions ($76.0 billion) and 3,998 purchase transactions ($4.3 billion). Multiple-day transactions are common for insiders. About 55% of all trading days of sales or purchases are part of multiple-day transactions. The majority of these multiple-day transactions last between 2-5 days (36% and 35% of all transaction days for sales and purchases, respectively). Multiple-day trading strategies that last longer than 20 trading days are rare (41 sale and 13 purchase transactions). However, about 66% of the total value of insider sales are completed within a single trading day. For purchases the picture is different. While 45% of all trading days belong to single-day trading strategies, these transactions only represent 37% of the total value of insiders' purchases. The table also shows that insiders trade significant proportions of shares. The typical insider package has a size of 25,000 (8,000) shares for sales (purchases) and represents 5.7% (6.5%) of the average daily $ trading volume (if traded at once). Furthermore, the size of the transactions - measured either in the number of shares, in the number of shares relative to shares outstanding, or in the $ trading volume relative to the average daily $ trading volume - increases monotonically with the length of the trading strategy. In particular, single-day strategies are on average much smaller than multiple-day trading strategies. This univariate relation is consistent with the trade execution literature and the idea of splitting up large packages into several smaller trades.

[20] For differences between NYSE/AMEX and NASDAQ see the discussion in Chordia, Roll, and Subrahmanyam (2001) and Huang and Stoll (1996a).

Based on the numbers presented in Panel A of Table II.1, I limit the sample to trading strategies that last between 2 and 20 trading days. I do not examine single-day trades, because the vast majority of these trades would not be classified as 'large trades' for which trade execution models are developed. By excluding single-day trades, I furthermore rule out the possibility that I try to explain the splitting of transactions that are privately executed, and thus, also not object of optimal trade execution models. I also follow Keim and Madhavan (1995, 1997) and exclude all trading strategies that are not completed within a reasonable window of time (20 trading days). The number of these transactions is negligible. Beside this, the sample is reduced due to the availability of TAQ data. The total TAQ sample covers 1,027 insiders from 725 firms listed at NYSE and 97 firms listed at AMEX. The 9,275 records are clustered into 2,863 trading strategies (2,437 sale and 426 purchase transactions). Panel B in Table II.1 provides summary statistics for this total TAQ sample and shows that the data requirements imply a tendency toward somewhat larger trades.

3.2 Empirical calibration of the model

To find the optimal trading strategies as solution to the system of linear equations (II.20)-(II.22), I need (1) insider-specific data on the absolute risk aversion coefficient (α) and the total number of shares traded (X) as well as (2) asset-specific microstructure data on the price impact coefficients (γ_1, γ_2, τ_1, τ_2) and stock price volatility (σ^2). Furthermore, I need the direction of trade (D) and the fundamental asset value at time $t = 0$ (m_0) to compute the expected trading revenues (costs).

3.2.1 Assumptions on general parameters

Data on the asset position traded (X) and the direction of trade (D) comes from the insider data set. I obtain X by aggregating the number of shares traded within a trading strategy.

In contrast to these parameters, the fundamental asset value m_0 and the level of risk aversion α are not observable. I proxy for the fundamental asset value m_0 with the stock price at time $t = 0$ (p_0). This is the CRSP closing price from the trading day before the initiation of the trading strategy. This approximation, however, does not affect the optimal solution derived from program (II.16), because p_0 is not contained in the partial derivatives.

I only need the stock price at time $t = 0$ to compute the value of the objective function, i.e., the certainty equivalent of the trading revenues (costs).

The absolute risk aversion of the traders, α, is the last unknown parameter. In order to derive a sensible value range for this parameter, I follow the approach of Baker and Hall (2004) which is based on Pratt (1964).[21] This approach makes use of the fact that the constant absolute risk aversion (CARA) α is equal to the constant relative risk aversion (CRRA) divided by the decision maker's accumulated wealth, i.e.,

$$\alpha = \frac{CRRA}{wealth} \tag{II.23}$$

Thus, I derive the CARA coefficient α by making reasonable assumptions on the CRRA coefficient and accumulated investor's wealth. In the field of executive compensation, a frequently used range for values of CRRA is about 2 to 3.[22] Therefore, I use a value of 2.5 as done in Baker and Hall (2004). However, accumulated wealth is the variable that predominantly determines the level of the CARA coefficient α. I approximate the investors' accumulated wealth with the help of the investor's shareholdings in the company's stock as reported in the insider database. I multiply the stock price at time $t = 0$ (p_0) with the number of shares held before the initiation of the trading strategy to derive a wealth estimate.[23] Overall, this equity proxy, however, is conservative as it only considers the equity component of the insider's total accumulated wealth.[24]

[21] I also experimented with deriving investor-specific αs from individual trading strategies. The idea behind this "reverse" engineering of α is the following: Find the α for which the optimal length of the trading period T^* equals the observed length of the trading period T. This procedure assumes that the investors chose the optimal trading horizon which is implied by a certain level of risk aversion. However, this approach is associated with several problems: First, the optimal length of the trading period T^* is constant over an interval of α values (instead of yielding a point estimate). The trading strategies for the different α values within this interval all have the same optimal horizon, but they (more or less) differ in the trade volume executed on the individual trading days. Second, due to nonlinearities in the optimization problem, this reverse engineering often yields two or more intervals for α values for each trading strategy. Thus, using one specific α value in the calculations requires an assumption on which value to chose. For insiders for which I have more than one trading strategy in the sample, this choice also has to consider α intervals that probably differ between trading strategies. Due to these reasons, I chose an approach to exogenously derive α values. Also see the paragraph discussing the sensitivity of the optimal solution to changes in α in Section 4.1.

[22] See, e.g., Dittmann and Maug (2007).

[23] In order to avoid that the estimates by construction are lower for purchase transactions than for sale transactions, I add the $ value of the purchase transactions to the value of the equity stake held before the transaction. The reasoning behind this adjustment is the following: For sale transactions, the equity stake held before the transaction includes the shares sold shortly afterwards. This is not the case for purchase transactions. This circumstance would imply systematically lower wealth estimates for purchase transactions, although the purchases require equivalent cash holdings. If I do not make this adjustment, the main results remain unchanged.

[24] I test the robustness of the results with respect to this calibration choice in Section 4.6.

3.2.2 Estimation of microstructure parameters

In this section, I explain the estimation of the microstructure parameters γ_1, γ_2, τ_1, and τ_2 from intraday TAQ data and σ^2 from daily CRSP data.

Price impact parameters. I use trades and quotes data from the TAQ database to estimate the four price impact parameters. The Appendix contains a detailed description of the data matching and cleaning procedures used for the TAQ data. There is no commonly used approach in the empirical literature I can follow to calculate the price effect of single trades and to estimate price impact functions for individual stocks.[25] In particular, I proceed in two steps. First, I compute the price effects for each trade. Second, I estimate the price impact functions using all trades and their price effects and trade volumes.

In the first step, I compute the price impact effects of single trades by using the quote midpoint from the first quote[26] at least one second before and after the trade as reference point to compute the different price impact components.[27] Following Holthausen, Leftwich, and Mayers (1990), I define the total price impact $TotalPI_i$ as the change from the pre-trade quote midpoint to the actual trade price (expressed as percentage of the pre-trade quote midpoint) and the permanent price impact $PermPI_i$ as the change from the pre-trade to the post-trade midpoint (also expressed as percentage of the pre-trade quote midpoint):

$$TotalPI_i = \frac{p_i - q_{pre}}{q_{pre}} \tag{II.24}$$

$$PermPI_i = \frac{q_{post} - q_{pre}}{q_{pre}}. \tag{II.25}$$

The temporary price impact for trade i, $TempPI_i$, is the difference between the total and permanent price impact:

$$TempPI_i = TotalPI_i - PermPI_i \tag{II.26}$$

[25]While computing price impact effects is frequently done in several ways (see, e.g., Holthausen, Leftwich, and Mayers, 1990, Keim and Madhaven, 1996, or Chan and Lakonishok, 1995), price impact functions, in particular on an individual stock level, are rarely estimated. One of the few examples is Chen, Stanzl, and Watanabe (2005).

[26]See Chen, Stanzl, and Watanabe (2005) for a discussion on using quote midpoints versus transaction prices.

[27]For the 1-second rule to match trades with subsequent quotes see Henker and Wang (2006).

The price impact effects are defined so that positive costs are experienced when both, the permanent and the total price impact have the same sign as the order flow. Thus, for a buy order, positive costs mean that the price moves upward, while for a sell order, negative costs mean that the price moves downward. I expect the average values of the price impact taken across many orders (separately for buys and sells), to have the same sign as the order flow. However, I repeatedly observe price impact effects that have the wrong sign (e.g., a price increase during a large sell order), even after applying commonly used procedures to discard erroneous trades and quotes (see Appendix). Observations with the wrong sign bias the estimation of the price impact functions or even cause the price impact coefficients to have of the wrong sign. I thus exclude observations with a wrong sign for the price effects from the estimation of the price impact functions in the next step.

In the second step, I estimate the coefficients of the price impact function based on the price effects calculated before. In particular, I estimate two price impact functions, one for temporary price effects and one for permanent price effects. I assume a linear functional form with intercepts and estimate the relevant price impact coefficients with the following OLS regressions:

$$TempPI_i = \tau_1 + \tau_2 n_i + \varepsilon_i \tag{II.27}$$

$$PermPI_i = \gamma_1 + \gamma_2 n_i + \varepsilon_i \tag{II.28}$$

Here, n_i denotes the trading volume of trade i measured in shares. τ_1, τ_2, γ_1, and γ_2 are the coefficients to be estimated. I run the above regressions separately for buys and sells, because of asymmetric responses of prices to buys and sells on major US stock exchanges.[28] Even after discarding price impact effects with the wrong sign from the estimation, I repeatedly obtain price impact coefficients that exhibit the wrong sign, e.g., if the number of trades is very small (<100). The phenomenon that estimation yields unexpected signs for price impact coefficients is already documented in the literature (e.g., Sadka, 2006). The unexpected estimates, however, lead to unreasonable or no optimization results in the trade execution

[28]See Holthausen, Leftwich, and Mayers (1987, 1990) and Keim and Madhaven (1996) for block trades and Chan and Lakonishok (1993, 1995) for large institutional trades.

model. Thus, I set all observations for which I obtain at least one price impact coefficient with a wrong sign to missing. Furthermore, I follow Sadka (2006) and estimate the price impact coefficients from all trades over the 20 trading days preceding the trading period of interest, while I set all observations with a trading history of $<$20 trading days to missing.

Daily stock price volatility. I calculate the daily stock price volatility from daily CRSP return data as squared standard deviation over the 20 trading days prior to trade execution.

Unit of measurement. All microstructure parameters are estimated in relative terms (%). However, the formulation of the trade execution model implies measurement in absolute terms ($/share). To convert the volatility and price impact parameters expressed as percentage into $, I scale the estimated variance and price impact coefficients by the stock price at closing on the day before the initiation of the trading strategy (p_0).

3.2.3 Descriptive statistics

Table II.2 provides summary statistics for all calibration parameters in the model grouped by the direction of trade (sales and purchases).

– Insert Table II.2 approximately here –

Panel A shows the total TAQ sample. It covers 2,437 (426) sale (purchase) strategies lasting between 2 (2) and 20 (20) trading days with a volume of less than 500 shares to 65.6 (9.3) million shares. The insiders executing these sales (purchases) hold a median equity stake of $11 ($22) million. The minimum and maximum wealth levels vary between $10,000 and $11.3 billion yielding α values between $2.5 * 10^{-4}$ and $2.2 * 10^{-10}$, respectively.[29]

Table II.2 also displays the estimated microstructure parameters γ_1, γ_2, τ_1, τ_2, and σ^2. The estimation of these parameters is based on about 100 to 160,000 transactions (executed over the estimation period of 20 trading days). The number of transactions is stock-specific and is usually larger for sales than for purchases. The price impact parameters in $ terms are comparable to other empirical estimations (e.g., Sadka, 2006) and larger for sales than

[29] For the level of accumulated wealth, I replace all zero values and all values below $10,000 with $10,000 in order to avoid that I lose observations due to a missing α value. To derive α, I divide $CRRA$=2.5 by the level of accumulated *wealth*.

for purchase transactions. However, these $ numbers are derived by multiplying the original percentage estimates by the stock price p_0 to derive the correct unit of measurement for the trade optimization model. Taking the significantly different median values for the stock price p_0 into account - $34.53 for sales and $13.75 for purchases - the price impact estimates for purchases are about twice the size of the estimates for sales. This means that purchases are more expensive to execute than sales. This asymmetry in price effects for sales and purchases is consistent with the literature on price effects of (large) institutional trades (e.g., Chan and Lakonishok, 1995; Keim and Madhavan, 1997).

Panel B in Table II.2 reports summary statistics for all calibration parameters for the final sample which is a subsample of the total TAQ sample and defined in Section 4.2. The final sample covers trading strategies with a specific trade pattern and is used in all subsequent analyses to test the predictive power of the trade execution model. A comparison of Panel A and B shows no significant differences between the total TAQ sample and the final sample used in my analyses.

4 Empirical results

I divide my empirical analysis into five parts. In Section 4.1, I commence with a numerical example and a comparative static analysis using the numbers from the empirical calibration. These preliminary analyses convey a better understanding of the theoretical solution provided in the Proposition in Section 2.3 and illustrate the main features of the optimal trading strategies. Section 4.2 to 4.5 form the main part of the empirical analysis. I start with inspecting the general shape of actual execution strategies of insiders in Section 4.2. I then conduct more detailed quantitative analyses to examine the explanatory power of the model along two dimensions. In a first step, I test the model's prediction on the per-period trade volume for an exogenously given trade horizon T. I refer to this dimension of the model as "trade pattern optimality". To test the "trade pattern optimality", I derive the length of the trade horizon for the optimization from the trade horizon actually chosen by the insider for the specific trade. In a second step, I test the model's prediction on the optimal length of the trading horizon and the decision whether a trade should be split up or not. I refer to this dimension of the model as "trade horizon optimality". In contrast to the first step of my analysis, I now endogenize T by running a second optimization over different trade horizons $T \in [1, 20]$. Afterwards, I compare the values for the objective function (certainty equivalents) for the different Ts and determine the optimal trade horizon T^{opt} which maximizes the objective function. The length of the optimal trade horizon depends the individual input parameters as described in the sensitivity analysis (Section 4.1). In Section 4.5, I examine the overall benefit from splitting up large trades by considering the "trade pattern" and the "trade horizon" dimension jointly. Thus, I compute the total optimization potential from optimal trade splitting and compare it to the optimization potential realized by insiders with their actual trading strategies. I conduct several robustness checks in Section 4.6, before I summarize and discuss the main results in Section 4.7.

4.1 Preliminary analyses

4.1.1 Numerical example

The parameters for this numerical example are derived from my sample. In particular, I use the median values for sale transactions displayed in Panel B of Table II.2. Consider a trader with a risk aversion coefficient $\alpha = \frac{2.5}{\$11{,}375{,}935} = 2.198 * 10^{-7}$ and the case of maximizing the expected trading revenues from the liquidation of 62,500 shares over $T = 3$ periods for a stock currently trading at $p_0 = \$34.53$ with the following microstructure parameters:

$$\gamma_1 = \$3.08 * 10^{-2}, \quad \gamma_2 = \$0.22 * 10^{-5}, \quad \tau_1 = \$2.38 * 10^{-2}, \quad \tau_2 = \$0.15 * 10^{-5}, \quad \sigma^2 = \$0.011 \ \cdot$$

To develop some intuition for these parameters, observe that the no-impact cost of selling 62,500 shares at \$34.53 is \$2,158,125. The immediate liquidation of the share block would result in a temporary price impact of \$7,338 and a permanent price impact of \$10,670. Taking the price movement risk for one day of \$5 into account, the certainty equivalent for selling the asset position becomes \$2,140,112. Thus, the full-impact trading revenues of immediate liquidation are \$18,013. Assuming a time period of 3 trading days, the model predicts optimal trade packages of 26,727, 20,830, and 14,942 shares. With this trading strategy, the certainty equivalent for the asset position increases to \$2,145,185, bringing the implementation costs down to $12,940. Using the model to optimize the length of the trading period results in trading over 5 trading days[30] with minimal implementation costs of $12,777. This is an average improvement of $8.4 cent/share compared to immediate liquidation and $0.3 cent/share compared to liquidation over 3 trading days. The impact of the price movement discount is marginal in this example due to the very low risk aversion coefficient which results from the high level of accumulated wealth of about $11.4 million. Assuming a wealth level of $1 million increases the price movement discount by factor 10.

4.1.2 Comparative static analysis

The sensitivity analysis is based on the above numerical example for T=3.[31] In addition to the median values for X, γ_1, γ_2, τ_1, τ_2, σ^2, and α, I use the 10th, 25th, 75th, and 90th percentile for each parameter. In particular, I set all parameters to the median values and then vary one variable at a time over the percentiles.

To illustrate how the individual parameters affect the optimality of the trading strategies, I start from the simple baseline or benchmark case which corresponds to the seminal model developed by Bertsimas and Lo (1998). I consider a risk-neutral trader, $\alpha = 0$, who does not care about the risk of the liquidation revenues, but about the expected value of the liquidation revenues only. Furthermore, consistent with Bertsimas and Lo (1998), I assume the price impact function to be linear in trade size comprising a temporary and a permanent component ($\gamma_2 > 0$ and $\tau_2 > 0$). This functional form implies that there are no fixed price impacts ($\gamma_1 = \tau_1 = 0$). Under these parameter assumptions, the optimal trading strategy for an exogenously determined T is to break up the total number of shares into T identical packages of size X/T. This optimal execution policy is called "naive strategy" (Bertsimas and Lo, 1998) or "straight-line trajectory" (Almgren and Chriss, 2001). In this benchmark case, it is not possible to determine the optimal length of the trading interval T, because traders would always prefer longer to shorter horizons, the limit being an execution policy of trading one share per day.

[30] The individual trade packages for the 5 day trading strategy have the following sizes: 24,283, 18,384, 12,494, 6,610, and 728 shares.

[31] I limit the trade horizon to T=3 periods, because for longer trade horizons I do not obtain optimal solutions from the model for a large number of parameter settings. For T=3, there is only one case with no solution. This is for the 10th percentile of the number of shares (see Figure II.6).

Risk aversion (α). Introducing risk aversion, $\alpha > 0$, causes the trader to care about the risk of exogenous price changes within the trading interval T. Thus, the trader balances the desire to realize the highest (lowest) level of trading revenues (costs) given the price impact of his sales and the desire to realize some confidence level given the market risk of the asset. Risk aversion causes trades to be shifted to earlier periods (compared to the straight-line policy). Risk averse traders sell relatively more upfront, and less in later periods, incurring higher price impact costs with their early trades, but at the same time reducing their exposure to random price shocks for their later trades. Figure II.1 shows the shares traded per period expressed as percentage of the total asset position. The horizontal line in Figure II.1 shows the optimal straight-line strategy of a risk-neutral trader (benchmark case, $\alpha = 0$). The other lines show the sequence of optimal trades for increasing values of absolute risk aversion. The graph shows that the liquidation speed increases with risk aversion. Concerning the optimal length of the trading interval T, an increase in the risk aversion coefficient leads to a shortening of the optimal execution horizon (not graphed).

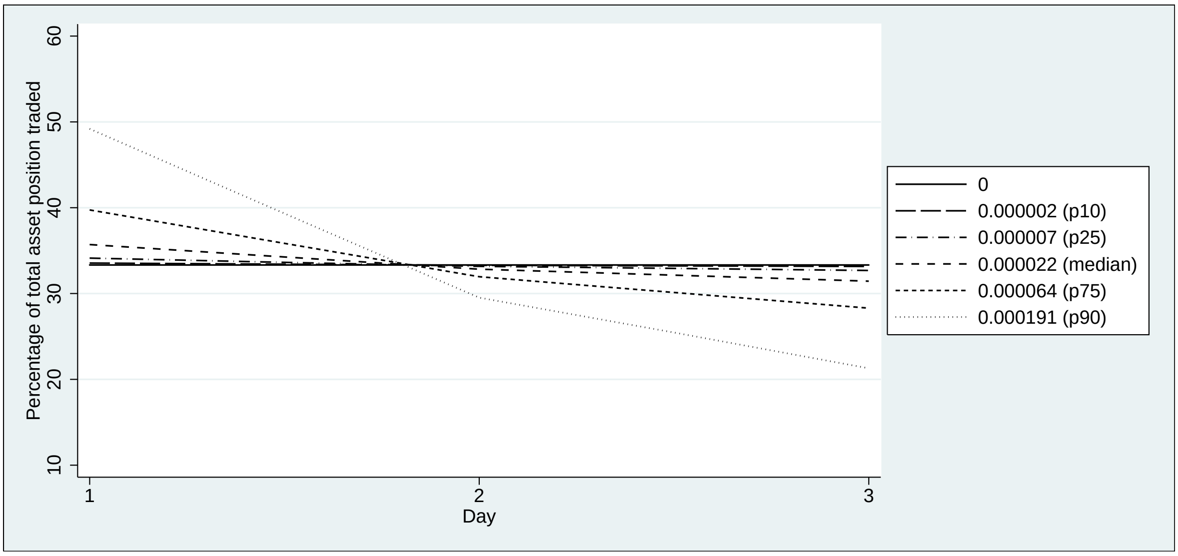

Figure II.1: **Optimal trading volume and risk aversion (α)**
Parameters are T=3, X=62,500 shares, $\gamma_2 = \$0.22 * 10^{-5}$, $\tau_2 = \$0.15 * 10^{-5}$, $\sigma^2 = \$0.011$, $\gamma_1 = \tau_1 = \$0$, and $CRRA$=2.5. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated *wealth*. The median wealth level of $11,375,935 as well as the four percentiles are scaled by 100.

The following observation associated with the sensitivity analysis concerning the risk aversion is notable: The risk aversion coefficients are estimated by scaling $CRRA$ by the level of accumulated wealth. The typical wealth levels in the sample are, however, very large - even though I use conservative estimates - and imply risk aversion coefficients close to zero. As a result, the trading strategies do not deviate significantly from the risk-neutral straight-line policy and are almost similar even for the most extreme values of α (10th and 90th percentile). To make the effects from changes in the level of risk aversion visible in the above analysis, I divided all wealth levels by 100 yielding a wealth range of $13,100 (10th percentile) to $1,319,276 (90th percentile). For all wealth levels above this scaled 90th percentile of about $1,000,000, decreases or increases in the level of wealth have no measurable effect on the optimal trading strategies.

Asset volatility (σ^2). An increase in the asset volatility has the same effect on the optimal trading policy as an increase in the trader's risk aversion. Thus, higher asset volatility causes traders to redistribute their trades from later to earlier periods or to reduce the optimal trading horizon, respectively. Risk aversion and asset volatility have the same impact on trading strategies, because both parameters affect the size of the price movement discount. Figure II.2 displays the trade policies for increasing asset volatility showing that higher volatility is associated with trading in earlier trading rounds. Alternatively, higher volatility results in longer trading horizons. The relation between asset volatility and trade horizon, however, is not linear.

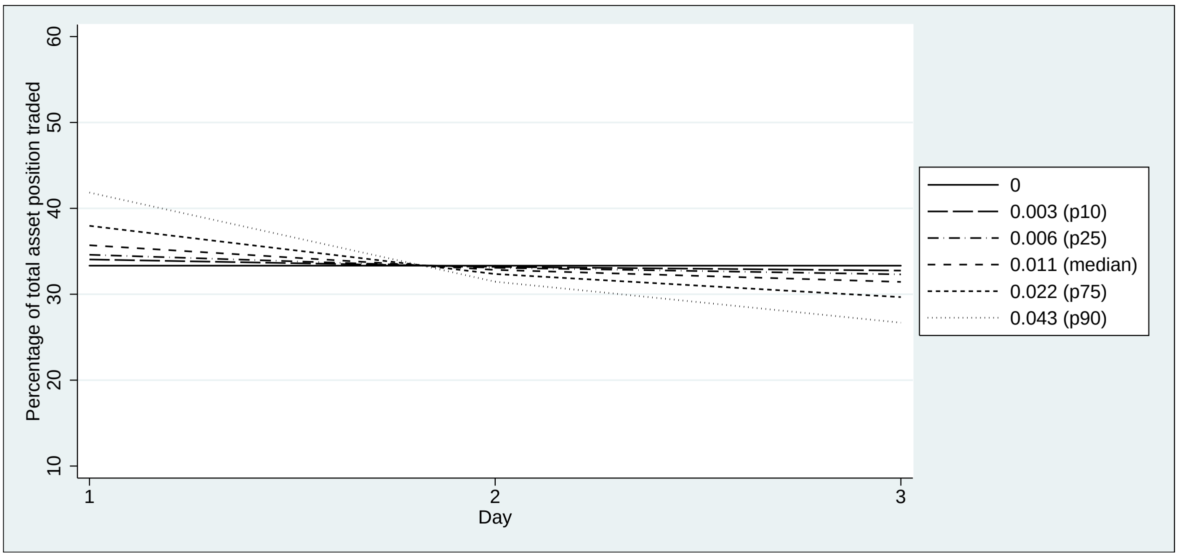

Figure II.2: **Optimal trading volume and asset volatility (σ^2)**

Parameters are T=3, X=62,500 shares, $\gamma_2 = \$0.22 * 10^{-5}$, $\tau_2 = \$0.15 * 10^{-5}$, $\gamma_1 = \tau_1 = \$0$, $CRRA$=2.5, and $wealth$=$113,759. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated $wealth$. The median wealth level of $11,375,935 is scaled by 100.

Asset volatility and risk aversion enter the same term in the objective function in a multiplicative way. Thus, extreme values of either variable offset the potential influence of the other variable. In particular, very low risk aversion coefficients (caused by very high levels of accumulated wealth) offset the impact of significant changes in the asset volatility. To make the effects from changes in the asset volatility visible, I scaled the median wealth level by 100 for the above analysis. Conversely, the comparably high wealth levels in the sample imply low risk aversion coefficients which neutralize the impact of the asset volatility.

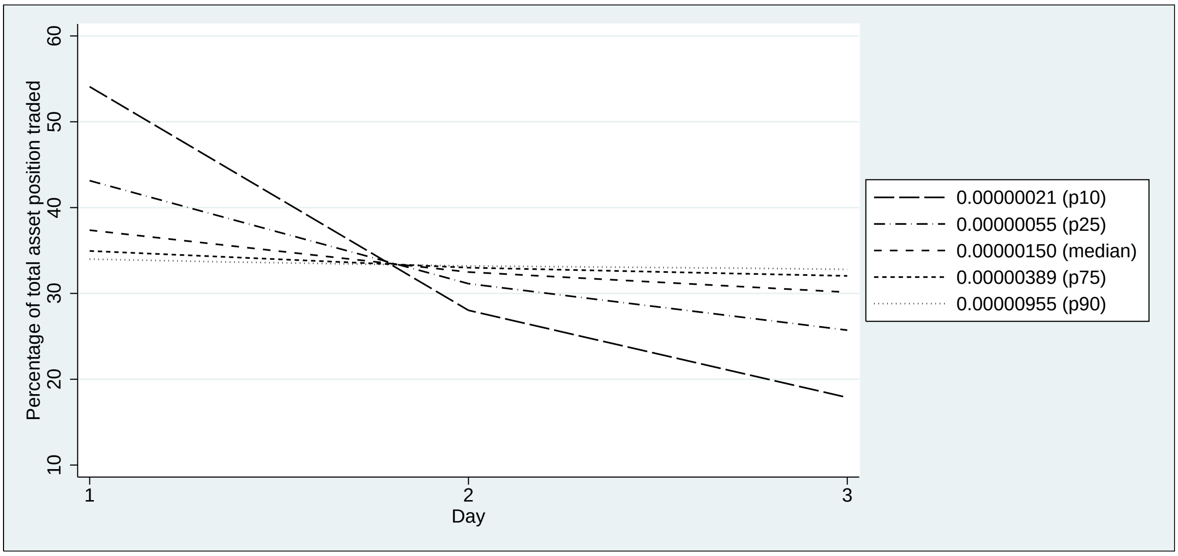

Figure II.3: **Optimal trading volume and variable temporary price impact (τ_2)**
Parameters are T=3, X=62,500 shares, $\gamma_1 = \gamma_2 = \tau_1 =$ \$0, $\sigma^2 =$ \$0.011, $CRRA$=2.5, and $wealth$=\$11,375,935. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated $wealth$. The median wealth level of \$11,375,935 is scaled by 100.

Variable price impact (γ_2 and τ_2). An increase in γ_2 and τ_2 indicates that the negative price effects of each unit traded get larger. There is, however, a significant difference between the two parameters. The temporary price effect τ_2 has no impact on futures prices, and thus, on trades carried out in subsequent trading periods. As every traded unit incurs a price discount of τ_2, the total temporary price effect is not affected by the size of the individual trade packages. Varying the size of τ_2 yet has an impact on the optimal trading strategy, because the trader trades off the total temporary price impact against the risk of price changes. Figure II.3 shows that the importance of the risk aversion decreases with the size of the temporary price effect. In case of a large temporary price impact, the optimal trading strategy is almost equal to the straight-line policy under risk neutrality, while for a small temporary price impact the risk aversion implies a front-loaded strategy.

In contrast to the temporary price impact τ_2, the variable permanent price impact γ_2 affects all subsequent trades via a change in the stock price. Figure II.4 shows the trade patterns for varying permanent price effects. A larger unit impact implies that traders prefer to trade smaller quantities in earlier periods. Thus, the larger the variable permanent price effect γ_2, the closer the trading strategies to the straight-line policy. Alternatively, the optimal number of trading days rises as a consequence of increasing unit price impacts, while keeping all other parameters constant (not graphed).

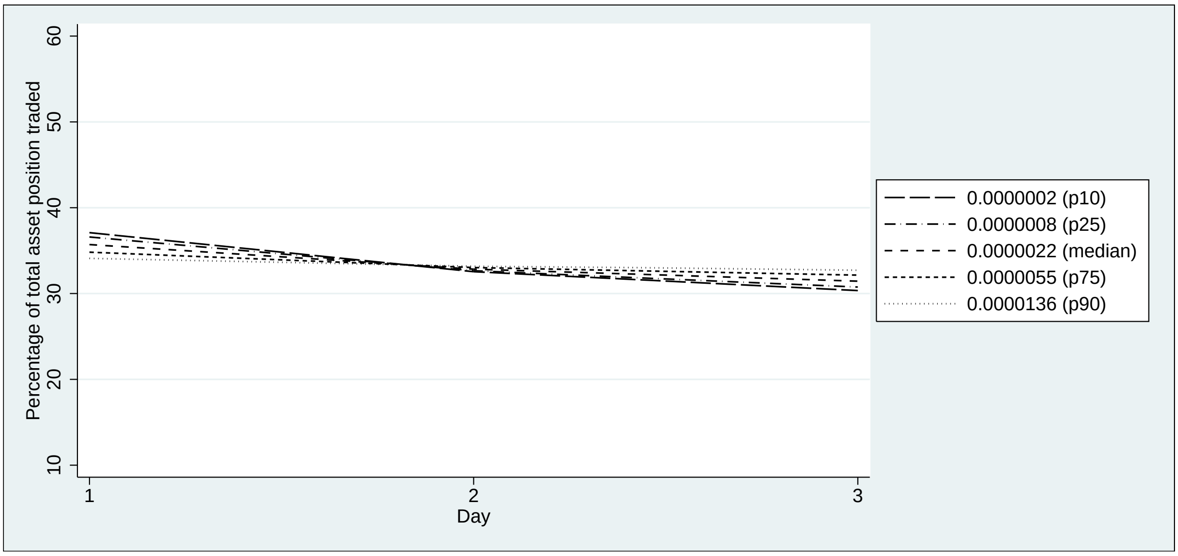

Figure II.4: **Optimal trading volume and variable permanent price impact (γ_2)**
Parameters are T=3, X=62,500 shares, τ_2 = \$0.15 $*$ 10^{-5}, $\gamma_1 = \tau_1 =$ \$0, σ^2 = \$0.011, $CRRA$=2.5, and $wealth$=\$11,375,935. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated $wealth$. The median wealth level of \$11,375,935 is scaled by 100.

Fixed price impact (γ_1 and τ_1). So far, the comparative static analysis did not include fixed price effects ($\gamma_1 = \tau_1 = 0$). Introducing fixed price impact costs every time an order takes place, diminishes the incentive to engage in multiple transactions over longer trading horizons. The larger the per-transaction costs, the larger the lots sold in each trading round and the smaller the number of trading rounds. This effect stems exclusively from the permanent component of the fixed price impact, γ_1. To see this, note that the temporary fixed price impact is represented by the constant term τ_1 that is not related to the decision variables $n_1, ..., n_T$ in equation (II.19). Thus, changes in τ_1 do not alter the pattern of the optimal trading strategy, but rather affect the level of the objective function, and thus, the certainty equivalent of the trading revenues (costs). Figure II.5 shows the optimal trading strategies for different values of permanent fixed effects.

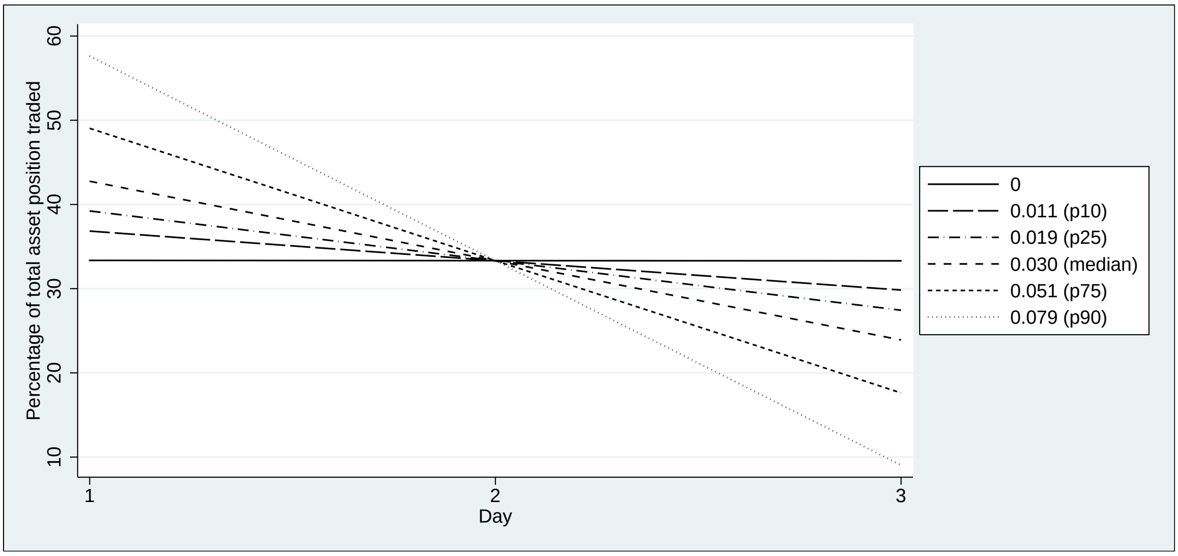

Figure II.5: **Optimal trading volume and fixed permanent price impact (γ_1)**
Parameters are T=3, X=62,500 shares, $\tau_1 = \$2.38 * 10^{-2}$, $\tau_2 = \$0.15 * 10^{-5}$, $\gamma_2 = \$0.22 * 10^{-5}$, $\sigma^2 = \$0.011$, $CRRA$=2.5, and $wealth$=\$11,375,935. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated $wealth$. The median wealth level of \$11,375,935 is scaled by 100.

Introducing fixed effects in the linear specification of price impact effects results in non-linear total price impact costs. This modification has a positive side effect concerning the scaling behavior of trading strategies. For $\gamma_1 = \tau_1 = 0$, the optimal trading strategies are scalable which means that the sale of 10,000 shares is executed with exactly the same selling speed as the sale of 1,000 shares. The optimal trade packages for 10,000 shares can be derived by multiplying the optimal trade packages for 1,000 shares by factor 10. However, this scaling behavior is inconsistent with the intuition that large asset positions are effectively less liquid, and hence, should be liquidated less rapidly than small positions. One way to model a more intuitive scaling behavior is to modify the price impact functions to be non-linear, e.g., by introducing fixed price effects γ_1 and τ_1.

Number of shares traded (X). Under the assumption of no fixed price effects, $\gamma_1 = \tau_1 = 0$, there is no monotonic relation between the size of the asset position X and the liquidation speed, because the liquidation speed is constant (scaling behavior).

Intuitively, one would expect that larger asset positions are sold over longer trading horizons and with a lower liquidation rate. Figure II.6 shows that for $\gamma_1, \tau_1 \neq 0$ an increase in the asset position implies such a decrease in execution speed. Again, however, the relation is not linear. As Schied and Schoeneborn (2009) show, an increase in the asset position is associated with two counteracting effects which both can set the direction of the overall effect. On the one hand, an increase in the asset position implies larger price effects, which would result in longer trading horizons or lower trading speed. On the other hand, an increase in the asset position increases the risk associated with the position, which would imply shorter trading horizons and higher execution speed. Which effect dominates at a time depends on the case-specific parameter constellation of price impact parameters, asset volatility, risk aversion, and size of the asset position.

