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SALLA PÖYRY

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June 22, 2014

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Part A

Theoretical Context and Central Findings

1 Introduction

The fundamental function of financial markets is to channel funds within an economy. To efficiently do so, the market needs to generate prices that accurately reflect all available information. And for investors to be able to fully interpret the signals that the prices provide, they need to appreciate and understand the dynamics that drive the discount rates that bring about the prices. That is, the dimensions of risk that matter in determining asset prices. The dynamics that capture the incorporation of information into prices are elegantly described by the Efficient Market Hypothesis in Fama's (1970) influential article "Efficient Capital Markets". A market in which prices always reflect all available information is called informationally efficient.

Complete and constant market efficiency is arguably an unattainable ideal. The research questions that are addressed in this thesis are all related to phenomena that have been associated with, or explained by, financial market frictions or imperfections. By frictions, I refer to factors that measure the difficulty, quantified as a cost or time, with which an asset is traded on a financial market (Stoll, 2000). Taxes and transaction costs are common and obvious examples of market frictions as they irrefutably affect virtually every transaction.[1] However, as noted in Lippman and McCall (1986), a friction could be any factor that impacts how long it takes to trade a given amount of an asset (at the optimal price). In the context of this thesis, I also consider market imperfections, defined as market features that contradict the assumptions of traditional efficient market theories.

First, let us define the perfect market before addressing its real-world limitations. The task of defining an organizing principle that captures market dynamics is often made manageable by making a number of simplifying assumptions. That is, we define a perfect setting. The perfect market assumptions include frictionless markets, fully rational investors, and equal access to market prices and information. For instance, the capital asset pricing model (CAPM) formulated by Sharpe (1964) and Lintner (1965) is derived using a number of simplifying assumptions.[2] Therefore, its suitability as a good model of risk does to some extent rely on the relevance of these assumptions. The assumptions, to name a few, describe a world without transactions costs or taxes as well as rational (identical utility maximizing) investors with homogenous expectations, well diversified holdings and

[1] See Constantinides (1984), Keynes (1936), Summers and Summers (1989) or Wurgler (2000) for tax related examinations.

[2] The CAPM models the theoretically appropriate required rate of return of an asset building on the earlier work by Markowitz (1952) and Tobin (1958) on diversification and modern portfolio theory. The CAPM was derived independently also by Mossin (1966) and Treynor (1962). Treynor's paper was not published until 1999.

equal holding periods. Another seminal piece of research, within the area of corporate finance, is by Modigliani and Miller (1958) describing capital structure choice. It does so under a similar banner of perfection that involves complete information and efficient markets as well as no frictions such as corporate taxes (and tax shields). Needless to say, while elegant, the worlds defined by economists are not always a reflection of reality. Or as noted by Stoll (2000), the early finance paradigm rested on abstractions of frictionless and efficient markets—useful abstractions but abstractions nevertheless.

One should not, however, reject a theory solely based on its assumptions. Friedman (1953) stated that "important and significant hypotheses will be found to have "assumptions" that are wildly inaccurate descriptive representations of reality". However, he continues by stating that the theories (hypotheses) do so in order to extract only the crucial elements sufficient to yield valid predictions—omitting what can be seen as predictively irrelevant details. Thus, when empirically testing the validity of a theory, it is useful to discuss the "irrelevancy" of the assumptions. But, the theory should not be rejected purely based on the plausibility of its assumptions without sufficiently addressing their relevance and broader implications.

The notion of fully efficient markets, as defined by the Efficient Market Hypothesis, was for a long time the bedrock of financial economics. However, in the 1970s, contradicting and anomalous evidence gradually began to emerge. By anomalous, I refer to empirical patterns that were not predicted by the existing theories.[3] Capturing the spirit of the era, Jensen (1978) claimed that in a manner similar to that described by Kuhn in "The Structure of Scientific Revolutions" finance had entered a new era where scattered empirical evidence had begun arising, which seemed to be inconsistent with the earlier theories on informational efficiency as characterized in Fama (1970).[4] At this point, Jensen was referring to phenomena such as the earnings-related anomalies summarized by Ball (1978).[5]

Since then, modern asset pricing research has shifted more to understanding discount-rate variation, both across assets and over time, rather than focusing on the information channel, as highlighted by early efficient market papers (see Cochrane, 2011). And as noted by Shiller (2003), regarding non-risk based models, behavioral finance has also be-

[3] The term anomaly can be traced to Kuhn (1970).

[4] Kuhn challenged the view of progress in "normal science" viewed as "development-by-accumulation" in a world that is largely known. He argued that periods in normal science were interrupted by periods of revolutionary science when "anomalies" are discovered that lead to new paradigms.

[5] The anomaly, documented by Ball and Brown (1968) already ten years earlier, involved a post-earnings announcement "drift" in the direction indicated by an earnings surprise. The finding implies significant return predictability.

come a vital part of research. This broader science perspective accounts for psychological and sociological elements and stands in sharp contradiction with the earlier theories regarding investor behavior. A range of empirical discoveries have forced us to re-examine, or at least revisit, prior theoretical predictions on the functioning of financial markets and the assumptions underlying the earlier theories.[6]

It should nonetheless be noted, that the anomalous empirical findings do not necessarily overturn the view that markets are competitive and, therefore, reasonably informationally efficient.[7] However, they do suggest that there are activities that systematically provide rewards for holding risks not captured by the CAPM. A rational and risk based explanation, therefore, needs to include additional risk factors.[8]

This thesis consists of four separate essays that examine various features of financial markets and investor behavior that have been associated with imperfect financial markets. The first essay examines the under-diversification of investors and its sources—that is, is under-diversification rational and driven by informational advantages, or the result of the behavioral biases of investors? The former source relies on market inefficiency to justify its existence whereas the latter is an imperfection in itself. In the second essay, I examine the impact of market fragmentation on private investors. This refers to a situation where an asset is traded simultaenously on multiple venues. It examines whether market functionality (price efficiency) deteriorated for private investors as a result of a regulatory change (MiFID I) that enabled market fragmentation on a large scale, but did not guarantee equal access to all market venues across all investor types. In the third essay, we explore the connection between firm-level asset changes and return momentum—the momentum anomaly being one of the most robust documented return anomalies. We document a novel and highly robust momentum interaction. While the existing theoretical literatures on risk-based or behavioral models do not offer a clear explanation to our empirical results, recent real options models appear to hold the most promise. In the last paper, we explore the relation between ownership structures and

[6]Significant findings that have forced us to question the suitability of the CAPM include the small-firm effect by Banz (1981), the size and book to market factors by Fama and French (1992, 1993) and the momentum anomaly idenitified by Jegadeesh and Titman (1993, 2001).