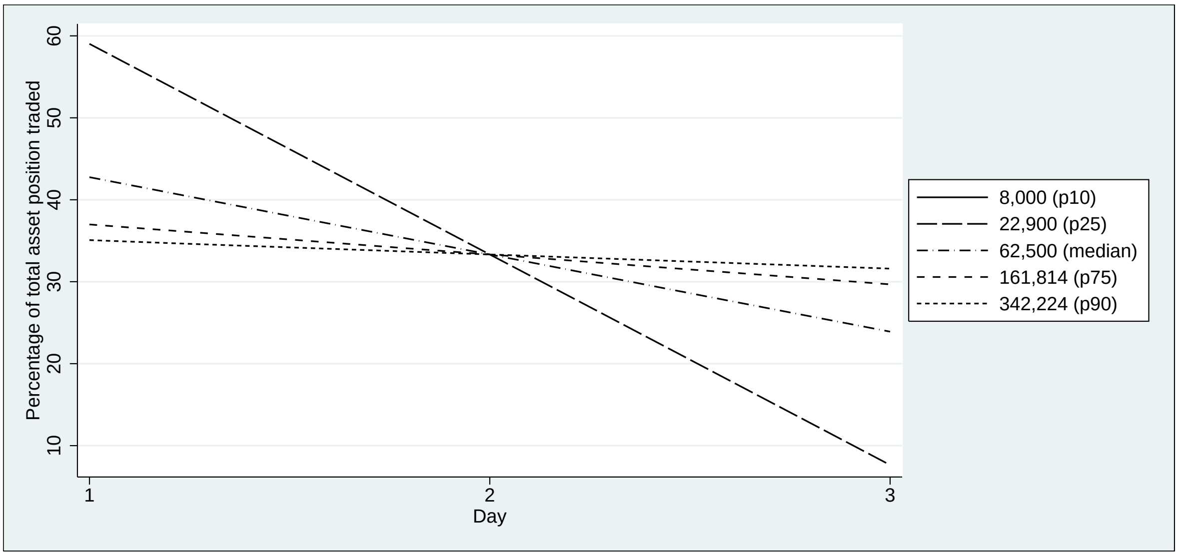

Figure II.6: **Optimal trading volume and size of the asset position (X)**
Parameters are T=3, X=62,500 shares, $\tau_1 = \$2.38 * 10^{-2}$, $\tau_2 = \$0.15 * 10^{-5}$, $\gamma_2 = \$3.08 * 10^{-2}$, $\gamma_2 = \$0.22 * 10^{-5}$, $\sigma^2 = \$0.011$, $CRRA$=2.5, and $wealth$=\$11,375,935. The risk aversion coefficient α is estimated by scaling $CRRA$ by the level of accumulated $wealth$. The median wealth level of \$11,375,935 is scaled by 100. For the 10th percentile (X=8,000 shares), the model provides no admissable solution.

In summary, the comparative static analysis shows two things: First, the optimal trading strategies have a universal form. In particular, the daily trade volume declines at a decreasing rate over the trading horizon. All trade execution models assuming risk aversion, no intertemporal updating, and no stock price drift, predict a decreasing and convex trade pattern which varies only in the degree of convexity. Thus, the optimal trading strategies derived in this paper represent a whole class of trade execution models. Second, the optimal trading strategies are the result of the complex interplay of different exogenous parameters and comprise non-monotonic relations, which cannot be tested in cross-sectional regressions.[32] Thus, I test the model via calibration which is also a more stringent test.

4.2 Trade pattern shape

Before I quantitatively examine the optimality of the actually observed trade patterns and trading horizons, I inspect the general shape of the actual trading strategies. Therefore, I distinguish four general trade patterns: "Straight" stands for the straight-line policy where an equal number of shares is traded each day. "Increase" ("Decrease") indicates a trading strategy where the volume traded per day increases (decreases) continuously over the individual days of the trading horizon. "Other" comprises all remaining non-monotonic trade patterns. As I do not require TAQ data for this analysis, I investigate the frequency of these trade patterns for the total NYSE & AMEX sample as well as the final sample.

Table II.3 shows the frequency distribution of trading strategies by length and trade pattern grouped by the direction of trade (sales and purchases). Panel A displays the results for the total NYSE & AMEX sample. Panel B reports the results for the final sample.

– Insert Table II.3 approximately here –

The proportions of the different trade patterns are approximately equal for all samples and for sale and purchase transactions. Straight-line policies account for about 10% of all multiple-day strategies. The other three types of trading strategies - decreasing, increasing, and non-monotone - are almost equally widespread and account for about 30%, 25%, and 35% of all multiple-day trading strategies, respectively. The table also shows that straight-line and non-monotone trade patterns are predominant for trades with a trading horizon longer than six days. In particular, non-monotone trade patterns are common for longer trading horizons. Strictly decreasing or increasing patterns are only observed for strategies that do not last longer than five trading days. Based on Table II.3, I reject the trade execution model for more than two-thirds of all multiple-day trading strategies. The model seems to have only predictive power for multiple-day trades with a short trading horizon, i.e., transactions

[32] See also the sensitivity analysis in Schied and Schoeneborn (2009) for non-monotonic relations.

that last between two and five trading days. This observation fits well with the static nature of the model. Static strategies are determined before trading starts and not updated over the course of trading in response to sign and size of stock price changes. Such static trade behavior is, in general, more adequate for shorter trading horizons.[33]

I now turn to the question whether the trade patterns not predicted by the model can be explained with other models and/or assumptions. Alternative models in the trade execution literature make predictions that may better fit with these alternative trading patterns. Straight-line policies are optimal for traders who are assumed to be risk neutral (Bertsimas and Lo, 1998). Risk neutrality implies a drop of the trade-off between execution risk and price impact costs. The optimal risk-neutral strategy solely minimizes the price impact which is to trade equally sized packages in each trading interval (Bertsimas and Lo, 1998). Non-monotone and/or increasing trade patterns require models with additional features and assumptions, which are largely uninvestigated in the theoretical trade execution literature.[34] Therefore, such models are not within the scope of this paper.

Result 1: *An examination of the actual trade patterns of insiders shows that the explanatory power of the trade execution model is limited to about 30% of all multiple-day trading strategies which exhibit a decreasing trade pattern and do not last longer than 5 trading days.*

For about 70% of the actual trading strategies the CARA model is rejected. These trading strategies exhibit increasing, straight-line, or non-monotone trade patterns and might only be explained with trade execution models incorporating alternative risk preferences and intertemporal updating. Models of this type are less common and developed, and thus, not subject of this paper.

In the next step of my empirical analysis, I focus on the trading strategies which are within the scope of the model used here. This means I focus on decreasing trading strategies. All other trading strategies - increasing, non-monotone, and straight-line strategies - are excluded from the forthcoming analyses.

[33]However, Schied and Schoeneborn (2009) show that dynamic trading strategies only generate added utility for traders with non-constant absolute risk aversion. This means that, in general, static trading strategies are optimal for traders with CARA utility, independent from the length of the trade horizon. See Section 4.7 for a discussion.

[34]A notable example is Schied and Schoeneborn (2009). See also Schoeneborn (2008) for a discrete-time version.

4.3 Trade pattern optimality

I examine the optimality of the lots distribution over individual trading days by assuming that the trading horizon chosen by the insider is exogenously determined. Thus, I calculate the optimal trading strategy for the observed length of the trading strategy and then compare the actually implemented trading strategy and the optimal policy derived from the model. The model, however, does not yield an admissible trading strategy for all exogenously given trade horizons. In particular, the non-negativity constraint $0 \leq n_t \leq X$ is frequently binding for longer trade horizons and/or lower levels of risk aversion.

I compare the optimal and the implemented trading strategy with the help of two measures. The most intuitive measure is the value of the objective function $M\left[\mathbb{E}\left(R\right), \mathbb{V}\left(R\right)\right] = \mathbb{E}\left(R\right) - \frac{\alpha}{2}\mathbb{V}\left(R\right)$, which can be thought of as a certainty equivalent for the total asset position X. If the value of the objective function is scaled by the size of the trading strategy X, the resulting figure corresponds to the shadow revenues (costs) per share. The difference in this measure between the optimal and actual trading strategy captures the financial implications from deviating from the optimal trading strategy. I express the difference in percentage terms by scaling it with the value of the optimal trading strategy. I denote this measure $FDEV$ (Financial DEViation) and use the following formula to calculate it:

$$FDEV = \frac{M^{opt} - M}{|M|} * 100 \tag{II.29}$$

where M^{opt} (M) is the value of the objective function for the optimal (actual) trading strategy. Taking the absolute value of the objective function in the denominator is necessary to get deviations that all have the same (positive) sign as the value of the objective function is negative for purchase transactions (cash outflow) and positive for sale transactions (cash inflow). $FDEV$ represents the return per share forfeited due to a non-optimal trade pattern. The magnitude of this deviation measure depends on the extent to which the actual daily trade volumes deviate from the optimal trade volumes, the magnitude of the microstructure parameters (price impact and volatility), and the size of the asset position.

To capture the mere extent of deviations in trade volumes, I use a second more ad-hoc measure to compare optimal and actual trading strategies. To calculate this measure, I compute the deviation in share volumes between the optimal and actual trading strategy for each trading day, scale this difference with the size of the total asset position, and sum up the daily percentages over all trading days. Finally, I divide the sum by two to limit the measure to the interval [0%, 100%]. I denote this measure $NDEV$ (n_t DEViation) and use the following formula to compute it:

$$NDEV = \frac{1}{2} * \sum_{t=1}^{T} \frac{\left| n_t^{opt} - n_t \right|}{X} * 100 \tag{II.30}$$

where n_t^{opt} (n_t) is the optimal (actual) trading volume in shares in period t and X is the total asset position to be traded. $NDEV$ represents the average share volume deviation between the optimal and actual trading strategy.

Before I analyze these deviation measures for the whole sample, I look at two trading strategies and the corresponding deviation measures. First, I consider the 3-day buying strategy of Steve Creamer, CEO of EnergySolutions Inc., who bought 1,000,000 shares in packages of 450,000, 319,200, and 230,800 shares in November 2008. The face value of the asset position ($X * p_0$) is \$4.42 million. The optimal trading policy derived from the model is slightly less front-loaded than the actual trading strategy and comprises three lots of 357,618, 330,963, and 311,419 shares. The average trade volume deviation $NDEV$ is 9.2%, while the sample median is 13.6%. The $FDEV$ measure yields a value of 0.11% which corresponds to an absolute value of \$5,276. For $FDEV$ the sample median is slightly lower (0.02%). Second, I look at the3-day selling strategy of Arif Shakeel, COO of Western Digital Corp, who sold 482,391 shares in packages of 472,400, 5,000, and 4,991 shares in February 2005. The face value of the asset position ($X * p_0$) is \$5.20 million. The optimal trading strategy for 3 trading days derived from the model is 179,537, 160,519, 142,335 shares. The average trade volume deviation $NDEV$ is large with 60.7% compared to the sample median of 14.9%. This trade volume deviation results in a financial deviation $FDEV$ of 0.75% (\$38,305) which is significantly higher than the sample median 0.02%.

Table II.4 displays the main distribution characteristics for the two deviation measures $FDEV$ (Panel A) and $NDEV$ (Panel B) for the sample of 766 transactions for which the model provides an optimal trading strategy for the actual trade horizon.

– Insert Table II.4 approximately here –

If the model would perfectly capture reality and all parameter estimates would be free of any bias, then the deviation measures would be zero for all observations in the sample. Thus, my analysis focuses on the distribution of the deviations, and in particular, the following distribution characteristics displayed in Table II.4: the number of zero values (zeros), the 95th percentile value (p95), and the degree of positive skewness (skew). The number of zero values shows for how many observations there is no deviation. The 95th percentile marks the upper bound for deviations while excluding extreme observations. Finally, the positive skewness indicates how much the distribution tail is pushed towards the ideal value of zero which indicates a perfect fit of the model.

For 242 of the 766 strategies - 213 sale and 29 purchase transactions - I find a $FDEV$ value of zero (rounded to 2 digits). This means the model perfectly predicts 32% of the trading strategies. The 95th percentile improvement associated with the optimal trading strategy is 0.75% (0.79%) for sales (purchases) which shows that the potential for improvement is limited. The percentage numbers correspond to absolute values for the whole asset position X of $38,305 and $9,459 respectively. Finally, the skewness values are positive and indicate that the deviation values tend to cluster towards the lower end of the scale (zero deviation). To determine the significance of the positive skewness, I calculate the standard error of skewness which can be approximated by the square root of 6/sample size.[35] Multiplying the standard error of skewness by ± 2.58 (1.96) yields the 99% (95%) confidence interval for the skewness. If the skewness is outside the confidence interval, the distribution is significantly skewed. I obtain a standard error of skewness of 0.005 for sales and of 0.024 for purchases. Thus, the distribution of deviations for sales and purchases is significantly skewed at the 1% level. Overall, the mean and median values for $FDEV$ indicate that the potential of financial optimization is larger for purchase than for sale transactions.

I now turn to the second deviation measure $NDEV$. This measure captures differences in the daily trade volumes and is, in contrast to $FDEV$, not affected by differences in the microstructure parameters and their impact on the financial deviation. Thus, $NDEV$ is a more direct measure to compare optimal and actual trading strategies. Furthermore, the results for this deviation measure are more precise than for $FDEV$, because the $FDEV$

[35]See Tabachnick and Fidell (1996), p. 72.

measure is based on US dollar and rounded to 2 digits. Thus, it is not surprising that I do not find any perfect matches (zeros) for $NDEV$. This implies, that even for the trading strategies with no deviation in $FDEV$, the daily trade volumes do not perfectly correspond to the trade volumes predicted by the model. The 95th percentile values with 41.9% for sales and 40.2% for purchases are much higher than for $FDEV$. The skewness toward zero values is still significant at the 1% level for sales and purchases. Also note that the mean and median deviations in trade volumes are somewhat larger for sales than for purchases. Thus, the model has a slightly higher predictive power for purchases than for sales in terms of the mere trading volume. However, after considering the larger price impact effects and volatility for purchase transactions displayed in Table II.2, the median financial implications associated with deviations from the optimal trading strategies ($FDEV$) are larger for purchases than for sales.[36] This means that smaller adjustments in trading volumes have larger financial implications for purchases than for sales.

For 92 transactions - 75 sales and 17 purchases - of the 858 multiple-day trading strategies with a decreasing trade pattern, the model finds no optimal trading strategy for the given length of the trading interval. The optimal solutions I obtain for these trading strategies do not meet the requirement that a sale (purchase) program does not include any additional buys (sales). These 92 transactions are comparably small measured in the number of shares, and in particular, when measured as percentage of average daily $ trading volume. The model predicts for these transactions an optimal horizon which is shorter than the trading horizon actually chosen by the insider. More specifically, the model predicts immediate execution within one day for 83 of the 92 transactions. I did not include these 92 transactions in the above analysis of optimal trade patterns, although the deviation measures $FDEV$ and $NDEV$ could be calculated, because the analysis of optimal trade horizons is subject of the next section. Thus, I postpone the examination of these transactions to the next section for consistency reasons.

[36] This conclusion seems to be inconsistent with the mean value for sales and purchases in Panel A of Table II.4. However, the mean figures for sales are biased due to one extreme observation with $FDEV$=277.97 (see Panel A in Table II.2, column "maximum value"). Excluding this extreme observation yields a mean value that is lower than the mean value of 0.22 for purchases.

Result 2: *Taking the actually observed trading horizons of insiders as given, the model provides for 11% of the transactions with decreasing trading strategies no optimal solution, but instead favors immediate execution or execution over shorter than actual trade horizons.*

For the remaining 89% of the transactions with an optimal solution, the average deviation in the number of shares traded per period is 17.6% for sale transactions and 16.8% for purchase transactions. Thus, the model's explanatory power in terms of shares traded does not significantly differ for purchase and sale transactions. For about 32% of all transactions with an optimal solution, the deviations in trade volumes are only marginal and/or price impact effects and volatility are low, implying that the financial deviations between actual and optimal trading strategies are 0% (when rounded to 2 digits). The financial deviations for the remaining strategies are of measurable size. The deviations, however, are for less than 5% of the transactions larger than 1%. In particular, the median financial deviation is 0.02% for sale transactions and 0.03% for purchase transactions.

4.4 Trade horizon optimality

I now investigate the optimality of the length of the trading horizon. In this step of the empirical analysis, I give up the assumption that the length of the trading period as actually observed is optimal. Instead, I use the model to derive the optimal length of the trading strategy. The model, however, does not directly aim at making predictions about this feature of the trading strategies. Thus, I use the following method to endogenize the trading horizon T within my modeling framework: I calculate optimal trading strategies for the grid of values $T \in [1, 20]$ and then determine the optimal trade horizon T^{opt} by selecting the horizon that gives the largest value for the objective function.[37] I define the metric $TDEV$ as the difference between the length of the trading periods:

$$TDEV = T^{opt} - T \tag{II.31}$$

where T^{opt} (T) represents the optimal (actual) length of the trading period. Thus, $TDEV > 0$ ($TDEV < 0$) indicates that the optimal trading interval should be longer

[37] I round the results for the optimization function to full \$. In case that (due to this rounding) several trading strategies with different trading horizons yield the same value for the objective function, I pick the trading strategy with the minimal T^{opt}.

(shorter) than actually chosen by the insider. The $TDEV$ metric replaces the $NDEV$ measure. Beside this, I also use the $FDEV$ metric to examine the financial implications associated with deviations in the length of the trading horizon. However, as the optimization of the trading horizon always comprises an optimization of the trade pattern, the $FDEV$ measure is the sum of the financial deviations from both optimizations. In contrast, $TDEV$ is a measure of the mere deviations in the trading horizon, and thus, better suited to analyze the predictive power of the model with respect to the trading horizon.

Table II.5 displays the main distribution characteristics for the two deviation measures $FDEV$ (Panel A) and $TDEV$ (Panel B) for the complete sample of 858 transactions that exhibit a decreasing trade pattern.

– Insert Table II.5 approximately here –

Panel A in Table II.5 reports the financial implications that are associated with the deviations in the trading horizon. The 95th percentile improvement associated with the optimal trading horizon is 2.09% (2.30%) for sales (purchases). A comparison of the mean and median $FDEV$ figures in Table II.4 and II.5 shows that the financial deviations are larger for the optimization of the trade horizon than for the optimization of the mere trade pattern within a given horizon as done in the last section. This result is consistent with the fact that the trading strategies optimized with respect to the trading horizon are also optimized with respect to the trade pattern. Thus, the financial deviations displayed in Panel A in Table II.5 include both optimization potentials. A separation of the financial effects from the two optimizations is impossible, because the trade horizon optimization always implies an optimization of the trade pattern. Panel A shows that for 111 (13%) of 858 trading strategies there is no financial improvement for switching from the actual to the optimal trade horizon and trade pattern as predicted by the model. Put in other words, 13% of all decreasing trading strategies are well predicted by the model. These 111 execution strategies are part of the 242 transactions identified in Table II.4 that exhibit an almost perfect trade pattern if the trading horizon is exogenously given. For the remaining 131 trading strategies with only marginal deviations in the trade pattern for the actually observed trade horizon, the model predicts a trading horizon of a different length to be optimal.

Panel B in Table II.5 shows that for 125 (15%) of 858 trading strategies - 97 sales and 28 purchases - the actual trading horizon corresponds to the optimal trading horizon. Beyond this, the positive median value in $TDEV$ indicates that the majority of the trading horizon deviations is positive. A positive value means that the optimal trading horizon is longer than the actual horizon. The maximum trading horizon is 20 trading days which corresponds to the maximum value of the grid values used for optimization.[38] For 96 transactions (11%) of the 858 trading strategies - 79 sales and 17 purchases - the optimal trading horizon is shorter than the horizon actually observed (results not tabulated). For 87 of the 96 transactions, the model predicts immediate execution within one day while the insiders actually traded over two to four trading days. Thus, in these cases, the insiders traded in a way which would have been predicted by the model for less risk averse insiders. For all remaining trading strategies (74%), the trading horizon predicted by the model is longer than the trading horizon chosen by the insiders. Thus, insiders in these cases actually seem to be more risk averse than assumed in my model. Overall, the median and mean deviations in trading horizons are somewhat larger for sales than for purchase transactions indicating that the optimization potential for purchase transactions is lower. Put differently, the explanatory power of the model with respect to the trading horizon is larger for purchases than for sales.

Result 3: *Allowing for an optimization over the trade horizon in addition to the trade pattern, the model correctly predicts the trading horizon for about 15% of the actual trading strategies. For the vast majority of the trading strategies (74%), the model predicts a longer trading horizon. For the remaining 11% of the transactions, most of which are small trades, the trading horizon predicted by the model is shorter than the acutal trading horizon.*

Due to the fact that trading strategies optimized with respect to the trade horizon are also optimized with respect to the trade pattern, the overall financial deviations are larger than for the mere optimization of trade patterns. For about 13% of all trading strategies, the policies predicted by the model match almost perfectly with the actual trading strategies along both optimization dimensions, i.e., with respect to the trade horizon as well as the trade pattern.

[38] Thus, for these transactions the optimal trading horizon could be even longer than 20 trading days.

4.5 Overall benefit from trade splitting

I conclude my empirical analysis with an examination of the overall benefit from splitting up large trades. So far, the theoretical trade execution literature focuses on the development of different models, but neglects the question what the overall financial impact of breaking up large trades - as predicted by these models - is. This is mainly due to the fact that these models are rarely applied to real data. In contrast to previous work, I use my large cross-sectional sample to shed light on the question how large the optimization potential of splitting up large trades is. This analysis also allows me to examine which percentage of the total optimization potential is realized by insiders with their actual trading strategies. I calculate the overall optimization potential by comparing immediate execution strategies with strategies that are optimized with respect to the trading horizon and the trade pattern. I consider both effects to get an estimate of the total magnitude of optimization. For this analysis, I exclude the 87 execution strategies from the sample for which immediate execution is optimal, because splitting up these trades offers no optimization potential.

Table II.6 reports summary statistics for the difference in the certainty equivalents (objective function) between immediate execution and optimal execution (expressed as percentage of the immediate execution value) grouped by size portfolios and the direction of the trade (sales and purchases). The size portfolios are terciles formed over all sale and purchase transactions. The size of the transactions is measured in \$ trading volume expressed as percentage of the average daily \$ trading volume over the 20 trading days prior to the transaction. The mean financial improvement is 1.56% (1.45%) for sale (purchase) transactions, while the median value is somewhat lower with 0.25% (0.42%). These mean values are significantly different from zero at the 1% level. However, the 95th percentile shows that the optimization potential is usually limited to typical maximum values of around 5%. The figures for the size terciles also show that the financial improvement is positively associated with trade size. This is consistent with the microstructure literature and the intuition that splitting up trades is more favorable for large trade volumes. The last column in Table II.6 shows the median improvement percentage scaled by the median trade size percentage. This ratio can be used as multiple to estimate the improvement potential based on the trade volume measured as percentage of the average daily trade volume. The trading size multiples for the total sample are 1.70x for sales and 1.60x for purchases. These numbers show that the optimization potential is also economically significant.

– Insert Table II.6 approximately here –

While Table II.6 focuses on the maximum impact from trade optimization, Table II.7 reports which percentage of the overall improvement potential is captured by insiders with their actual trading strategies. More specifically, Table II.7 shows which portion of the optimization potential remains on the table, because insiders do not completely optimize their trading strategies as predicted by the model. The two columns in Table II.7 display how the total optimization potential is split between switching from immediate to actual execution and switching from actual to optimal execution. While actual purchase transactions exhaust about 72% of the total optimization potential, the percentage for sales is slightly lower with 67%. Thus, about one third of the total improvement potential is forfeited by insider's actual trading strategies. While differences between sales and purchases are negligible, the percentages realized and forfeited vary systematically with the size of the transaction. The percentage of the optimization potential forfeited increases continuously as the overall transaction size gets larger. These numbers can be interpreted in two ways: One way of thinking is that the model has higher predictive power for smaller trades. An alternative way suggests that insiders execute larger trades less optimally. Both interpretations, however, might result from the fact that the findings for large trades are biased by a certain number of block transactions which where not executed in the open market. While I use a trade size filter in the construction of the sample, I can not fully rule out the possibility that in particular some of the very large trades where not executed in the open market. Trading in the upstairs market is per definition less associated with trade splitting. This potential bias works against positive findings for the model, because it increases the percentage of improvement forfeited. Taking this fact into consideration, the numbers in Table II.7 show the model in an even more positive light.

Result 4: *The overall effect from optimally breaking up large trades is statistically and economically significant. On average, the improvement in the certainty equivalent by breaking* *up large trades is 1.7x the trade size for sales and 1.6x for purchase transactions. Independent of the trade direction, the optimization potential is positively related to the trade volume as the price impact from own trading depends on the trade size.*

Insiders with their actual trading strategies utilize slightly more than two thirds of the overall optimization potential from optimal trade splitting, while about one third of the potential is forfeited. The fact that such a large portion of the overall optimization potential is realized by insiders provides further evidence in support of the model and shows that the deviations in the trade horizon and trade pattern detected in the previous sections are within a range that does not question the overall validity of the trade execution model.

4.6 Robustness checks

In this section, I check the robustness of my main results derived in the previous sections. During these analyses I keep the same modeling framework as before. Thus, the general shape of the trade patterns of the optimal trading strategies is not affected. All predicted trading strategies are decreasing and convex. However, the alternative specifications tested in this robustness section might affect the degree of convexity as well as the length of the optimal trading horizon. The critical parameters in the model are the level of risk aversion as well as the price impact functions and parameters.

Level of risk aversion. The level of risk aversion affects the trader's preference for executing trades in earlier trading rounds, and thus, his/her preference for splitting up trades. The level of risk aversion is mainly determined by the wealth estimates which vary between \$10,000 and \$11.2 billion (see Panel B in Table II.2), even though I used a conservative wealth level estimate based on the equity holdings around the transaction. Very high wealth estimates bring the risk aversion coefficient close to zero which implies risk neutral behavior. Risk neutral behavior means that the trader does not care about the risk of the liquidation revenues, but only about the expected value of the liquidation revenues. In contrast, very low wealth estimates imply high risk version coefficients, and thus, a strong preference to execute trades immediately, because the risk of the liquidation revenues has more weight.

To check the robustness of the wealth level estimates, I use three alternative proxies for the insider's accumulated level of wealth. First, I censor the wealth variable at the 25th and 75th percentile, setting extreme values to the 25th percentile ($4,006,181) and the 75th percentile ($37,999,924), respectively. Second, I assume a constant wealth level of $11,210,768 for all insiders which corresponds to the median wealth level including sales and purchases. However, these variations are all above the threshold level of about $1 million which I identified in the sensitivity analysis to cause recognizable changes in trading patterns. Thus, I finally use for all traders a constant wealth level of $500,000 which is well below this threshold. Table II.8 reports the key indicators from Table II.4 to II.7 for the three scenarios used to test the robustness of the results. Column (1) summarizes the results from my previous calculations. The remaining three columns show the results for the robustness checks.

– Insert Table II.8 approximately here –

As expected, robustness check 1 - wealth censored at the 25th and 75th percentile - and robustness check 2 - median wealth - only reveal minimal changes in the results. Even for robustness check 3 - constant wealth of $500,000 - the changes are comparably small. The fit of the trade patterns and the length of the trading horizon is slightly better as indicated by the mean and median deviation measures and the slightly higher positive skewness in Panel A and B. Furthermore, Panel C displays that the overall benefit from trade splitting is smaller due to the higher risk aversion implied by the lower wealth level.

Overall, the robustness checks with respect to risk aversion emphasize the stability of my main results. Only assuming significantly lower levels of wealth, and thus much higher risk aversion, would imply significant changes in the optimal trading strategies with a trend towards no trade splitting.

Price impact functions and parameters. The robustness checks concerning the price impact comprise the estimation of the price impact coefficients as well as the assumed linear form of the price impact function.

I start with two robustness checks examining the impact of variations in the price impact parameters. First, I replace the stock- and time-specific price impact estimates with median values (across sales and purchases). I derive the median values by multiplying the median percentage parameters with the individual stock prices prior to the transaction. With this robustness check, I address the fact that price impact functions are frequently estimated across stocks (e.g., Obizhaeva, 2007; Chen, Stanzl, and Watanabe, 2005) and purchases and sales (e.g., Glosten and Harris, 1988). Second, I address the issue of systematic changes in liquidity during the course of a trading day. Empirical studies provide evidence that stock market illiquidity at NYSE follows a U-shaped or reversed J-shaped pattern with the highest liquidity during the central hours and the early afternoon (e.g., McInish and Van Ness, 2002). Assuming that traders execute their trades during the most liquid trading hours, I re-estimate the price impact parameters from trades occurring between 11:00am to 3:00pm (instead of using full trading hours from 9:30am to 4:00pm).

Finally, I use an alternative functional form for the price impact function. In particular, I drop the intercept in the linear permanent price impact function making the slope parameter γ the sole parameter that specifies the permanent price impact function. I test this alternative functional form, because theoretical literature on the topic argues that this is the only specification that fulfills no arbitrage arguments (Huberman and Stanzl, 2004).[39] Nevertheless, my main calculations are not based on this functional form, because empirical studies on price impact effects fail to find evidence in support of this functional form (e.g., Obizhaeva, 2007). Meanwhile, my assumption of no buys (sells) during a sell (buy) transaction avoides that traders in my model can profit from the potential arbitrage opportunities associated with this functional form of the permanent price impact function.

Table II.9 displays the key characteristics from Table II.4 to II.7 for the three scenarios used to test the robustness of the results with respect to the price impact. Column (1) summarizes the results from my main calculations. The remaining three columns show the results for the robustness checks. Note that, in contrast to Table II.8, the number of observations varies for the last two robustness checks, because I re-estimate the price impact parameters and exclude observations with negative coefficient estimates. Table II.10 reports means and medians for the calibration parameters used in the robustness checks.

[39] Almgren and Chriss (2001) also use a linear functional form without intercept for the permanent price impact function in their seminal paper.

– Insert Table II.9 approximately here –

– Insert Table II.10 approximately here –

Column (2) in Table II.10 displays summary statistics for the parameter values when stock specific values are replaced by median values. As I use median percentage values and scale them by the individual stock prices, the parameter estimates vary over observations when measured in $ terms. In particular, the sample medians of the price impact parameters for sales (purchases) are slightly higher (lower) than in the main calculations. For instance, the median fixed permanent price impact for sales is now $\$3.71 * 10^{-5}$ compared to $\$2.93 * 10^{-5}$ in my main calculations. The optimization results for these price impact parameters are displayed in column (2) in Table II.9. While the results are slightly worse for sale transactions, the results for purchase transactions improve considerably. Panel A shows that the percentage of strategies with zero financial deviation rises from 24% to 37% for purchases and the positive skewness increases from 5.0 to 5.7. Furthermore, as displayed in Panel B, the accuracy of the prediction concerning the trade horizon is improved increasing the percentage of strategies with zero financial deviation from 11% to 16% for purchase transactions, while remaining constant for sale transactions. Overall, using median price impact parameters yields a more balanced picture with regard to purchase and sale transactions. One possible interpretation of this result is that less specific estimates for price impact parameters - no differentiation between sales and purchases and no stock-specific estimation - are used in real world applications of trade execution models. Finally, looking at Panel C in Table II.9, the overall benefit from trade splitting is reduced. This is due to the fact that the relation from fixed to variable price effects increased. As a result, the incentive to split up positions into several trades is lowered, and thus, diminishes the value created from trade splitting.

In addition, robustness check 2 displayed in column (3) in Table II.10 indicates that the (median) price impact parameters estimated for trading hours 11:00am to 3:00pm tend to be equal or lower than the parameter estimates for full trading hours. Such lower estimates are in line with other empirical findings demonstrating that liquidity is highest during the central trading hours within a day. As shown in the sensitivity analysis, lower price impact coefficients give more weight to a traders' risk aversion. For high levels of risk aversion, lower price impact effects result in more front-loaded trading or shorter optimal trading horizons. For low levels of risk aversion, the optimal trading strategies get closer to the straight-line policy with a preference for longer trade horizons. Comparing the optimal trading strategies from this robustness check to the optimal trading strategies in my main calculations, yields two results (not tabulated): First, the mean of the optimal trading horizon increases for sales (purchases) from 5.3 (4.9) days to 5.8 (5.7) days. Second, the optimal trading strategies become less convex as the mean deviation from straight-line trading decreases.[40] The results of comparing these optimal trading strategies with the actual trading strategies are displayed in column (3) in Table II.9. Overall, the numbers show that the predictive power of the model decreases for the lower price impact parameters. In particular, in Panel A and B most means and medians for the different deviation measures increase. Moreover, the positive skewness comes down which is an indicator for less clustering towards the lower end of the tail (zero deviation). Taken together, these results suggest that the more straight-line optimal trading policies are less descriptive of insider's actual trading behavior. Note, however, that my sample only includes actual trading strategies with a "decreasing" trade pattern, while about 10% of the total transactions exhibit a straight-line pattern and are not included.

Column (4) in Table II.10 describes the price impact parameters used for the last robustness check. The fixed permanent price impact is zero by definition. As a result, the variable permanent price impacts are about six times larger than the coefficients obtained in a regression with intercept. As discussed in the sensitivity analysis, no fixed price impact and a larger variable price impact causes trades to be split more evenly over the trading horizon and results in longer optimal trading horizons. To see this straight-line splitting effect in the optimal trading strategies, the level of risk aversion needs to be low, as it is the case in my sample. Otherwise, high risk aversion would outweigh the incentive from the variable price impact effects to split trades evenly. As expected, the optimal trading strategies for this alternative price impact specification show the following properties (results not tabulated): First, the convex decline in the trade volumes of the optimal trading strategies is almost neg-

[40] To assess the convexity of the optimal trading patterns in comparison to straight-line policies, I computed the $NDEV$ measure from Section 4.3 using $n_t^{straight}$ instead of n_t^{opt}. The mean $NDEV$ decreases from 8.9% (9.8%) to 8.0% (9.1%) for sales (purchases).

ligible. The optimal trading strategies are more or less straight-line policies. In particular, the $NDEV$ measure using straight-line policies as reference point has a mean value of 0.0% (0.3%) for sales (purchases) compared to 8.9% (9.8%) in my main calculations. Consistent with this evidence, the mean optimal trading horizon increases to 19.7 (19.0) days for sales (purchases) from previously 5.3 (4.9) days. This fact implies that the model predicts an optimal trading horizon of 20 days for the majority of the transactions. However, 20 trading days is the maximum grid value used in my analysis. For the given parameter constellation, traders would even like to trade over longer horizons.

The strong change in the price impact parameters also has a huge impact on the results displayed in column (4) of Table II.9. All mean and median values for deviation measures reported in Panel A and B increase significantly, indicating that the predictive power of the model is poor. At the same time, the skewness values decrease, some even become negative, indicating that non-zero deviations get numerous. In particular, the trade horizon dimension shows a poor fit. The larger variable price impact effects are associated with an increase in the overall benefit from the trade splitting. Panel C presents the respective figures showing a significant increase for sales and purchases. The significantly lower fit of this calibration is also reflected in the figures of Panel D. For the first time, the percentage of the forfeited optimization potential is larger than the realized proportion of the improvement effects.

Taken together, the robustness checks show two things: First, the results of my main analyses are robust along reasonable variations in the crucial parameters. Second, the optimization results are sensible to major assumptions, e.g., with regard to the price impact functions. Optimization under these assumptions, however, results in implausible findings.

4.7 Summary and discussion of main results

In summary, I began my empirical analysis (result 1) by documenting that splitting up large trades over several trading days is a phenomenon frequently seen for trades executed by corporate insiders. More specifically, about 55% of all daily trade observations are part of trading sequences that last several, usually two to five, days. The trading patterns within these sequences, i.e., the development of the daily trade volumes, can be grouped into four general categories: increasing, decreasing, constant, and all remaining others. Trade schedules with a constant trade volume account for about 10% of all trading strategies, while the three other trade schedules each account for 30%. Capturing these diverse trade patterns in trade execution models requires diverging assumptions. Therefore, in my analysis, I focus on trades characterized by decreasing trade patterns, as these represent standard trade execution models. In consequence, the explanatory power of my model is limited to about one third of all multiple-day trading strategies. Nevertheless, for certain parameter values, the model predicts trading patterns which are almost constant. Thus, the model calibrated in this paper can explain up to 40% of all multiple-day trading strategies.

The main assumptions of my model are that traders are presumed to show constant absolute risk aversion and price impact functions are defined to be of linear form consisting of a fixed and variable component as well as temporary and permanent effects. In a first step (result 2), I compute the optimal trading strategies for the trading horizon actually chosen by the insider. For about 10% of the observations, the model fails to provide an admissible solution for the given horizon. For the remaining observations, the model predicts trading strategies which are less declining than the actually observed trading strategies. The financial implications of these diverging trading strategies, however, are on average low (around 0.02-0.03%) due to the small dimension of the price impact parameters. For about 32% of the observations, the financial deviation expressed as percentage of the certainty equivalent of the chosen trading strategy is even smaller than 0.00%. Thus, while minor deviations from the optimal solution seem to exist in daily trade volumes, the resulting financial implications from further optimization are small.

Going beyond this analysis, in a second step (result 3), I compute the optimal trading strategies for the range of 2 to 20 trading days and subsequently determine the trading horizon that maximizes the trading proceeds. This use of the model widens its original scope, as models of this type are originally developed for exogenously given trade horizons. This additional analysis allows me to examine the optimality of the trade horizon chosen by the insiders. Doing so reveals that the model correctly predicts about 15% of the actual trading horizons. For the vast majority of the transactions (about 75%), however, the predicted trading horizon is on average about 3 days longer than the actual trading horizon. To make a statement concerning the comparison of the model's predictive power regarding the trade pattern and trade horizon dimension is impossible, because the trade horizon optimization always comprises also a trade pattern optimization. Both dimensions are closely linked in as much as that predicting less declining trade patterns and longer trade horizons are two sides of the same coin. For about 13% of all observations, the optimal trading strategies are congruent to the actually observed trading strategies.

Third, I use my large cross-sectional data set to evaluate the overall benefit from trade splitting (result 4). This analysis is of interest as my previous analyses only provided evidence of a rather low improvement potential for the optimization of the actual trading strategies. I find that the overall effect of breaking up large trades is economically and statistically significant. The percentage improvement in the certainty equivalent is on average more than 1.5 times the trade size (measured in $ trading volume expressed as percentage of the average daily $ trading volume over the 20 trading days prior to the transaction). Insiders realize slightly more than two thirds of this overall improvement potential with their actual trading strategies. This realization ratio provides additional evidence in support of the model, because it shows that the identified deviations in the trade pattern and trade horizon are of minor importance for the overall improvement potential. Thus, these deviations do not question the overall validity of the model.

Finally, my robustness checks with regard to the risk aversion of the traders and price impact parameters yield the following important insights: The risk version estimated by using conservative wealth levels is very low. As shown in the sensitivity analysis, low risk aversion implies a tendency towards straight-line trading strategies. Even for a considerably higher level of risk aversion, the steepness of the trade volume decline improves only marginally. This is a first indication of the minor importance of the level of risk aversion for the degree of convexity of the trading strategies in a real world setting. The robustness checks with regard to the functional form of the permanent price impact parameters provide further support for this conjecture. Banishing fixed permanent price effects results in trading strategies almost congruent to straight-line policies. The previously included fixed price effect provides an incentive not to break up large trades over too many periods. Thus, the pattern of declining trade volumes in my calibration of the model is not primarily caused by high risk aversion of the traders, but is due to the assumed functional form of the price impact function which includes fixed effects. To improve the predictive power of the model further, the average steepness of the predicted trade patterns needs to be increased. Parameters affecting the steepness are the functional form of the price impact function and the level of risk aversion.

To adequately assess the obtained results, they need to be put in perspective to the main properties and assumptions of the applied trade execution model as well as the insider data used. As previously described, I analyze the complex trade execution decision of insiders with a stylized model. The model's main focus lies in examining the actual trading behavior of insiders with respect to splitting up larges trades over several days. For this purpose, the model is stylized with respect to the following dimensions: First, it is of static nature by assuming that trading strategies have to be defined before trading is started. Thus, changes in market conditions, for instance, do not cause revision, replacement, or cancellation of the commenced trading strategies. Within this static framework, however, the assumption of constant absolute risk aversion as used here stands out against alternatives of non-constant absolute risk aversion, because only under the first assumption statically determined strategies are also optimal in a dynamic setting (Schied, Schoeneborn, and Tehranchi, 2010). Put differently, allowing for intertemporal updating in the model adds no additional insights for CARA investors.[41] Second, the model assumes constant or time-invariant liquidity over the execution period. Time-varying liquidity parameters can be easily incorporated in the model by replacing γ_1, γ_2, τ_1, and τ_2 with parameters $\gamma_{1,t}$, $\gamma_{2,t}$, $\tau_{1,t}$, and $\tau_{2,t}$.[42] This results in optimal trading strategies that trade larger volumes during more liquid trading hours (Huberman and Stanzl, 2005). The main issue in using time-varying price impact parameters arises from the necessity to forecast and/or estimate these parameters. A potential approach could be the estimation of price impact parameters by trading day, given that liquidity is usually lower on Mondays and Fridays compared to the other days of the week. Because the model requires all price impact parameters to be known before trading starts, however, a rolling estimation of price impact parameters over a certain period of trading days done prior to each trading day within a trading sequence is not covered by the model.[43] Third, the model

[41]Only a few papers developing and solving theoretical trade execution models consider dynamic strategies. See, e.g., Subramanian and Jarrow (2001) and He and Mamaysky (2005).

[42]See Almgren and Chriss (2001), Moench, 2009, and Jondeau, Perilla, and Rockinger, 2010.

[43]See Almgren and Chriss (2001). This is also an issue of time-consistency and dynamic optimization.

assumes a minimum trading period of one day, partly owing to the insider data used.[44] The choice of this minimum trade period seems to be at a large scale on first sight, especially, as some trade execution papers optimize trading over 30-minute intervals within trading days (e.g., Moench, 2009, Jondeau, Perilla, and Rockinger, 2010). Zooming into trading days and probably trying to explain intraday trading strategies based on algorithmic trading, however, is not the focus of stylized trade execution models. Therefore, the minimum trading period of one trading day is a simplifying, but reasonable compromise to investigate the main idea of splitting up large trades into several packages.

The limitations and opportunities inherent in the insider data are a second issue to be considered when assessing the overall results of this paper. On the one hand, insider transactions are particularly well suited to examine strategies to break up large trades, because insiders often own and trade quite significant asset positions in their own company. Furthermore, as large shareholders become insiders by definition as soon as they own more than 10% of the firm's equity[45], it might be hard to find a significant number of other individuals who trade sufficiently large asset positions. On the other hand, insider data also has some shortcomings and limitations. First, insiders have access to non-public information and even with insider trading laws in place, their trading behavior might be affected by this information. Second, the disclosure rules concerning insider trading do not allow limiting the sample to open market transactions only. Thus, the data set might also include transactions that are privately negotiated. This is in particular relevant with respect to the fact that there is a limit to the volume that is instantaneously executable in the open market. Therefore, I exclude transactions with extremely large trade volumes above certain thresholds from my analysis, but there is no common rule or understanding which asset positions are executable in the open market. Overall, the potential effect of these insider data limitations is hardly quantifiable without analyzing proprietary trading data of other individuals.

[44] See also Almgren and Chriss (2001) and Dubil (2002) for the use of trading days.

[45] See the definition in Section 16 of the Securities Exchange Act.

5 Conclusion

By empirically calibrating a stylized trade execution model, I analyze the frequently observable practice of corporate insiders to break up large asset positions into several trades. To the best of my knowledge, this is the first empirical and structural test of such a model. The model adopted in this paper utilizes an expected utility framework and assumes traders to be risk averse and price impact functions to be linear. It generates optimal trading strategies of decreasing and convex form which are representative for standard trade execution models. The empirical calibration of the model provides evidence on how asset-specific microstructure parameters such as price impact and price volatility as well as individual-specific risk aversion affect the execution behavior for large trades. The key insight of the analysis is that trade execution models predicting decreasing trading strategies are a promising candidate for analyzing the trade execution of large asset positions. Given the simplicity of the model and the complexity of the individual's trading decision, the predictive power of the model is commendable. The results, however, are sensitive to the functional form of the price impact functions and the level of absolute risk aversion of the trader as well as their interplay. So far, little research is available on the estimation of price impact functions for individual stocks and their functional form. Such research, however, is a necessary prerequisite for successfully calibrating theoretical trade execution models with empirical data.

The results in this paper can be interpreted in two ways, but both lines of reasoning imply searching for and applying richer trade execution models that better capture real world insider trading behavior. On the one hand, based on the obtained results, it can be argued that insiders do not fully optimize the way in which they trade shares of their own company. However, top managers and large shareholder, the insiders considered in this paper, are usually well-educated and highly rational individuals with manifold experience in share trading. Thus, it is unlikely that they deviate from actions that could make them better off. A potential explanation for less than optimal trading behavior may be found in fundamental human behavioral biases, such as loss aversion. In this respect, leaving behind the expected utility framework that is traditionally used in the theoretical trade execution literature promises to be an enlightening path for future theoretical and empirical research. In contrast to this interpretation, it is also possible to question the stylized trade execution model used in this paper due to its limited explanatory power for actual insider trading behavior. Addressing this concern within the basic framework adopted in this paper, alternative non-linear price impact functions such as square root and power functions would provide a topic of future inquiry. Furthermore, future trade execution models should target increasing or non-monotone trading patterns. To explain these patterns, models would need to incorporate alternative assumptions on the insider's risk attitude (e.g., increasing or decreasing risk aversion) as well as additional assumptions on the stock price process (e.g., drift) and the possibility of intertemporal updating of trading strategies. Although the theoretical trade execution literature has tentatively begun to develop models that exhibit these features, their empirical calibration will be a challenging task for future research.

Appendix

Procedures of data matching and cleaning for TAQ data

A. Matching of trades and quotes and identifying buy and sell orders

A matching of trades and quotes is required for the computation of the price impact variables and the identification of the direction of the trade (buy vs. sell). The most widely used method to match trades and quotes and infer a buy and sell classification of trades is the Lee-Ready algorithm (Lee and Ready, 1991). The algorithm consists of a quote-rule and a tick-rule used as a tie-breaker for mid-quote trades. The quote rule applies information about the proximity to prevailing quotes in order to infer trade direction. Trades at prices above the midpoint of the bid and ask are classified as buys. Trades below the midpoint are classified as sells. However, some trades are executed at the bid-ask midpoint. These trades can be either ignored by removing such trades or can be handled by the tick-rule. The tick-rule classifies a midpoint trade as a buy if it is executed at a higher price than the previous trade (i.e., if it is an “uptick") and as a sell if it is executed at a lower price (“downtick"). To apply this Lee-Ready algorithm one needs to match trades data with quotes information. Lee and Ready (1991) suggest matching trade prices with 5-second old quotes because prior to the computerization of the trade process, new quotes were often reported prior to the prices of trades that generated them. Henker and Wang (2006) have investigated what time lag is appropriate in recent days for NYSE.[46] I follow Henker and Wang (2006) and use a 1-second quote delay (also for matching trades with subsequent quotes) and do not apply the tick-rule by discarding trades executed at the midpoint from my calculations.

B. Cleaning of raw data

Before matching trades and quotes with the above procedure, I filter out invalid trades and quotes from TAQ raw data by excluding all observations that do not fulfill the following conditions:

- ☐ Trades and quotes occur during regular trading hours (9:30am to 4:00pm) and have a positive size (trades), depth (quotes), and price (trades and quotes).

- ☐ For trades, I additionally require that:
  (1) TAQ’s CORR field (correction indicator) is equal to 0, 1, or 2 (“good trades”).
  (2) TAQ’s COND field (sale condition) is not O, Z, B, T, L, G, W, J, K, or Q (i.e., deleting trades with special sale conditions).

- ☐ For quotes, I additionally require that:
  (1) TAQ’s MODE field (quote condition) is equal to 1, 2, 3, 5, 6, 8, 10, 12, 16, 17, 18, or 21-26 (i.e., omitting quotes indicated to be associated with trading halts or designated order imbalances or to be non-firm quotes).
  (2) The ask price is higher than the bid price.
  (3) The difference between the bid and ask price is $\leqq$10% of the quote midpoint (i.e., eliminating erroneous quotes, see Huang and Stoll, 1996a).

- ☐ In the presence of multiple trades or quotes at the same time, I proceed as follows:
  (1) For trades, I aggregate the trade volumes and calculate a volume-weighted average price (see Engle and Russell, 1998).
  (2) For quotes, I average all quote midpoints (arbitrary choice, because no guidance in the literature which quote should be selected).

- ☐ The first trade and quote after opening each day is discarded (i.e., avoiding after hours liquidity effects, see Barclay and Hendershott, 2004).

[46] Alternative suggestions are 2 seconds (Vergote, 2005) and 0 seconds (Peterson and Sirri, 2003).

Table II.1: **Summary statistics insider trading activity**

This table reports key characteristics for insider trades grouped by direction of the trade (sales and purchases) and the length of the trading strategy (five length categories). Panel A displays the total NYSE & AMEX sample from the IFDF database. Panel B displays the final sample that is limited to trading strategies with a length of 2-20 trading days for which TAQ data is available. The length of the trading strategies is measured in trading days. The number of shares outstanding is measured at the day before the initiation of the trading strategy. The average daily \$ trading volume is computed over the 20 trading days prior to the initiation of the trading strategy.

	Length of trading strategy (trading days)					
	1	**2-5**	**6-10**	**11-20**	**>20**	**Total**
Panel A: Total NYSE & AMEX sample						
Sales						
Number of trading strategies	10,995	3,371	282	93	41	14,782
Number of trading days	10,995	8,786	2,076	1,359	1,490	24,706
	45%	36%	8%	6%	6%	
Total \$ trading volume (\$ million)	50,312	16,566	3,525	4,235	1,403	76,040
	66%	22%	5%	6%	2%	
Median number of shares (000)	20	48	100	210	521	25
Median \$ trading volume (\$ 000)	0.6	1.4	3.0	5.3	25.2	0.8
Median number of shares to shares outstanding (%)	0.0%	0.1%	0.3%	0.4%	0.7%	0.0%
Median \$ trading volume to average daily \$ trading volume (%)	3.7%	17.8%	60.6%	65.5%	143.5%	5.7%
Median duration (trading days)	1	2	7	14	28	1
Purchases						
Number of trading strategies	2,987	904	72	22	13	3,998
Number of trading days	2,987	2,318	516	306	521	6,648
	45%	35%	8%	5%	8%	
Total \$ trading volume (\$ million)	1,595	1,172	896	396	279	4,339
	37%	27%	21%	9%	6%	
Median number of shares (000)	5	20	167	355	644	8
Median \$ trading volume (\$ 000)	0.04	0.1	2.8	3.0	12.5	0.1
Median number of shares to shares outstanding (%)	0.0%	0.1%	0.4%	0.9%	1.7%	0.0%
Median \$ trading volume to average daily \$ trading volume (%)	3.1%	30.9%	144.7%	298.8%	557.9%	6.5%
Median duration (trading days)	1	2	7	12	30	1
Panel B: Total TAQ sample						
Sales						
Number of trading strategies		2,201	184	52		2,437
Number of trading days		5,707	1,371	740		7,818
		73%	18%	9%		
Total \$ trading volume (\$ million)		12,395	1,754	978		15,128
		82%	12%	6%		
Median number of shares (000)		57	132	218		63
Median \$ trading volume (\$ 000)		2.0	3.8	5.7		2.2
Median number of shares to shares outstanding (%)		0.1%	0.3%	0.4%		0.1%
Median \$ trading volume to average daily \$ trading volume (%)		14.3%	58.5%	56.7%		15.6%
Median duration (trading days)		2	7	14		2
Purchases						
Number of trading strategies		368	48	10		426
Number of trading days		954	351	152		1,457
		65%	24%	10%		
Total \$ trading volume (\$ million)		829	685	212		1,726
		48%	40%	12%		
Median number of shares (000)		45	223	932		52
Median \$ trading volume (\$ 000)		0.4	4.7	14.1		0.6
Median number of shares to shares outstanding (%)		0.1%	0.5%	1.8%		0.1%
Median \$ trading volume to average daily \$ trading volume (%)		20.8%	128.1%	330.1%		28.4%
Median duration (trading days)		2	7	15		2

Table II.2: **Summary statistics calibration parameters**

This table displays the number of observations, minimum, mean, median, maximum, standard deviation (sd), and the 25th and 75th percentiles (p25 and p75) of the nine parameters necessary to calibrate the trade execution model grouped by the direction of the trade (sales and purchases). Price impact is abbreviated as PI.

Variable	**Symbol**	**N**	**min**	**p25**	**mean**	**median**	**p75**	**max**	**sd**
				Panel A: Total TAQ Sample					
Sales									
Number of shares (000)	X	2,437	0	23	196	63	162	65,600	1,520
Trading horizon (days)	T	2,437	2.0	2.0	3.2	2.0	3.0	20.0	2.3
Fixed permanent PI ($/share)	γ_1*10^{-2}	2,437	0.18	1.92	4.54	3.08	5.14	165.84	7.92
Variable permanent PI ($/share)	γ_2*10^{-5}	2,437	0.00	0.08	0.80	0.22	0.55	138.24	4.78
Fixed temporary PI ($/share)	τ_1*10^{-2}	2,437	0.36	1.55	3.49	2.38	3.80	114.47	6.23
Variable temporary PI ($/share)	τ_2*10^{-5}	2,437	0.00	0.06	0.53	0.15	0.39	153.36	3.78
Asset volatility ($/share)/day	σ^2	2,437	0.000	0.006	0.021	0.011	0.022	0.839	0.046
Stock price at t=0 ($/share)	p_0	2,437	0.99	20.88	40.19	34.53	48.57	791.25	51.15
Wealth ($ million)	wealth	2,437	0	4	237	11	35	11,300	1,150
Purchases									
Number of shares (000)	X	426	0	19	221	52	174	9,260	630
Trading horizon (days)	T	426	2.0	2.0	3.4	2.0	4.0	20.0	2.6
Fixed permanent PI ($/share)	γ_1*10^{-2}	426	0.17	1.41	3.21	2.19	3.72	74.08	4.38
Variable permanent PI ($/share)	γ_2*10^{-5}	426	0.00	0.06	0.53	0.16	0.47	14.74	1.21
Fixed temporary PI ($/share)	τ_1*10^{-2}	426	0.35	1.18	2.60	1.74	2.80	65.23	3.77
Variable temporary PI ($/share)	τ_2*10^{-5}	426	0.00	0.03	0.38	0.10	0.29	19.60	1.27
Asset volatility ($/share)/day	σ^2	426	0.000	0.004	0.024	0.010	0.026	0.966	0.061
Stock price at t=0 ($/share)	p_0	426	0.44	6.26	18.23	13.75	24.15	436.70	25.60
Wealth ($ million)	wealth	426	0	3	215	22	205	3,840	479
				Panel B: Final sample					
Sales									
Number of shares (000)	X	718	0	22	245	60	130	65,600	2,497
Trading horizon (days)	T	718	2.0	2.0	2.2	2.0	2.0	5.0	0.4
Fixed permanent PI ($/share)	γ_1*10^{-2}	718	0.18	1.92	4.03	2.93	4.95	100.73	4.85
Variable permanent PI ($/share)	γ_2*10^{-5}	718	0.00	0.07	0.49	0.19	0.49	16.38	1.16
Fixed temporary PI ($/share)	τ_1*10^{-2}	718	0.45	1.50	2.98	2.23	3.68	75.32	3.57
Variable temporary PI ($/share)	τ_2*10^{-5}	718	0.00	0.05	0.33	0.13	0.31	12.53	0.73
Asset volatility ($/share)/day	σ^2	718	0.000	0.005	0.019	0.011	0.021	0.322	0.025
Stock price at t=0 ($/share)	p_0	718	0.99	20.55	37.27	34.28	49.71	686.00	31.85
Wealth ($ million)	wealth	718	0	4	235	11	34	11,200	1,180
Purchases									
Number of shares (000)	X	140	0	20	120	41	109	1,906	238
Trading horizon (days)	T	140	2.0	2.0	2.2	2.0	2.0	4.0	0.4
Fixed permanent PI ($/share)	γ_1*10^{-2}	140	0.28	1.36	3.49	2.00	3.86	74.08	6.55
Variable permanent PI ($/share)	γ_2*10^{-5}	140	0.00	0.04	0.58	0.15	0.50	14.74	1.53
Fixed temporary PI ($/share)	τ_1*10^{-2}	140	0.35	1.13	2.96	1.82	3.01	65.23	5.69
Variable temporary PI ($/share)	τ_2*10^{-5}	140	0.00	0.02	0.46	0.10	0.30	19.60	1.76
Asset volatility ($/share)/day	σ^2	140	0.001	0.005	0.025	0.011	0.024	0.598	0.057
Stock price at t=0 ($/share)	p_0	140	0.44	5.67	18.24	11.82	21.07	436.70	37.96
Wealth ($ million)	wealth	140	0	2	174	13	117	3,690	500

Table II.3: **Trade pattern shape**

This table displays the frequency distribution of trading strategies by the length of the trading strategy and the shape of the trade pattern grouped by the direction of the trade (sales and purchases). Panel A (B) reports the figures for the total NYSE & AMEX (Final) sample limited to trading strategies with a length of 2-20 trading days. The length of the trading strategies is measured in trading days. The definition of the trade patterns is the following: "Straight" stands for straight-line policy where an equal number of shares is traded each day. "Increase" ("Decrease") indicates trading strategies where the volume traded per day increases (decreases) continuously over the individual days of the trading horizon. "Other" comprises all other non-monotonic trade patterns.

Length of trading strategy (days)	**Trade pattern**				
	Decrease	**Increase**	**Straight**	**Other**	**Total**
			Panel A: Total NYSE & AMEX sample		
Sales					
2-5	1.107	920	356	988	3.371
6-10			19	263	282
11-20			10	83	93
Total	1.107	920	385	1.334	3.746
	30%	25%	10%	36%	
Purchases					
2-5	318	248	106	232	904
6-10			1	71	72
11-20			2	20	22
Total	318	248	109	323	998
	32%	25%	11%	32%	
			Panel B: Total TAQ sample		
Sales					
2-5	718	594	263	626	2201
6-10			16	168	184
11-20			3	49	52
Total	718	594	282	843	2.437
	29%	24%	12%	35%	
Purchases					
2-5	140	89	44	95	368
6-10			1	47	48
11-20				10	10
Total	140	89	45	152	426
	33%	21%	11%	36%	

Table II.4: **Trade pattern optimality**

This table shows the minimum, mean, median, maximum, standard deviation (sd), skewness (skew), the number of zeros (zero), and the 5th and 95th percentiles (p5 and p95) for two metrics designed to measure to what extent the theoretical model predicts the trade patterns actually observed. Panel A (B) reports the figures for $FDEV$ ($NDEV$). $FDEV$ represents the return per share forfeited due to a non-optimal trade pattern. It is the difference in the certainty equivalent between the optimal and the actual trading strategy (expressed as percentage of the value for the actual strategy). $NDEV$ is the average share volume deviation between the optimal and actual trading strategy. It is the sum of the absolute percentage deviations over all trading days scaled by two. The sample in this table includes 766 observations (out of 858). For these observations the model provides an admissible solution for the exogenously given trade horizon.

Length of trading strategy (days)	**N**	**min**	**p5**	**mean**	**median**	**p95**	**max**	**skew**	**zeros**
				Panel A: FDEV (%)					
Sales									
2	559	0.00	0.00	0.78	0.02	0.78	277.97	22.6	192
3	77	0.00	0.00	0.27	0.03	0.75	10.93	8.1	19
4	6	0.00	0.00	0.15	0.02	0.46	0.46	0.7	2
5	1	0.37	0.37	0.37	0.37	0.37	0.37	0.0	0
Total	643	0.00	0.00	0.71	0.02	0.75	277.97	24.2	213
Purchases									
2	101	0.00	0.00	0.19	0.02	0.74	2.36	3.3	27
3	22	0.00	0.00	0.38	0.06	1.43	4.23	3.5	2
4									
5									
Total	123	0.00	0.00	0.22	0.03	0.79	4.23	5.0	29
				Panel B: NDEV (%)					
Sales									
2	559	0.1	1.1	17.4	14.8	42.0	48.1	0.6	0
3	77	2.4	3.0	18.3	14.6	46.9	60.7	1.1	0
4	6	3.6	3.6	20.9	19.8	36.7	36.7	0.1	0
5	1	29.1	29.1	29.1	29.1	29.1	29.1	0.0	0
Total	643	0.1	1.2	17.6	14.9	41.9	60.7	0.6	0
Purchases									
2	101	0.0	0.7	17.1	14.6	40.6	47.2	0.6	0
3	22	2.5	4.0	15.0	11.5	31.7	33.2	0.5	0
4									
5									
Total	123	0.0	1.0	16.8	13.6	40.2	47.2	0.6	0

Table II.5: **Trade horizon optimality**

This table displays the minimum, mean, median, maximum, standard deviation (sd), skewness (skew), the number of zeros (zeros), and the 5th and 95th percentiles (p5 and p95) for two metrics designed to measure to what extent the theoretical model predicts the length of the trading horizon actually observed. Panel A (B) reports the figures for $FDEV$ ($TDEV$). $FDEV$ represents the return per share forfeited due to a non-optimal trade pattern. It is the difference in the certainty equivalent between the optimal and the actual trading strategy (expressed as percentage of the value for the actual strategy). $TDEV$ is the difference in the length of the trading period between the optimal and the actual trading strategy (measured in trading days). $TDEV>0$ ($TDEV<0$) indicates that the optimal trading interval should be longer (shorter) than actually chosen by the insider. The sample in this table includes all 858 observations with a decreasing trade pattern (see Table II.3).

Length of trading strategy (days)	**N**	**min**	**p5**	**mean**	**median**	**p95**	**max**	**skew**	**zeros**
				Panel A: FDEV (%)					
Sales									
2	621	0.00	0.00	1.95	0.06	2.32	704.27	23.4	83
3	87	0.00	0.00	0.41	0.09	1.08	12.87	8.0	11
4	8	0.00	0.00	0.16	0.06	0.61	0.61	1.3	1
5	2	0.01	0.01	0.19	0.19	0.37	0.37	0.0	0
Total	718	0.00	0.00	1.74	0.06	2.09	704.27	25.2	95
Purchases									
2	115	0.00	0.00	0.47	0.08	2.12	6.26	3.5	16
3	24	0.01	0.01	0.94	0.20	4.30	9.34	3.4	0
4	1	0.01	0.01	0.01	0.01	0.01	0.01	0	0
5									
Total	140	0.00	0.00	0.55	0.08	2.30	9.34	4.5	16
				Panel B: TDEV (trading days)					
Sales									
2	621	-1.0	-1.0	3.1	2.0	12.0	18.0	1.7	82
3	87	-2.0	-2.0	3.2	3.0	10.0	17.0	1.0	13
4	8	-3.0	-3.0	1.9	2.0	6.0	6.0	-0.2	1
5	2	-1.0	-1.0	-0.5	-0.5	0.0	0.0	0.0	1
Total	718	-3.0	-1.0	3.1	2.0	12.0	18.0	1.6	97
Purchases									
2	115	-1.0	-1.0	2.4	1.0	8.0	18.0	1.8	25
3	24	-1.0	-1.0	4.3	3.0	17.0	17.0	1.4	3
4	1	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	0
5									
Total	140	-1.0	-1.0	2.7	1.5	10.0	18.0	1.9	28

Table II.6: **Total optimization benefit from trade splitting**

This table displays the minimum, mean, median, maximum, and the 5th and 95th percentiles (p5 and p95) for the improvement in the certainty equivalent due to switching from immediate execution in a single trade to optimal execution. The improvement is expressed as percentage of the certainty equivalent for immediate execution. In order to avoid distortions in the calculation of the sample mean, the percentage improvement is set to the maximum value of 100% whenever the actual value is larger. Overall, three sales transactions are subject to this cut-off rule. The results are grouped by the direction of the trade (sales and purchases) and by size portfolios. The portfolios are formed as size terciles of over all sales and purchases for which the optimal trade horizon is 2 days or longer. The size of the transactions is measured in terms of the $ trading volume relative to the average daily $ trading volume over the 20 trading days prior to the transaction. The sample in this table includes 771 observations (out of 858). I exclude all observations from this analysis for which the model predicts immediate execution to be optimal, i.e., there is no benefit from trade splitting.

		$ trading volume to average daily $ trading volume (%)		**Improvement in certainty equivalent optimal vs. immediate execution (%)**						**% improvement to % trading volume**
Size group	**N**	**mean**	**median**	**min**	**p5**	**mean**	**median**	**p95**	**max**	**(medians)**
Sales										
small	226	0.05	0.05	0.00	0.00	0.15	0.08	0.48	1.40	1.72
medium	223	0.16	0.15	0.00	0.02	0.74	0.34	2.36	12.39	2.21
large	196	1.31	0.49	0.00	0.04	4.13	0.92	12.37	100.00	1.87
Total	645	0.47	0.15	0.00	0.01	1.56	0.25	4.49	100.00	1.70
Purchases										
small	31	0.04	0.03	0.00	0.00	0.21	0.09	0.85	1.02	3.25
medium	34	0.17	0.15	0.01	0.01	0.64	0.32	2.58	3.86	2.07
large	61	0.85	0.56	0.02	0.04	2.52	1.54	8.09	18.28	2.77
Total	126	0.47	0.26	0.00	0.01	1.45	0.42	5.50	18.28	1.61

Table II.7: **Realized optimization benefit from trade splitting**

This table displays which proportion of the total improvement potential due to trade splitting is realized and forfeited, respectively, by insiders with their actual trade execution strategies. The total improvement potential is the improvement in the certainty equivalent due to switching from immediate execution in a single trade to optimal execution. The realized improvement potential is the improvement for switching from immediate to actual execution (expressed as percentage of total improvement potential), while the forfeited improvement potential is the improvement for switching from actual to optimal execution (expressed as percentage of total improvement potential) not captured with the actual execution strategy. The results are grouped by the direction of the trade (sales and purchases) and by size portfolios. The portfolios are formed as size terciles of over all sales and purchases for which the optimal trade horizon is 2 days or longer. The size of the transactions is measured in terms of the $ trading volume relative to the average daily $ trading volume over the 20 trading days prior to the transaction. The sample in this table includes 771 observations (out of 858). I exclude all observations from this analysis for which the model predicts immediate execution to be optimal, i.e., there is no benefit from trade splitting.

		$ trading volume to average daily $ trading volume (%)		**Median improvement in certainty equivalent optimal vs. immediate execution (%)**	
Size group	**N**	**mean**	**median**	**Realized with actual execution**	**Forfeited with actual execution**
Sales					
small	226	0.05	0.05	75.5	24.6
medium	223	0.16	0.15	67.3	32.7
large	196	1.31	0.49	61.1	38.9
Total	645	0.47	0.15	67.3	32.7
Purchases					
small	31	0.04	0.03	84.0	16.0
medium	34	0.17	0.15	75.8	24.2
large	61	0.85	0.56	63.8	36.2
Total	126	0.47	0.26	71.9	28.2

Table II.8: **Robustness checks risk aversion**

This table summarizes the key indicators from Table II.4-II.7 (Panel A-D) for my base line calculations (column 1) and three robustness checks concerning the risk aversion parameter (column 2, 3, and 4). The risk aversion is estimated by scaling the constant relative risk aversion ($CRRA$) coefficient of 2.5 by the level of accumulated wealth. For the robustness checks, I vary the level of accumulated wealth in the following way: In column (2), I censor the wealth variable to the 25th and 75th percentile ($4 million and $37 million). In column (2), I use the median wealth level of $11.2 million. In column (3), I use a constant wealth level of $0.5 million. For a definition of $FDEV$, $NDEV$, and $TDEV$ see the relevant Tables II.4 and II.5. Bold (italic) figures in column (2), (3), and (4) indicate numbers that are higher (lower) than numbers in column (1).

	(1) Wealth estimated from equity holdings		**(2) Wealth censored at 25th and 75th percentile**		**(3) Wealth set to sample median**		**(4) Wealth set to constant value of $500,000**	
	Sales	**Repurchases**	**Sales**	**Repurchases**	**Sales**	**Repurchases**	**Sales**	**Repurchases**
Panel A: Trade pattern optimality (Table 4)								
N	643	123	643	123	643	123	643	123
FDEV								
mean	0.71	0.22	0.71	0.23	0.71	0.23	**0.76**	0.21
median	0.02	0.03	0.02	*0.02*	0.02	0.02	0.02	0.02
skew	24.2	5.0	24.2	5.0	24.2	5.0	**24.6**	*4.7*
zeros (#)	213	29	213	30	212	29	213	30
zeros (%)	33%	24%	33%	24%	33%	24%	33%	24%
NDEV								
mean	17.6	16.8	17.6	16.8	17.6	16.8	*17.2*	*16.3*
median	14.9	13.6	14.9	*13.1*	14.9	13.3	*14.4*	13.7
skew	0.63	0.64	0.63	0.64	0.63	0.65	**0.65**	*0.59*
zeros (#)	0	0	0	0	0	0	1	0
zeros (%)	0%	0%	0%	0%	0%	0%	0%	0%
Panel B: Trade horizon optimality (Table 5)								
N	718	140	718	140	718	140	718	140
FDEV								
mean	1.74	0.55	1.74	0.55	1.73	0.55	1.73	*0.50*
median	0.02	0.08	**0.06**	0.08	0.06	0.08	0.06	0.08
skew	25.2	4.5	25.2	4.5	25.2	4.4	**25.8**	*3.9*
zeros (#)	97	16	*96*	*17*	95	16	98	**18**
zeros (%)	14%	11%	13%	12%	13%	11%	14%	13%
TDEV								
mean	3.12	2.72	3.12	2.74	3.12	2.72	*2.93*	*2.46*
median	2.0	1.5	2.0	**2.0**	2.0	2.0	2.0	**2.0**
skew	1.63	1.87	1.63	1.89	1.63	1.86	1.60	1.84
zeros (#)	97	28	99	26	98	27	100	29
zeros (%)	14%	20%	14%	19%	14%	19%	14%	21%
Panel C: Overall benefit from trade splitting (Table 6)								
N	645	126	645	126	645	126	645	126
mean	1.56	1.45	1.56	1.45	1.56	1.45	*1.51*	*1.38*
median	0.25	0.42	0.25	0.42	0.25	0.42	0.25	0.42
p95	4.49	5.50	4.49	5.50	4.48	5.49	*4.39*	*5.36*
Panel D: Realized optimization potential from trade splitting (Table 7)								
N	645	126	645	126	645	126	645	126
Realized	67.3	71.9	67.2	72.2	67.2	72.2	**68.3**	71.9
Forfeited	32.7	28.2	32.8	27.9	32.8	27.9	*31.7*	28.2

Table II.9: **Robustness checks price impact**

This table summarizes the key indicators from Table II.4 to II.7 for my main calculations (column 1) and three robustness checks concerning the price impact parameters (column 2 and 3) and the type of the price impact function (column 4). The robustness checks cover the following cases: In column (2), I use the median price impact parameters instead of the stock- and time-specific parameters. Therefore, I scale the median percentage price impact parameters with the individual stock prices. In column (3), I use price impact parameters estimated during the most liquid trading hours of the day (11:00am to 3:00pm). In column (4), I use a linear price impact function without intercept for the permanent price effect. Bold (italic) figures in column (2), (3), and (4) indicate numbers that are higher (lower) than numbers in column (1). Price impact is abbreviated as PI.