[7]It should also be noted that all the perfect market assumptions do not need to be met for the market to be informationally efficient. I.e. it might be the case that all information is instantaneously impounded into prices even if the market is imperfect (e.g. in the presence of frictions such as transaction costs), as noted in Fama (1970).

[8]Cochrane (1999) notes that asset pricing theory has recognized already since Merton (1973, 1971) the theoretical possibility that we need factors, state variables or sources of priced risk, beyond movements in the market portfolio to explain realized returns.

capital structures in Russia. This is a market plagued by severe institutional imperfections and inefficiencies. Overall, all four essays examine research questions that would be irrelevant in a perfect market as assumed in the early treatments of the efficient markets model—that is, in a world with no predictability of returns, informational advantages or institutional weaknesses.

The purpose of this introduction is provide an overview of the relevant theoretical background to the research questions that are examined, and to present and discuss the central findings of the essays. The rest of the introduction proceeds as follows. Section 2 provides a brief theoretical background. Section 3 presents the main results of the essays and their contribution.

2 Theoretical background

This section presents an overview of the relevant theoretical background for the essays. First, I summarize existing research that describes efficient capital markets. Second, I provide an overview of relevant anomalous market phenomena. Finally, I present some behavioral models of finance and briefly discuss the relevance of regulation and institutions for market functionality.

2.1 The functioning financial market

Fama (1970) states that the ideal is a market where firms can make production-investment decisions, and investors can choose among the securities, under the assumption that security prices at any time “fully reflect” all available information. This constitutes an “efficient” market. Since future information is unpredictable, we also expect asset prices to be unpredictable. From this follows the associated notion that prices follow random walks.

Subsequent papers have, however, shown that returns are predictable—for example, from past returns, dividend yields, and various term-structure variables (see e.g. Fama, 1991). At least, when adjusting for risk according to the CAPM. Despite these findings, drawing any conclusions on market efficiency is a greater challenge as it must be tested jointly with an asset-pricing model (Fama, 1970), and it might well be that the CAPM is wrongly defined. Under the earlier assumption that returns are entirely unpredictable, the documented variation in price-dividend ratios was assumed to be due to variation in expected cashflows. However, now it seems all price-dividend variation corresponds to discount-rate variation (Cochrane, 2008). Thus, the apparent predictability does not necessarily entail inefficiency.

In modern theoretical work, the main emphasis has shifted to finding an appropriate pricing model that captures the relevant risk factors and dynamic variation in risk premia (discount rates)—while information is assumed to be rapidly incorporated. As concluded and well described by Cochrane (2011), understanding discount rate variation is the central organizing question of current asset pricing.[9] A functioning financial market can therefore be defined as a market that rationally and correctly prices all available information using consistent discount rates—with risk premia, that may be captured by multiple factors and factor premia that can vary across time. The risk premia are then systematically reflected in the cost of capital of firms.

2.2 The anomalous financial market

Following the wave of anomalous discoveries, Fama and French (1993, 1996) introduced size and value factors based on empirical results showing that value firms and small firms co-moved together to an extent not explained by the CAPM.

While the Fama-French model is an empirical improvement to the CAPM, several expected return strategies have nonetheless emerged that cannot be explained with market, value, and size betas. The momentum anomaly first documented by Jegadeesh and Titman (1993) is one of the most robust anomalies. It involves a simple trading strategy that buys stocks with the highest returns over the past three to 12 months and sells stocks with the lowest returns over the same horizon and produces profits that are large after market, value, and size based adjustments for risk (see e.g. Fama and French, 1996). Several risk based and behavioral models have been suggested for the anomaly but no universally accepted explanation has emerged.[10] Another example of a robust anomaly is return predictability based on past accruals, equity issues and other accounting-related sorts (Fama and French, 2008). These are examples of anomalies that continue to present significant challenges to existing theories on asset returns.

While it may be challenging to test the overall efficiency of the market, other papers have focused on identifying more temporary or local inefficiencies. The Flash Crash in

[9] Theoretical work has been done using consumption-based asset pricing models. See e.g. Campbell and Cochrane (1999), Yogo (2006) for related references. See Merton (1973) for a more comprehensive Intertemporal Capital Asset Pricing Model (ICAPM).

[10] Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) present behavioral explanations for momentum. Berk et al. (1999), Johnson (2002) and Sagi and Seasholes (2007) provide theoretical models that explain momentum.

May 2010 when the Dow Jones Industrial Average plunged about 9% only to recover the losses within minutes is an example of an occurence generally seen as a temporary market failure. As evidenced by this one-day plunge, temporary inefficiencies can feasibly emerge on asset markets. Local inefficiencies refer to situations where the ability to identify mispricing (inefficiencies) differ across investors. Findings relating to informational advantages imply, contrary to many model assumptions, that expectations on future cash flows or access to information may be heterogenous. The informational advantages can be based on sophistication, ability or actual information. As shown by Grinblatt and Keloharju (2000), different investor categories trade and perform differently. Ivkovíc et al. (2008) also find that investors perform differently. Specifically, they find that investors with concentrated portfolios outperform investors with more diversified portfolios after standard risk adjustments. They argue that individual investors hold concentrated portfolios if they are able to identify stocks with high expected returns. That is, rational investors need to assess the trade-off between the benefits of higher stock returns with the costs of higher risk due to the under-diversification. Irrespective of the source of the outperformance, we would not expect to find significant and systematic differences in investor risk-adjusted performance in an efficient market setting. If systematic outperformance is found, this would suggest some level of inefficiency on the market.

2.3 Behavioral theories

The traditional assumptions of market efficiency have struggled to survive the challenges presented by the previously described anomalies. Yet, a complete risk-based alternative theory has not emerged. The behavioral literature offers alternative explanations to many of the documented empirical regularities. The theories stem mainly from cognitive biases—for example, investor overreaction, underreaction and some even accommodate both types of judgement bias (Barberis et al. 1998, Daniel et al 1998).[11] Barberis et al. (1998) present a model of investor sentiment, which is consistent with the empirical findings of underreaction of stock prices to news such as earnings announcements, and overreaction of stock prices to a series of good or bad news that have been documented in earlier research. The momentum anomaly has also been explained with various behavioral theories (see e.g. Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999).