	(1)		**(2)**		**(3)**		**(4)**	
γ_1			**yes**				**no**	
PI Values	**Stock-specific**		**Sample median**		**Stock-specific**		**Stock-specific**	
Trading hours	**9:30am-4:00pm**		**9:30am-4:00pm**		**11:00am-3:00pm**		**9:30am-4:00pm**	
	Sales	**Purchases**	**Sales**	**Purchases**	**Sales**	**Purchases**	**Sales**	**Purchases**
Panel A: Trade pattern optimality (Table 4)								
N	643	123	642	125	571	102	718	140
FDEV								
mean	0.71	0.22	0.47	0.12	0.61	**0.24**	**1.72**	**0.59**
median	0.02	0.03	0.02	0.01	0.02	**0.25**	**0.09**	**0.16**
skew	24.2	5.0	24.0	5.7	*17.7*	*3.7*	*19.2*	*2.9*
zeros (#)	213	29	207	46	*190*	*24*	*107*	*17*
zeros (%)	33%	24%	32%	**37%**	33%	24%	*15%*	*12%*
NDEV								
mean	17.6	16.8	17.4	15.8	**18.1**	**17.8**	**22.4**	**21.6**
median	14.9	13.6	14.5	14.0	**15.6**	**17.7**	**21.4**	**21.5**
skew	0.63	0.64	0.66	0.82	*0.60*	*0.45*	*0.32*	*0.25*
zeros (#)	0	0	0	0	0	0	0	0
zeros (%)	0%	0%	0%	0%	0%	0%	0%	0%
Panel B: Trade horizon optimality (Table 5)								
N	718	140	718	140	616	111	718	140
FDEV								
mean	1.74	0.55	1.34	0.29	*1.27*	**0.64**	**5.56**	**2.63**
median	0.02	0.08	0.06	0.03	**0.06**	**0.10**	**0.7**	**1.3**
skew	25.2	4.5	25.5	5.6	*13.2*	*3.2*	*19.6*	*1.8*
zeros (#)	97	16	112	23	*80*	*11*	*0*	*4*
zeros (%)	14%	11%	**16%**	**16%**	13%	*10%*	*0%*	*3%*
TDEV								
mean	3.12	2.72	2.80	2.26	**3.62**	**3.57**	**17.54**	**16.83**
median	2.0	1.5	2.0	1.0	2.0	**2.0**	**18.0**	**18.0**
skew	1.63	1.87	1.86	1.89	*1.39*	*1.37*	*-6.39*	*-3.38*
zeros (#)	97	28	110	28	*73*	*18*	*0*	*0*
zeros (%)	14%	20%	15%	20%	*12%*	*16%*	*0%*	*0%*
Panel C: Overall benefit from trade splitting (Table 6)								
N	645	126	653	125	571	102	717	140
mean	1.56	1.45	*1.35*	*0.69*	**4.64**	**1.55**	**4.57**	**4.67**
median	0.25	0.42	*0.28*	*0.14*	**1.11**	**0.56**	**1.25**	**2.31**
p95	4.49	5.50	*3.20*	*3.23*	**11.48**	**5.59**	**19.91**	**18.54**
Panel D: Realized optimization potential from trade splitting (Table 7)								
N	645	126	653	125	571	102	717	140
Realized	67.3	71.9	*65.1*	**75.6**	*64.5*	*66.2*	*46.8*	*47.0*
Forfeited	32.7	28.2	**34.9**	*24.4*	**35.5**	**33.9**	**53.2**	**53.1**

Table II.10: **Summary statistics calibration parameters for robustness checks**

This table displays the number of observations, mean, and median of the nine parameters necessary to calibrate the trade execution model grouped by the direction of the trade (sales and purchases). Column (1) displays the numbers for my main calculation as previously reported in Panel B in Table II.2. Column (2), (3), and (4) displays the parameters for the three scenarios used to check the robustness of my main calculations with respect to the price impact parameters. The corresponding optimization results are reported in column (2), (3), and (4) in Table II.9. Bold (italic) figures in column (2), (3), and (4) indicate numbers that are higher (lower) than numbers in column (1). Price impact is abbreviated as PI. For the symbol of the parameters see Table II.2.

	(1)		**(2)**		**(3)**		**(4)**	
γ_1			**yes**				**no**	
PI Values	**Stock-specific**		**Sample median**		**Stock-specific**		**Stock-specific**	
Trading hours	**9:30am-4:00pm**		**9:30am-4:00pm**		**11:00am-3:00pm**		**9:30am-4:00pm**	
Variable	**mean**	**median**	**mean**	**median**	**mean**	**median**	**mean**	**median**
Sales								
N	718	718	718	718	616	616	718	718
Number of shares (000)	245	60	245	60	263	63	245	60
Trading horizon (days)	2.2	2.0	2.2	2.0	2.1	2.0	2.2	2.0
Fixed perm. PI ($/share)	4.03	2.93	**4.04**	**3.71**	*3.57*	*2.49*	-	-
Variable perm. PI ($/share)	0.49	0.19	*0.26*	**0.24**	0.49	0.18	**2.76**	**1.17**
Fixed temp. PI ($/share)	2.98	2.23	**3.00**	**2.75**	*2.55*	*1.89*	2.98	2.23
Variable temp. PI ($/share)	0.33	0.13	*0.17*	**0.15**	**0.37**	0.13	0.33	0.13
Asset volatility ($/share)/day	0.019	0.011	0.019	0.011	0.019	0.012	0.019	0.011
Stock price at t=0 ($/share)	37.27	34.28	37.27	34.28	38.56	35.31	37.27	34.28
Wealth ($ million)	235	11	235	11	271	12	235	11
Purchases								
N	140	140	140	140	111	111	140	140
Number of shares (000)	120	41	120	401	135	43	120,426	41
Trading horizon (days)	2.2	2.0	2.2	2.0	2.2	2.0	2.2	2.0
Fixed perm. PI ($/share)	3.49	2.00	*1.97*	*1.28*	*3.24*	*1.83*	-	-
Variable perm. PI ($/share)	0.58	0.15	*0.13*	*0.08*	**0.68**	**0.20**	**4.22**	**0.94**
Fixed temp. PI ($/share)	2.96	1.82	*1.47*	*0.95*	*2.73*	*1.48*	2.96	1.82
Variable temp. PI ($/share)	0.46	0.10	*0.08*	*0.05*	0.49	*0.08*	0.46	0.10
Asset volatility ($/share)/day	0.025	0.011	0.025	0.011	0.028	0.013	0.025	0.011
Stock price at t=0 ($/share)	18.24	11.82	18.24	11.82	20.20	13.03	18.24	11.82
Wealth ($ million)	174	13	174	13	208	13	174	13

Chapter III

Repurchasing Shares in the Open Stock Market: Beneficial or Harmful to Stock Market Liquidity?

1 Introduction

The annual volume of stock repurchase programs increased tremendously since the introduction of SEC Rule 10b-18 providing safe harbor guidelines[1] in 1982. These days, share repurchases have surpassed cash dividends as the dominant payout channel.[2] The most popular repurchase method are open market repurchases (OMRs) where firms anonymously reacquire their shares at stock exchanges.[3] Compared to other traders, the repurchasing firms usually trade very large volumes and the managers who execute the repurchase programs possess non-public information about the firm. The combination of these two facts raises the question whether and how open market share repurchases affect a stock's market

[1]SEC Rule 10b-18 sets forth conditions concerning the manner, timing, volume, and price of share repurchases with which issuers must comply in order to obtain a safe harbor from liability for market manipulation.

[2]See, e.g., Fama and French (2001) and DeAngelo, DeAngelo, and Skinner (2008).

[3]Grullon and Ikenberry (2000) report that less than 10% of the total market volume of all share repurchase programs is attributable to self-tender offers or privately negotiated transactions. Banyi, Dyl, and Kahle (2008) also report that about 90% of all repurchases are executed via the open market. The data set used in this study supports this evidence.

liquidity, which is inversely related to a firms' cost of capital. By answering this question, the paper contributes to the long debate about the liquidity impact of open market repurchases. It is the first study that is based on actual repurchase data and covers a sizable cross-section. The findings show that open market share repurchases are not associated with previously unrecognized liquidity costs that stem from adverse selection related to an increase in the fraction of informed market participants.

I use a novel data set to test two non-mutually exclusive hypotheses proposed by Barclay and Smith (1988). The competing market maker hypothesis predicts that stock market liquidity will improve if firms submit price stabilizing buy limit orders and thereby compete with the specialist making the market. In contrast, the information asymmetry hypothesis predicts that liquidity will deteriorate if managers are better informed as well as willing and able to trade on inside information during repurchases. Beside making different predictions about the final liquidity impact of share repurchases, the competing hypotheses also differ with respect to the main transmission channels of the liquidity effect. There are two primary mechanisms through which open market repurchases can affect firms' market liquidity: altering the firms trading characteristics or changing its information environment. The first channel captures (real) order processing and inventory holding costs, while the second channel captures adverse selection costs. Stoll (2000) refers to the first channel as real friction and to the second channel as informational friction. The information asymmetry hypothesis predicts an increase in the probability of informed trading that deteriorates liquidity, and thus, refers to the informational friction component of liquidity. In contrast, the competing market maker hypothesis predicts an increase in trading volume and a reduction in stock price volatility, and thus, refers to the real friction component of liquidity. However, disentangling real and informational friction effects is difficult, in particular due to measurement problems of the non-real (informational) frictions. Thus, choosing a method to disentangle real and informational components and testing the competing hypotheses are inseparable problems. For this reason, I focus on real friction effects which are easier to measure and follow the suggestion of Stoll (2000) to approximate informational effects by the difference between total and real effects. I validate the results obtained with this procedure by examining the change in informational proxies.

The empirical analysis is based on newly available data on quarterly share repurchases of firms. Until 2004, US firms did not have to disclose information on their actual share repurchases. Since then, all repurchasing firms are obliged by the SEC to report on a monthly basis the total number of shares repurchased, the average price paid per share, the number of shares that were purchased as part of a publicly announced repurchase plan, and the maximum number (or dollar value) of shares remaining under public plans. This regulation applies to all quarterly and annual filings for periods ending on or after March 15, 2004. This change in corporate disclosure allows me to analyze actual share repurchase data for the first time. Previous US evidence is limited to share repurchase announcements or estimates of repurchase volumes.[4] I obtain actual repurchase figures from COMPUSTAT where monthly repurchase volumes are summarized on a quarterly basis.[5]

I divide the empirical analysis in four main sections. In the first section, I examine the impact of OMRs on firm's real friction costs - inventory holding and order processing costs - proxied by trading activity and risk variables (turnover, number of trades, volatility). I find a significant increase in share turnover and number of trades during OMRs relative to periods without OMRs. In the second section, I investigate the relation between OMRs and firm's total liquidity, including bid-ask spreads and depth as measures of total liquidity. I find a beneficial liquidity effect, which reveals in lower bid-ask spreads and larger (bid-side) depths. Any beneficial or harmful liquidity effect, however, disappears after controlling for the observed positive real friction effects. This means I find no evidence for an impact of OMRs on informational frictions. In the third section, I validate the indirectly obtained results on informational frictions by using three alternative proxies for adverse selection costs. These analyses confirm the previous findings as I do not find a significant relation between OMRs and the probability of informed trading and adverse selection costs, respectively. In the last section, I investigate the persistence of the observed liquidity effects. Consistent with expectations, I find that the beneficial liquidity effects are transitory and limited to actual repurchase periods.

[4] Barclay and Smith (1988), Singh, Zaman, and Krishnamurti (1994), Wiggins (1994), Franz, Rao, and Tripathy (1995), Miller and McConnell (1995) examine repurchase announcements, while Kim (2005) estimates repurchase volumes from firms' cash flow statements.

[5] For a study that uses hand-collected monthly data from S&P 500 firms' 10-K and 10-Q filings see Ben-Rephael, Oded, and Wohl (2011). They examine the timing ability of managers and returns in the course of open market repurchases.

The remainder of the paper is organized as follows: In Section 2, I provide an overview on the related empirical literature and explain the US regulation concerning the execution and disclosure of open market repurchases. In Section 3, I lay out the main hypotheses. In Section 4, I describe the construction of the data set and the definition of the variables. In Section 5, I present and interpret the empirical findings, before I conclude in Section 6 with a brief summary and discussion of future areas of research. The Appendix contains a definition of all variables used in the empirical analysis (Appendix A) and a description of the data matching and cleaning procedures for the TAQ database (Appendix B).

2 Background and related literature

Previous studies that empirically test the liquidity effect of share repurchases are rare and their results inconclusive. The topic is very much uninvestigated due to the fact that only a few countries very recently obliged firms to disclose details of their repurchase activities.

2.1 International evidence and differences to the US

Most suitable for empirical analysis are countries with a strict disclosure regulation where firms are obliged to disclose and report their repurchase activity on a daily basis and without delay. Brockman and Chung (2001) are the first who use a data set of daily repurchase data to examine the liquidity impact of share repurchases for firms listed at the Hong Kong stock exchange. They find a negative effect on market liquidity for repurchase days, which is consistent with the information asymmetry hypothesis. Ginglinger and Hamon (2007) find similar results for French firms buying back shares at the Paris stock exchange, while for Italy De Cesari, Espenlaub, and Khurshed (2008), for Sweden De Ridder and Rasbrant (2009), and for Canada McNally and Smith (2011) find a significant improvement in market liquidity in the course of open market share repurchases.

The empirical results from non-US countries are not applicable to the US due to significant *differences in the regulatory environment* concerning share repurchases. The US is the country with the longest history of share repurchases, but the laxest share repurchase regulation. Repurchase programs usually require an authorization by the board of directors.

With such an authorization, companies may repurchase their own shares for various purposes without limits on the equity proportion or buyback period. In contrast, in most other countries share repurchases are much more regulated. For instance, in countries from the European Union or in Hong Kong, share repurchase programs have to be approved by the annual shareholder meeting. These repurchase authorizations are usually only valid for about 12-24 months and limited to a maximum of 10% of the outstanding capital. Furthermore, often rules are in place that set an upper bound on the repurchase quantity within a calendar month (e.g., 25% of previous month's trading volume). Finally, additional restrictions frequently prohibit trading in periods before regular events of information disclosure and/or limit trading to non-affiliated outsiders or non-blockholders. These regulatory differences between countries might affect the liquidity changes associated with repurchase programs via the actual repurchase volume and via the repurchase behavior of managers.

Differences in share repurchase regulation between the US and other countries are accompanied by *differences in disclosure requirements*. Since 2004, US firms are required to disclose their actual share repurchase activity in their quarterly reports. In other countries, the disclosure requirements concerning actual share repurchases are much stricter. In Hong Kong and Sweden, for instance, firms have to disclose the price and volume of their share repurchase transactions by the morning of the following business day. In Canada, companies must report their repurchases with date, price, and quantities of shares acquired within 10 days after the trade, while companies in France are required to publicly report the number of shares repurchased during the previous month at the beginning of the following month. Finally, in Italy repurchase activity is disclosed on an annual basis. However, the timeliness and aggregation level of the disclosure information potentially affects market liquidity via the information level of investors and the market maker, but also via the repurchase behavior of managers. If there is no timely disclosure regime, other traders may not learn about a firms' repurchases until several months later or traders have to infer from order flows that firms are conducting repurchases. At the same time, such a noninstant monitoring regime makes it easier for managers to profit from trading on their private information.

Taken together, these regulatory differences regarding the execution and disclosure of open market repurchases speak in favor of a US-specific analysis, which I conduct here.

2.2 US evidence

As disclosure on actual share repurchase activity was not mandatory before 2004, previous US studies were limited to announcements of share repurchase programs to study the liquidity effects of share repurchases.[6] Barclay and Smith (1988), the first who address the liquidity issue, find that spreads widen after repurchase announcements, i.e., liquidity decreases. Several papers refine and extend Barclay and Smith's (1988) study, but derive conflicting results. Singh, Zaman, and Krishnamurti (1994) and Miller and McConnell (1995) conclude that repurchase announcements do not affect liquidity, while Wiggins (1994) and Franz, Rao, and Tripathy (1995) find an increase in liquidity after repurchase announcements.

Announcements of repurchase programs are a disclosure requirement of all major US stock exchanges (e.g., NYSE and NASDAQ) and typically specify a maximum repurchase volume (either stated in terms of US dollars or number of shares), all authorized forms of repurchases (e.g., open market, and/or privately negotiated, and/or tender offer), and a date of expiry. However, firms are not bound to these repurchase announcements. The actual implementation of the repurchase programs is left to their discretion. This leads to the fact that some firms make overlapping and/or continuously ongoing share repurchase announcements. As a result, announcements are just an indication that firms may be buyers in the open market, but are not necessarily tied to actual share repurchase activity. Indeed, actual repurchase rates and repurchase durations vary considerably.[7] Thus, the question whether share repurchases affect liquidity can only be convincingly addressed if actual share repurchase data is available. The change in SEC disclose rules by the end of 2003 makes

[6] The exceptions being Cook, Krigman, and Leach (2004), Kim (2005), Ahn, Cao, and Choe (2001), as well as Nayar, Singh, and Zebedee (2008). Ahn, Cao, and Choe (2001) and Nayar, Singh, and Zebedee (2008) circumvent the data-availability problem by studying self-tender offers. For this type of share repurchases, the timing, quantity and price of the shares repurchased are known. They find a positive, but transitory liquidity effect, which is limited to the relatively short tender offer period, but the long-term liquidity is not enhanced by this form of repurchases. Cook, Krigman, and Leach (2004) and Kim (2005) analyze open market share repurchases. Cook, Krigman, and Leach (2004) are the first who use actual repurchase data gathered via a survey among 500 firms. Their final sample comprises 64 firms listed on the NYSE and NASDAQ. They find no support for the idea that repurchase trading is motivated by the opportunity to profit from proprietary information. However, this result is not surprising against the background of a potential self-selection bias in their surveyed data. Kim (2005) uses rough estimates of firms' actual share repurchases calculated from firms' cash flow statement. He finds no evidence for a liquidity change in the course of open market share repurchase programs. However, these estimates of actual repurchase activity are not without problems (Banyi, Dyl, and Kahle, 2008).

[7] See Stephens and Weisbach (1998), Jagannathan, Stephens, and Weisbach (2000), and Bonaimé (2010). However, in all these papers the actual share repurchase volume is only estimated from cash flows and/or other figures.

it now possible to address this liquidity question in an US environment considering the country-specific execution and disclosure regulation for share repurchase programs.

3 Hypotheses

The main hypotheses on the liquidity effect of corporate share repurchases go back to Barclay and Smith (1988). They propose two different, but non-mutually exclusive hypotheses: the competing market maker hypothesis and the information asymmetry hypothesis.

The *competing market maker hypothesis* assumes that firms repurchase shares without regard to private information and thereby compete with the market maker of the security. By placing limit orders, the repurchasing firm establishes a lower bound on the stock price (bid price). This has the effect of systematically reducing stock price volatility by temporarily fading out a part of the lower tail of the return distribution. Because bid-ask spreads are a positive function of return volatility, a systematic reduction in volatility could have the effect of reducing bid-ask spreads at the time of the share repurchase. At the same time, the price support might attract other traders, and thus, result in an increased trading activity. Trading activity is negatively associated with spreads, and thus, an increase in trading levels should imply lower spreads. By placing limit orders (and supporting the price), the repurchase activity also improves the depth at the bid-side (and the ask-side). Overall, under this hypothesis the share repurchase should improve the stock's liquidity.

The *information asymmetry hypothesis* assumes that managers have inside information and are willing (and able) to trade on this information. The main prediction under this hypothesis is that the market maker increases spreads as reaction to OMRs due to the increased probability of trading with informed managers. At the same time, trading activity is a negative function of the number of potentially informed traders in the market, and thus, an increase in the probability of informed trading might imply a lower level of trading activity. Overall, under this hypothesis the share repurchase should reduce the stock's liquidity. However, SEC Rule 10b-18 covering share repurchases aims to protect non-informed market participants by restricting the firm's opportunity to benefit from private information in their trading. In particular, firms can only post buy limit orders with a price that is equal or higher than the current bid (or the last independent trade if higher than the current bid).

The above arguments lead to the following hypotheses that relate open market repurchases to changes in equity liquidity:

Hypothesis 1 (Competing market maker): OMRs are associated with an increase in equity liquidity (narrower spreads and larger depths).

Hypothesis 2 (Information asymmetry): OMRs are associated with a decrease in equity liquidity (wider spreads and lower depths).

Based on the above hypotheses on the overall liquidity effect, I derive and test the following hypotheses concerning the specific determinants of the changes in equity liquidity:

Hypothesis 1a (Competing market maker): OMRs are associated with an increase in trading activity.

Hypothesis 1b (Competing market maker): OMRs are associated with a decrease in return volatility.

Hypothesis 2a (Information asymmetry): OMRs are associated with a decrease in trading activity.

Hypothesis 2b (Information asymmetry): OMRs are associated with an increase in adverse selection costs.

Barclay and Smith (1988)'s hypotheses differ with regard to the mechanism through which open market repurchases affect stock market liquidity measured with transaction costs. The information asymmetry hypothesis relies on informational arguments, while the competing market maker hypothesis relies on real trading costs. Stoll (2000) refers to the first mechanism as an informational cost effect and to the second mechanism as a real cost effect. Both effects add up to total transaction costs. The higher the total transaction cost, the lower the stock's market liquidity. Distinguishing the two cost components, however, is difficult due to measurement problems and their partial interdependence.

The real cost effect captures costs related to order processing and inventory holding. The order processing costs depend on the level of trading activity (e.g., turnover, number of trades), while the inventory holding costs are related to the risk of adverse price changes of the security (e.g., return volatility). Previous empirical studies in the field of market microstructure provide evidence for the negative relation between trading activity and transaction costs and the positive relation between the risk of price changes and transaction costs.[8]

[8]See Benston and Hagerman (1974), Stoll (1978), and Ho and Stoll (1981).

The informational cost effect is less tangible, and thus, is usually measured as the difference between total and real transaction costs. This cost component compensates the traders for potential losses from trading against better informed market participants (e.g., insiders). Previous research shows that transaction costs rise in the presence of informed traders.[9] The impact of open market repurchases on the informational cost component depends on the managers' possibility to use private information while trading against uninformed traders. The regulation in SEC Rule 10b-18 as well as the obligation to publicly announce repurchase authorizations aim at restricting such informed trading.

Because each of the two hypotheses corresponds to a change in one of the cost components, the differentiation between real and informational cost effects is crucial to testing the hypotheses of Barclay and Smith (1988). I thereby follow the idea of Stoll (2000) to consider informational friction effects as a plug variable that is equivalent to the gap between real friction effects and total transaction costs. I check the robustness of the results obtained with this approach by also directly measuring informational friction effects with the help of available proxy variables.[10]

4 Data sources, sample selection, and variable definitions

In this section I describe the sample selection procedure, data sources, and the construction of the main variables. I also provide summary statistics on the data set.

4.1 Construction of the data set

The initial sample includes all firms from the NYSE Composite Index, which covers approximately 2,000 stocks.[11] The index consists of all common stocks listed at the NYSE, including listings of foreign corporations. From this initial sample, I exclude all non-US firms having a primary listing in a foreign country (ADRs), all firms not incorporated in the US (non-US firms), all firms with more than one class of publicly listed common stock (dual

[9] See Copeland and Galai (1983) and Glosten and Milgrom (1985).

[10] For this procedure see also Brockman, Chung, and Yan (2009). They use this approach to examine the liquidity effects associated with block ownership.

[11] I include only firms listed at the NYSE. I exclude firms listed at NASDAQ because of structural differences between these exchanges which are reflected in firm's liquidity characteristics. See the discussion in Chordia, Roll, and Subrahmanyam (2001) and Huang and Stoll (1996b).

common class firms), and all firms from the financial sector (SIC codes 6000-6999). The sample period covers 5 years and includes all fiscal quarters ending between March 2004 and December 2008.

The data for this study comes from multiple sources: I obtain accounting and actual repurchase data from COMPUSTAT, share repurchase announcement data from the Securities Data Corporation's (SDC) Merger & Acquisitions database, and intraday trading data from the Trades and Quotes (TAQ) database. I use identifier data from CRSP (historical CUSIPs) for merging these databases. I supplement the data set with I/B/E/S data on analyst coverage and daily CRSP data on the cumulative adjustment factors for the number of shares and stock prices. I use these adjustment factors for data from CRSP, TAQ, and SDC to make the number of shares and stock prices comparable over time by adjusting them for stock splits and other capital measures. The final universe of observations comprises all firm-quarters in the intersection of these data sources with four or more (consecutive) quarters of non-missing data.[12] This universe represents approximately 65% of the total market capitalization of the NYSE Composite Index and about 87% of the market capitalization of the relevant subsample of firms (excluding ADRs, non-US firms, financial firms, etc.).

The universe of observations is an unbalanced panel, which consists of 13,396 quarterly observations for 829 firms, an average of about 16.2 quarters per firm. The minimum number of quarters per firm is 4, while the maximum number of quarters per firm is 20, consistent with a 5 year sample period. Of the 13,396 firm-quarters, 5,825 observations are repurchase quarters (43%). Of the 829 firms in the final sample, 191 firms never repurchase shares in the open market during the sample period ("non-repurchaser"). For the 638 firms that repurchase

[12] To keep the maximum number of observations in the sample, (1) I impute missing data with the help of several algorithms based on data cross relationships within databases and (2) I hand-collected missing data on actual share repurchases. Firstly, I complete the quarterly COMPUSTAT data set with the help of quarterly year-to-date and annual data, both from the COMPUSTAT database. In particular, I apply the following algorithms to all relevant items from the Income and Cash Flow Statement: If quarterly data is missing for one quarter within a fiscal year, I use annual COMPUSTAT data and replace the missing values with the difference between the annual value and the sum of the three available quarters. If quarterly year-to-date data for the last quarter of a fiscal year is missing, I use annual COMPUSTAT data to replace the missing values. Finally, if quarterly year-to-date data exhibits a zero value for the last fiscal quarter within a year, I plug in zero values for all subsequent quarters within the same fiscal year. Secondly, I hand-collect missing data on actual share repurchases from firms' 10-Q and 10-K forms downloaded from the SEC website (www.sec.gov) or NYSE website (www.nyse.com). The data retrieved from these 10-Q and 10-K filings includes the number of shares repurchased and the average repurchase price. I limit this procedure of manual data collection to all firms with only one quarter of missing data (219 firms and firm-quarters, respectively) to keep the amount of data gathering manageable. Overall, I obtain the necessary data for 110 of the 219 firms (randomly selected) and thereby increase the sample by 2,218 firm-quarter observation.

shares in the open market during at least one quarter of the sample period ("repurchaser"), I have 10,767 quarterly observations. Out of the 638 firms that conduct repurchases in at least one quarter, 72 firms repurchase shares over all quarters of the sample period (1,112 firm-quarter observations).

Due to the specific research question of this paper, I restrict the analysis to the sample of firms that exhibit a varying repurchase activity. I exclude all firms that never or continuously repurchase shares over the complete sample period, because I cannot observe changes in repurchase activity and possibly related liquidity effects for these firms. This "within-firm-variance sample" covers 566 firms with 9,655 firm-quarters (thereof 4,713 repurchase quarters, 49%) and allows me to make specific inferences about repurchasing firms while circumventing a potential self-selection bias in cross-sectional regressions that might stem from the fact that repurchasing firms are a non-random draw from the overall population of firms.

Based on the "within-firm-variance sample", I define a second sample that focuses on repurchase events, and in particular, the beginning of repurchase activities. This "initiation-event sample" is made up of all non-repurchase quarters that are directly followed by a repurchase quarter. This sample covers 538 firms and 2,258 firm-quarter observations, which belong to 1,129 initiation events. This subsample offers the cleanest setting to study the liquidity impact of share repurchases, because it compares subsequent non-repurchase and repurchase quarters at the cost of dropping a certain number of firm-quarter observations.

4.2 Definition of variables

Measure of share repurchase activity. I obtain data on actual share repurchase volumes from COMPUSTAT (item "cshopq""). The COMPUSTAT figures are gathered from the section "Issuer Purchases of Equity Securities" of firm's 10-Q and 10-K filings. The reported figures include all types of repurchases. To derive the number of shares repurchased in the open market ($RepIntens$), I reduce the total number of shares repurchased (as reported in COMPUSTAT) by the number of shares repurchased via self-tender offers or privately negotiated transactions (as reported in SDC). This construction of the $RepIntens$ variable limits the noise associated with non-open market transactions, but fails to make the variable free of any bias. This is due to two facts. First, the SDC database is not complete with respect to all non-open market repurchases. SDC covers self-tender offers and privately negotiated transactions, but coverage is incomplete.[13] Furthermore, the SDC database does not cover share repurchases from employees who frequently sell shares to their company to offset tax withholding obligations that occur upon vesting of restricted shares or other stock incentive awards. Second, firms from time to time enter special repurchase agreements with investment banks such as accelerated share repurchase transactions or put warrants where the reporting of the transaction and actual execution in the open market do not take place at the same time. These transactions also bias the $RepIntens$ variable.

In order to control for potential liquidity effects from other repurchases, in particular self-tender offers, I construct a second repurchase variable ($RepOtherIntens$) that proxies for the number of shares repurchased via non-open market transactions as stated in SDC.[14]

Measures of market liquidity. The first set of dependent variables covers different dimensions of stock market liquidity. The main measure of stock market liquidity are bid-ask spreads, which measure the price dimension of liquidity. Additionally, I compute quoted depths that represent the quantity dimension of liquidity. Spreads and depths are both measures of total trading frictions. This implies that changes in these variables might result either from changes in real and/or informational frictions. All variables are calculated from TAQ data by averaging daily values over all days within a fiscal quarter. Appendix B contains a description of the data matching and cleaning procedures for the TAQ data.

I use two bid-ask spread measures: quoted absolute spreads and effective absolute spreads. Quoted spreads ($QSPREAD$) are the absolute difference between the quoted bid and ask price. Effective spreads ($ESPREAD$) are twice the absolute difference between the trade price and the midpoint of the quoted bid and ask price. Effective (quoted) spreads measure the round trip cost if trades are executed at actual (quoted) prices. The higher the spreads, the lower the liquidity in the market. Thus, larger values of spreads represent illiquidity.

The depth measures I use are total depth ($DEPTH$), bid-side depth ($BDEPTH$), and ask-side depth ($ADEPTH$). Depth at the bid (ask) is calculated as the daily average number of shares quoted at the highest (lowest) bid (ask) price. I calculate the average over all quotes

[13] See Banyi, Dyl, and Kahle (2008).

[14] Ahn, Cao, and Choe (2001) and Nayar, Singh, and Zebedee (2008) show that for self-tender offers there is a transitory liquidity effect during the tender offer period.

matched to trades. Total depth is the sum of bid and ask depth. The larger the depths, the larger the number of shares the market maker or limit order traders are willing to trade and the more liquid the market in the stock.

Proxies for real friction costs. The second set of dependent and independent variables corresponds to real friction effects. I follow the microstructure literature, e.g., Stoll (2000), and use a standard set of three variables.[15] To account for order processing costs I use two trading activity variables: $TURNOVER$ represents the average daily trading volume measured in shares. $TRADES$ represents the average daily number of trades executed. Both variables are assumed to be negatively associated with spreads. Both variables also proxy for the riskiness of accepting inventory, and thus, inventory holding costs. I additionally measure the risk of adverse stock price changes to account for inventory holding costs. $VOLA$ represents the daily return variance within the fiscal quarter. This variable is assumed to be positively related to bid-ask spreads.

Proxies for informational friction costs. The above liquidity and real friction variables offer the opportunity to indirectly test the information asymmetry hypothesis by examining the effect of open market repurchases on bid-ask spreads and depths (dependent variables) while controlling for real friction effects (independent variables). A more direct test requires an approximation of the informational friction costs. The market microstructure literature developed such more direct measures of adverse selection costs based on stock market activity. The calculation of these measures requires intraday trading data from the TAQ database.

Ideally, I would like to directly measure the change in the probability of trading with informed managers. Easley, Kiefer, O'Hara, and Paperman (1996) developed an estimate of the market makers beliefs of informed trading based on the actual order flow. The Probability of Informed Trading (PIN) represents the percentage of trades that are expected to be information-based. However, despite of its popularity in empirical research in finance and accounting, its reliability is controversially discussed in the literature.[16] For this reason,

[15]For a systematic review of the variable specifications used in seminal papers see Bollen, Smith, and Whaley (2004).

[16]Other papers that use the PIN measure are, e.g., Brown, Hillegeist, and Lo (2004), Ellul and Pagano (2006), Brown, Hillegeist, and Lo (2009). For a controversial discussion of the measure see, e.g., Aktas, de Bodt, Declerck, and Van Oppens (2007).

I only use this measure to check the robustness of the results obtained via the indirect approach. For the same reason, I also rely on two alternative proxies for the change in adverse selection costs: the Adverse Selection Component ($ADSC$) proposed by Lin, Sanger, and Booth (1995) and the Information Component ($InfComp$) proposed by Stoll (2000). Both variables measures the percentage component of spreads that is due to adverse selection costs.[17] The calculation of these measures capturing informational frictions is explained in detail in Appendix A. However, the Adverse Selection Component uses effective spreads as a reference point, while the Information Component refers to quoted spreads. To account for differences in absolute spreads, I multiply the percentages values with quoted and effective absolute spreads, respectively.

Other company characteristics. I also use a few other variables such as firm size, S&P 500 index inclusion, ownership structure, leverage, and analyst coverage as controls in the regressions. These are all standard control variables in the finance and accounting literature. I explain the rationale for their inclusion later in the relevant sections. Appendix A provides detailed definitions and the data sources for all these variables.

4.3 Summary statistics

Table III.1 reports summary statistics for the "within-firm-variance sample" (Panel A) and the "initiation-event sample" (Panel B).

– Please insert Table III.1 here –

The repurchase figures in Panel A show that the size of open market share repurchases varies between 0 million and 121.4 million shares per quarter with an average of 1.0 million shares per quarter. Turning to total market liquidity measures, the table displays that the average quoted (effective) spread is \$0.193 (\$0.078). As known from the microstructure literature, effective spreads are lower than quoted spreads. The average quoted total (ask and bid) depth is 1,840 (1,010 and 830) shares. Next, the table contains summary statistics for real friction proxies: The average daily turnover is 1.01 million shares. The average

[17] For a study on the relation between the Probability of Informed Trading and Adverse Selection Components see Chung and Li (2003).

number of trades per day is 1,800. The daily return volatility during the quarter is 0.21%. The real friction proxies are followed by informational friction proxies: The Probability of Informed Trading varies between 0% and 100% and is on average 11.8%. The adverse selection (information) component is on average 74.7% (69.7%). Finally, Panel A in Table III.1 shows that sample firms have on average a market capitalization of $4,865 million, a share price of $32.71, analyst coverage of 8.5 analysts, and leverage of 37.3%. On average, firms are owned by 20.8 million shareholders and issue 1.5 million shares per quarter. Figures displayed in Panel B for the initiation-event sample are not significantly different from the figures presented in Panel A.

5 Empirical results

5.1 Univariate tests

The most intuitive way to test the hypotheses on the liquidity effect of share repurchases is to compare the liquidity between non-repurchase and repurchase periods. I use a paired t-test and a Wilcoxon matched-pairs signed-ranks test to test for differences in liquidity measures between repurchase and non-repurchase periods. The null hypothesis in these tests is that the mean and median change in the liquidity measures is zero, respectively. The results for these tests are reported in Table III.2. Panel A (B) in Table III.2 display the results for the within-firm-variance (initiation-event) sample.

– Please insert Table III.2 here –

I start with examining the changes in spreads and depths as measures of total liquidity. Table III.2 shows that spreads ($QSPREAD$ and $ESPREAD$) are not significantly different in repurchase and non-repurchase periods, while the change is always positive (with one exception). This result holds across means and medians and is independent from the sample considered, and thus, the unit of aggregation (firms vs. repurchase events). The change in depth is always negative, but changes are only significant for medians. A reduction in depth is consistent with an increase in spreads, implying an adverse liquidity effect.

Next, I look at the real friction proxies turnover, number of trades, and return volatility. The average number of $TRADES$ and the $TURNOVER$ volume is significantly larger during repurchase periods (the exception being $TURNOVER$ in Panel A). For $VOLA$, the results are less clear. In mean tests I find a significantly lower volatility, while in median tests the difference is significantly positive. In the microstructure literature, higher trading activity (turnover and trades) and lower volatility are associated with lower real friction effects and higher liquidity. Thus, the significant improvements in real friction proxies and the non-significant changes in overall liquidity are a puzzling result. One explanation for this finding could be that informational friction effects offset real friction effects, implying no change in overall liquidity. An alternative explanation for this result could be that market makers do not adjust spreads in response to temporary changes in real friction proxies caused by repurchases. The univariate results for the real friction proxies are consistent with the competing market maker hypothesis (Hypothesis 1a and 1b).

Finally, I examine changes in the informational friction proxies Probability of Informed Trading, Adverse Selection Component, and Information Component. I find a positive effect (lower adverse selection costs) for PIN and $ADSC$, while for $InfComp$ the change is negative (higher adverse selection cost). For the initiation event sample, only the change in $InfComp$ is significant. However, analyzing $InfComp$ expressed in \$ terms ($=InfComp * QSPREAD$) the significant results disappear. This indicates that the information component expressed as percentage of quoted spreads changes, while at the same time the quoted spreads expressed in \$ changes in a way that the information component expressed in \$ remains unchanged. Overall, for informational friction proxies I find only little evidence for a significant change during repurchase periods. The univariate results for the informational friction proxies reject the information asymmetry hypothesis (Hypothesis 2b).

Finally, Table III.2 also shows the percentage of positive sign changes which varies between 39-67% (depending on the sample and variable considered). This shows that the direction of the variable changes is heterogeneous across firms as all positive and negative changes are inside the middle third (close to 50%). Consistent over both samples, $TRADES$ is the variable with largest proportion of positive sign changes (64% in Panel A and 67% in Panel B), while the lowest proportion of positive sign changes is observable for $ADEPTH$

(39% in Panel A and 40% in Panel B).

Overall, the univariate results have limited explanatory power. The results provide evidence for a positive change in real friction proxies, while informational friction proxies and total liquidity measures show no significant changes. The complex interplay of real and informational friction effects requires a multivariate analysis of the overall liquidity effects.