Fama (1998) nonetheless defends market efficiency, even if he calls the post-earnings announcement drift first documented by Ball and Brown (1968) robust to the extent of

[11] Other biases include the disposition effect, mental accounting, framing, conservativeness, representativeness. See Ritter (2003) and Shiller (2003) for an overview of cognitive biases and behavioral theories.

being "above suspicion". For there to emerge a behavioral alternative, Fama challenges researchers to try to understand what causes the market to overreact in some circumstances and underreact in others—that is, the behavioral models should universally explain the anomalies in a common framework, like risk-based pricing models try to do.

While behavioralists have equally failed to produce a universal or complete alternative theory, there is plenty of evidence in support of behavioral theories that suggests investors are not always fully rational (in the conventional 'utility maximizing' sense).

First, while shareholder portfolio concentration may also be driven informational advantages, it should be noted that evidence of under-diversification is extensive and consistent across many countries. In most cases, investors hold less than 5 stocks on average (see Barber and Odean, 2000; Goetzmann and Kumar, 2008; Grinblatt and Keloharju, 2000, 2001). This degree of under-diversification is difficult to explain with rational explanations alone.

In fact, Goetzmann and Kumar (2008) find that the level of under-diversification is greater among younger, low-income, less-educated, and less-sophisticated investors. Grindblatt et al. (2011) find that higher IQ investors are more likely to hold mutual funds and a larger numbers of stocks than lower IQ investors—these findings imply that cognitive ability is a significant determinant when discussing portfolio selection and performance. Investors have also been shown to mostly hold local stocks as shown, for example, in French and Poterba (1991), Grinblatt and Keloharju (2001b) and Huberman (2001). And finally, factors such as firm visibility have been shown to impact portfolio choice (Barber and Odean, 2008).

Behavioral finance argues that some financial market phenomena can best be understood using models in which some agents are not fully rational—that is, investor behavior builds on limits to arbitrage and psychology. Given the inability of risk based theories to fully explain financial market dynamics, it seems appropriate to also consider these possibilities. In this thesis, behavioral explanations are discussed in relation to many of the empirical findings.

2.4 Regulatory and institutional settings

As stated, anomalies indicate either market inefficiency (resulting in profit opportunities and predictability) or inadequacies in the existing risk-based theoretical models being employed. In the case of market inefficiencies, the disturbances can easily result from regulatory or institutional weaknesses, which feasibly can evolve over time.

Most pricing models do not explicitly consider the regulatory or institutional environment as both are subject to change—or alternatively, they are considered marginal in terms of magnitude. Yet, regulation changes that impact market structure can impact the efficiency of the market, at least temporarily. O'Hara (2003) asserts that asset pricing often ignores the central fact that asset prices evolve in financial markets. In her view, models need to incorporate the transactions costs of liquidity and the risks of price discovery. Both of these elements, liquidity and price discovery, can easily be affected by regulatory changes. They involve the microstructure of financial markets and are also relevant when discussing the efficiency of markets.

An institutional feature examined in the second essay of the thesis is fragmented trading. This refers to a situation in which the same asset is traded on multiple venues simultaneously. As noted by Hasbrouck (1995), when homogeneous securities trade in multiple markets, it is interesting to determine where price discovery (the incorporation of new information) occurs. His statement implies that some venues might systematically lead others—simultaneity often being impossible if transaction prices are determined independently. These types of market features can easily impact the efficiency of short-term pricing. In fact, as discussed and examined in the essay, the impact of market fragmentation on liquidity and price discovery is a relevant question. Another widely examined regulatory example with regards to price efficiency involves short-selling constraints (Saffi and Sigurdsson, 2011; Beber and Pagano, 2013). In fact, short-selling constraints have been shown to affect stock price efficiency. Beber and Pagano (2013) find that these constraints are detrimental for liquidity and price discovery. Acknowledging the effect that regulation can have on market efficiency is important in any financial policy discussion.

The critical role of the regulatory and institutional setting are accentuated when examining financial markets in developing economies. In fact, the weaknesses can be severe to the extent that they noticeably affect the operational efficiency of the market, referring to the way resources are employed. With regards to pricing, poor investor protection in emerging markets has been shown to discourage informed trading resulting in worse price efficiency (Morck et al, 2000; Jin and Myers, 2006). And far beyond short-term price efficiency, aspects such as weak legal investor protection can severely impact the economic growth of an economy (e.g., Shleifer and Vishny, 1997). Weak corporate governance impedes effective resource allocation and slows productivity growth. Levine and Servos (1998) shows that stock market liquidity and banking development both positively predict growth, capital accumulation, and productivity improvements. These results depict the extremes in terms of the economic implications of regulation and institutional settings. Needless to say, the effects of regulation are noticeable for market efficiency even when considering less severe weaknesses than the ones found in developing economy settings.

The final essay of this thesis examines a Russian setting. The research question illustrates a perhaps more economically tangible consequence of an imperfect market settings—that is, unequal access of firms to external financing. In this particular case, the financial market is clearly not efficiently serving its fundamental function of allocating capital.

3 Summary and contribution of the essays

This thesis consists of four essays. Two of the essays are single authored and the two remaining are coauthored. This section provides an overview of the essays.

3.1 Essay 1: What drives shareholder portfolio concentration across firms?

In the first essay, I examine the under-diversification that is widely exhibited investors by analyzing the firm characteristics that drive the average portfolio concentration of shareholders across stocks. The examination sheds light on the underlying drivers of under-diversification—particularly, is it motivated, in part, by rational reasoning?

The under-diversification of investors has been extensively documented and is consistent across many countries. Barber and Odean (2000) report that a typical investor in the U.S. holds 4 stocks. Grinblatt and Keloharju (2000, 2001) examine Finnish portfolios and similarly find that investors are severely under-diversified holding an average number of 2.4 stocks for individuals and 2.9 for domestic institutions. These findings raise a number of questions as the results are quite clearly difficult to reconcile with the theoretical predictions dating back to the seminal work by Markowitz (1952)—that is, that investors should hold a value-weighted market index as an optimal risky asset.

The under-diversification of investors could partly be explained by informational advantages. That is, the ability of investors to identify underpriced stocks when combined with the limitations set by costly diversification and information acquisition (see Ivkovíc et al., 2008; Ekholm and Maury, 2013). However, the results in Goetzmann and Kumar (2008)—that the level of under-diversification is greater among younger, low-income, less-educated, and less-sophisticated investors—imply the opposite. Based on these results, one would expect under-diversification, on average, to be driven by behavioral biases and limitations in cognitive skills, rather than rational reasoning.

In my essay, “What drives shareholder portfolio concentration across firms?”, I analyze the firm-level drivers that impact the average portfolio concentration of its shareholders using data from the Finnish Central Securities Depository (FCSD) legal liability accounts to calculate the average holding weights of a stock in the portfolios of its shareholders.

The analysis uncovers systematic variation whereby the average portfolio weight of a stock increases with firm-specific risk and value uncertainty as evidenced by a higher average weight in stocks with higher past return volatility, no analyst coverage and less synchronous price movements. Positive future earnings surprises are also characteristic of stocks with higher average portfolio weights.

The findings consistently indicate that information related aspects are significant drivers of shareholder portfolio composition. The results contradict the claim that ignorance, or behavioral bias, alone underlie the under-diversification of individual investors. The findings also have implications for the price efficiency of stocks as the existence of informational advantages imply that the ability to identify mispriced stocks differs across investors.

3.2 Essay 2: Does stock market fragmentation harm private investors? A post-MiFID analysis

In the second essay, “Does stock market fragmentation harm private investors? A post-MiFID analysis “, I analyze the impact of market fragmentation as enabled by the Markets in Financial Instruments Directive (MiFID) in November 2007 on private investors.

The directive introduced less regulated trading venues enabling anonymous and pre-trade unobservable order placements alongside regulated exchange markets across all European member states. Despite being considerable in size, the new venues with varying degrees of pre- and post-trade transparency are unavailable to all investors.

The question that emerges from this recent market development is whether retail investors are put at a disadvantage as information is increasingly kept outside public view. As noted by Ye (2011), although the intended purpose of the less transparent venues was to facilitate large liquidity trades, the benefit of anonymity in electronic crossing networks may also have attracted informed traders to these venues. This raises concerns that informed traders can create toxic order flow or harm price discovery by being able to hide their trades in these venues.

I examine the trading activity of private investors and estimate the effect of the introduction of multi-market trading on these stock transactions. The evidence suggests that market fragmentation has not hampered market price discovery or liquidity on the main exchange to the extent that it would have affected retail investors. While the examination provides no evidence of a harmful effect, increased activity on alternate exchanges does seem to coincide with lower intraday price dispersion and volatility among retail investors, but even that effect is trivial in terms of economic magnitude. Trading on alternate venues, particularly dark pool venues with less pre-trade transparency, appears to be concentrated in stocks with less price uncertainty (lower intra-day volatility) and greater liquidity, as predicted by the model in Zhu (2013). The trades also mainly consist of larger orders that benefit from the lower transactions costs and smaller risk of price impact enabled by these markets—as also intended by regulators.

The findings in my essay suggest that fragmented trading should not directly be associated with poorer market quality or increased short-term volatility—at least not, based on the impact it has had on private investor transactions. The liquidity or price discovery on the primary stock exchange appears not to have been significantly affected by the regulation change. The results have policy implications as the discussion has been ongoing regarding the need to further regulate multimarket trading. My results suggest that there is no need to further regulate these venues based on the effect they have had private investors.

3.3 Essay 3: Firm Expansion and Stock Price Momentum

In the third essay, coauthored with Peter Nyberg, we explore the relation between stock price momentum, an anomaly first documented by Jegadeesh and Titman (1993), and firm expansion. A momentum strategy involves buying stocks with the highest returns over the past three to 12 months and selling stocks with the lowest returns over the same horizon. This strategy produces profits that remain large after any standard adjustments of risk (see e.g. Fama and French, 1996). Yet, despite its simplicity, researchers have not been able to identify the source of the profits—that is, a widely accepted explanation for the anomaly has not emerged. Building on a growing literature that models the relation between firm-level investment decisions and expected returns, we investigate the role of firm-level asset expansion as a source of momentum profits.

We find that momentum profits are large and significant for firms that have experienced large asset expansions or contractions, whereas they otherwise are small and often insignificant. This interaction pattern is not subsumed by previously documented drivers of momentum. The pattern is also present in market states where prior literature has documented an absence of momentum profits. Furthermore, we find a positive time-series relationship between aggregate asset growth and return momentum that is stronger than that of variables related to business cycles and investor sentiment, which have previously been linked to momentum profitability.

The momentum interaction that we document is highly robust and dominates many of the previously identified momentum drivers. These findings are significant for the effort to understand the underlying causes of the return anomaly. Existing behavioral theories for momentum do not appear fully compatible with our results. Hirshleifer (2001) emphasizes that if the behavioral biases postulated by Barberis et al. (1998) and Daniel et al. (1998) drive return momentum, we should observe particularly strong post-earnings announcement drifts (PEADs) in the groups of stocks that show strong momentum. Our results do not provide much evidence that the PEADs are concentrated among firms that have experienced large asset reductions or expansions. This implies that the interaction that we document is not driven by the same psychological biases that have been previously used to explain momentum.

Our evidence does support the view that asset growth is an important determinant of expected returns and, thus, also the momentum effect. While most existing models of firm investment and momentum cannot explain our results, recent real options models appear to hold the most promise. Our findings also suggest that investment, or asset growth, should be considered in future work aiming to model expected returns.

3.4 Essay 4: Influential ownership and capital structure

In the fourth essay, coauthored with Benjamin Maury, we explore the relation between ownership structures and capital structures in Russia—an economy with a state-run banking sector, weak corporate governance, and highly concentrated ownership.

The paper sets out to examine how the exceptional institutional environment has affected the capital structures of Russian firms focusing on three central aspects that are characteristic features of the Russian market: namely, high ownership concentration (Guriev and Rachinsky, 2005), high frequency of politically connected firms (Faccio, 2006), and weak legal investor protection (e.g., Shleifer and Vishny, 1997).

We find that firms with the state as controlling shareholder have significantly higher leverage than firms controlled by domestic private controlling shareholders other than oligarchs. Both firms controlled by the state or oligarchs finance their growth with more debt than other firms. Profitability is negatively related to leverage across all types of controlling owners indicating a preference for internal funding over debt. The results indicate that firms with owners that have political influence or ties to large financial groups enjoy better access to debt.

Our results confirm that Russian firms have not had equal access to debt financing to finance their operations and growth. Our main contribution is documenting that both state and oligarch controlled firms appear to have better possibilities to optimize their capital structures than do other firms. The wider economic implications of the result are considerable. The inequality in the availability of external financing may deter the development of the economy by reinforcing the already dominant status of Russia's financially and politically influential elite. The result imply the economy is not operationally efficient.

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Part B

The Essays

Essay 1

What drives shareholder portfolio concentration across firms?