5.2 Real friction effects

In this section I examine the impact of open market repurchases on the real friction proxies turnover, number of trades, and return volatility in a multivariate setting. The main regression specification is a pooled cross-sectional OLS regression based on quarterly observations. Subscripts i and t indicate firm i and quarter t, respectively. The regression model is specified as follows:

$$\begin{aligned}
&\log(REAL_FRICTION_{it}) = \alpha + \beta_0 * \log(RepIntens_{it}) \\
&\quad + \gamma_0 \log(RepOtherIntens_{it}) + \gamma_1 \log(SIZE_{it}) + \gamma_2 \log(SHAREHOLDERS_{it}) \\
&\quad + \gamma_3 \log(ISSUANCE_{it}) + \gamma_4 SP500Dummy_i + \delta \log(X_{it}) + \varepsilon_{it}.
\end{aligned}$$

$RepIntens$ is the main variable of interest. The real friction proxies ($REAL\_FRICTION$) include $TURNOVER$, the number of $TRADES$, and $VOLA$. General control variables are firm size ($SIZE$), concentration of ownership ($SHAREHOLDERS$), and S&P 500 index inclusion ($SP500Dummy$). I include $SIZE$ and $SP500Dummy$ to control for differences in firm size as well as public attention, respectively. With the variable $SHAREHOLDERS$ I control for differences in block ownership which affect the secondary market liquidity as block ownership restricts the free float. Furthermore, I control for non-open market repurchase activities ($RepOtherIntens$) and simultaneous equity issuance activities ($ISSUANCE$).[18] X represents control variables that are specific to the different dependent variables. For the trading activity variables $TURNOVER$ and $TRADES$, I control additionally for return

[18] I control for non-open market repurchase activities, because Ahn, Cao, and Choe (2001) and Nayar, Singh, and Zebedee (2008) show that repurchase tender offers have a positive liquidity effect. Furthermore, I control for the simultaneous issuance of equity which might offset the open market share repurchases.

volatility. For the risk variable $VOLA$, I control additionally for changes in leverage.[19] I follow Petersen (2009) and cluster standard errors at the firm level to account for correlation in the repurchase decision variable across time within a firm. The coefficient estimates resulting from this log-log specification can be interpreted as elasticities.

– Please insert Table III.3 here –

Column (1) in Table III.3 reports the regression results using the logarithm of $TURNOVER$ as dependent variable. The $RepIntens$ coefficients are positive and significant in both samples. This result is consistent with the univariate results displayed in Table III.2. It supports the competing market maker hypothesis (Hypothesis 1a) and rejects the information asymmetry hypothesis (Hypothesis 2a). The result is also economically significant: a one-standard-deviation increase in repurchase activity (3.5 million shares as reported in Panel B of Table III.1) leads to a 13.9% increase in share turnover. The signs of the coefficients on the control variables are consistent with expectations.

Column (2) in Table III.3 reports the regression results using the logarithm of the number of $TRADES$ as dependent variable. The results are similar to $TURNOVER$. Open market repurchase activity positively affects the number of trades. This effect is again significant in both samples. Additional regressions (not tabulated) with average trade size as dependent variable reveal a positive, but insignificant relation between repurchase activity and trade size. Thus, the source of the increase in turnover is an increase in the number of trades as opposed to an increase in the average trade size.

Column (3) in Table III.3 reports the regression results using the logarithm of $VOLA$ as dependent variable. The coefficients have the expected negative sign (Hypothesis 1b). The results for the initiation-event sample, however, are insignificant, meaning that open market repurchases result in a decrease in return volatility, which is not statistically significant.

Overall, the results in Table III.3 show a favorable effect of open market repurchases on real friction proxies. Open market share repurchases increase the turnover and the number of trades and reduce the volatility compared to non-repurchase quarters. However, the decrease

[19] I control for leverage, because share repurchases reduce the equity-debt-ratio by lowering shareholder's equity (and in case of a debt-finance repurchase by additionally increasing the financial liabilities). An increase in leverage makes the equity riskier and returns more volatile. See Kim (2007) for an empirical study on return volatility decline in the course of open market repurchase announcements.

in return volatility predicted under the competing market maker hypothesis is insignificant (Hypothesis 1b). The positive trading activity effects are consistent with the competing market maker hypothesis (Hypothesis 1a) and reject the information asymmetry hypothesis (Hypothesis 2a). The beneficial impact of repurchases on real friction proxies should ceteris paribus be associated with an improvement in total stock market liquidity measured with spreads and depth if there are no negative effects from informational frictions.

5.3 Liquidity effects

After examining the real friction effects, I examine the impact of open market repurchases on the change in total liquidity. I first examine whether OMRs impact the firm's total liquidity. Therefore, I regress different spread and depth measures on $RepIntens$. I then determine whether the impact of open market repurchases is due to real friction effects, or informational friction effects, or both. I do so by including real friction proxies as additional control variables in the spread and depth regressions. If share repurchases impact liquidity via informational friction effects, the coefficient on $RepIntens$ should remain significant after controlling for real friction effects. And to provide support for the information asymmetry hypothesis, the coefficient estimate should have a positive sign.

The baseline regression specification is as follows:

$$
\begin{aligned}
&\log\left(LIQUIDITY_{it}\right) = \alpha + \beta_0 * \log\left(RepIntens_{it}\right)\\
&\quad + \mu_0 \log\left(TURNOVER_{it}\right) + \mu_1 \log\left(TRADES\right) + \mu_2 \log\left(VOLA_{it}\right)\\
&\quad + \gamma_0 \log\left(RepOtherIntens_{it}\right) + \gamma_1 \log\left(SIZE_{it}\right) + \gamma_2 \log\left(SHAREHOLDERS_{it}\right)\\
&\quad + \gamma_3 \log\left(ISSUANCE_{it}\right) + \gamma_4 SP500Dummy_i + \varepsilon_{it}.
\end{aligned}
$$

For each liquidity measures ($LIQUIDITY_{it}$), I fit two regressions: The first regression only includes the $RepIntens$ variable (and the general control variables). The second regression additionally includes the logarithm of the real friction proxies $TURNOVER$, the number of $TRADES$, and $VOLA$. This two-step procedure allows me, on the one hand, to examine the impact of repurchases on firm's market liquidity, and on the other hand, to disentangle the real friction and informational friction effects.

Table III.4 reports the regression results for the dependent variable spreads. Quoted spreads are displayed in columns (1) and (2) and effective spreads in column (3) and (4). In the regression on spreads, I substitute the control variable market capitalization ($SIZE$) by the average share price ($PRICE$) as spreads are measured on a per share basis.

– Please insert Table III.4 here –

The *RepIntens* coefficients in column (1) and (3) are negative and significant in both samples, implying that open market repurchases lead to a reduction in spreads, and thus, an increase in firms' market liquidity. This result corresponds to the findings of other studies that are based on actual data.[20] The result is also economically significant: a one-standard-deviation increase in repurchase activity (3.5 million shares as reported in Panel B of Table III.1) leads to a 16.3% and 13.2% decrease in quoted and effective spreads, respectively. The coefficients for the control variables in the regression mostly have the expected sign. For example, larger firms and firms with diverse ownership exhibit lower spreads.

However, after controlling for the real friction effects in column (2) and (4), the favorable reduction in spreads becomes significantly smaller in Panel A and disappears and becomes insignificant in Panel B. Put it differently, after controlling for the changes in real friction effects - approximated by turnover, the number of trades, and return volatility - I do not find a considerable effect of open market repurchases on stock market liquidity. The difference in the results between Panel A and B indicates that an appropriate sample definition has an impact on the obtained results. The results in Panel A seem to be biased by effects which are not related to open-market share repurchases. Beside this, the coefficient estimates for the real friction proxies in most cases have the expected sign and are highly significant. Only the positive effect of turnover on quoted spreads is somewhat surprising and not consistent with microstructure theory, but not unusual in empirical studies (e.g., Stoll, 2000).

Table III.5 reports the regression results for the dependent variable depth. This liquidity measure represent the quantity dimension of liquidity.

[20] In particular, Cook, Krigman, and Leach (2004) and Ben-Rephael, Oded, and Wohl (2011) find narrower spreads during repurchase periods. Cook, Krigman, and Leach (2004) use a sample of 64 firms for which they gather actual repurchase data via a questionnaire. In contrast, Ben-Rephael, Oded, and Wohl (2011) cover a large cross-section (S&P 500 Index) and hand-collect actual repurchase data on a monthly basis from firms' 10-Q and 10-K filings.

– Please insert Table III.5 here –

The *RepIntens* coefficients are positive in all regressions. The results in column (1), (3), and (5) are highly significant with only one exception, implying higher quoted quantities during repurchase periods. This result of improved liquidity is consistent with the result of lower spreads from Table III.4. Furthermore, the positive liquidity effect is still significant after controlling for the real friction effects in Panel A (columns 2, 4, and 6). However, in Panel B, this only holds for the positive liquidity effect on bid-side depth (column 6). This evidence in Panel B is consistent with the competing market maker hypothesis which predicts that the buy limit orders of the repurchasing firms increase (asymmetrically) the bid-side of depth. Again, the difference in the results between Panel A and B is related to a proper definition of the sample. Panel A is the broader sample and the results seem to be driven by effects not associated with open-market repurchases. Finally, the coefficient estimates for the real friction proxies in both Panels in most cases have the expected sign and are highly significant.

Overall, the results in Tables III.4 and III.5 paint a coherent picture regarding the total liquidity effect of open market share repurchases: market liquidity improves in the price dimension (spreads) as well as the quantity dimension (depths). This result supports the competing market maker hypothesis (Hypothesis 1) and rejects the information asymmetry hypothesis (Hypothesis 2). Even after disentangling real and informational friction effects (by controlling for real friction effects), I find no evidence for negative informational effects which have been predicted by the information asymmetry hypothesis (Hypothesis 2b).

Taken together, the results in Tables III.3, III.4, and III.5 indicate that repurchasing shares in the open market has a positive impact on a firm's liquidity via reduced real friction costs. The reduction in real friction costs is implied by an increase in trading activity. I find little evidence that open market share repurchases cause a change in informational friction costs. If share repurchases had been responsible for a change in informational friction costs, then I would have found significant coefficients for the repurchase variable even after controlling for the real friction effects. These findings support Barclay and Smith (1988)'s competing market maker hypothesis, which predicts an improvement in market liquidity.

5.4 Informational friction effects

In this section, I validate the previous findings by directly examining the impact of open market repurchases on variables proxying for informational frictions. If OMRs exacerbate higher informational friction costs (that counteract lower real friction costs), I should find a positive effect of share repurchases on these proxies for informational frictions.

To conduct this test, I use the following baseline regression:

$$\begin{aligned}
&\log\left(INF_FRICTION_{it}\right) = \alpha + \beta_0 * \log\left(RepIntens_{it}\right) \\
&\quad + \mu_0 \log\left(TURNOVER_{it}\right) + \mu_1 \log\left(TRADES\right) + \mu_2 \log\left(VOLA_{it}\right) \\
&\quad + \gamma_0 \log\left(RepOtherIntens_{it}\right) + \gamma_1 \log\left(SIZE_{it}\right) + \gamma_2 \log\left(SHAREHOLDERS_{it}\right) \\
&\quad + \gamma_3 \log\left(ISSUANCE_{it}\right) + \gamma_4 SP500Dummy_i + \gamma_5 \log\left(ANALYST_{it}\right) + \varepsilon_{it}.
\end{aligned}$$

I use three proxies for informational frictions ($INF\_FRICTION$) in this regression: The first dependent variable is the Probability of Informed Trading (PIN). The other two dependent variables are the Adverse Selection Component ($ADSC$) and Information Component ($InfComp$). Both variables measure the percentage component of spreads that is attributable to adverse selection costs. However, the Adverse Selection Component refers to effective spreads, while the Information Component refers to quoted spreads. Therefore, I multiply both variables with the absolute effective and quoted spreads respectively to derive the dependent variables for the above regression. As in the regressions on spreads before, I substitute the control variable market capitalization ($SIZE$) by the average share price ($PRICE$) in these regressions. Beyond this, I use the same control variables as in the previous regressions. However, I additionally control for the general information environment of the company. In the literature, $SIZE$ and analyst coverage ($ANALYST$) are common proxies for the general degree of information asymmetry. Thus, I include analyst coverage as an additional control variable in the regressions. As in the previous section, I fit two regressions for each dependent variable, one with real friction controls and one without.[21]

I report the results for the informational friction regressions in Table III.6.

[21] Controlling for real frictions in regressions on informational frictions is necessary, because of an inverse relation between real frictions and informational frictions. See, e.g., Stoll (2000).

– Please insert Table III.6 here –

For the PIN variable in column (1), I find negative coefficients in both samples. However, only the coefficient in the initiation-event sample is significant at the 10% level. After controlling for the known real friction effects in column (2), the coefficient in Panel B becomes insignificant, implying that share repurchases are not associated with significant changes in the probability of informed trading. The results for the spread-based measures of adverse selection costs are similar. Significant coefficients in column (3) and (5) become insignificant and close to zero after controlling for real friction effects in column (4) and (6). The coefficients for the control variables mostly have the expected sign. For example, larger analyst coverage is associated with a lower probability of informed trading and lower informational spread components.

Taken together, the results in Table III.6 support the previous findings from Table III.4. The improvement in the firm's liquidity is entirely attributable to real friction effects of share repurchases. Table III.6 shows that share repurchases do not affect the informational cost component (after controlling for real friction effects). These findings again reject the information asymmetry hypothesis (Hypothesis 2b). All results provide evidence in support of the competing market maker hypothesis.

5.5 Persistence of the liquidity effects

In this section I investigate the persistence of the observed liquidity effects. In particular, I address the questions: Does the liquidity effects disappear with the discontinuation of an open market repurchase program? Or is an aftermath or long-term liquidity effect observable? The previous analyses do not explicitly address these questions. The within-firm-variance sample allows me to analyze changes in liquidity between repurchase and non -repurchase periods. However, it is not clear which non-repurchase periods - before or after a repurchase, or both - drive the results in this sample. With the initiation-event sample I examine the liquidity effects at the beginning (or resumption) of a repurchase period, because I compare liquidity between initial repurchase quarters and preceding non-repurchase quarters. Following the same line of reasoning, I now define a corresponding discontinuation-event sample. This sample only includes final repurchase quarters and subsequent non-repurchase quarters and allows me to investigate the liquidity effects at the end (or interruption) of a repurchase program. If open market share repurchases change liquidity beyond the actual repurchase period, I would expect to find for the discontinuation-event sample insignificant coefficient estimates in the regressions previously run on the initiation-event sample.

Table III.7 displays the results for the complete set of regressions presented in Tables III.3-III.6 for the discontinuation-event sample.

– Please insert Table III.7 here –

The results in Table III.7 are similar to the results found for the initiation-event sample, indicating that the observed liquidity effects disappear with the conclusion (or interruption) of the open market share repurchase program. This means that the observed improvement in liquidity is transitory and limited to actual repurchase periods.

6 Summary and conclusion

This paper investigates the question whether actual open market share repurchases influence a firm's stock liquidity. It extends the previous literature on liquidity effects of open market share repurchases by using newly available data on actual share repurchase volumes instead of investigating liquidity effects around non-binding share repurchase announcements or using estimates of repurchase volumes. In particular, I test two non-mutually exclusive hypotheses on the liquidity effect of open market repurchases. The competing market maker hypothesis predicts that stock market liquidity will improve. In contrast, the information asymmetry hypothesis predicts that liquidity will deteriorate if managers are better informed and willing (and able) to trade on inside information. Beside making different predictions about the overall liquidity impact of share repurchases, the hypotheses also differ with respect to the main transmission channels. The competing market maker hypothesis predicts a positive effect via real friction effects, while the information asymmetry hypothesis predicts a negative effect via informational friction effects.

The analyses reveal that open market share repurchases significantly increase depth and reduce bid-ask spreads. The beneficial spread effect is attributable to a reduction in the real friction component of spreads. The real friction costs decrease due to an increase in trading activity (turnover and number of trades). This increase in trading activity is primarily due to an increase in the number of trades rather than an increase in the average trade size. After controlling for these real friction effects, I find no evidence that open market repurchases have a negative impact on spreads via informational friction effects. Thus, firms don't have to consider previously unrecognized liquidity costs when making the decision to repurchase shares in the open market. The lack of a negative relation between open market repurchases and informational frictions suggests that SEC Rule 10b-18 is an effective way to protect uninformed market participants against trading of informed managers. In summary, the results are consistent with Barclay and Smith (1988)'s competing market maker hypothesis which predicts a beneficial liquidity effect. I find no evidence for a harmful liquidity effect of open market repurchases. Consistent with expectations, the liquidity improvement associated with open market repurchases is transitory and limited to actual repurchase periods. I find no evidence for a long-term liquidity effect.

This paper is the first attempt to examine the impact of actual share repurchases for US firms as opposed to repurchase announcements or estimates of repurchase activity used in previous US studies. However, actual repurchase data provided by COMPUSTAT only utilizes a minimum amount of information on repurchases provided in firms' 10-Q and 10-K filings. COMPUSTAT provides aggregated quarterly figures while firms report monthly numbers in their annual and quarterly reports. Often firms only repurchase during one or two months within a quarter or the repurchase volume varies considerably over the months within a quarter. Furthermore, firms usually explain how they repurchase the shares, e.g., via privately negotiated transactions, self-tender offers, open market transactions, or other special and individual repurchase agreements. Making use of this additional information by collecting data from 10-K and 10-Q filings would researchers allow to significantly improve the data basis. Such hand-collected data has much greater precision concerning the exact timing and volume of open market repurchases. Another extension of this study which is also related to data availability is the inclusion of share repurchase motives into the analysis of liquidity changes. This seems to be a promising area of future research as in particular differences in the information policy regarding share repurchase motives as well as differing motives for share repurchases might have an impact on the informational effects. A priori, there is no reason to assume that changes in the information environment around OMRs are the same across firms. However, the coverage of repurchase authorizations (and their motives) in the SDC M&A database is incomplete. Thus, these kinds of analyses also require additional collecting of data from firms' press releases. Finally, the evidence provided in this paper could be extended by comparing the liquidity effect of open market repurchases for different types of stock exchanges, e.g., NYSE versus NASDAQ.

Appendix

A. Variable definitions and data sources

Variable	Description	Source
RepIntens	Open market repurchase volume measured in million shares over fiscal quarters. Computed from the quarterly COMPUSTAT item "cshopq" which states the total number of shares repurchased. Non-open market repurchases as stated in SDC are subtracted. The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") at the end of fiscal quarter.**	COMPUSTAT SDC
RepOtherIntens	Non-open market repurchase volume measured in million shares over fiscal quarters. Computed from the SDC item "common shares acquired" which states the number of shares repurchased. Includes all transactions which are not categorized as "open market purchase". The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") at the end of fiscal quarter.**	SDC
QSPREAD	Quoted absolute spread measured in $ as average over all tradings days within the fiscal quarter. Per trading day, the quoted spread is calculated as the (equally-weighted) average of $B_t - A_t$ over all quotes matched to trades where A_t is the quoted ask price and B_t is the quoted bid price. Subscript t denotes transaction t within a day. The variable is adjusted for capital measures using CRSP price adjustment factors ("FACPR") on a daily basis.*	TAQ
ESPREAD	Effective absolute spread measured in $ as average over all tradings days within the fiscal quarter. Per trading day, the effective spread is calculated as the (equally-weighted) average of $2 * \|P_t - Q_t\|$ over all quotes matched to trades where P_t is the price at which the transaction is executed and Q_t is the quote midpoint calculated as $Q_t = (A_t + B_t)/2$ where A_t is the quoted ask price and B_t is the quoted bid price. Subscript t denotes transaction t within a day. The variable is adjusted for capital measures using CRSP price adjustment factors ("FACPR") on a daily basis.*	TAQ
DEPTH	Total average number of shares quoted at the bid and ask price measured in 000 shares and calculated as $ADEPTH + BDEPTH$.*	TAQ
ADEPTH	Ask-side depth measured in 000 shares as average over all trading days within the fiscal quarter. Per trading day, the ask depth is calculated as average over all quotes matched to trades. The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") on a daily basis.*	TAQ
BDEPTH	Bid-side depth measured in 000 shares as average over all trading days within the fiscal quarter. The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") on a daily basis.*	TAQ

* Only calculated when more than 50 trading days per fiscal quarter available. Otherwise set to missing. ** Log transformation for regressions based on 1 plus variable of interest.

Variable	Description	Source
$TURNOVER$	Average daily trading volume measured in million shares over all trading days within the fiscal quarter. The daily trading volume is calculated as the sum of the trading volume of all trades during the day. The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") on a daily basis.*	TAQ
$TRADES$	Average daily number of 000 trades computed over all trading days within the fiscal quarter. The variable is adjusted for capital measures using CRSP share adjustment factors ("FACSHR") on a daily basis.*	TAQ
$VOLA$	Standard deviation of daily stock returns over the fiscal quarter multiplied by the square root of the number of trading days per firm within the fiscal quarter. Daily returns are calculated from average daily stock prices with the following formula: $$r_t = \log\left(1 + \frac{(AvgP_d - AvgP_{d-1})}{AvgP_{d-1}}\right)$$ Average daily stock prices are defined as the average of the (equally-weighted) transaction prices P_t within a day. Subscript d denotes day d within the quarter.*	TAQ
PIN	Probability of Informed Trading based on Easley, Kiefer, O'Hara, and Paperman (1996). PIN represents the percentage of trades that are expected to be information-based each day. It is defined to be a number between zero and one. Maximum likelihood estimation is based on the daily number of buys and sells over fiscal quarters using the NLMIXED procedure in SAS. Quarterly observations out of range [0,1] are set to missing.*/**	TAQ
$ADSC$	Adverse Selection Component of the effective spread based on Lin, Sanger, and Booth (1995). $ADSC$ is measured in % and computed as the average over all daily values within the fiscal quarter. Daily adverse selection components are estimated from all trades within a trading day as a coefficient from the regression of the change in quotes on the half-signed effective spread. In particular, the following regression is estimated without an intercept: $$\log(Q_t) - \log(Q_{t-1}) = ADSC_t * (\log(P_{t-1}) - \log(Q_{t-1})) + \varepsilon_t$$ where P_{t-1} is the price at which the previous transaction is executed and Q_t is the quote midpoint calculated as $Q_t = (A_t + B_t)/2$ where A_t is the quoted ask price and B_t is the quoted bid price. Subscript t denotes transaction t within a day. Daily observations out of range [0,1] are set to missing values before the quarterly average is calculated.*/**	TAQ
$SP500Dummy$	S&P 500 index inclusion. Dummy has the value of 1 if the company is part of the S&P 500 Index at least during the sample period (for available quarterly observations), and 0 otherwise. Computed from the monthly CRSP/COMPUSTAT Merged data item S&P Major Index Code - Historical ("spmim").	COMPUSTAT

* Only calculated when more than 50 trading days per fiscal quarter available. Otherwise set to missing. ** Log transformation for regressions based on 1 plus variable of interest.

Variable	Description	Source
$InfComp$	Information Component of the quoted spread based on Stoll (2000). $InfComp$ is measured in % and computed as the average over all daily values within the fiscal quarter. Daily values are calculated as: $$InfComp_d = 1 - \frac{Traded\,Spread_d}{Quoted\,Spread_d}$$ with subscript d denoting the day within the quarter. $Traded\ Spread = \frac{1}{m}\sum_{t=1}^{m}\left(P_t^A\right) - \frac{1}{n}\sum_{t=1}^{n}\left(P_t^B\right)$ and $Quoted\,Spread = \frac{1}{T}\sum_{t=1}^{T}\left(A_t - B_t\right)$ with T denoting the total number of transactions per day, m denoting the transactions at the ask price P_t^A, and n denoting the transactions at the bid price P_t^B. A_t (B_t) is the quoted ask (bid) price. Daily observations out of the range [0,1] are set to missing values before the quarterly average is calculated.*/**	TAQ
$SIZE$	Market capitalization of the common/ordinary equity measured in million $ at the end of the fiscal quarter. Computed from the quarterly COMPUSTAT items common shares outstanding ("cshoq") and the stock price at the fiscal quarter end ("prccq").	COMPUSTAT
$PRICE$	Stock price measured in $ at the end of the fiscal quarter. Computed from the quarterly COMPUSTAT item price at fiscal quarter end ("prccq"). Adjusted for capital measures with CRSP price adjustment factors ("FACPR") on a quarter end basis.	COMPUSTAT
$SHAREHOLDERS$	Number of shareholders measured in millions at the end of the fiscal quarter. Computed from the annual COMPUSTAT item number of shareholders ("cshr") at the end of the current and previous year by using straight-line adjustment for fiscal quarters.	COMPUSTAT
$ISSUANCE$	Equity issuance measured in million shares over fiscal quarters. Computed as the sum of $RepIntens$, $RepOtherIntens$, and the change in the number of outstanding shares calculated from the quarterly COMPUSTAT item common shares outstanding ("cshoq") by subtracting the value at the beginning of the quarter from the value at the end of the quarter.**	COMPUSTAT
$ANALYST$	Average number of analysts following the security. Computed as the 3 month average over the fiscal quarter. Monthly values are computed by using the detail history file and counting the number of analysts that made EPS forecasts over the one year period ending six months prior to the end of the fiscal quarter.**	I/B/E/S
$LEVERAGE$	Market leverage measured in % at the fiscal quarter end. Computed by scaling the quarterly COMPUSTAT item total liabilities ("lt") by the sum of the quarterly COMPUSTAT items total assets ("at"), market value of common equity ("mvce"), total common/ordinary equity ("ceq"), and balance sheet deferred taxes ("txdb").	COMPUSTAT

* Only calculated when more than 50 trading days per fiscal quarter available. Otherwise set to missing. ** Log transformation for regressions based on 1 plus variable of interest.

B. Procedures of data matching and cleaning for TAQ

B.1 Matching of trades and quotes and identifying buy and sell orders

A matching of trades and quotes is required for the computation of the liquidity measures listed above. The most widely used method to match trades and quotes and infer a buy and sell classification of trades is the Lee-Ready algorithm (Lee and Ready, 1991). The algorithm consists of a quote-rule and a tick-rule used as a tie-breaker for mid-quote trades. The quote rule applies information about the proximity to prevailing quotes in order to infer trade direction. Trades at prices above the midpoint of the bid and ask are classified as buys. Trades below the midpoint are classified as sells. However, some trades are executed at the bid-ask midpoint. These trades can be either ignored by removing such trades or can be handled by the tick-rule. The tick-rule classifies a midpoint trade as a buy if it is executed at a higher price than the previous trade (i.e., if it is an “uptick") and as a sell if it is executed at a lower price (“downtick"). To apply this Lee-Ready algorithm one needs to match trade price data with quotes. Lee and Ready (1991) suggest matching trade prices with 5-second old quotes because prior to the computerization of the trade process, new quotes were often reported prior to the prices of trades that generated them. Because of the very recent TAQ sample (2004-2008), I follow Henker and Wang (2006) and use a 1-second quote delay.

B.2 Cleaning of raw data

Before matching trades and quotes with the above procedure, I filter out invalid trades and quotes from TAQ raw data by excluding all observations that do not fulfill the following conditions:

- ☐ Trades and quotes occur during regular trading hours (9:30am to 4:00pm) and have a positive size, depth, and price.

- ☐ For trades, I additionally require that:
  (1) TAQ’s CORR field (correction indicator) is equal to 0, 1, or 2 (“regular trades”, “original trade which was later corrected”, or “symbol correction”).
  (2) TAQ’s COND field (sale condition) is either blank or equal to *, @, E, J, K, (“regular trade”, “NYSE Direct trade”, “Rule 127 trade”, or “Rule 155 trade”, i.e., omitting trades indicated to be exchange acquisitions or distributions or to involve nonstandard settlement conditions).
  (3) The absolute price change to the previous trade is less than 50%.

- ☐ For quotes, I additionally require that:
  (1) TAQ’s MODE field (quote condition) is equal to 1, 2, 3, 5, 6, 8, 10, 12, 16, 17, 18, or 21-26 (i.e., omitting quotes indicated to be associated with trading halts or designated order imbalances or to be non-firm quotes).
  (2) The ask price is higher than the bid price, but not larger than 150% of the bid price.

Finally, following Easley, Kiefer, O’Hara, and Paperman (1996), Huang and Stoll (1997), and Henker and Wang (2006), I bunch all consecutive trades executed at the same price with no intervening quote revisions. The trade volume for the bunched trade is the sum of all the trades bunched together.

Table III.1: **Summary statistics**

This table shows the mean, median, standard deviation (sd), minimum, and maximum for repurchase, liquidity, and control variables. The sample includes firm quarters with non-missing data ending between March 2004 and December 2008 for firms listed at NYSE. Panel A (B) shows the results for the within-firm-variance (initiation-event) sample. For a definition of the different subsamples see Section 4.1. For a definition of the variables and a description of the data sources see Appendix A.

Variables	**N**	**mean**	**median**	**sd**	**min**	**max**
Panel A: Within-firm-variance sample						
Repurchase Variables						
RepIntens (million shares per quarter)	9,655	1.0	0.0	4.4	0.0	121.4
RepOtherIntens (million shares per quarter)	9,655	0.1	0.0	2.2	0.0	121.9
Liquidity Variables						
QSPREAD ($)	9,655	0.193	0.125	0.409	0.011	19.338
ESPREAD ($)	9,655	0.078	0.051	0.191	0.009	5.341
DEPTH ('000 shares)	9,655	1.84	1.11	4.56	0.20	141.64
ADEPTH ('000 shares)	9,655	1.01	0.59	2.61	0.11	85.90
BDEPTH ('000 shares)	9,655	0.83	0.51	1.99	0.08	58.56
TURNOVER (million shares per day)	9,655	1.01	0.42	2.10	0.00	45.60
TRADES ('000 per day)	9,655	1.8	1.2	2.2	0.0	30.2
VOLA (% per day over quarter)	9,655	0.21	0.14	0.27	0.01	4.19
PIN (%)	9,655	11.8	10.6	7.5	0.0	100.0
ADSC (%)	9,655	74.7	76.4	9.9	16.4	93.2
ADSC*ESPREAD ($)	9,655	0.059	0.038	0.139	0.002	4.211
InfComp (%)	9,655	69.7	70.1	9.1	34.6	94.1
InfComp*QSPREAD ($)	9,655	0.143	0.087	0.310	0.005	15.465
Control variables						
SIZE (million $)	9,655	4,865	1,698	11,683	16	256,906
PRICE ($)	9,655	32.71	26.41	47.39	0.88	936.22
SHAREHOLDERS (million)	9,655	20.8	3.5	94.3	0.0	2,600.0
ISSUANCE (million shares per quarter)	9,655	1.5	0.2	27.1	0.0	2,435.0
ANALYST (#)	9,655	8.5	7.0	6.4	0.0	38.0
LEVERAGE (%)	9,655	37.3	36.0	18.5	2.3	97.8
Panel B: Initiation-event sample						
Repurchase Variables						
RepIntens (million shares per quarter)	2,258	0.7	0.0	3.5	0.0	99.0
RepOtherIntens (million shares per quarter)	2,258	0.2	0.0	3.7	0.0	121.9
Liquidity Variables						
QSPREAD ($)	2,258	0.181	0.121	0.368	0.013	7.631
ESPREAD ($)	2,258	0.078	0.051	0.215	0.010	5.341
DEPTH ('000 shares)	2,258	1.66	1.06	3.08	0.23	70.50
ADEPTH ('000 shares)	2,258	0.93	0.57	1.87	0.12	45.86
BDEPTH ('000 shares)	2,258	0.73	0.48	1.24	0.11	24.64
TURNOVER (million shares per day)	2,258	0.88	0.41	1.54	0.00	24.89
TRADES ('000 per day)	2,258	1.7	1.1	1.8	0.0	15.4
VOLA (% per day over quarter)	2,258	0.19	0.14	0.22	0.02	3.30
PIN (%)	2,258	11.7	10.6	7.2	0.0	100.0
ADSC (%)	2,258	74.9	76.3	9.5	36.2	91.1
ADSC*ESPREAD ($)	2,258	0.059	0.038	0.159	0.004	4.211
InfComp (%)	2,258	69.6	70.0	8.8	39.6	94.1
InfComp*QSPREAD ($)	2,258	0.133	0.085	0.274	0.006	6.278
Control variables						
SIZE (million $)	2,258	4,186	1,633	8,251	35	108,329
PRICE ($)	2,258	32.54	26.52	44.90	1.82	801.99
SHAREHOLDERS (million)	2,258	19.8	3.5	103.3	0.0	2,500.0
ISSUANCE (million shares per quarter)	2,258	1.2	0.2	9.6	0.0	373.0
ANALYST (#)	2,258	8.3	7.0	6.4	0.0	37.3
LEVERAGE (%)	2,258	36.2	35.0	17.7	2.4	96.7

Table III.2: **Univariate tests**

This table displays the mean and median for all liquidity-related variables for repurchase and non-repurchase periods. For a definition of the variables and a description of the data sources see Appendix A. In Panel A, the set of means and medians is calculated across all repurchase and non-repurchase quarters per firm. In Panel B, the set of means and medians is calculated across the repurchase and non-repurchase quarters per repurchase event. The difference in these means and medians between the two periods is then computed per firm and repurchase event, respectively. The parametric paired t-test tests the null hypothesis that the mean of the differences is zero. The non-parametric Wilcoxon matched-pairs signed-ranks test tests the null hypothesis that both distributions are the same. All p-values are reported on the basis of two-tail significance levels. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Means				**Medians**				
Variables	**N**	**Non-Re-purchase**	**Re-purchase**	**Diffe-rence**		**Non-Re purchase**	**Re-purchase**	**Diffe-rence**	**% Positive**	
Panel A: Within-firm-variance sample										
QSPREAD	566	0.189	0.182	-0.007		0.131	0.122	-0.005	45	*
ESPREAD	566	0.075	0.077	0.001		0.050	0.050	0.000	49	
DEPTH	566	1.84	1.75	-0.09		1.15	1.03	-0.11	40	***
ADEPTH	566	1.02	0.96	-0.06		0.62	0.55	-0.06	39	***
BDEPTH	566	0.83	0.80	-0.03		0.53	0.48	-0.03	42	***
TURNOVER	566	0.96	0.99	0.03		0.39	0.44	0.02	58	***
TRADES	566	1.7	1.9	0.3	***	1.0	1.3	0.1	64	***
VOLA	566	0.24	0.21	-0.03	***	0.15	0.14	0.00	53	
PIN	566	12.0	11.6	-0.4	**	11.1	10.4	-0.6	42	***
ADSC	566	75.0	74.6	-0.4		77.2	76.6	-0.3	48	
ADSC*ESPREAD	566	0.056	0.058	0.001		0.037	0.039	0.000	50	
InfComp	566	69.1	70.3	1.2	***	70.0	70.9	1.4	60	***
InfComp*QSPREAD	566	0.138	0.136	-0.003		0.090	0.086	-0.002	48	
Panel B: Initiation-event sample										
QSPREAD	1,129	0.181	0.181	0.000		0.123	0.120	0.000	50	
ESPREAD	1,129	0.077	0.079	0.002		0.051	0.051	0.001	52	
DEPTH	1,129	1.67	1.65	-0.02		1.08	1.03	-0.03	42	***
ADEPTH	1,129	0.93	0.92	-0.02		0.59	0.55	-0.02	40	***
BDEPTH	1,129	0.74	0.73	-0.01		0.49	0.48	-0.01	46	**
TURNOVER	1,129	0.87	0.90	0.03	**	0.40	0.42	0.01	56	***
TRADES	1,129	1.7	1.8	0.1	**	1.1	1.2	0.1	67	***
VOLA	1,129	0.20	0.17	-0.03	***	0.14	0.14	0.00	53	***
PIN	1,129	11.8	11.7	-0.1		10.6	10.6	-0.2	48	
ADSC	1,129	75.0	74.7	-0.3		76.7	75.9	0.2	52	
ADSC*ESPREAD	1,129	0.058	0.060	0.002		0.038	0.039	0.001	53	
InfComp	1,129	69.2	70.0	0.8	***	69.5	70.6	1.0	57	***
InfComp*QSPREAD	1,129	0.133	0.134	0.001		0.085	0.085	0.001	53	

Table III.3: **Real friction effects - Turnover, number of trades, and return volatility**

This table reports OLS regression results for the dependent variables $TURNOVER$, $TRADES$, and $VOLA$. Panel A (B) shows the results for the within-firm-variance (initiation-event) sample. For a definition of the different subsamples see Section 4.1. For a definition of the variables and a description of the data sources see Appendix A. Standard errors are clustered at the firm-level. Regression intercepts are not shown. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent variables	**(1)**		**(2)**		**(3)**	
	Dependent variables					
	log(TURNOVER)		**log(TRADES)**		**log(VOLA)**	
Panel A: Within-firm-variance sample						
log(RepIntens)	0.079	***	0.074	***	-0.041	***
log(SIZE)	0.746	***	0.749	***	-0.335	***
log(SHAREHOLDERS)	0.015		-0.005		-0.017	***
log(ISSUANCE)	0.247	***	-0.044		0.047	***
log(RepOtherIntens)	0.135	**	-0.084	*	0.019	
SP500Dummy	0.196	*	-0.072		0.090	***
log(VOLA)	0.455	***	0.402	***		
log(LEVERAGE)					-0.022	
log(TURNOVER)					0.136	***
log(TRADES)					0.134	***
R2	0.67		0.64		0.18	
N	9,655		9,655		9,655	
Panel B: Initiation-event sample						
log(RepIntens)	0.139	***	0.117	***	-0.031	
log(SIZE)	0.742	***	0.734	***	-0.312	***
log(SHAREHOLDERS)	0.015		-0.017		-0.031	***
log(ISSUANCE)	0.210	***	-0.061	*	0.022	
log(RepOtherIntens)	0.145	**	-0.035		0.011	
SP500Dummy	0.214	*	-0.027		0.042	
log(VOLA)	0.555	***	0.492	***		
log(LEVERAGE)					-0.027	
log(TURNOVER)					0.116	***
log(TRADES)					0.165	***
R2	0.65		0.63		0.22	
N	2,258		2,258		2,258	

Table III.4: **Liquidity effects - Spread**

This table reports OLS regression results for the dependent variables $QSPREAD$ and $ESPREAD$. Panel A (B) shows the results for the within-firm-variance (initiation-event) sample. For a definition of the different subsamples see Section 4.1. For a definition of the variables and a description of the data sources see Appendix A. Standard errors are clustered at the firm-level. Regression intercepts are not shown. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent variables	**(1)**		**(2)**		**(3)**		**(4)**	
	Dependent variables							
	log(QSPREAD)				**log(ESPREAD)**			
Panel A: Within-firm-variance sample								
log(RepIntens)	-0.163	***	-0.042	***	-0.132	***	-0.031	***
log(PRICE)	0.546	***	0.842	***	0.554	***	0.714	***
log(SHAREHOLDERS)	-0.048	***	-0.014	**	-0.048	***	-0.016	***
log(ISSUANCE)	-0.133	***	-0.048	***	-0.121	***	-0.006	
log(RepOtherIntens)	-0.009		-0.015		-0.001		0.030	
SP500Dummy	-0.375	***	-0.069	**	-0.406	***	-0.089	***
log(VOLA)			0.303	***			0.268	***
log(TURNOVER)			0.146	***			-0.085	***
log(TRADES)			-0.567	***			-0.238	***
R2	0.28		0.53		0.36		0.55	
N	9,655		9,655		9,655		9,655	
Panel B: Initiation-event sample								
log(RepIntens)	-0.074	***	0.017		-0.070	***	0.008	
log(PRICE)	0.548	***	0.872	***	0.574	***	0.748	***
log(SHAREHOLDERS)	-0.029	**	-0.002		-0.039	***	-0.008	
log(ISSUANCE)	-0.110	***	-0.045	*	-0.123	***	-0.012	
log(RepOtherIntens)	-0.057		-0.051		-0.051		-0.011	
SP500Dummy	-0.415	***	-0.121	**	-0.452	***	-0.125	***
log(VOLA)			0.308	***			0.271	***
log(TURNOVER)			0.230	***			-0.052	
log(TRADES)			-0.661	***			-0.288	***
R2	0.25		0.49		0.34		0.54	
N	2,258		2,258		2,258		2,258	

Table III.5: **Liquidity effects - Depth**

This table reports OLS regression results for the dependent variables *DEPTH*, *ADEPTH* and *BDEPTH*. Panel A (B) shows the results for the within-firm-variance (initiation-event) sample. For a definition of the different subsamples see Section 4.1. For a definition of the variables and a description of the data sources see Appendix A. Standard errors are clustered at the firm-level. Regression intercepts are not shown. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent variables	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
	Dependent variables											
	log(DEPTH)				**log(ADEPTH)**				**log(BDEPTH)**			
Panel A: Within-firm-variance sample												
log(RepIntens)	0.084	***	0.068	***	0.065	**	0.049	***	0.103	***	0.089	***
log(SIZE)	-0.061	***	-0.139	***	-0.051	**	-0.128	***	-0.068	***	-0.151	***
log(SHAREHOLDERS)	0.046	***	0.023	***	0.047	***	0.022	***	0.046	***	0.025	***
log(ISSUANCE)	0.361	***	0.028		0.381	***	0.030		0.334	***	0.025	
log(RepOtherIntens)	0.261	***	0.018		0.274	***	0.017		0.243	***	0.019	
SP500Dummy	0.370	***	0.057	*	0.374	***	0.043		0.361	***	0.073	**
log(VOLA)			-0.116	***			-0.130	***			-0.100	***
log(TURNOVER)			1.118	***			1.183	***			1.035	***
log(TRADES)			-0.992	***			-1.057	***			-0.901	***
R2	0.23		0.81		0.22		0.80		0.23		0.78	
N	9,655		9,655		9,655		9,655		9,655		9,655	
Panel B: Initiation-event sample												
log(RepIntens)	0.061	**	0.021		0.043		0.003		0.080	***	0.040	***
log(SIZE)	-0.043	*	-0.147	***	-0.032		-0.135	***	-0.050	**	-0.160	***
log(SHAREHOLDERS)	0.057	***	0.023	***	0.057	***	0.020	***	0.056	***	0.026	***
log(ISSUANCE)	0.327	***	0.027		0.345	***	0.026		0.302	***	0.027	
log(RepOtherIntens)	0.279	***	0.078	**	0.295	***	0.081	**	0.258	***	0.074	*
SP500Dummy	0.317	***	0.048		0.314	***	0.029		0.316	***	0.068	*
log(VOLA)			-0.154	***			-0.178	***			-0.128	***
log(TURNOVER)			1.137	***			1.212	***			1.043	***
log(TRADES)			-1.011	***			-1.091	***			-0.904	***
R2	0.21		0.81		0.20		0.80		0.22		0.80	
N	2,258		2,258		2,258		2,258		2,258		2,258	

Table III.6: **Informational friction effects - Probability of Informed Trading, Adverse Selection Component, and Information Component**

This table reports OLS regression results for the dependent variables PIN, $ADSC * ESPREAD$, and $InfComp*QSPREAD$. Panel A (B) shows the results for the within-firm-variance (initiation-event) sample. For a definition of the different subsamples see Section 4.1. For a definition of the variables and a description of the data sources see Appendix A. Standard errors are clustered at the firm-level. Regression intercepts are not shown. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent variables	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**	
	Dependent variables											
	log(PIN)				**log(ADSC*ESPREAD)**				**log(InfComp*QSPREAD)**			
Panel A: Within-firm-variance sample												
log(RepIntens)	-0.011		-0.002		-0.007	**	-0.002		-0.012	***	-0.001	
log(SIZE)	-0.097	***	-0.026	*								
log(PRICE)					0.057	***	0.071	***	0.096	***	0.129	***
log(SHAREHOLDERS)	-0.008		-0.007		-0.004	**	-0.002	**	-0.008	***	-0.003	*
log(ISSUANCE)	0.042	***	0.034	**	-0.001		0.000		-0.005		-0.002	
log(RepOtherIntens)	0.111	***	0.100	***	0.001		0.001		-0.002		-0.003	
log(ANALYST)	-0.131	***	-0.021		-0.026	***	-0.006		-0.058	***	-0.005	
SP500Dummy	-0.136	***	-0.156	***	0.000		0.005		-0.002		0.010	
log(VOLA)			-0.024	**			0.021	***			0.046	***
log(TURNOVER)			0.024				0.009				0.021	**
log(TRADES)			-0.198	***			-0.034	**			-0.084	***
R2	0.13		0.16		0.26		0.33		0.27		0.40	
N	9,655		9,655		9,655		9,655		9,655		9,655	
Panel B: Initiation-event sample												
log(RepIntens)	-0.055	*	-0.036		-0.004	*	0.000		-0.006	*	0.003	
log(SIZE)	-0.108	***	-0.040									
log(PRICE)					0.060	***	0.075	***	0.096	***	0.130	***
log(SHAREHOLDERS)	-0.017	*	-0.021	**	-0.004	*	-0.002		-0.005	*	-0.002	
log(ISSUANCE)	0.020		0.016		-0.004		-0.002		-0.009	**	-0.008	**
log(RepOtherIntens)	0.100	**	0.103	**	-0.001		0.000		-0.006	*	-0.005	
log(ANALYST)	-0.104	***	0.018		-0.029	***	-0.005		-0.057	***	-0.009	
SP500Dummy	-0.097	*	-0.113	**	0.006		0.010		0.004		0.010	
log(VOLA)			-0.061	**			0.019	***			0.038	***
log(TURNOVER)			0.007				0.012	*			0.032	***
log(TRADES)			-0.197	***			-0.042	**			-0.091	***
R2	0.13		0.17		0.25		0.32		0.27		0.38	
N	2,258		2,258		2,258		2,258		2,258		2,258	

Table III.7: **Discontinuation-event sample**

This table reports OLS regression results for the discontinuation-event sample. Panel A covers real friction effects (see Table III.3). Panel B and C cover total liquidity measured in spreads and depth (see also Table III.4 and III.5). Panel D covers informational friction effects (see Table III.6). For a definition of the variables and a description of the data sources see Appendix A. Standard errors are clustered at the firm-level. Regression intercepts are not shown. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent variables	Dependent variables (1)	(2)	(3)	(4)	(5)	(6)
Panel A: Real friction effects						
	log(TURNOVER)		**log(TRADES)**		**log(VOLA)**	
log(RepIntens)	0.097***		0.054**		0.009	
log(SIZE)	0.725***		0.742***		-0.345***	
log(SHAREHOLDERS)	0.027		-0.001		-0.019**	
log(ISSUANCE)	0.224***		-0.088**		0.032	
log(RepOtherIntens)	0.149**		-0.017		-0.119***	
SP500Dummy	0.220*		-0.014		0.073	
log(VOLA)	0.638***		0.603***			
log(LEVERAGE)					-0.008	
log(TURNOVER)					0.079**	
log(TRADES)					0.234***	
R2	0.65		0.65		0.26	
N	2,106		2,106		2,106	
Panel B: Liquidity effects - Spreads						
	log(QSPREAD)		**log(ESPREAD)**			
log(RepIntens)	-0.080***	-0.024	-0.076***	-0.019		
log(PRICE)	0.589***	0.879***	0.598***	0.762***		
log(SHAREHOLDERS)	-0.047***	-0.010	-0.047***	-0.010		
log(ISSUANCE)	-0.154***	-0.080***	-0.155***	-0.030		
log(RepOtherIntens)	-0.057	-0.043	-0.019	0.025		
SP500Dummy	-0.421***	-0.086	-0.452***	-0.100**		
log(VOLA)		0.368***		0.318***		
log(TURNOVER)		0.206***		-0.056		
log(TRADES)		-0.636***		-0.297***		
R2	0.29	0.53	0.37	0.57		
N	2,106	2,106	2,106	2,106		
Panel C: Liquidity effects - Depths						
	log(DEPTH)		**log(ADEPTH)**		**log(BDEPTH)**	
log(RepIntens)	0.083***	0.026*	0.069**	0.010	0.097***	0.042***
log(SIZE)	-0.070***	-0.163***	-0.056**	-0.148***	-0.082***	-0.178***
log(SHAREHOLDERS)	0.060***	0.027***	0.061***	0.026***	0.058***	0.029***
log(ISSUANCE)	0.386***	0.038	0.403***	0.034	0.366***	0.044*
log(RepOtherIntens)	0.254**	0.060	0.275**	0.066	0.229**	0.054
SP500Dummy	0.331***	0.065*	0.315***	0.036	0.347***	0.096***
log(VOLA)		-0.152***		-0.180***		-0.121***
log(TURNOVER)		1.164***		1.230***		1.077***
log(TRADES)		-1.017***		-1.087***		-0.921***
R2	0.20	0.82	0.19	0.81	0.21	0.79
N	2,106	2,106	2,106	2,106	2,106	2,106
Panel D: Informational friction effects						
	log(PIN)		**log(ADSC*ESPREAD)**		**log(InfComp*QSPREAD)**	
log(RepIntens)	-0.061**	-0.056*	-0.003	-0.002	-0.004	-0.001
log(SIZE)	-0.092***	-0.036				
log(PRICE)			0.066***	0.080***	0.104***	0.136***
log(SHAREHOLDERS)	-0.022***	-0.022***	-0.005*	-0.002	-0.006**	-0.001
log(ISSUANCE)	0.073**	0.048	-0.003	-0.001	-0.010**	-0.007*
log(RepOtherIntens)	0.181***	0.156**	0.001	0.003	0.001	0.003
log(ANALYST)	-0.134***	-0.034	-0.034**	-0.009**	-0.061***	-0.007
SP500Dummy	-0.124**	-0.143***	0.007	0.014	0.001	0.015
log(VOLA)		-0.016		0.028***		0.060***
log(TURNOVER)		0.056		0.009		0.026***
log(TRADES)		-0.205***		-0.038**		-0.089***
R2	0.14	0.16	0.27	0.33	0.29	0.41
N	2,106	2,106	2,106	2,106	2,106	2,106

Chapter IV

Measuring the Quality of Corporate Governance: Is there a Uniform Standard?[1]

1 Introduction

In this paper, we investigate if there is a uniform standard for measuring the quality of corporate governance. An emerging literature in corporate governance investigates governance indices and typically follows a “tick-box”-approach, which constructs a comprehensive index of governance provisions that are deemed desirable by simply adding the number of such provisions for each company. Some recent papers show that only a small number of corporate governance attributes that are included in these indices can be consistently related to firm valuation.[2] However, the attributes in these papers relate so far only to the institutional environment in the US and it is unclear whether they have any relevance for firms domiciled outside the US.

We address the heterogeneity of attributes that identify the quality of corporate governance provisions across institutional environments. Our starting point is the hypothesis that what is a good provision in one country may not at all be also a good provision in

[1]This chapter is joint work with Prof. Ernst Maug, Ph.D., from the University of Mannheim.

[2]The first paper to show that only a small number of provisions can be related to firm value is Bebchuk, Cohen, and FerrelI (2009) using IRRC governance data. Brown and Caylor (2006) use ISS governance data and a different regression approach, but obtain a similar conclusion.

another country. For example, Bebchuk, Cohen, and Ferrell's (2009) Entrenchment index is largely based on the extent to which managers can entrench themselves against takeovers, particularly hostile takeovers. However, hostile takeovers play very little or no role in most civil law countries, so we expect that takeover provisions are accordingly less important.[3] Entrenchment provisions as well as governance provisions related to executive compensation or the independence of the board of directors and its committees also focus on the conflict of interest between shareholders and management, which is important for firms with a dispersed ownership structure. However, most firms outside the common law countries have concentrated equity ownership, so we hypothesize that for these firms governance attributes that regulate the shareholder-management conflict are less important, whereas provisions that relate to the conflict between large and small shareholders are more important.

Based on the literature on firms outside the US we also suspect that countries overregulate corporate governance and impose attributes that are deemed desirable on all firms, thereby restricting the scope to private contracting. However, those firms that decide not to choose certain governance attributes may have good reasons for doing so and regulation may then impose unnecessary costs for compliance with these regulations.[4] In this sense, there may be "too much of a good thing."[5]

Finally, governance attributes can be substitutes as well as complements. An example for a substitute may be the independence of the compensation committee: this provision may become less necessary if shareholders have to approve all compensation provisions and if shareholders are also sufficiently informed about the costs and benefits of compensation plans.[6] An example for complementary provisions could be the ability of the board to hire outside advisors: This provision may be of little value if the board itself is chaired by the CEO and has only a minority of independent directors, so that board independence becomes

[3]For a sample from 1993 to 2001, Martynova and Renneboog (2006) count 162 hostile bids for targets in 29 European countries. Of these 92 bids were for targets in the UK, 14 in France, 11 in Sweden, and 3 in Germany.

[4]The literature on the question whether the Sarbanes-Oxley act (SOX) has imposed excessive regulation is controversial. Romano (2005) argues that the act was ill-conceived. Chhaochharia and Grinstein (2007) find that SOX imposed costs on small firms that reduce their value. Doidge, Karolyi, and Stulz (2009) do not find evidence consistent with the hypothesis that overregulation by the SOX has reduced cross-listings in New York.

[5]This view is expressed by Arcot and Bruno (2009) and Bruno and Claessens (2010).

[6]See Thomas and Martin (1999) and Morgan and Poulsen (2001) for evidence on how shareholder proposals affect executive compensation.

a complement. These relationships lead to non-linear interaction effects between different corporate governance attributes. Given that many governance attributes are mandated in most countries, the effectiveness of firm-level governance then depends on those provisions that are already in place by law (or are prevented by law).

We therefore hypothesize that governance provisions depend on the institutional environment, because of these non-linear relationships as well as the different conflicts of interests highlighted above. These are naturally difficult to capture by "tick-box"-indices, which simply add different provisions. We therefore first investigate the marginal contribution of each governance attribute separately, using selection techniques that have been used previously in the literature. A comparison of four different approaches reveals that stepwise regressions seem to be more robust than the other approaches. In a second step we then construct parsimonious governance indices and relate them to firm valuation. Ideally, we would conduct this analysis at the country-level to capture all institutional differences. However, our data set is heavily skewed towards the common law countries and we would have sufficient data for only four countries to conduct a country-level analysis (Canada, Japan, UK, US), three of which are English legal origin countries. We therefore conduct our analysis for pooled samples of all firms that share the same legal origin.

We find evidence consistent with all our hypotheses. We first determine which governance attributes display a statistically significant relationship with firm valuation in each legal origin sample and find that the sets of attributes that are included for each of the legal origin samples hardly overlap. Moreover, we find that some attributes have a negative relation to firm value in some of the samples, so there is evidence that there can be "too much of a good thing," and advice on good governance should include reflections on the institutional environment. We then construct a parsimonious governance index for each legal origin sample and find that the indices are not highly correlated with each other. Each index is significantly related to firm value in its own sample, so we concur with the previous literature that good governance pays. The provisions excluded from each of the indices have no explanatory power for the relevant sample, so we can exclude the possibility that our procedures have eliminated provisions that are relevant for firm values. In contrast, the governance index for one legal origin sample has generally no explanatory power for firm values in any of the other samples. We are therefore led to the conclusion that governance indices are highly dependent on the institutional and economic environment and that there is no uniform standard against which the quality of corporate governance can be measured. What is good in one country is therefore not necessarily also good in another country.

The rest of the paper is organized as follows: In Section 2 we introduce the data set. In Section 3 we present our regression analysis and perform the selection of value-relevant governance attributes. In Section 4 we continue with constructing parsimonious governance indices and studying their properties and relation to firm values. Finally, we present a robustness checks in Section 5, while Section 6 concludes.

2 Data and research design

In this section, we describe our sample selection process, the research design, and the main variables.

2.1 Sample selection

Our source for governance data is the Corporate Governance Database compiled by Institutional Shareholder Service (ISS), one of the largest corporate governance data providers for institutional investors. In 2002, ISS started to collect firm-level governance data for US firms. The US coverage includes the S&P 500, S&P 400, S&P 600, and Russell 3000 indices plus 2,300 additional companies. In 2003, ISS extended its database to non-US firms. The non-US universe includes firms from four partly overlapping indices. UK coverage is based on the FTSE All Share Index (98% coverage of total market capitalization). Canadian coverage is based on the S&P/TSX Composite Index (71% coverage of total market capitalization). Other countries are tracked on the basis of the MSCI EAFE Index (20 developed markets, 85% coverage of market capitalization in each country), and the FTSE All-World Developed Index (20 developed markets, 90% coverage of the market capitalization in each country). For 2005 the ISS database covers in total about 8,000 firms from 23 countries.

Our US data set contains 12 quarterly observations for the years 2003, 2004, and 2005. Our non-US data set is composed of 10 quarterly observations for the same period, because

ISS started data surveying in the second half of 2003. In this paper, we focus exclusively on the 2005 sample, because this sample offers the largest sample size and the best data quality in terms of the smallest number of missing values. However, coverage for US firms and non-US firms still differs significantly.

To derive the final sample, we first exclude all firms whose country of listing and incorporation differs. This reduces the initial sample by about 50 firms. This exclusion yields the sample that is denoted with "ISS universe" in Table IV.1. Table IV.1 summarizes the remaining steps for the construction of our final data set.

– Insert Table IV.1 approximately here –

Starting from the "ISS universe" of 7,941 firms, we follow the usual practice to exclude all financial firms from the sample.[7] We then use the fiscal year end-date of each firm to select the closest quarterly ISS observation. For a number of firms we find no suitable ISS observation, because either single quarterly observations were missing, or because ISS tracking started one or more quarters after the firm's fiscal year end-date. If only single quarterly observations were missing, we selected the last available ISS observation prior to the firm's fiscal year end-date. If ISS tracking started one or more quarters after the firm's fiscal year end-date, we had to exclude these observations from the sample. This second step leaves a sample of 6,120 firms. Of these we can successfully merge 4,589 observations to Worldscope and Datastream. The US coverage is larger than the international coverage (as it is often the case). We therefore reduce the US sample and select a subsample with propensity score matching based on Sales, Net Income, Total Assets, and two-digit SIC codes. The remaining US sample consists of 832 of the original 2,990 firms. The final sample for all countries has 2,431 firms.

Table IV.1 also shows the differences in the attribute coverage between non-US and US firms. For US firms included in the sample, on average 2% of the governance attributes are missing. Non-US firms have on average almost six times as many missing values with significant differences between the individual countries. The percentage of missing values varies from 3% for Australian and Canadian firms to 21% for firms from Greece.

[7] Financial firms are usually excluded, because they are subject to special laws, regulations, and accounting standards and their corporate governance, financial structure, and accounting ratios differ substantially from firms in other industries.

2.2 Firm characteristics

We use several accounting and other financial variables in this paper that are all obtained from either Thomson Financial's Worldscope or Datastream. We use a simple approximation of Tobin's Q as measure of firm value, which defines Tobin's Q as the ratio of the market value to the book value of the assets.[8] The market value of assets is computed as the book value of assets plus the market value of common equity less the book value of common equity.[9] Firms' market value of common equity is determined 90 calendar days after the firm's fiscal year end-date. We estimate the *Age* of a firm by calculating the number of months between the firm's first trading day and the firm's fiscal year end-date. The variables *PPE* and *Leverage* are defined as property, plant, and equipment to assets and total debt to assets, respectively. We compute firm-specific *Risk* as the annualized standard deviation of daily stock returns over the year ending with the fiscal year end-date. We finally create an indicator variable for cross-listings in the US. *ADR* is a dummy variable equal to 1 if the firm has an American Depository Receipt (ADR) and zero otherwise.

To create our final data set we correct for the differing ISS coverage of US and non-US firms. The non-US universe is limited to the largest companies in each country, while the US universe also includes mid-size and small companies. We use a propensity score matching approach to identify a subsample of US firms that is comparable to the non-US sample in terms of size and industry classification. The industry matching is based on two-digit SIC-codes. The propensity scores for the match are derived from a Probit regression of an indicator variable (that is 1 for all non-US firms and zero otherwise) on Sales, Net Income, Total Assets, and industry dummies. The propensity score equals the probability that a firm with certain characteristics is a non-US firm. We use a nearest neighbor matching algorithm with replacement to allow US firms to be used more than once as closest match in order to improve the matching quality. The final US sample consists of all US firms that were matched at least once. Table IV.2 reports the average firm characteristics for the matched

[8] Tobin's Q is defined as the firm's market value divided by the replacement value of the assets. However, Perfect and Wiles (1994) showed that replacement values can be estimated by the firm's book value of assets without biasing results. For a detailed discussion of different measures of Tobin's Q see also Whited and Erickson (2006).

[9] Balance sheet deferred taxes are not considered in this simple approximation of the market value of assets. See also Klapper and Love (2004), Durnev and Kim (2005), Black, Jang, and Kim (2006b), Bruno and Claessens (2010), and Chhaochharia and Laeven (2009).

US sample in comparison to the non-US sample and the non-matched US sample.

– Insert Table IV.2 approximately here –

Table IV.2 shows that the average firm in the overall US sample of 2,990 firms is about one-third of the size of the non-US firms in terms of Sales, Net Income, and Total Assets. Our matching approach significantly reduces this gap, but without closing it completely. This matching approach excludes the majority of mid-size and small US firms. Table IV.2 also reports the mean values of the firm characteristics used in later regressions. In comparison to the non-US firms, the matched US firms have a higher Tobin's Q, are younger, have less tangible assets, are riskier, and have slightly higher leverage. Table IV.3 displays descriptive statistics for the firm characteristics in the final sample.

– Insert Table IV.3 approximately here –

Panel A shows descriptive statistics for the overall sample. The average firm in our sample has a Tobin's Q (TQ) of 1.91, *Sales* of $6,061 million, a firm *Age* of about 20 years, a PPE ratio and an annualized standard deviation of daily stock returns (*Risk*) of about 31%, and a *Leverage* of 23%. 14% of all firms in the sample are cross-listed in the US. Panel B reports the mean and median of the same firm characteristics for four subsamples. The subsamples are formed by grouping countries by their legal origin. The figures show that English and Scandinavian law firms have the highest Tobin's Q. This is consistent with the figures on *Sales* and *Age* for French and German law firms, which are larger and older.

2.3 Governance provisions

ISS tracks 55 individual governance provisions for all non-US firms and 61 governance attributes for US firms. The 61 US governance attributes comprise the 55 non-US attributes until the second quarter in 2005. Starting in the third quarter of 2005, ISS replaced six of the 55 non-US governance provisions with six other attributes not tracked in the non-US sample. We use these attributes in the following way: First, in order to keep as many of the 55 non-US attributes as possible, we supplement the US observations from the third and fourth quarter by the second quarter observations for the six excluded attributes (if available for the firm in question).[10] Second, we exclude four of the 55 non-US governance attributes from our analysis, because they cover special poison pill features, which apply only to a small subset of firms.[11] Third, we split two attributes into two separate governance provisions. On the one hand, we use the attribute "Options grants align with company performance and the burn rate is reasonable" to create the two attributes *Option grants alignment* (a52) and *Option burn rate* (a37). On the other hand, we split the attribute "No poison pill is in place and blank check preferred stock is not authorized" into the two provisions *Poison pill* (a45) and *Blank check preferred stock* (a38). This three-step procedure leaves us with a data set of 53 governance attributes per firm, more than in any other study conducted with ISS data.

Each governance attribute has between two and seven mutually exclusive assessment categories. Most attributes have three answer categories: two of them indicate the presence or absence of a characteristic and the third indicates missing information. We use a binary coding for the governance attributes that is common in the literature.[12] We assign a value of one to an attribute if the company meets a minimally required corporate governance standard as defined by ISS and assign zero otherwise.[13]Appendix A provides an overview on the 53 governance attributes together with a definition of the minimally required corporate governance standard. To complete the coding of the governance attributes, we set all missing observations to zero. This means, we make the (conservative) assumption that the firms with missing values did not adopt the respective provision.[14]

[10]These are the six attributes *Directors retirement age* (a47), *Directors term limits* (a48), *Auditor rotation* (a49), *Option repricing* (a50), *Pension plans* (a51), and *Corporate loans* (a53).

[11]These provisions cover the four poison pill features three-year independent director evaluation, sunset provision, qualified offer clause, and trigger.

[12]Studies using IRRC data: Gompers, Ishii, and Metrick (2003), Bebchuk, Cohen, and FerrelI (2009), and Cremers and Nair (2005). Studies using ISS data: Brown and Caylor (2006), Bruno and Claessens (2010), Aggarwal, Erel, Stulz, and Williamson (2010), and Chhaochharia and Laeven (2009).

[13]The following two exceptions apply: First, ISS defines the minimal governance standard for the attribute *Officers and directors ownership* (a17) as "Officers and directors should have a significant ownership position in their company's stock.". Similar to Brown and Caylor (2006) and Aggarwal, Erel, Stulz, and Williamson (2010), we interpret significant as "at least 1% but not over 30% of shares outstanding". Second, ISS defines the minimal governance level for the attribute *Directors education* (a18) as "All board members should participate in an "ISS accredited" director education program.". Similar to Brown and Caylor (2006), we define minimally required as "At least one director has participated in an ISS accredited director education program". This adjustment is necessary because otherwise this attribute would not exhibit any variation over all non-US observations.

[14]We also experimented with other procedures to handle the missing values. About 9% of the 128,843 data fields (53 attributes*2,341 firms) are missing. Excluding single governance attributes or firms from the sample is not a reasonable approach, because these missing values are spread over 35 (out of 53) governance attributes and 1,938 (out of 2,431) firms.

Table IV.4 summarizes the frequency of the 53 governance attributes by country.

– Insert Table IV.4 approximately here –

Table IV.4 reports a high variation in the percentage of firms that adopted certain governance provisions, both across provisions and across countries. We highlight the following observations:

- ☐ Only few firms, notably in Spain, the US, and Italy provide shareholders with *Cumulative voting rights* (a07).
- ☐ A policy that limits outside directorship to four or fewer boards (a23) is only in place in a minority of firms in the Netherlands, the UK, and the US.
- ☐ Most firms require a supermajority vote to change the charter/bylaws (a39), the exception being firms in Greece, the Netherlands, and the US.
- ☐ *State anti-takeover provisions* (a46) are in place in all countries, except in Ireland and the UK.

Five governance provisions stand out, because they are adopted by almost all firms in almost all countries:

- ☐ Virtually all firms respond to shareholder proposals (a19).
- ☐ *Blank check preferred stock* (a38) is usually not authorized, with the exception being US and Canadian firms.
- ☐ Shareholders can call *Special meetings* (a42). The exception are about a quarter of the firms from Singapore and about three fifth of firms from the US.
- ☐ Boards usually cannot amend bylaws without shareholder approval (a43), the exception being the majority of firms in Italy and virtually all firms in the US.
- ☐ *Poison pills* (a45) are not a common governance practice. They are only used frequently in Belgium, Canada, the Netherlands, and the US.

Some governance attributes exhibit a very strong variation across countries:

- □ Annually elected boards (a05) are common in Canada, Finland, and Sweden, while classified boards are the rule in many other countries, e.g., Germany, Italy, and Singapore.
- □ The performance of the board is regularly reviewed (a12) in almost all Canadian and German firms, but not in Greece, Hong Kong, and Japan.

The last row in Table IV.4 states the number of attributes with no variation within the respective country. This number ranges from 1 for the US to 32 for Austria and indicates the extent to which governance is regulated, respectively, the extent to which governance is left to the contracting parties. On average, English law countries have only 5.3 governance attributes with no within-country variation, whereas the numbers for French law (17.3), German law (19.8), and Scandinavian law (22.1) are substantially higher.[15] Hence, English law countries impose less homogeneity of governance on firms and leave more scope to private contracting compared to civil law countries.

2.4 Research design

In order to examine the relation between a firm's corporate governance and its valuation, we use the following OLS regression specification:

$$\begin{aligned}\log(TQ_i) = \quad & \beta_0 + \sum_{k=1}^{K} \beta_k * CG_{ik} + \sum_{j=1}^{J} \beta_j * X_{ij} \\ & + IndustryDummies_{ix} + CountryDummies_{iy} + \varepsilon_i.\end{aligned}$$

Index i denotes the individual firms. CG_{ik} stands for one or more ($k \geq 1$) individual governance provisions and/or comprehensive or parsimonious governance indices. X_{ij} denotes firm-level control variables. The firm-level controls are the six firm characteristics log($Sales$), log(Age), PPE, $Risk$, $Leverage$, and ADR. We include these control variables to address the endogeneity problem caused by omitted variables. These controls are either observable "joint determinants" or proxy variables for unobservable firm characteristics that

[15] These numbers are not tabulated. They are calculated as averages of the numbers of provisions without variation in each country as reported in Table IV.4, weighted by the number of observations from each country.

affect the level of corporate governance and firm value. The association of these control variables with governance was examined by Klapper and Love (2004), Durnev and Kim (2005), Black, Jang, and Kim (2006a), Gillan, Hartzell, and Starks (2007), and Doidge, Karolyi, and Stulz (2004). We use *Sales* and firm *Age* as an indicator for firm size. *PPE* proxies for the tangibility/intangibility of the firm's assets. *Risk* measures the firm-specific uncertainty. *Leverage* is a proxy for managerial discretion and therefore for agency problems. *ADR* is an indicator for cross-listings in the US. We do not include value drivers (e.g., ROA or sales growth) as controls in our regressions, even though these have been shown to be reliably related to Tobin's Q. The reason is that we want to measure the relationship between firm value and corporate governance, irrespective of the transmission mechanism. Hence, if improvements in corporate governance affect profitability or growth, then we want to measure this aspect rather than control for it, so we leave out these firm-level controls.[16]

We winsorize extreme percentiles (1st and 99th) of the variables Tobin's Q, *PPE*, *Risk*, and *Leverage* in order to avoid that extreme observations or outliers distort the regression results. We furthermore use a logarithm-transformation for Tobin's Q, *Sales*, and *Age*, because the distributions of these variables are highly skewed. The industry dummies are based on the Worldscope classification of 25 industry groups (including financial firms).

A White- and Breusch-Pagan-test for homoskedasticity suggest the presence of heteroskedasticity. This fact implies that OLS estimates are unbiased, but the reported standard errors are incorrect. For this reason, White (robust) standard errors are commonly used for statistical inference.[17] Beyond this, Rogers (clustered-robust) standard errors can be used to assess the significance of the estimated OLS coefficients.[18] These clustered-robust standard errors also take into account the correlation of errors within clusters. In the regression setting above, one would ideally allow for a clustering of errors along the industry dimension and along the country dimension, or at least one-way clustering along the country dimension.[19] However, clustered-robust standard errors only yield correct inference if the number

[16] See, e.g., Klapper and Love (2004), Bebchuk, Cohen, and Ferrell (2009), Durnev and Kim (2005), Bruno and Claessens (2010), Aggarwal, Erel, Stulz, and Williamson (2010), or Chhaochharia and Laeven (2009).

[17] See Greene (2003), p. 222-224.

[18] See Rogers (1993). For a comparison of different approaches to estimate standard errors in finance data sets see Petersen (2009). For multi-way clustering and the importance of the according cluster-robust inference see, e.g., Cameron, Gelbach, and Miller (2006).

[19] See, e.g., Aggarwal, Erel, Stulz, and Williamson (2010) and Bruno and Claessens (2010) for the use of clustered standard errors at the country level.

of clusters is sufficiently large ($\geq$50) and if the number of observations is evenly distributed over all clusters.[20] Both prerequisites are violated in our data as we have only 23 countries (24 industries) with between 10 and 832 (10 and 347) observations. We therefore use White standard errors for inference.

3 Analysis

The first step of our analysis is the construction of parsimonious corporate governance indices. Previous research for the US shows that only a small number of governance provisions can be related to firm value, whereas many other governance provisions do not seem to have any reliable relationship with firm value. Following the discussion in the Introduction, we expect that there are significant cross-country differences with respect to the relevance of governance provisions. Comprehensive indices cover this heterogeneity, because they may be significant in all countries, even though the relevant provisions differ from country to country. We construct parsimonious indices using four different methods:

The BCF-approach. The first approach was pioneered by Bebchuk, Cohen, and Ferrell (2009) for IRRC governance data and modified for ISS data by Brown and Caylor (2006). We run 53 separate regressions of the logarithm of Tobin's Q on (1) provision i, where i is any of the 53 attributes, (2) an index of all the other 52 attributes (which is equivalent to the comprehensive index minus attribute i), and (3) the set of controls and dummies as described in the research design section (2.4).[21] We then select all those governance attributes that are significant at least at the 10%-level in these regressions.

The ALL-approach. The ALL-approach follows Brown and Caylor (2006) and simultaneously includes all 53 attributes in a regression of the logarithm of Tobin's Q and uses the same control variables as the BCF-approach. We then also select those attributes that are significant at least at the 10%-level. The main advantage of this approach relative to the BCF-approach is that it does not aggregate the other provisions. However, many of the

[20] See Kézdi (2004).

[21] Bebchuk, Cohen, and Ferrell (2009) use three other variants of this approach, in particular one where component (2) is replaced by dummy variables for each of the remaining attributes, and show that these modifications lead to very similar results.

provisions are highly correlated within countries and therefore with the country dummies, which gives rise to multicollinearity problems.[22]

The AIC-approach. Our third approach applies a stepwise regression technique. We include all dummy variables and control variables as in the BCF-approach and the ALL-approach. We use a backward elimination procedure that can only affect the governance attributes, but not the controls and dummies. At each step, the attribute with the highest p-value in a two-sided test for significance is eliminated. We then use the Akaike Information Criterion (AIC) to choose the best of these regression specifications.[23] We select the regression that minimizes the AIC, which is defined as -2*L + 2*p, where L represents the maximized log-likelihood of the regression and p stands for the number of parameters used in this regression. The idea here is to judge the regression by its goodness of fit, but to penalize the inclusion of additional parameters, so that the regression that is finally chosen trades off improvements in the explained variation against the inclusion of additional parameters.[24]

The STEP-approach. Finally, we alter the AIC-approach by no longer using the AIC to select a regression specification. The elimination process for the governance provisions is the same as in the AIC-approach above, but the procedure stops once the regression only contains attributes with p-values below 10%. This approach is also inspired by Brown and Caylor (2006). However, we use backward elimination instead of forward selection.