What drives shareholder portfolio concentration across firms?*

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Abstract

This paper examines the under-diversification widely exhibited by investors by analysing the firm characteristics that drive the average portfolio concentration of shareholders across stocks. The analysis uncovers systematic variation whereby the average portfolio weight of a stock increases with firm-specific risk and value uncertainty as evidenced by a higher average weight in stocks with higher past return volatility, no analyst coverage and less synchronous price movements. Positive future earnings surprises are also characteristic of stocks with higher average portfolio weights. The findings suggest that information advantages are significant contributing factors to the portfolio choices of investors.

*JEL Classifications: G11. Keywords: portfolio choice, concentration, information asymmetry.

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1 Introduction

Most asset pricing models assume that securities are traded by diversified and rational investors with marginal pricing power. In fact, most rational models of portfolio choice build on the assumption that investors receive no compensation or risk adjustment for holding idiosyncratic risk implying, as in the capital asset pricing model (CAPM) formulated by Sharpe (1964) and Lintner (1965), that investors should hold a value-weighted market index as an optimal risky asset. These financial dogmas have, however, been challenged by a wide variety of empirical work.

An apparent and obvious fallacy in the assumptions used to derive the predictions on portfolio choice pertains to the widely documented under-diversification of investors. Previous papers that study the portfolio composition of investors consistently find that a large portion of individual investors choose to concentrate their portfolios in a small number of stocks. The evidence of under-diversification is extensive and consistent across many countries. Barber and Odean (2000) report that a typical investor in the U.S. holds 4 stocks while Goetzmann and Kumar (2008) find that the average holding increases from four to seven over the period 1991-1996.[1] Grinblatt and Keloharju (2000, 2001) examine Finnish portfolios and similarly find that investors are severely under-diversified holding an average number of 2.4 stocks for individuals and 2.9 for institutions.

Having established that most investors have severely under-diversified equity portfolios comprising of a handful of stocks, the question emerges as to how shareholders choose and weight the stocks that they hold. This question is closely related to the assumption of informational efficiency (Fama 1970, 1991). If expectations are heterogenous and informational advantages exist, portfolio holdings and concentrations are expected to vary across investors. Ivković et al. (2008) find that investments made by individuals that concentrate their portfolios in a few stocks outperform those made by individuals with more diversified portfolios. They also find that the outperformance is stronger for stocks not included in the S&P 500 index and local stocks—that is, in stocks where mispricing is more likely to be found or easier to identify. This evidence suggests that concentrated investors may be able to successfully exploit information asymmetries and, thus, generate significant abnormal returns. Ekholm and Maury (2013) find corroborating evidence in a study that utilizes Finnish data. They find that average shareholder portfolio concentration is significantly and positively related to future operational performance, valuation

[1] For additional evidence of under-diversification among U.S. households, see e.g. Blume and Friend (1975) and Kelly (1995). Guiso et al. (2002) includes references on papers that examine portfolios across different countries.

and abnormal stock returns.

However, the empirical evidence regarding the ability and informational advantages of concentrated shareholders is not conclusive. Goetzmann and Kumar (2008) find that the level of under-diversification is greater among younger, low-income, less-educated, and less-sophisticated investors. This result is highly inconsistent with the idea that concentration reflects informational advantages. On a related note, Grindblatt et al. (2011) find that higher IQ investors are more likely to hold mutual funds and a larger numbers of stocks than lower IQ investors. Based on these latter results, one would expect shareholder concentration in a stock to be a function of behavioral factors, such as visibility as implied by Barber and Odean (2008), or factors that amplify misguided efforts to outsmart the market—rather than information asymmetry or informational advantages. Investors have also been shown to mostly hold local stocks as shown, for example, in French and Poterba (1991), Grinblatt and Keloharju (2001) and Huberman (2001). Based on these results, one would expect behavioral drivers to be at play when examining shareholder portfolio concentration.

This paper sets out to identify the firm-level drivers that impact the average shareholder portfolio concentration across domestic stocks, i.e. what determines the average weight of a stock in the portfolios of its investors. The average portfolio weight of stock across all shareholders is estimated using an extensive and detailed Finnish data set. As the data enables the precise estimation of the average portfolio weight of a stock across all domestic institutional and retail investors, the examination enables the identification of the aggregate drivers of portfolio concentration. Some investors can understandably be more informed or skilled than others in choosing their shareholdings for a wide variety of individual reasons. This makes it more difficult to draw broad conclusions from a smaller subgroup of investors without identifying the source and consistency of the informational ability. Thus, it is interesting to examine the drivers of portfolio composition on an aggregated level as made possible by the comprehensive Finnish data. The findings can also be seen as having wider implications as the aggregate shareholder base can easily be related to pricing related features across stocks. Building on the findings by Ivković et al. (2008) that concentrated investors outperform diversified investors, we would also expect firms with more concentrated shareholders to differ from firms with more diversified shareholders, in terms of their characteristics and pricing related features.

The empirical investigation sets out with a descriptive analysis consisting of a regression of the average portfolio weight of a stock against a number of firm-level characteristics. Firstly, the data reveals a similar level of under-diversification as reported by previous studies. The examination also shows that the average portfolio weight of a stock is higher in firms with a lower beta, higher past returns, larger market capitalization, higher stock price and a broader shareholder base. The average weight is also higher in stocks with higher past return volatility and lower turnover—as well as being higher in stocks without analyst coverage. Among the stocks with analyst coverage, the average weight is higher in stocks that have an average recommendation by analysts that is more favourable. The results imply that investors do not load heavily on stocks with significant systematic risk, as evidenced by the negative relation to beta. Shareholders nonetheless display an appetite for risk by overweighting stocks with significant risk for mispricing, i.e. stocks with higher volatility, lower turnover and no analyst coverage. Investors also seem to overweight stocks that are deemed attractively priced by analysts, which indicates at least some level of price informativeness.

Having established that the average shareholder concentration is related to firm fundamentals, the second part of the empirical analysis investigates the relationship between average portfolio weight with return related features that have previously been linked to information asymmetry or mispricing.

While the previous results are more descriptive and do not provide direct evidence of the importance of information related drivers on portfolio concentration in a stock, the next examination provides more direct evidence of the significance of information related drivers in the portfolio choice of shareholders. In the next step of the analysis, a regression is estimated of earnings surprise against average portfolio weight and other relevant firm-level controls. If a higher average portfolio weight is driven by an information advantage held by under-diversified shareholders, we would expect a positive relationship between average portfolio weight and future earnings surprise. The results confirm this finding. While variables such as past return- and earnings volatility have an amplifying effect on earnings reaction (the absolute value of earnings surprise), average portfolio concentration is the only variable with significant predictive power on the direction of the surprise. The finding is highly robust and remains intact even when excluding the smaller and more illiquid stocks as well as when controlling for the effects of extreme values. The abnormal level of concentration in a stock (measured as the residual from the regression of average concentration against firm-level characteristics) is also positively and significantly related to future earnings surprise. This evidence suggests that behavioral biases or other impacting drivers alone do not drive portfolio concentration on an aggregate level.

The final test involves investigating the relationship between shareholder portfolio concentration and the amount of firm-specific information incorporated into share prices, measured as in Gul et al. (2010) by stock price synchronicity. The results show that the synchronicity of stocks with a higher average weight across shareholder portfolios is smaller than in firms with a smaller average portfolio weight. This result supports the notion that firms with more concentrated shareholders are more severely affected by informational asymmetry or have a larger amount of firm-specific risk priced in their stock returns.

When combining the evidence, the empirical analysis consistently indicates that information related aspects are significant drivers of shareholder portfolio composition. It is not necessarily the case that highly concentrated shareholders impact the return features of stocks, such as synchronicity, but the relationship appears to exist. That is, in the case of synchronicity, it is more plausible that investors with concentrated holdings choose certain types of stocks—that is, with greater information asymmetry and a larger firm-specific price component—rather than impact the return characteristics of the stocks, or the flow of information into prices, through their trading. The results nonetheless indicate that information advantages and ability are related to the portfolio choice of investors on an aggregate level. That is, information advantages or information related drivers can help explain why some investors concentrate their stock portfolios in a few stocks. The evidence is not conclusive but it nonetheless contradicts the claim that ignorance, or behavioral bias, alone underlie the under-diversification of individual investors.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the results. Section 4 discusses the findings and concludes the paper.

2 Data and empirical analysis

2.1 Data sources

An important data source is the unique shareholder register of publicly listed Finnish firms upheld by Euroclear Finland Ltd responsible for maintaining the Finnish Central Securities Depository (FCSD) legal liability accounts—a data source also employed by Grinblatt and Keloharju (2000, 2001). Below, is a description of the shareholder register as well as other data sources used in the analysis.

The Finnish FCSD shareholder register contains entries of all transactions in the shares of publicly traded Finnish firms from the 2nd of January 1995 and onwards, as well as the balance of the register as of the 1st of January 1995. The dataset enables the identification of the holdings of each retail and institutional investor that has participated in the Finnish stock market within the sample period with the exception of foreign holdings that are netted under nominee-registered shareholdings. For individual investors and domestic institutions, the data enables the compilation of the portfolio value in euros for each shareholder by combining the balance of register as of the 1st of January 1995 with the transaction entries. Thus, the portfolios correspond to the total equity portfolio of the individuals invested in the Finnish public equities market.[2]

The relevant records of accounting data and stock price data have been extracted from Thomson Reuters Datastream. The sample covers a panel of Finnish firms listed on the Helsinki stock exchange 1996-2006. Some of the firms in the Finnish sample have dual voting share classes. However, only the more liquid low voting share class is considered in the main empirical analysis as the ownership of the other class tends to be highly concentrated and static.

2.2 Methodology and variable definitions

The main variable of interest captures the average weight of a stock in the portfolios of its shareholders. The measure is described in Ekholm and Maury (2013)[3] and is estimated by first compiling the portfolio holdings of all retail and institutional investors individually on the 31st of December each year and then calculating the relative weight of each stock in each shareholder's portfolio. The sample covers all institutional and private holdings and transactions on an investor level. The average weight of a stock in the portfolios of its owners is used as a measure of portfolio concentration, average portfolio weight ($PW_{i,t}$). The measure is calculated from the weight of each share, calculated each year in Euros on the 31st of December across all shareholders on 31st of December. The average is the equally-weighted average across all shareholders. That is, the measure is calculated as:

$$V_{x,t} = \sum_{i=0}^{n}(S_{i,x,t} * P_{i,t}) \qquad \text{and} \qquad PW_{i,t} = \frac{\sum_{x=0}^{N}(S_{i,x,t}*P_{i,t})/V_{x,t}}{N_{i,t}}$$

where $V_{x,t}$ is the value of shareholder x portfolio at time t consisting of shareholder x holdings S across companies i with price P. The measure $PW_{i,t}$ is the average portfolio weight of stock i in the portfolios of its N shareholders, that is equally-weighted

[2]The data set covers direct investments into Finnish equities, i.e. funds and foreign stock holdings are not covered. Grinblatt et al. (2011) nonetheless report that only 22% of those who own individual stocks in Finland also own funds meaning that the stock ownership in itself is highly informative of the level of diversification. The end-of-2000 values of Finnish households' mutual fund and individual stock holdings were 5.2 billion and 23.7 billion euros, respectively. Data from the Finnish tax data set in 2000 reveal that only 0.1% of individuals with stock holdings have foreign assets.

[3]I thank the authors Anders Ekholm and Benjamin Maury for providing the data on average shareholder portfolio weight.

average value of the holdings, stock price multiplied by quantity, divided by the total stock portfolio value of all shareholders with holdings in stock i. Only investors that hold shares in stock i on December 31 of year t are included in the average for firm i at year t. The arithmetic average largely reflects the concentration across domestic private investors since the number of shareholders (shareholder base) is dominated by domestic private shareholders in terms of the number of individual investors. The total number of stocks in the sample is denoted n.[4]

The averages are not adjusted with the expected average portfolio weight of a stock as predicted by the CAPM—that is, the value-weighted market weight of a stock—since the empirical finding is that shareholders actually hold portfolios that are far from this prediction. Since investors hold less than 4 stocks on average, it seems inappropriate to make a theoretical adjustment that is based on the assumption that investors hold a portfolio comprising of all the stocks on the market. Since the relative weight of the largest companies is considerable, this would imply making a sizeable adjustment to the largest stocks while making only a marginal adjustment to the small cap stocks. Yet, the shareholder portfolios are concentrated across all stocks. This would distort the results as the deviation from the theoretical prediction would largely by explained by firm size, i.e. the basis for the adjustment.

The empirical analysis starts with a panel regression of the average portfolio weight of a stock against a number of firm-level characteristics to understand the drivers of the measure. The regressions are estimated as OLS panel data regressions with industry and year controls. A firm fixed effects model is not used as many variables do not vary sufficiently on firm-level. The results are not sensitive to using a censored regression model. The firm-specific variables considered consist of 1) stock price and return related measures, 2) accounting and size measures, 3) ownership measures, and 4) analyst coverage and consensus recommendation.