Our regression methodology encounters one additional problem. Many attributes have very little within-sample variation, so that they are highly correlated with the country dummies. We therefore eliminate all attributes from each legal origin sample that have identical

[22]Multicollinearity inflates standard errors. Variance inflation factors (VIFs) are a common measure to assess the degree to which collinearity of the independent variables increases the standard errors for these variables. A VIF of one indicates the absence of any correlations and the use of correct standard errors. A VIF of around or greater than ten indicates that collinearity is associated with this variable and that standard errors are inflated by a factor greater three. The majority of variables with VIFs greater than ten are country dummies.

[23]See Greene (2003), pp. 159-160.

[24]We also experimented with the Bayesian Information Criterion (BIC), which is similar to the AIC, but replaces 2 by log(n) in the second argument in the equation, where n stands for the number of observations. For log(n)>2, BIC favors more parsimonious models than AIC, because it penalizes specifications with more parameters more. In our model, the regression that is chosen by BIC typically contains no governance attributes (except for the Scandinavian law sample). The reason is that a large proportion of the explained variation comes from the dummy variables and control variables included in the regression, so that the additional explanatory power of the governance attributes is judged to be too small. We therefore do not adopt this approach.

values for more than 95% of the firms in that sample, i.e., all attributes where the percentage of firms that have the governance provision is either above 95% or below 5%. This step eliminates 4 attributes from the English law sample, 10 attributes from the French law sample, 24 attributes for German law firms, and 20 attributes for Scandinavian law firms. This highlights once more that the German law countries and the Scandinavian law countries are more highly regulated, whereas English law countries leave more governance attributes to private contracting. We will later provide a robustness check where we include all attributes. Note that some variables we exclude may be economically important, yet we cannot detect their relevance because of a lack of within-sample variation.

– Insert Table IV.5 approximately here –

Table IV.5 presents the results for all 28 attributes that were significant in at least one of the four samples for at least one methodology. The other 25 attributes that were never significant are omitted from the table. The four methodologies used here generate broadly similar results. If an attribute is included by one approach, then it is mostly also significant with at least one other approach. Only the BCF- and the AIC-approach include attributes that are not included by any other approach. This is not surprising, because, on the one hand, AIC is the only approach that does not require a maximum p-value for inclusion in the final regression. AIC therefore imposes less stringent requirements and includes more attributes. On the other hand, the BCF-approach just includes two governance related regressors in each regression. BCF therefore enhances the association with individual governance provisions. The ALL-approach and the STEP-approach never include any attribute that is not included by at least one other approach. There are still eleven cases where the ALL-approach and the STEP-approach disagree as to whether a specific attribute should be included for a particular sample. In seven cases the STEP-approach identifies an attribute that is not significant in the ALL-approach. In five of these seven cases the decision of the STEP-approach is corroborated by the BCF-approach, which is never the case for the four cases where the ALL-approach identifies an attribute but not the STEP-approach. We therefore conclude that the STEP-approach delivers decisions that cohere better with those of the other approaches and rely on the STEP-approach for most of our remaining discussion.

The number of attributes included depends on the sample as well as on the selection approach. The ALL-approach is the most conservative and includes on average 4.5 attributes, whereas the AIC-approach includes on average 8.3 attributes. Across all four approaches, five to ten attributes are included for the German law sample, whereas for the Scandinavian law sample the same number ranges from one to six. This differing number of included attributes is only partially explained by sample size (which is smaller for German law than for English law). It is also not related to the average within-sample variation of the attributes (which is highest for English law and lowest for German law).

Negative regression coefficients. The first and most striking observation is that a large number of the regression coefficients - 35 out of 84 - is negative, and a third of the negative coefficients are statistically significant at the 5%-level or higher. Interestingly, most of the negative coefficients cluster in the German legal origin sample, where three attributes (identified by the STEP-approach) have consistently negative coefficients across all approaches:

- *Board size* (a06) indicates whether the size of the board is within the recommended interval of 6 to 15 members. More than 70% of all German legal origin companies have boards that are within this size limit, and these are spread evenly across the four German legal origin countries. However, with the exception of one German and one Swiss company, all companies in Austria, Germany, and Switzerland with boards outside the recommended size range have less than 6 members, whereas in Japan 86% of the 137 boards outside the recommended range have more than 15 members.

- *Auditor ratification* (a27) requires that auditors are ratified at the most recent annual general meeting. This attribute is shared by 90% of all German legal origin firms, which are spread very evenly across countries.

- *Executives stock ownership requirements* (a32) require executives to hold stock as part of their contract. This is the case for 75% of the managers for Swiss companies, but only for one German company and no other Austrian or Japanese company.

For Scandinavian law firms no attribute has a negative association with Tobin's Q, and for English law and French law firms there are three other attributes with a negative sign:

- For English law countries, *Board amendments* (a43), which prevent the board from changing the bylaws without shareholder approval, has a negative coefficient for all approaches. This attribute is shared by all companies in the English law sample other than the US firms and one UK company. In the US, only 21 out of 832 companies have boards that cannot amend the bylaws. This difference reflects the general difference between the US, where the relationship and the board follows the model of a representative democracy, and most other countries, where this role is modeled on a direct democracy with more direct shareholder involvement. Zetsche (2005) argues that direct shareholder involvement is optimal for concentrated ownership, whereas dispersed ownership calls for limits to shareholder rights in order to prevent abuse of direct intervention rights by dissident shareholders. We therefore suspect that the US-model, which limits shareholder rights, is in fact optimal for many companies that allow boards to amend the bylaws.

- For French law countries, *Nominating committees* (a02) that are comprised solely of independent directors are negatively associated with firm value. This also seems to be a country effect, as 21 of the 34 companies that staff their nominating committees only with independent directors are from the Netherlands. Furthermore, *Board attendance* (a21), which requires directors to attend at least 75% of the board meetings, has a negative coefficient. However, this effect is not attributable to a particular country, as regular board attendance in not common in all of these countries.

Hence, for three of the six attributes that are negatively and significantly associated with firm valuation, the effect seems to be driven by one country. Then it may be the case that this is an isolated country-effect, where a particular institution either destroys value in the context of the particular institutions of that country, or this requirement is implemented in a way that is different from the original intention of this requirement. However, for *Board size* (a06) and *Auditor ratification* (a27) in the context of German law countries and *Board attendance* (a21) in the French law sample, the effect cannot be attributed to one single country. It is also plausible that those companies that deviate from the norm actually benefit from doing so. Other authors have argued before that legislation on corporate governance may lead to overregulation and that there can be "too much of a good thing".[25]

No overlap between samples. A second salient feature of our results is that there is little overlap between the attributes that are included for the different legal origin samples.[26] The following overlaps can be observed in Table IV.5: The ALL-approach and the AIC-approach only include one attribute (a01) for two of the legal origin subsamples. The BCF-, AIC-, and STEP-approach all include *Board structure* (a05) for the English law and for the Scandinavian law sample. The AIC-approach and STEP-approach both include (1) *Executives stock ownership requirements* (a32) for English law and for German law firms, but with negative coefficients for the German law sample (see discussion above), and (2) *Option repricing policy* (a30) for the French law and Scandinavian law sample with a positive coefficient. The AIC-approach produces another four overlaps between two legal origin subsamples (for a02, a21, a27, and a33), but in three cases the coefficients have the opposite sign and in the other case the coefficients in the respective AIC-regressions are insignificant. Referring to the STEP-approach, this means that only three of the 18 identified governance attributes overlap in two of the four subsamples.

From this we conclude that there is hardly any overlap between the attributes that indicate good corporate governance in the different legal origin subsamples. What indicates good corporate governance in the context of one legal origin subsample bears little or no relation to what indicates good corporate governance in any of the other subsamples.

The first candidate explanation for the lack of overlap, we investigate, concerns institutions that are so homogeneous within one subsample that they were either excluded from our analysis or still had insufficient within-sample variation to generate significant results. Lack of within-sample variation for a particular attribute does not preclude that such an attribute has a large economic impact (positive or negative). Such an effect would simply not be measurable with our methodology. We first investigate this hypothesis informally

[25] See Arcot and Bruno (2009) and Bruno and Claessens (2010).

[26] To support this argument we also checked for each attribute identified in the STEP-approach that its regression coefficient is at least once significantly different from the coefficients in the other subsamples in pairwise comparisons. We compare the regression coefficients from a regression of Tobin's Q on all these attributes for each of the legal origin subsamples. For 10 of the 15 attributes at least one of the six pairwise t-tests on the coefficients rejected the null hypothesis of equal coefficients. No significant difference was observable for the attributes *Compensation committee* (a03), *Meetings outside directors* (a13), *Board attendance* (a21), *Board amendments* (a43), and *Unequal voting rights* (a44).

and identify some variables that potentially match this description:

- ☐ *Board structure* (a05), which mandates annually elected boards (no staggered or classified boards) is significant for English law and for Scandinavian law, but not available for French law, where only less than 2% of the firms (5 out of 264) have annually elected boards. However, a significant proportion of Japanese and Swiss firms (about 30% of the German legal origin firms) have this attribute, without any detectable implication for firm value.

- ☐ *Executives stock ownership requirements* (a32) and *Directors stock ownership requirements* (a33) are both significant for German law firms (although the coefficient on the first attribute is negative, see discussion above). Both attributes are not included for Scandinavian law firms because of lack of within-sample variation. However, the (negative) German law evidence is inconsistent with the (positive) English law evidence and there is no significant result for both attributes for French law firms, even though both attributes are available there.

- ☐ *Unequal voting rights* (a44), which rules out deviations from the one-share, one-vote policy, is significantly related to firm value for English legal origin countries, but this attribute is mandatory for German legal origin firms (which all have it), so that the effect is not measurable for this sample. This may also be true for the French legal origin sample, because the majority of French firms deviates from having equal voting rights in the French law sample.[27]

Another potential explanation for the lack of overlap may be that countries and therefore also our legal origin samples attract different industries. Optimal governance regulations may well be different for different industries, e.g., because firms have a different asset structure and require different specific investments. We test this hypothesis by investigating the industry correlations of each attribute.

– Insert Table IV.6 approximately here –

[27]ISS classifies French double-voting rights as violation of the one-share, one-vote policy. These double-voting rights do not depend on the type of shares (there is only one class of shares) but on the duration of ownership, where double-voting rights accrue to investors who hold the shares for longer than a minimum period of time specified by the bylaws (typically 2 to 4 years). Roosenboom and Schramade (2006) find that this practice is harmful.

We consider those 15 attributes that have a significant coefficient for the STEP-approach for at least one of the samples, and we select only those industries with at least three firms in this industry in each of the subsamples, which leaves us with 15 industries.[28] Then we rank the industries for each attribute and each sample, so that the industry where most firms have this attribute receives a rank of one, and the industry where the smallest number of firms have this attribute receives a rank of fifteen. Table IV.6 shows the rank correlations for each pair of samples from this exercise. If governance practices would cluster by industry, then we would expect that the ranking of industries is more or less the same in all subsamples, i.e., the attributes that are important for an industry should give this industry a low rank in each sample. It appears that the rank correlations are fairly randomly distributed, and that there are slightly more negative coefficients (47) than positive coefficients (37). For some samples the correlation cannot be computed, because the attribute has no variation for that sample. There is no evidence of any industry clustering of governance attributes, so this cannot account for the lack of overlap between legal origin samples we observe.

Finally, we investigate the hypothesis that the identification results are mainly driven by within-sample variation of individual attributes. For that purpose we compare the average standard deviation of the identified attributes to those that were excluded (results not tabulated). It turns out that for French and German law the average standard deviation of the attributes identified by the STEP-approach is lower than the standard deviation of the other attributes. For English and Scandinavian law this is not the case, but the average standard deviation of the identified attributes (0.46 and 0.46) is only marginally above that of the included attributes (0.43 and 0.45). Overall, we conclude that the lack of within-sample variation cannot explain the lack of overlap across the different legal origin samples.

We can draw three conclusions from the discussion in this section: First, there is little agreement of what measures the quality of corporate governance between legal origin samples. Governance quality has to be measured at a level that reflects institutional differences. Potentially, this should be the country level, but we choose the legal origin level, which offers a better trade-off of sample size and institutional homogeneity. Second, the apparent lack of agreement between samples is not a consequence of industry clustering across countries

[28]The excluded industries are: aerospace, apparel, automotive, beverages, electrical, metal producers, recreation, textiles, and tobacco.

and/or legal origins. Third, this lack of agreement is also not caused by a statistical artifact. At least we cannot detect any pattern that would allow us to attribute these findings to sample size, within-sample variation of governance attributes, or the stringency of regulation.

4 Parsimonious governance indices

4.1 Constructing parsimonious indices

From Section 3 we conclude that governance quality has to be measured at the level of the legal origin samples and that we cannot simply construct a comprehensive governance measure (index) that reflects a uniform latent variable to which we might refer as the quality of corporate governance. We now proceed to construct parsimonious corporate governance indices for each of the legal origin samples separately. We construct an index for a particular sample by considering all the attributes that are identified by the STEP-approach. We add the scores for attributes that have a positive coefficient in the STEP-regression, and subtract the scores for all attributes that have a negative coefficient. By this procedure we obtain a corporate governance index for each legal origin sample ($EnglishCG$, $FrenchCG$, $GermanCG$, $ScandCG$). We have experimented with alternatives to this design, where we weighted the attributes by their regression coefficients, which gives each attribute a weight proportional to its regression coefficient, without obtaining materially different results (not reported). We also constructed indices based on the other three selection approaches, again, without obtaining materially different results (not reported). Appendix B lists all governance indices used in our analysis and provides a definition for each index. We follow the literature and construct an index of all other provisions by adding the scores from all the attributes that are not included in the respective parsimonious index, and therefore obtain four other provisions indices ($EnglishOP$, $FrenchOP$, $GermanOP$, $ScandOP$).

In addition to the governance indices based on our own procedure, we also include the entrenchment index suggested by Bebchuk, Cohen, and FerrelI (2009) ($BebchukCG$) and the Gov-7-index proposed by Brown and Caylor (2006) ($BrownCG$). These authors derive their respective index from US firms only and we include them in order to be able to compare their results to ours. Again, we construct another provisions index from all attributes not included in the respective indices (*BebchukOP*, *BrownOP*). In addition to these parsimonious indices, we also construct several comprehensive governance indices. *COMP* is the index of all 53 governance attributes.[29] We are also interested in the question whether country-level attributes or firm-level attributes are more important and therefore split the *COMP*-index into a country-level and a firm-level subindex. We construct an index *CountryCG* of country-specific provisions, defined as sum over all provisions shared by all firms within a country, normalized by the total number of country-specific provisions. *FirmCG* is the complementary index of all firm-specific provisions within a country and captures all attributes that show some within-country variation. In a second approach to the same problem, we create a firm-level subindex by using the country median of *COMP* as proxy for the country-level governance (*CountryMedCG*). The complementary firm-level index *FirmMedDevCG* is defined as the number of attributes a firm chooses above the median of *COMP* for its country. Our approach to this question differs from that of Chhaochharia and Laeven (2009), who select a subset of indicators they deem to be relevant and then define country-level governance as the minimal level of each attribute achieved in a certain country.

– Insert Table IV.7 approximately here –

Table IV.7 reports descriptive statistics on all governance indices listed in Appendix B. We make the different indices comparable by normalizing them, so that the minimum value of the index across all observations equals 0, and the maximum observation equals 1. Without such a normalization some statistics would not be comparable across indices and we could not compare the coefficients in our regressions. We report the minimum and the maximum of the raw indices in Panel A of Table IV.7. Panel B shows that *COMP*, the comprehensive index of all provisions, is highest for English law (0.61) and significantly lower for the three civil law samples (between 0.36 and 0.42), which accords with the previous literature.[30] Panel B also reports that *EnglishCG* is lower than *EnglishOP*, showing that firms in English law countries have on average more other provisions, which cannot be reliably related to firm valuation, than provisions that have a significant relationship to firm valuation. A similar pattern can be observed for *GermanCG*, although it is less pronounced.

[29] Gompers, Ishii, and Metrick (2003) analyze such a comprehensive index.

[30] See, e.g., **?**'s "Anti-director-rights Index", recoded by Spamann (2010) and revised and extended by Djankov, La Porta, Lopez-de Silanes, and Shleifer (2008).

We also report the standard deviation and quartiles for all indices to investigate if there is sufficient within-sample variation. Only the German law sample shows little variation, where the standard deviation for 11 of 17 indices is 0.1 or less, which is never the case for the French or English law sample, and only twice for the Scandinavian law sample.

– Insert Table IV.8 approximately here –

Panel A in Table IV.8 presents the correlations of all eleven corporate governance indices in our analysis (we exclude the six other provisions indices). The most important observation from Table IV.8 is that the correlations among the four legal origin indices are generally low and often negative, which is true if the correlations are calculated for the whole sample (Panel A) or separately for each legal origin sample (Panel B). In the whole sample, *ScandCG* is positively correlated with all other legal origin indices, whereas the correlations of the other legal origin indices are always low and have varying signs. Only the correlation between *EnglishCG* and *ScandCG* is somewhat higher at 0.65, which suggests a higher similarity of Scandinavian law and English law governance systems than between these and the other two. Table IV.8 therefore corroborates our earlier finding that the governance indices of attributes that are related to valuation in one sample are different and show little overlap in the attributes included, so correlations are accordingly low.

Second, we observe that the Bebchuk entrenchment index has little or no correlation with all other indices. This is not surprising, given that it mainly rests on anti-takeover provisions, which have little relevance in civil law countries, where internal governance provisions are more important. By contrast, the index suggested by Brown and Caylor also includes internal governance provisions and has higher correlations, even though it is optimized for the US.

Surprisingly, *CountryCG* is negatively correlated with all other indices except *BebchukCG*, in particular with *FirmMedDevCG* (-0.29), *FirmCG* (-0.30), and *COMP* (-0.28). This shows that country-level governance and firm-level governance are substitutes: firms, where a large proportion of governance provisions are mandated by law, do not choose firm-level governance provisions in addition to those required by regulation. In contrast, the index of firm-specific attributes, *FirmCG*, is positively correlated with all indices except *FrenchCG*, in particular with *COMP* (0.99), *CountryMedCG* (0.73), and *FirmMedDevCG* (0.72).

Hence, the content of all indices is to a large extent firm-specific and contains very little in the way of country-specific provisions. The correlation between $FirmCG$ and $CountryCG$ is negative and significant, so country-level provisions and firm-level provisions seem to substitute for each other.

Panel B of Table IV.8 displays the correlations of the four legal origin indices for the four different samples. Only the correlations between $EnglishCG$ and $ScandCG$ are positive, large, and significant in three of the four subsamples. All other correlations are low in all samples. The correlations with $FrenchCG$ are mostly insignificant and often negative. These findings support the notion that the measurement of the quality of corporate governance has to be context-dependent.

4.2 Valuation analysis

We now use the governance indices constructed in the previous section to run regressions along the lines of the previous literature on governance indices.[31] In the regressions of Tobin's Q on the governance indices we use the six firm characteristics log($Sales$), log(Age), PPE, $Risk$, $Leverage$, and ADR as controls and include industry and country dummies.

– Insert Table IV.9 approximately here –

Table IV.9 shows regressions with the logarithm of Tobin's Q as dependent variable and governance indices as the independent variables for the pooled sample. Regression (1) only uses one index as an explanatory variable, whereas regressions (2) to (5) have two indices that attempt to break down the impact of the quality of corporate governance into two components. Regression (1) shows that governance matters for valuation. This result has become standard in this governance literature and demonstrates that the quality of governance matters for company valuation. The effect is also economically large: an increase in the scaled $COMP$-index by one standard deviation (0.18, see Table IV.7) increases Tobin's Q by 5.5%. Similarly, moving from the first quartile of $COMP$ (0.36) to the third quartile (0.67) increases Tobin's Q by 9.5%. Regression (2) and (3) decompose the effects summarized

[31] An incomplete list includes Gompers, Ishii, and Metrick (2003), Klapper and Love (2004), Bebchuk, Cohen, and Ferrell (2009), Durnev and Kim (2005), Brown and Caylor (2006), Black, Jang, and Kim (2006b), Black, Jang, and Kim (2006a), and Gillan, Hartzell, and Starks (2007).

in $COMP$ into a country-component (which is identical for all firms in the same country) and a firm-specific component. We therefore do not include country dummies in these regressions. Interestingly, only the firm-specific index $FirmCG$ is relevant in regression (3), whereas the country-index $CountryCG$ does not have any explanatory power at all. For the second decomposition of $COMP$ into $CountryMedCG$ and $FirmMedDevCG$, where the subindices were positively related, both governance measures are highly significant. This lends support to the results of Durnev and Kim (2005) who also find that firm-level governance is more important than country-level governance using a different methodology.[32]

For the indices suggested by Bebchuk, Cohen, and FerrelI (2009) and by Brown and Caylor (2006), we always enter their index as well as the respective other provisions index, which is always equal to $COMP$ minus the index in question. This way we can establish whether there is more explanatory power in the index compared to the provisions excluded from the index. Regressions (4) and (5) show that in both cases, the index itself is insignificant, whereas the corresponding other provisions index is highly significant and has a similar magnitude to the coefficient in regressions (1) to (3).[33]

– Insert Table IV.10 approximately here –

In Table IV.10 we apply the methodology of Table IV.9 to the four legal origin samples. For each sample, we regress the logarithm of Tobin's Q on the four legal origin indices and also enter the complementary other provisions index in each case as well as our controls. In all cases we find that the legal origin specific index is related to Tobin's Q in the sample for which it was optimized (regressions (1), (6), (11), (16)). These indices are always statistically significant at the 1%-level and the other provisions index is never significant in any of these four regressions. Interestingly, compared to $COMP$, economic significance is sometimes even larger: a one standard deviation increase in $ScandCG$ increases Tobin's Q by 25.3%, for $FrenchCG$ the same number is 8.4%. For the other 12 regressions, where a legal origin-specific governance index enters together with the corresponding other provisions index in

[32] Durnev and Kim (2005) measure country-level governance with legal environment variables.

[33] In non-tabulated analyses we run regressions (4) and (5) again on two samples of US firms, our matched sample, which covers mostly large firms, and the complete sample of all US firms. With our control variables we never find $BebchukCG$ to be significant. $BrownCG$ is significantly related to valuation for the comprehensive sample of all US firms. In all cases, the other provisions indices are significant.

a sample for which it was not optimized, it is either (1) the other provisions index that is significant (four cases), whereas the governance index itself remains insignificant, or (2) both indices are insignificant (five cases). Only the *ScandCG* is also significant in the English law and French law sample and the *EnglishCG* in the Scandinavian law sample. This supports the findings on earlier tables that Scandinavian law is closer to English law than the other civil law countries. Overall, the results in Table IV.10 are therefore consistent with the view that the quality of corporate governance has to be measured with respect to the institutional environment and that there is no comprehensive "one size fits all" indicator that can measure the quality of corporate governance.

5 Robustness check

We derive our parsimonious governance indices in Table IV.5 by limiting the considered attributes to those attributes that are not identical for more than 95% of the firms of the respective sample. In this section we perform a robustness check to demonstrate that this decision does not cause our results, at least for the most part.

– Insert Table IV.11 approximately here –

Table IV.11 is structured in the same way as Table IV.5, but now all attributes (instead of attributes with sufficient variation only) are considered. We display only those attributes that are included by the STEP-approach in Table IV.5, but are not included if all attributes are considered, and those that are not included by the STEP-approach in Table IV.5, but are included if all attributes are considered.

The most important observations in Table IV.11 are: First, most coefficients that were significant in Table IV.5 are still significant and have the same sign, the exceptions being *Option grants alignment* (a52) for German law and *Meetings outside directors* (a13) for Scandinavian law. The level of significance for these coefficients changes only slightly for some attributes, for example for *Board attendance* (a21) in the French law sample, and *Executives stock ownership requirements* (a32) and *Directors stock ownership requirements* (a33) in the German law sample. Second, the majority of the additional coefficients is negative (6 out of 10), clusters in the German law sample (8 out of 10), and affects governance attributes excluded in Table IV.5 due to minimal variation (6 out of 10). The negative association of *Vote requirement mergers* (a40) in the German law sample is caused by one Japanese and one Swiss firm. The same applies to the attributes *Special meetings* (a42) and *Board amendments* (a43) whose coefficients are attributable to one Japanese firm and one German firm, respectively. The negative effect of *Outside advisors* (a15) is driven by 24 firms from all four countries, the majority of them from Austria (13). The additional positive coefficients in the French law and Scandinavian law sample can be traced back to similar observations. The significance of *Written consent* (a41) in the French law sample is driven by one Belgium firm, while the significant coefficient for the attribute *Governance committee* (a04) is caused by five firms from Finland and Norway.

From this, we can draw the following conclusion: to get reliable results, it is sensible to exclude these rarely observed governance attributes, because the estimation results are otherwise distorted by extreme observations. The results presented in Table IV.5 and the derived parsimonious governance indices are robust to these extreme observations.

6 Conclusion

In this paper we investigate which firm-level corporate governance attributes affect firm values and the extent to which the relationship between governance attributes and firm value depends on the institutional environment. We partition a sample of 2,431 firms from 23 countries into subsamples according to the legal origin of the country of domicile and apply a range of techniques that have been suggested in the literature to identify those governance attributes that are consistently related to firm value in each subsample. We construct governance indices based on these attributes. We then relate these governance indices, which are specific to the legal origin of each sample, and relate them to firm valuation.

Our main finding is that the quality of corporate governance cannot be measured by one single indicator that is uniform or even similar across all four legal origin subsamples. In fact, there is practically no overlap between the governance attributes that are consistently related to firm value across the legal origin samples. Moreover, some of the attributes that are considered significant in the literature – typically based on an analysis for US firms –

have negative coefficients for the samples of civil law countries, which suggest that some governance provisions that add value in one institutional context may be harmful to firms in another institutional context.

Our findings are conform to those in the previous literature that governance pays, as firm valuation is consistently related to measures of the quality of corporate governance. For each legal origin sample we can identify a small number of provisions (between one and ten, depending on the sample and the selection approach) that capture essentially all value-relevant aspects of corporate governance. However, with the exception of some similarities between Scandinavian law countries and English law countries, the governance indices that capture the value relevant-aspects for one sample are never related to firm valuation in any of the other samples. From this we conclude that the value-relevant aspects of corporate governance differ across institutional environments.

Our research design has some limitations, which we acknowledge, and which should be addressed in future work. First, we analyze only one cross-section for the year 2005. Hence, we cannot assess how stable our results are over time, and whether they are specific to the period of our analysis. To some extent, the sample sizes we have for earlier periods prevents us from extending our analysis, as we found that sample size is partially relevant for the number of attributes that are included in the governance index. Second, sample size prevents us also from conducting meaningful analysis at the country level. This would be desirable as the institutional environment is heterogeneous, even within the set of countries that share the same legal origin.

Future research should also address the relevance of ownership structure for corporate governance. Ownership concentration and the identity of large investors varies widely across the countries and firms included in our analysis.[34] The conflicts of interests and therefore the problems to be solved by the governance structure of the firm differ between widely held firms, where manager-shareholder conflicts dominate, and closely held firms, where the main conflict is between small and large shareholders. Including the ownership structure of the firm in the analysis would therefore be important.

[34]See, e.g., La Porta, Lopez-de Silanes, and Shleifer (1999) and Durnev and Kim (2005).

Appendix

A. Coding governance provisions

This Appendix defines the minimally required corporate governance standard for each of the 53 governance provisions. Each governance provisions is coded as a dummy variable equal to 1 if the firm fulfills the minimally required governance standard and zero otherwise.

No.	Name	Minimally required corporate governance standard
a01	*Board independence*	Board controlled by a supermajority (> 66.7%) of independent outsiders
a02	*Nominating committee*	Committee comprised solely of independent outsiders
a03	*Compensation committee*	Committee comprised solely of independent outsiders
a04	*Governance committee*	Governance committee exists
a05	*Board structure*	Board annually elected (no staggered/classified board)
a06	*Board size*	Board size not less than 6 or more than 15 members
a07	*Cumulative voting*	Shareholders have cumulative voting rights
a08	*CEO boards served on*	CEO serves on the boards of less than 3 public companies
a09	*Former CEOs on board*	No former CEO on the board
a10	*Chairman/CEO separation*	Chairman and CEO positions separated
a11	*Governance guidelines*	Governance guidelines publicly disclosed
a12	*Board performance reviews*	Performance of the board reviewed regularly
a13	*Meetings outside directors*	Outside directors meet without CEO
a14	*CEO succession plan*	Board approved succession plan in place for CEO
a15	*Outside advisors*	Board has the express authority to hire / has its own outside advisors
a16	*Directors resignation*	Directors required to submit resignation upon a change in job
a17	*Officers and directors ownership*	Officers + directors ownership as % of shares outstanding$\geq$1% and $\leq$30%
a18	*Directors education*	At least one director participated in ISS accredited director education program
a19	*Response to shareholder proposals*	Board does not ignore shareholder proposals
a20	*Change board size*	Shareholder approval required to increase/decrease the size of the board
a21	*Board attendance*	All directors attended 75% of board meetings or had a valid excuse
a22	*Board vacancies*	Shareholders vote on directors selected to fill vacancies
a23	*Directors boards served on*	Policy on outside directorships with 4 or fewer boards as limit
a24	*CEO related party transactions*	CEO not listed as having related-party transactions in proxy statement
a25	*Audit committee*	Committee comprised solely of independent outsiders
a26	*Audit fees*	Consulting fees (audit related and other) less than audit fees
a27	*Auditor ratification*	Auditors ratified at most recent annual meeting
a28	*Directors stock ownership*	All directors with more than one year of service own stock
a29	*Cost of option plans*	Last time shareholders voted on an option plan, ISS deemed cost reasonable
a30	*Option repricing policy*	Repricing prohibited
a31	*Shareholder approval*	All stock-incentive plans adopted with shareholder approval
a32	*Executives stock ownership requirements*	Executives subject to stock ownership requirements
a33	*Directors stock ownership requirements*	Directors subject to stock ownership requirements

No.	Name	Minimally required corporate governance standard
a32	*Executives stock ownership requirements*	Executives subject to stock ownership requirements
a33	*Directors stock ownership requirements*	Directors subject to stock ownership requirements
a34	*Compensation committee interlocks*	No interlocks among compensation committee members across companies
a35	*Director compensation*	Directors receive all or a portion of their fees in stock
a36	*Option expensing*	Company expenses options
a37	*Option burn rate*	Options burn rate reasonable (average annual option grants≤3% of outstanding shares over past 3 years)
a38	*Blank check preferred stock*	Blank check preferred stock not authorized
a39	*Vote requirement charter/bylaw*	Simple majority vote (not supermajority) required to amend charter/bylaws
a40	*Vote requirement mergers*	Simple majority (not supermajority) vote required to approve mergers
a41	*Written consent*	Shareholders may act by written consent
a42	*Special meetings*	Shareholders may call special meetings
a43	*Board amendments*	Board cannot amend bylaws without shareholder approval or can only do so under limited circumstances
a44	*Unequal voting rights*	One-share, one-vote policy
a45	*Poison pill*	Company has no poison pill in place
a46	*State anti-takeover provisions*	Company incorporated in state without any state anti-takeover provisions
a47	*Directors retirement age*	Mandatory retirement age for directors in place
a48	*Directors term limits*	Director term limits in place
a49	*Auditor rotation*	Policy disclosed regarding auditor rotation
a50	*Option repricing*	No option repricing within last three years
a51	*Pension plans*	Non-employee directors do not participate in pension plan
a52	*Option grants alignment*	Options grants align with company performance
a53	*Corporate loans*	Company does not provide loans to executives for exercising options

B. Definition governance indices

This Appendix lists all constructed corporate governance indices and their definition.

Governance index	**Definition**
COMP	- covers all 53 governance attributes
CountryCG	- covers the attributes that show no variation within a country (either all 1 or 0) - = sum over country-specific attributes / number of country-specific attributes - calculation based on the total ISS universe excluding financial firms, i.e., figures differ from Table IV.4
FirmCG	- covers the attributes that show variation within a country, i.e., are firm-specific - = sum over firm-specific attributes / number of firm-specific attributes
CountryMedCG	- = median of *COMP* for each country
FirmMedDevCG	- number of attributes a company chooses below or above the country median (deviation from country median) - = *COMP* - *CountryMedCG*
EnglishCG	- covers 5 attributes: *Board independence* (a01), *Board structure* (a05), *Executives stock ownership requirements* (a32), *Board amendments* (a43), and *Unequal voting rights* (a44)
FrenchCG	- covers 4 attributes: *Nominating committee* (a02), *Compensation committee* (a03), *Board attendance* (a21), and *Option repricing policy* (a30)
GermanCG	- covers 6 attributes: *Board size* (a06), *Board performance reviews* (a12), *Auditor ratification* (a27), *Executives stock ownership requirements* (a32), *Directors stock ownership requirements* (a33), and *Option grants alignment* (a52)
ScandCG	- covers 3 attributes: *Board structure* (a05), *Meetings outside directors* (a13), and *Option repricing policy* (a30)
EnglishOP/ *FrenchOP* / *GermanOP* / *ScandOP*	- other provisions index - covers all attributes that are not included in the parsimonious governance indices for the respective legal origin samples - = *COMP* - *EnglishCG* / *FrenchCG* / *GermanCG* / *ScandCG*
BebchukCG	- Entrenchment Index of Bebchuk, Cohen, and Ferrell (2009) - covers only 5 instead of 6 attributes: *Board structure* (a05), *Vote requirement charter/bylaw* (a39), *Vote requirement mergers* (a40), *Board amendments* (a43), *Poison pill* (a45) - attribute Golden parachutes not included, because not tracked by ISS
BebchukOP	- other provisions index - covers 48 attributes and is different from Bebchuk, Cohen, Ferrell's other provision index of 18 remaining IRRC attributes - = *COMP* - *BebchukCG*
BrownCG	- Gov-7 Index of Brown and Caylor (2006) - covers 7 attributes: *Board structure* (a05), *Governance guidelines* (a11), *Board attendance* (a21), *Executives stock ownership requirements* (a32), *Option burn rate* (a37), *Poison pill* (a45), and *Option repricing* (a50)
BrownOP	- other provisions index - covers 2 attributes more than Brown and Caylor's Gov-44 Index: *Option grants alignment* (a52) and *Unequal voting rights* (a44) - = *COMP* - *BrownCG*

Table IV.1: **Sample derivation**

This table provides details on the derivation of our final sample from the ISS universe for the year 2005. The ISS universe comprises all companies that are listed and incorporated in the 23 developed countries listed below. About 50 firms incorporated in other countries (e.g., Bermuda, China, Barbados, or Hungary) are excluded from the sample. % denotes the percentage of missing values per firm for the tracked governance provisions.

	ISS universe		Non-financial firms		Worldscope matched firms		Firms with complete financial data		Final sample (with matched US firms)		Percentage of all firms
Country	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	
Australia	132	5	99	4	75	4	66	3	66	3	50
Austria	20	16	15	14	14	14	13	14	13	14	65
Belgium	26	20	18	20	18	20	18	20	18	20	69
Canada	186	5	162	5	161	5	149	5	149	5	80
Denmark	23	12	20	12	20	12	19	12	19	12	83
Finland	32	9	29	9	29	9	29	9	29	9	91
France	88	9	77	10	77	10	74	10	74	10	84
Germany	88	12	76	12	76	12	73	12	73	12	83
Greece	44	21	38	21	38	21	35	21	35	21	80
Hong Kong	114	16	81	15	71	15	69	15	69	15	61
Ireland	16	9	11	9	11	9	10	9	10	9	63
Italy	73	8	47	7	47	7	44	7	44	7	60
Japan	604	16	517	16	460	16	455	16	455	16	75
Netherlands	51	11	44	11	44	11	38	10	38	10	75
New Zealand	20	5	17	5	14	4	13	4	13	4	65
Norway	23	15	21	14	21	14	19	14	19	14	83
Portugal	14	16	11	16	11	16	11	16	11	16	79
Singapore	58	14	46	14	44	14	44	14	44	14	76
Spain	55	19	46	19	45	19	44	19	44	19	80
Sweden	47	11	38	11	38	11	34	10	34	10	72
Switzerland	60	10	48	10	48	10	48	10	48	10	80
United Kingdom	547	5	465	5	320	6	294	5	294	5	54
Non-US	**2,321**	**11**	**1,926**	**11**	**1,682**	**11**	**1,599**	**11**	**1,599**	**11**	**69**
US	5,620	3	4,493	3	4,438	3	2,990	2	832	2	15
Total	**7,941**	**5**	**6,419**	**5**	**6,120**	**3**	**4,589**	**5**	**2,431**	**8**	**31**

Table IV.2: **Summary statistics matching non-US vs. US firms**

This table reports the mean values of the main firm characteristics for non-US firms and matched and non-matched US firms. The firm characteristics Sales (Worldscope item "wc07240"), Net Income (Worldscope item "wc07250"), and Total Assets (Worldscope item "wc07230") are used for the propensity score matching of US and non-US firms. The propensity score equals the probability that a firm with certain characteristics is not a US firm. This probability is estimated in a Probit regression. An indicator variable that equals one if a firm is a non-US firm and zero otherwise is regressed on *Sales*, net income, total assets, and industry dummies. Tobin's Q (*TQ*) is calculated as the book value of assets (Worldscope item "wc07230" or "wc02999") plus the market value of common equity (Datastream item "MV") less the book value of common equity (Worldscope item "wc07220" or "wc03501") divided by the book value of assets (Worldscope item "wc07230" or "wc02999"). *Sales* are Net Sales/Revenues in million $ (Worldscope item "wc07240"). *Age* is the number of months between the first trading day as reported in Datastream (item "BDATE") and the firm's fiscal year end-date in 2005 (Worldscope item "wc05350"). *PPE* is property, plant, and equipment (Worldscope item "wc02501") to total assets (Worldscope item "wc02999"). *Risk* is the annualized standard deviation of daily stock returns (Datastream item "RI") over the year ending with the firm's fiscal year end-date in 2005 (Worldscope item "wc05350"). *Leverage* is total debt (Worldscope item "wc03255") to total assets (Worldscope item "wc02999"). *ADR* (Worldscope item "wc11496") is a dummy variable, equal to one if a firm has an American Depository Receipt (ADR), and zero otherwise.