The return measures included in the regression are the CAPM beta measured on past year daily returns ($Beta$). Due to concerns relating to thin trading, the results for the CAPM beta are also confirmed using a beta estimated using weekly returns; the results are

[4]Foreign shareholdings are available on a custody level. I.e. the ultimate owner cannot be precisely identified. A high level of concentration on custody level nonetheless is likely to indicate a concentrated ownership of the custody account. Thus, portfolio concentration on a custody level is expected to correlate positively with concentration on an investor level. As the average portfolio concentration is an arithmetic average across shareholders, this data limitation does not significantly affect the measure. The measure is largely driven by the average portfolio concentration of domestic private investors. The correlation between the average portfolio concentration ($PW_{i,t}$) and portfolio concentration across private domestic investors is 0.97 measured for all common stocks.

unchanged. Past 12 month return ($Past\,\mathrm{Re}\,t$), standard deviation of daily returns over past year ($\mathrm{Re}\,tVol$), annual trading volume divided by shares outstanding ($Turnover$) and the natural logarithm of share price on the 31st of December ($Ln\,\mathrm{Pr}\,ice$) are also included. The share price is included to account for the preference for skewed returns in lottery stocks (i.e. very low priced stocks with a relatively small probability of a large payoff) displayed by some investors, as noted by Kumar (2009) and Bali et al. (2011).[5]

Following Grullon et al. (2004) and Bodnaruk and Östberg (2013), firm size can be expected to impact the shareholder base, and arguably also portfolio weight, through its influence on firm visibility and coverage. Hence, firm size is included as a variable and measured as the natural logarithm of market capitalization on the 31st of December ($LnMCap$).[6] In addition, the following accounting measures are included: earnings volatility estimated over past 5 year earnings before interest and taxes ($EarningsVol$), operational performance measured as earnings before interest and taxes over total assets (ROA), and the book-to-market ratio measured as total assets over market capitalization on the 31st of December each respective year (BM).

The ownership measures included as explanatory variables are the concentration of ownership capturing block ownership present, which is calculated as a Herfindahl index for shareholders that hold at least 5% of the shares outstanding ($Hfi5$). As noted in Gul et al. (2010), the presence of large controlling shareholders may impact the availability of information from the firm as owners may have an interest to more selectively disclose information. While this may be less of a concern in a transparent market, such as in Finland, effects may nonetheless exist due to a lower free-float of shares and diminished investor interest (demand for information).

The number of shares held by private shareholder over the number shares held by institutional investors ($PrivShare$) and the breadth of the shareholder base measured as the natural logarithm of the number of shareholders covered by the FCSD register ($LnShareh$) are also included. The breadth of the shareholder base does not take into account shareholders with nominee registered holdings. Thomson Reuters Datastream includes a measure of the number of shareholders in a company as reported in the an-

[5] Using proprietary data, Kumar (2009) shows that certain groups of individual investors appear to exhibit a preference for lottery-type stocks, which he defines as low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness.

[6] As shareholders do not hold a portfolio corresponding to the value-weighted market index, a mechanical relation does not arise between variables such as past returns or market capitalization. Measured as an average across investors and inspecting the relation between firm size and average portfolio concentration across stocks, the results are not mechanically driven by the past return performance or size of the stock in a passively chosen portfolio.

nual accounts of the company—however, the measure is only available for a subsample of the observations. The correlation between the logarithm of the measure taken from the annual reports and *LnShareh*, defined as previously stated, is nonetheless 0.9789. Private ownership is also considered as a variable (*PrivShare*) as the portfolio measure is estimated across all shareholders and portfolio concentration may systematically vary between private and institutional shareholders; thus, inducing a systematic relation with private ownership. This measure inversely capturing institutional ownership covered by the FCSD register is also expected to sufficiently capture (correlate) with foreign institutional interest across shares.

The measures included to analyze the effect of analyst coverage and recommendations are a dummy that equals one for firms with analyst coverage (*Analystdummy*), a variable for the number of analysts following the firm (*Analystcov*), and the consesus analyst recommendation by analysts (*Analystrec*). The measure capturing the consensus analyst recommendation (*Analystrec*) ranges from 1 to 5 where the low values depict the most favorable recommendations. Values between 1-1.49 depict consensus recommendations corresponding to a 'Strong Buy', 1.5-2.49 depict a 'Buy', 2.5-3.49 a 'Hold', 3.5-4.49 an 'Underperform', and 4.5-5 a 'Sell' rating. The analyst ratings are measured at year-end each year.

The estimated model is the following (where *industry* and *year* are vectors of industry and year controls):

$$PW_{i,t} = c + \beta_1 Beta_{i,t} + \beta_2 PastRet_{i,t} + \beta_3 RetVol_{i,t} + \beta_4 Turnover_{i,t} + \beta_5 LnPrice_{i,t} + \beta_6 LnMCap_{i,t} + \beta_7 EarningsVol_{i,t} + \beta_8 ROA_{i,t} + \beta_9 BM_{i,t} + \beta_{10} Hfi5_{i,t} + \beta_{11} PrivShare_{i,t} + \beta_{12} LnShareh_{i,t} + \beta_{13} PrivShare_{i,t} + \beta_{14} Analystdummy_{i,t} + \beta_{15} Analystcov_{i,t} + \beta_{16} Analystrec_{i,t} + \beta industry + \beta year + \epsilon_{i,t}$$

2.3 Relation to price reactions surrounding earnings announcements

The second section of the empirical analysis examines whether average portfolio weight has consequences for return-related measures at the firm-level. While the tests do not examine a direct causal relationship, the results nonetheless indicate whether the measure captures significant variation across firms that is closely related to pricing.

Firstly, a regression is estimated of earnings surprise against average portfolio weight. If a higher average portfolio weight were partially driven by an information advantage held by the under-diversified shareholders, we would expect a positive relationship between average portfolio weight and future earnings surprise. Earnings surprise is measured as the cumulative announcement-day excess return measured from one day before and one day after the announcement of the financial statement for the previous year, i.e. the average portfolio weight in year t is related to the announcement of the result for year t as announced during the first quarter in year $t+1$. The excess return is calculated as the difference between the daily raw return and the value-weighted, capped market index (OMX Helsinki Cap)[7]. The variables are calculated as follows:

$$ABR = \sum_{j=t-1}^{t+1} (r_{i,j} - r_{m,j})$$

The analysis begins with univariate regressions of earnings surprise and average portfolio concentration. The earnings surprise (ABR) is regressed against average portfolio concentration (PW) as well as dummies defined on annually sorted tercile groups dividing firms into low, medium and high $PW_{i,t}$.