Sample	**Non-US firms**	**US firms**		
N	1,599	832	2,158	2,990
Variable		**Matched**	**Non-matched**	**All**
Sales (million $)	6,696	4,841	1,581	2,488
Net Income (million $)	390	301	83	144
Assets (million $)	8,510	5,333	2,032	2,950
Propensity score	0.42	0.38	0.28	0.31
TQ	1.8	2.5	3.2	3.0
Age (months)	258	219	176	188
PPE (%)	0.33	0.27	0.21	0.23
Risk (annualized)	0.27	0.40	0.62	0.56
Leverage (%)	0.23	0.25	0.24	0.25
ADR (%)	0.21	-	-	-

Table IV.3: **Descriptive statistics firm characteristics**

This table displays descriptive statistics for the main firm characteristics. Panel A displays the mean, standard deviation (sd), minimum, median, 25th and 75th percentile (p25 and p75), and maximum for the total sample. Panel B displays the mean and median for the four legal origin subsamples. Tobin's Q (TQ) is calculated as the book value of assets (Worldscope item "wc07230" or "wc02999") plus the market value of common equity (Datastream item "MV") less the book value of common equity (Worldscope item "wc07220" or "wc03501") divided by the book value of assets (Worldscope item "wc07230" or "wc02999"). *Sales* are Net Sales/Revenues in million $ (Worldscope item "wc07240"). *Age* is the number of months between the first trading day as reported in Datastream (item "BDATE") and the firm's fiscal year end-date in 2005 (Worldscope item "wc05350"). *PPE* is property, plant, and equipment (Worldscope item "wc02501") to total assets ("wc02999"). *Risk* is the annualized standard deviation of daily stock returns (Datastream item "RI") over the year ending with the firm's fiscal year end-date in 2005 (Worldscope item "wc05350"). *Leverage* is total debt (Worldscope item "wc03255") to total assets (Worldscope item "wc02999"). *ADR* (Worldscope item "wc11496") is a dummy variable, equal to one if a firm has an American Depository Receipt, and zero otherwise. The variables Tobin's Q, *PPE*, *Risk*, and *Leverage* are winsorized at the 1st and 99th percentile.

Panel A: Total sample (2,431 observations)

Variable	mean	sd	skew	min	p25	median	p75	max
TQ	1.91	1.25	2.77	0.77	1.19	1.51	2.14	8.15
Sales (million $)	6,061	16,100	9.86	0	550	1,720	5,189	328,000
Age (months)	245	138	0.09	13	119	220	393	500
PPE (%)	0.31	0.22	0.75	0.01	0.13	0.27	0.44	0.90
Risk (annulized)	0.31	0.15	2.25	0.13	0.21	0.27	0.35	1.03
Leverage (%)	0.23	0.18	0.77	0.00	0.08	0.22	0.34	0.82
ADR (%)	0.14	0.35	2.06	0	-	-	-	1

Panel B: Legal origin subsamples

Legal origin	English law	French law	German law	Scandinavian law
Countries	Australia	Belgium	Austria	Denmark
	Canada	France	Germany	Norway
	Hong Kong	Greece	Japan	Norway
	Ireland	Italy	Switzerland	Sweden
	New Zealand	Netherlands		
	Singapore	Portugal		
	UK	Spain		
	US			
N	1,477	264	589	101

Variable	English law mean	English law median	French law mean	French law median	German law mean	German law median	Scandinavian law mean	Scandinavian law median
TQ	2.08	1.65	1.86	1.50	1.51	1.23	2.04	1.71
Sales (million $)	4,451	1,073	9,657	2,748	8,623	3,082	5,261	1,988
Age (months)	227	191	229	213	305	393	189	187
PPE (%)	0.31	0.26	0.31	0.28	0.31	0.29	0.28	0.23
Risk (annualized)	0.34	0.30	0.23	0.21	0.26	0.26	0.28	0.24
Leverage (%)	0.23	0.21	0.28	0.28	0.21	0.18	0.23	0.22
ADR (%)	0.10	-	0.24	-	0.19	-	0.23	-

Table IV.4: **Summary statistics governance provisions**

This table displays the percentage of firms that exhibit the respective governance provision. For an explanation of the governance provisions see Appendix A. Bold figures indicate that either no firm (0%) or all firms (100%) in the country have the provision in place. All missing observations are set to zero. All governance attributes that exhibit no missing values in the final sample are marked with a +.

	English law									French law								German law					Scandinavian law					
	Australia	Canada	Hong Kong	Ireland	New Zealand	Singapore	UK	US	TOTAL	Belgium	France	Greece	Italy	Netherlands	Portugal	Spain	TOTAL	Austria	Germany	Japan	Switzerland	TOTAL	Denmark	Finland	Norway	Sweden	TOTAL	TOTAL
Firm-year observations	**66**	**149**	**69**	**10**	**13**	**44**	**294**	**832**	**1,477**	**18**	**74**	**35**	**44**	**38**	**11**	**44**	**264**	**13**	**73**	**455**	**48**	**589**	**19**	**29**	**19**	**34**	**101**	**2,431**
a01 *Board independence*	26	53	**0**	20	23	21	4	61	43	**0**	5	**0**	**0**	68	9	7	13	8	29	**0**	50	8	53	59	53	32	48	31
a02 *Nominating committee+*	14	62	7	20	**0**	14	28	74	55	11	7	**0**	**0**	55	**0**	14	13	**0**	1	0	17	2	**0**	31	5	3	11	36
a03 *Compensation committee+*	24	73	12	40	8	18	68	84	71	17	10	**0**	**0**	58	**0**	14	14	**0**	3	0	31	3	11	38	42	18	27	46
a04 *Governance committee+*	21	97	1	10	23	2	5	82	58	11	19	6	11	18	36	98	29	**0**	10	1	19	3	**0**	10	11	**0**	5	40
a05 *Board structure*	2	99	6	**0**	**0**	**0**	8	46	38	**0**	1	3	**0**	5	**0**	2	2	**0**	**0**	36	21	30	58	86	21	**100**	73	33
a06 *Board size*	92	96	91	70	92	98	94	93	93	83	78	91	82	76	91	71	80	85	82	70	77	72	74	79	58	97	80	86
a07 *Cumulative voting*	**0**	2	**0**	**0**	**0**	**0**	0	7	4	**0**	**0**	**0**	32	**0**	**0**	5	6	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	3
a08 *CEO boards served on*	97	86	91	**100**	**100**	82	96	98	95	28	54	77	64	68	64	93	66	85	62	12	85	25	90	62	63	85	75	74
a09 *Former CEOs on board*	91	68	84	80	54	80	85	77	79	33	69	54	71	68	9	7	52	92	66	53	65	56	63	86	74	62	71	70
a10 *Chairman/CEO separation*	85	62	65	50	62	68	14	40	41	78	39	34	61	84	55	57	55	**100**	88	1	31	16	53	28	68	85	59	37
a11 *Governance guidelines+*	89	**100**	39	80	**100**	68	69	72	74	28	88	11	91	92	**100**	**100**	77	69	63	1	90	17	68	**100**	58	68	75	60
a12 *Board performance reviews+*	70	95	**0**	50	77	5	81	75	72	11	50	**0**	2	66	9	59	35	**0**	92	**0**	17	13	32	76	53	27	47	53
a13 *Meetings outside directors+*	30	89	6	50	15	5	54	77	65	6	22	**0**	**0**	71	**0**	**0**	17	92	97	**0**	10	15	68	17	21	6	24	46
a14 *CEO succession plan+*	42	56	**0**	20	23	2	33	59	48	6	8	14	**0**	3	**0**	**0**	5	**100**	32	**0**	54	11	**0**	10	16	**0**	6	32
a15 *Outside advisors+*	94	97	19	90	**100**	75	95	97	92	17	**0**	6	5	53	**0**	82	24	**100**	4	1	10	4	**0**	3	5	**0**	2	60
a16 *Directors resignation+*	**0**	4	**0**	**0**	**0**	**0**	0	37	21	**0**	**0**	**0**	**0**	**0**	**0**	61	10	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	14
a17 *Officers and directors ownership*	12	19	19	50	8	23	32	75	53	6	23	20	14	5	18	34	19	**0**	12	20	10	18	16	31	32	27	27	40
a18 *Directors education+*	**0**	2	**0**	**0**	**0**	**0**	**0**	39	22	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	1	**0**	**0**	0	**0**	**0**	**0**	**0**	**0**	14
a19 *Response to shareholder proposals+*	**100**	99	**100**	**100**	**100**	**100**	**100**	100	100	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	100
a20 *Change board size*	5	97	**100**	**0**	**0**	**100**	0	6	21	**100**	28	**100**	**100**	24	9	14	51	**0**	**100**	99	44	93	16	**100**	58	**0**	43	43
a21 *Board attendance*	92	68	15	40	**100**	55	74	**100**	86	61	54	**0**	14	24	**0**	2	25	8	12	**0**	19	3	**0**	83	**0**	27	33	57
a22 *Board vacancies*	6	**100**	**0**	60	8	**0**	73	53	55	**100**	99	**100**	**100**	92	**100**	**100**	98	**100**	**100**	100	75	98	**100**	**100**	**100**	**100**	**100**	72
a23 *Directors boards served on+*	**0**	1	**0**	**0**	**0**	**0**	18	13	11	**0**	**0**	**0**	**0**	8	**0**	2	2	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	7
a24 *CEO related party transactions*	92	95	84	90	**100**	89	92	84	87	17	62	17	77	37	82	21	46	46	78	93	38	86	90	24	21	27	37	80
a25 *Audit committee+*	32	87	55	40	23	43	68	93	80	17	22	6	7	53	18	7	19	**0**	3	1	52	5	11	48	26	27	30	53
a26 *Audit fees*	80	84	25	60	54	48	55	99	82	22	91	6	89	40	36	71	61	31	22	95	81	83	47	66	84	74	68	80
a27 *Auditor ratification*	18	85	91	70	62	86	80	73	74	17	41	97	34	53	9	86	53	92	95	89	92	90	95	**100**	11	21	55	75
a28 *Directors stock ownership*	52	73	1	30	23	2	59	85	70	**0**	58	**0**	**0**	3	**0**	21	20	**0**	1	72	54	60	11	48	16	32	30	60
a29 *Cost of option plans*	55	75	4	90	46	7	85	67	66	44	38	9	59	71	**0**	34	41	31	60	34	2	34	53	93	32	68	65	56
a30 *Option repricing policy*	5	11	**0**	**0**	15	**0**	3	83	49	6	91	94	59	18	55	5	54	92	93	99	88	97	21	97	16	24	43	61

Table IV.4: **Summary statistics governance provisions (continued)**

	English law									French law							
	Australia	Canada	Hong Kong	Ireland	New Zealand	Singapore	UK	US	TOTAL	Belgium	France	Greece	Italy	Netherlands	Portugal	Spain	TOTAL
Firm-year observations	66	149	69	10	13	44	294	832	1,477	18	74	35	44	38	11	44	264
a31 *Shareholder approval*	99	94	88	100	92	93	100	81	88	100	96	80	100	34	82	64	80
a32 *Executives stock ownership requirements*	14	42	0	0	0	0	35	26	26	0	41	0	0	3	9	11	14
a33 *Directors stock ownership requirements+*	17	69	0	0	0	0	4	28	24	0	68	0	0	0	0	0	19
a34 *Compensation committee interlocks*	67	100	0	60	92	0	72	100	85	28	32	9	64	84	18	14	38
a35 *Director compensation*	18	64	0	0	15	0	12	92	61	0	12	14	5	16	27	36	16
a36 *Option expensing*	2	97	1	50	0	2	63	9	28	6	41	37	59	87	46	9	42
a37 *Option burn rate*	50	36	44	30	46	66	39	13	25	33	54	23	55	63	46	5	41
a38 *Blank check preferred stock+*	100	38	100	100	100	100	100	11	43	100	100	100	100	100	100	100	100
a39 *Vote requirement charter/bylaw*	2	0	1	0	0	0	0	42	24	0	0	97	0	42	0	0	19
a40 *Vote requirement mergers*	2	21	94	0	0	0	0	64	43	0	0	0	0	74	0	0	11
a41 *Written consent*	64	2	94	0	92	0	1	49	36	6	0	0	0	0	0	0	0
a42 *Special meetings*	99	100	99	100	100	75	100	41	66	100	99	100	100	97	100	100	99
a43 *Board amendments*	100	100	100	100	100	100	100	3	45	100	99	100	41	97	100	100	89
a44 *Unequal voting rights+*	96	27	100	100	100	100	100	78	80	94	41	100	100	68	82	96	77
a45 *Poison pill+*	100	69	100	100	100	100	100	54	71	44	96	100	100	26	100	100	84
a46 *State anti-takeover provisions+*	0	0	0	100	0	0	100	2	22	0	0	0	0	0	0	0	0
a47 *Directors retirement age*	17	16	0	0	15	2	25	30	24	50	95	0	2	18	0	57	42
a48 *Directors term limits*	21	4	0	20	8	2	19	2	7	0	0	3	2	68	0	5	11
a49 *Auditor rotation*	64	5	0	20	69	0	14	57	39	0	91	0	98	13	0	98	60
a50 *Option repricing*	97	97	3	90	100	0	99	93	88	50	91	94	86	61	46	16	69
a51 *Pension plans*	96	99	100	80	69	100	98	97	97	39	84	26	75	100	55	80	72
a52 *Option grants alignment*	53	55	54	30	54	73	67	70	66	39	69	23	55	79	46	5	48
a53 *Corporate loans*	85	83	3	60	69	2	81	70	69	28	91	31	82	95	36	30	65
# attributes = 0	5	2	17	14	13	17	2	0	0	15	10	18	16	6	21	8	2
# attributes = 100	4	5	7	9	12	7	5	1	0	7	2	8	8	3	7	7	2
# attributes with no variation	9	7	24	23	25	24	7	1	0	22	12	26	24	9	28	15	4

	German law					Scandinavian law					
	Austria	Germany	Japan	Switzerland	TOTAL	Denmark	Finland	Norway	Sweden	TOTAL	TOTAL
Firm-year observations	13	73	455	48	589	19	29	19	34	101	2,431
a31 *Shareholder approval*	92	63	100	33	89	58	100	53	71	73	87
a32 *Executives stock ownership requirements*	0	1	0	75	6	0	3	0	0	1	19
a33 *Directors stock ownership requirements+*	0	0	0	73	6	5	0	0	0	1	18
a34 *Compensation committee interlocks*	15	45	2	54	12	37	76	32	53	52	61
a35 *Director compensation*	0	3	1	40	4	0	35	5	0	11	41
a36 *Option expensing*	62	64	0	83	16	68	97	37	38	60	28
a37 *Option burn rate*	62	51	33	67	39	74	35	42	56	50	32
a38 *Blank check preferred stock+*	100	100	100	100	100	100	100	100	100	100	66
a39 *Vote requirement charter/bylaw*	0	14	0	2	2	0	0	0	0	0	17
a40 *Vote requirement mergers*	0	0	0	2	0	0	0	0	3	1	27
a41 *Written consent*	0	0	0	0	0	0	0	0	0	0	22
a42 *Special meetings*	100	100	100	100	100	100	100	100	100	100	79
a43 *Board amendments*	100	99	100	100	100	100	100	100	100	100	65
a44 *Unequal voting rights+*	100	100	100	100	100	74	69	100	65	74	84
a45 *Poison pill+*	100	100	100	98	100	100	100	100	100	100	81
a46 *State anti-takeover provisions+*	0	0	0	0	0	0	0	0	0	0	13
a47 *Directors retirement age*	39	70	0	44	13	63	38	26	0	28	24
a48 *Directors term limits*	0	0	0	6	1	0	0	0	0	0	6
a49 *Auditor rotation*	92	93	88	4	82	0	3	21	0	5	50
a50 *Option repricing*	92	95	100	96	99	84	97	58	100	88	89
a51 *Pension plans*	100	93	2	83	22	37	38	47	77	52	75
a52 *Option grants alignment*	62	63	37	77	44	90	38	53	56	56	58
a53 *Corporate loans*	69	36	0	90	13	74	62	26	53	54	54
# attributes = 0	21	9	15	6	5	17	10	12	17	8	
# attributes = 100	11	7	6	5	3	6	10	7	8	6	
# attributes with no variation	32	16	21	11	8	23	20	19	25	14	

Table IV.5: **Identified governance provisions**

This table displays the regression coefficients for the four different regression approaches for each of the legal origin subsamples. In all regressions we use the logarithm of Tobin's Q as dependent variable and include the controls log($Sales$), log(Age), PPE, $Risk$, $Leverage$, and an ADR dummy as well as industry and country dummies. Inference is based on robust standard errors. We exclude all governance attributes with insufficient variation (below 5% and above 95%) in each of the subsamples. The BCF-approach refers to a set of regressions with (1) each individual governance attribute and (2) a comprehensive index over all remaining governance attributes as regressors. The ALL-approach refers to one regression on all individual governance attributes. The AIC-approach refers to a forward selection procedure based on p-values for two-sided tests of significance. The elimination affects only governance attributes. The elimination stops if the minimal AIC is reached. The STEP-approach uses the same elimination technique as the AIC-approach, but the governance provisions with the largest p-values are stepwise eliminated until only attributes with p-values below 10% remain in the regression. The table only reports the significant coefficients for the BCF-, ALL-, and STEP-approach. Governance provisions that were never significant in any of the approaches are omitted from the table. Bold figures indicate negative coefficients. All p-values are reported on the basis of two-tail significance level. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All governance attributes that exhibit no missing values in the final sample are marked with a +.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Sample	English law				French law				German law				Scandinavian law			
N	1,477				264				589				101			
Approach	**BCF**	**ALL**	**AIC**	**STEP**	**BCF**	**ALL**	**AIC**	**STEP**	**BCF**	**ALL**	**AIC**	**STEP**	**BCF**	**ALL**	**AIC**	**STEP**
a01 *Board independence*	0.073**	0.072**	0.069**	0.071**						**-0.146***	**-0.153***					
a02 *Nominating committee+*					**-0.151***	**-0.310****	**-0.339*****	**-0.270*****	--	--	--	--			0.206	
a03 *Compensation committee+*							0.213**	0.151*	--	--	--	--				
a04 *Governance committee+*			**-0.076***						--	--	--	--	--	--	--	--
a05 *Board structure*	0.059*		0.088***	0.079**	--	--	--	--					0.422**	0.460*	0.451***	0.403**
a06 *Board size*									**-0.066***	**-0.083****	**-0.076****	**-0.079****				
a08 *CEO boards served on*	--	--	--	--			0.070									
a12 *Board performance reviews+*	**-0.065***								0.181*	0.307**	0.284**	0.239**				
a13 *Meetings outside directors+*													0.302*		0.223	0.255*
a16 *Directors resignation+*						0.262*	0.191		--	--	--	--	--	--	--	--
a17 *Officers and directors ownership*			0.043													
a21 *Board attendance*					**-0.109***		**-0.093**	**-0.107***	--	--	--	--			**-0.203**	
a25 *Audit committee+*											0.120					
a27 *Auditor ratification*							0.069		**-0.144*****	**-0.263***	**-0.117***	**-0.126****				
a28 *Directors stock ownership*					**-0.144***											
a29 *Cost of option plans*											**-0.053**					
a30 *Option repricing policy*					0.151**	0.198**	0.175***	0.166**	--	--	--	--			0.362*	0.329*
a31 *Shareholder approval*										**-0.138***	**-0.141***					
a32 *Executives stock ownership requirements*	0.051*	0.061*	0.057*	0.053*						**-0.305***	**-0.354*****	**-0.368*****	--	--	--	--
a33 *Directors stock ownership requirements+*							**-0.161***			0.415**	0.400***	0.399***	--	--	--	--
a37 *Option burn rate*									0.117***							
a41 *Written consent*			-0.046		--	--	--	--	--	--	--	--	--	--	--	--
a43 *Board amendments*	**-0.148****		**-0.117***	**-0.135****					--	--	--	--	--	--	--	--
a44 *Unequal voting rights+*	0.093**	0.101**	0.095***	0.094**					--	--	--	--				
a47 *Directors retirement age*						**-0.168***	**-0.139***									
a50 *Option repricing*									--	--	--	--			**-0.215**	
a52 *Option grants alignment*									0.142***		0.125***	0.097***				
R2 adjusted	-	18%	19%	19%	-	30%	37%	35%	-	37%	38%	37%	-	3%	33%	31%
# identified attributes	6	3	8	5	4	4	9	4	5	7	10	6	2	1	6	3

Table IV.6: **Industry rank correlations identified governance provisions**

This table reports industry rank correlation coefficients for each pair of legal origin subsamples. We consider those 15 governance provisions that have a significant coefficient for the STEP-approach for at least one of the subsamples. We select all industries with at least three firms in this industry in each of the subsamples, which leaves us with 15 industries. For each attribute we rank industries in each subsample so that the industry where most firms have this attribute receives a rank of one, and the industry where the smallest number of firms have this attribute receives a rank of fifteen. For the German and Scandinavian sample the correlations for the attributes *Board amendments* (a43) and *Unequal voting rights* (a44) cannot be computed, because these attributes show no variation in these samples.

		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample 1		**English**	**English**	**English**	**French**	**French**	**German**
Sample 2		**French**	**German**	**Scand**	**German**	**Scand**	**Scand**
a01	*Board independence*	0.39	0.04	0.67***	0.05	0.31	0.18
a02	*Nominating committee+*	0.26	0.22	0.25	0.02	-0.36	-0.16
a03	*Compensation committee+*	0.25	0.15	0.12	0.24	-0.03	0.27
a05	*Board structure*	-0.30	0.17	-0.09	-0.30	-0.36	0.40
a06	*Board size*	-0.24	0.01	0.05	0.58**	0.02	-0.16
a12	*Board performance reviews+*	-0.18	-0.45*	0.08	0.52**	0.13	-0.13
a13	*Meetings outside directors+*	-0.28	-0.14	-0.05	-0.49*	-0.02	0.29
a21	*Board attendance*	-0.02	-0.54**	-0.18	0.08	-0.38	-0.17
a27	*Auditor ratification*	-0.24	-0.60**	-0.38	0.32	-0.02	-0.05
a30	*Option repricing policy*	-0.33	-0.13	0.08	-0.09	-0.36	0.45*
a32	*Executives stock ownership require.*	-0.64**	-0.09	-0.31	0.11	0.06	-0.06
a33	*Directors stock ownership require.+*	-0.61**	-0.14	-0.25	0.28	-0.12	-0.13
a43	*Board amendments*	-0.67***	0.31	.	0.19	.	.
a44	*Unequal voting rights+*	-0.18	.	-0.14	.	0.02	.
a52	*Option grants alignment*	-0.05	-0.55**	0.10	0.39	-0.13	-0.13

Table IV.7: **Descriptive statistics governance indices**

This table displays descriptive statistics for all constructed governance indices. For a definition of the governance indices see Appendix B. Panel A reports the minimum and maximum of the raw indices and the mean, median, 25th and 75th percentile (p25 and p75), and standard deviation (sd) for the normalized indices for the total sample. Panel B reports the mean and standard deviation (sd) of the normalized indices for the four legal origin subsamples.

Panel A: Total sample (2,431 observations)

			After transforming [min,max] to [0,1]				
Governance index	**min**	**max**	**p25**	**mean**	**median**	**p75**	**sd**
COMP	6	45	0.36	0.52	0.18	0.67	0.18
CountryMedCG	17	33	0.15	0.54	0.30	0.76	0.30
FirmMedDevCG	-20	16	0.49	0.57	0.12	0.63	0.12
CountryCG	0.00	0.71	0.00	0.42	0.35	0.64	0.35
FirmCG	0.06	0.88	0.39	0.52	0.17	0.66	0.17
BebchukCG	0	5	0.40	0.45	0.18	0.60	0.18
BebchukOP	5	42	0.35	0.51	0.19	0.65	0.19
BrownCG	0	7	0.43	0.53	0.18	0.71	0.18
BrownOP	5	40	0.34	0.50	0.17	0.63	0.17
EnglishCG	-1	4	0.20	0.40	0.22	0.60	0.22
EnglishOP	5	41	0.36	0.52	0.19	0.67	0.19
FrenchCG	-2	2	0.50	0.54	0.18	0.75	0.18
FrenchOP	6	41	0.37	0.52	0.17	0.66	0.17
GermanCG	-3	2	0.33	0.41	0.16	0.50	0.16
GermanOP	6	39	0.36	0.52	0.18	0.67	0.18
ScandCG	0	3.0	0.33	0.47	0.30	0.67	0.30
ScandOP	6	42	0.36	0.52	0.18	0.67	0.18

Panel B: Legal origin subsamples

Sample	**English law**		**French law**		**German law**		**Scandinavian law**	
N	1,477		264		589		101	
Governance index	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
COMP	0.61	0.15	0.41	0.13	0.36	0.10	0.42	0.12
CountryMedCG	0.72	0.19	0.34	0.21	0.20	0.20	0.33	0.17
FirmMedDevCG	0.58	0.14	0.54	0.12	0.55	0.07	0.56	0.11
CountryCG	0.36	0.43	0.50	0.12	0.52	0.05	0.57	0.09
FirmCG	0.60	0.15	0.43	0.16	0.39	0.11	0.45	0.15
BebchukCG	0.44	0.21	0.41	0.14	0.46	0.10	0.55	0.09
BebchukOP	0.61	0.16	0.40	0.14	0.34	0.10	0.40	0.13
BrownCG	0.58	0.17	0.45	0.19	0.42	0.14	0.60	0.18
BrownOP	0.59	0.15	0.39	0.12	0.34	0.09	0.38	0.11
EnglishCG	0.48	0.23	0.23	0.12	0.29	0.12	0.39	0.18
EnglishOP	0.62	0.15	0.41	0.14	0.35	0.10	0.40	0.12
FrenchCG	0.45	0.15	0.57	0.15	0.74	0.06	0.56	0.15
FrenchOP	0.60	0.15	0.42	0.13	0.37	0.10	0.44	0.11
GermanCG	0.45	0.14	0.42	0.19	0.32	0.13	0.45	0.16
GermanOP	0.61	0.15	0.40	0.13	0.35	0.09	0.42	0.13
ScandCG	0.51	0.33	0.24	0.20	0.47	0.17	0.47	0.26
ScandOP	0.61	0.15	0.42	0.13	0.35	0.10	0.42	0.12

Table IV.8: **Univariate analysis governance indices**

This table displays the Pearson correlation coefficients for the calculated governance indices. For a definition of governance indices see Appendix B. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Total sample (2,431 observations)

Governance index	**COMP**	**Country Med**	**Firm MedDev**	**Country**	**Firm**	**Bebchuk**	**Brown**	**English**	**French**	**German**
CountryMed	0.78 ***	-								
FirmMedDev	0.69 ***	0.08 ***	-							
Country	-0.28 ***	-0.13 ***	-0.29 ***	-						
Firm	0.99 ***	0.73 ***	0.72 ***	-0.30 ***	-					
Bebchuk	0.01	-0.06 ***	0.09 ***	0.12 ***	0.01	-				
Brown	0.70 ***	0.55 ***	0.47 ***	-0.01	0.71 ***	0.27 ***	-			
English	0.69 ***	0.48 ***	0.54 ***	-0.54 ***	0.67 ***	0.07 ***	0.45 ***	-		
French	-0.39 ***	-0.51 ***	-0.03	-0.03	-0.34 ***	0.03	-0.34 ***	-0.16 ***	-	
German	0.43 ***	0.41 ***	0.21 ***	-0.15 ***	0.44 ***	-0.08 ***	0.45 ***	0.18 ***	-0.24 ***	-
Scand	0.57 ***	0.36 ***	0.49 ***	-0.46 ***	0.57 ***	0.23 ***	0.46 ***	0.65 ***	0.15 ***	0.22 ***

Panel B: Legal origin subsamples

Sample	**English law**		**French law**		**German law**		**Scandinavian law**	
N	1,477		264		589		101	
EnglishCG vs. FrenchCG	0.20	***	-0.09		-0.02		0.11	
EnglishCG vs. GermanCG	0.10	***	-0.11	*	0.09	**	0.18	*
EnglishCG vs. ScandCG	0.71	***	-0.04		0.55	***	0.42	***
FrenchCG vs. GermanCG	-0.03		-0.10	*	-0.09	**	0.18	*
FrenchCG vs. ScandCG	0.28	***	0.46	***	0.07		0.14	
GermanCG vs. ScandCG	0.27	***	0.29	***	0.18	***	-0.10	

Table IV.9: **Multivariate analysis governance indices**

This table displays the regression results of the logarithm of Tobin's Q on several governance indices for the total sample. In all regressions we include the controls log(*Sales*), log(*Age*), *PPE*, *Risk*, *Leverage*, and an *ADR* dummy as well as industry and country dummies. Inference is based on robust standard errors. All p-values are reported on the basis of two-tail significance level. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Sample	**(1) Total**	**(2) Total**	**(3) Total**	**(4) Total**	**(5) Total**
N	2,431	2,431	2,431	2,431	2,431
COMP	0.288***	-	-	-	-
CountryMedCG	-	0.260***	-	-	-
FirmMedDevCG	-	0.305***	-	-	-
CountryCG	-	-	-0.022	-	-
FirmCG	-	-	0.486***	-	-
BebchukCG	-	-	-	0.041	-
BebchukOP	-	-	-	0.272***	-
BrownCG	-	-	-	-	0.109
BrownOP	-	-	-	-	0.212**
log(Sales)	-0.048***	-0.054***	-0.059***	-0.048***	-0.048***
log(Age)	-0.095***	-0.109***	-0.110***	-0.095***	-0.095***
PPE	-0.096*	-0.133**	-0.133**	-0.095*	-0.094*
Risk	-0.355***	-0.406***	-0.408***	-0.356***	-0.356***
Leverage	-0.310***	-0.262***	-0.260***	-0.310***	-0.311***
ADR	0.080***	0.094***	0.085***	0.080***	0.080***
Country dummies	yes	no	no	yes	yes
Industry dummies	yes	yes	yes	yes	yes
R2 adjusted	25.1%	23.1%	22.8%	25.1%	25.1%

Table IV.10: **Multivariate analysis parsimonious governance indices**

This table displays the regression results of the logarithm of Tobin's Q on the parsimonious governance indices for all legal origin subsamples. In all regressions we include the controls log(*Sales*), log(*Age*), *PPE*, *Risk*, *Leverage*, and an *ADR* dummy as well as industry and country dummies. Inference is based on robust standard errors. All p-values are reported on the basis of two-tail significance level. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Sample	**English law**				**French law**			
N	1,477				264			
EnglishCG	0.385***	-	-	-	-0.074	-	-	-
EnglishOP	-0.060	-	-	-	0.183	-	-	-
FrenchCG	-	0.029	-	-	-	0.545***	-	-
FrenchOP	-	0.247**	-	-	-	0.197	-	-
GermanCG	-	-	-0.142	-	-	-	-0.181	-
GermanOP	-	-	0.245**	-	-	-	0.248	-
ScandCG	-	-	-	0.126*	-	-	-	0.243*
ScandOP	-	-	-	0.133	-	-	-	0.016
log(Sales)	-0.049***	-0.049***	-0.049***	-0.050***	-0.061**	-0.055**	-0.061**	-0.058**
log(Age)	-0.074***	-0.074***	-0.070***	-0.074***	-0.196***	-0.206***	-0.189***	-0.200***
PPE	-0.06	-0.061	-0.06	-0.062	-0.390***	-0.420***	-0.384**	-0.397***
Risk	-0.382***	-0.365***	-0.388***	-0.365***	-0.906***	-0.867***	-0.954***	-0.897***
Leverage	-0.338***	-0.333***	-0.333***	-0.336***	-0.491**	-0.520**	-0.483**	-0.515**
ADR	0.06	0.077*	0.075*	0.077*	0.011	0.006	0.008	0.016
Country dummies	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes	yes	yes	yes
R2 adjusted	18.9%	17.7%	17.8%	17.9%	32.7%	35.3%	33.1%	33.3%

	(9)	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Sample	**German law**				**Scandinavian law**			
N	589				101			
EnglishCG	-0.066	-	-	-	0.656**	-	-	-
EnglishOP	0.250	-	-	-	0.505	-	-	-
FrenchCG	-	0.004	-	-	-	0.510	-	-
FrenchOP	-	0.165	-	-	-	1.245**	-	-
GermanCG	-	-	0.626***	-	-	-	0.097	-
GermanOP	-	-	-0.061	-	-	-	1.282**	-
ScandCG	-	-	-	0.030	-	-	-	0.979***
ScandOP	-	-	-	0.185	-	-	-	0.009
log(Sales)	-0.016	-0.016	-0.011	-0.016	-0.038	-0.053	-0.046	-0.032
log(Age)	-0.163***	-0.164***	-0.153***	-0.164***	-0.074	-0.062	-0.081	-0.111
PPE	-0.114	-0.112	-0.149	-0.111	-0.007	0.112	0.096	0.082
Risk	0.117	0.118	0.157	0.116	-1.1	-1.098	-0.944	-0.873
Leverage	-0.265***	-0.262***	-0.215**	-0.260***	-0.242	-0.36	-0.397	-0.393
ADR	0.118***	0.116***	0.111***	0.116***	-0.174	-0.213*	-0.19	-0.104
Country dummies	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes	yes	yes	yes
R2 adjusted	33.5%	33.4%	37.1%	33.5%	21.4%	21.1%	19.9%	31.9%

Table IV.11: **STEP-approach results including all governance provisions**

This table displays the regression coefficients for the STEP-approach for each of the legal origin subsamples. In all regressions we use the logarithm of Tobin's Q as dependent variable and include the controls log($Sales$), log(Age), PPE, $Risk$, $Leverage$, and an ADR dummy as well as industry and country dummies. Inference is based on robust standard errors. In contrast to Table IV.5, we do not exclude any governance provisions. Attributes identified in Table IV.5 are shaded grey. Attributes excluded in Table IV.5 are marked with frames. Bold figures indicate negative coefficients. All p-values are reported on the basis of two-tail significance level. One, two, and three asterisks (*,**,***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All governance attributes that exhibit no missing values in the final sample are marked with a +.

Sample	**(1) English law**	**(2) French law**	**(3) German law**	**(4) Scandinavian law**
N	1,477	264	589	101
Approach	**STEP**	**STEP**	**STEP**	**STEP**
a01 *Board independence*	0.071**		**-0.165****	
a02 *Nominating committee+*		**-0.273*****		
a03 *Compensation committee+*		0.159*		
a04 *Governance committee+*				0.631**
a05 *Board structure*	0.079**			0.386**
a06 *Board size*			**-0.074****	
a12 *Board performance reviews+*			0.374***	
a13 *Meetings outside directors+*				
a15 *Outside advisors+*			**-0.257****	
a21 *Board attendance*		**-0.119****		
a25 *Audit committee+*			0.168*	
a27 *Auditor ratification*			**-0.135****	
a30 *Option repricing policy*		0.170**		0.382*
a31 *Shareholder approval*			**-0.164****	
a32 *Executives stock ownership requirements*	0.053*		**-0.212****	
a33 *Directors stock ownership requirements+*			0.212*	
a37 *Option burn rate*			0.073**	
a40 *Vote requirement mergers*			**-0.493*****	
a41 *Written consent*		0.824***		
a42 *Special meetings*			**-0.311***	
a43 *Board amendments*	**-0.135****		**-0.225***	
a44 *Unequal voting rights+*	0.094**			
a52 *Option grants alignment*				
R2 adjusted	19%	36%	38%	36%
# identified attributes	5	5	13	3

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