The regressions are also estimated with a variable on portfolio concentration that is calculated solely for shareholders with an ownership that exceeds 0.1% ($PW01_{i,t}$)—that is, an average portfolio weight when only considering the largest shareholders at year-end each year. A break-point of a 0.1% shareholding corresponds approximately to the 100 largest shareholders in firms (excluding nominee registered ownership). This captures significant shareholders without lesser limits and costs of diversification. The larger shareholder category consists to a larger extent of institutional and more sophisticated shareholders that potentially can be expected to have a greater informational advantage. Larger shareholders, nonetheless, have greater liquidity constraints as they cannot acquire or sell considerable positions in less liquid stocks without having a price impact with their transactions. Comparing the results between all shareholders and solely the largest shareholders also provides evidence of differences in ability- and information related drivers in the portfolio concentration of different investor groups.

The included control variables are: past earnings volatility ($EarnVol$), past returns ($PastRet$), past return volatility ($RetVol$), firm size ($LnMCap$), share turnover ($Turnover$), natural logarithm of price ($LnPrice$), the breadth of ownership measured as the natural logarithm of the number of shareholders on the 31st of December ($LnShareh$), the share of private ownership ($PrivShare$), a dummy indicating the presence of analyst coverage ($Analystdummy$), a variable for the number of analysts following the firm ($Analystcov$), and the consensus analyst recommendation by analysts ($Analystrec$). The regression is an OLS regression with year controls. The individual earnings announcement

[7]The Nasdaq OMX capped index is constructed such that he market value of securities issued by the same body may not exceed 10 per cent of the index total market value.

surprises are independent events and there should be no firm-level depence across events or endogeneity concerns. The estimated model is the following (where controls is a vector of controls and year a vector of time dummies):

$$ABR_{i,t} = c + \beta_1 PW_{i,t} + \beta controls + \beta year + \epsilon_{i,t}$$

The earnings surprise ($ABR_{i,t}$) is the annual result for firm i announced in the first quarter of year $t+1$. The regression is estimated with earnings surprise and absolute value of earnings surprise as the dependent variable. The level of earnings reaction ($|ABR|$) is considered to test the relation of the variables to value uncertainty separately from mispricing (measured as earnings surprise). The models are estimated for average portfolio weight ($PW_{i,t}$) and average portfolio weight across the largest shareholders with ownership exceeding 0.1% ($PW01_{i,t}$). Where absolute value of earnings surprise is defined as:

$$|ABR| = \left| \sum_{j=t-1}^{t+1} (r_{i,j} - r_{m,j}) \right|$$

To assure the robustness of the results, a number of alternate model specifications are also considered. These robustness tests are described in detail in Section 3 following the main results.

2.4 Relation to stock price synchronicity

As an additional dimension, the relationship between the stock price synchronicity and average portfolio weight is analyzed. Roll (1988) finds that a large portion of return variation is not explained by changes in market factors or announcements of relevant public information, which he interprets as an indication of the amount of private and firm-specific information flowing into stock prices via informed trading. In this paper, a regression is run similar to the setup in Gul et al. (2010). A firm-fixed effects regression with year controls of stock price synchronicity is estimated against average portfolio weight and control variables in line with the variables used in earlier studies. Stock price synchronicity is measured by first estimating a market model for each fiscal year. Daily stock returns are regressed against the value-weighted, capped market index (OMX Helsinki Cap). Lagged market returns are included to alleviate concerns over potential non-synchronous trading biases (Scholes and Williams, 1977; French et al., 1987). The synchronicity measure is equal to the R^2 of the market model estimated each year. As estimated in Gul et al. (2010), the variable $R^2_{i,t}$ ($SYNCH_{i,t}$) is estimated with the following model:

$$r_{i,t} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t-1} + \epsilon_{i,t}$$

The control variables are: past returns ($Pastret$), return volatility ($RetVol$), share turnover ($Turnover$), firm size ($LnMCap$), leverage measured as interest bearing debt over total assets ($Leverage$), past earnings volatility ($EarnVol$) and book-to-market (BM). The model is estimated for average portfolio weight ($PW_{i,t}$) and average portfolio weight across the largest shareholders with ownership exceeding 0.1% ($PW01_{i,t}$). For each year, an average is calculated of $PW_{i,t}$ and $PW_{i,t-1}$ ($PW_{average_{t,t-1}}$), which is used to explain the stock price synchronicity in that period (t)—this is done for PW and $PW01$. The estimated firm-fixed effects model is the following:

$$SYNCH_{i,t} = c_i + \beta_1 PW_{i,average_{t,t-1}} + \beta controls + \beta year + \epsilon_{i,t}$$

3 Summary statistics and results

The summary statistics are presented in Table 1, Panels A and B. As evidenced in Panel A of Table 1, the data reveals a similar under-diversification of investors as reported in previous studies. The average portfolio weight of a stock in the portfolios of investors is 0.2649. This implies on aggregate across all stocks and investors an average of 4 stocks in the portfolios of shareholders. The standard deviation is 0.1304.

The panel includes observations for 119 firms over the period 1995-2006. The average portfolio weight across the firms also displays significant within-firm variation. The average within-firm standard deviation is 0.0431 for $PW_{i,t}$. The within standarard deviation is the average deviation from each firm's average calculated across the unbalanced panels. The descriptive statistics for the explanatory variables are reported in Panel B of Table 1 and the correlations are reported in Table 2.

Table 3 reports the results for the panel regression on the determinants of average portfolio weight. The results in Column (1) include only stock price measures whereas Columns (2) and (3) also include the accounting and size as well as ownership measures, respectively. Columns (4) and (5) consider differences in analyst coverage and analyst recommendations across the firms. The results show that the average portfolio weight of a stock is higher in firms with lower beta, higher past returns, larger market capitalization and a broader shareholder base. The results regarding past returns and size can be interpreted as evidence of a behavioral effect whereby visibility has a positive impact on average portfolio weight. A larger market capitalization and high past returns can both be seen as proxies for firm visibility or investor attention as shown by Barber and Odean (2008) for extreme returns and Bodnaruk and Östberg (2013) for firm size. A mechancial relation could arise if all stocks were passively held in the portfolios of investors. However, as the portfolios on average are highly concentrated and holdings have been acquired and sold over each year by the shareholders considered, this is not a major concern. An alternate measure of shareholder recognition as argued by Merton (1987) is the shareholder base. The variable measuring the breadth of the shareholder base ($LnShareh$) also has a positive and significant effect on average portfolio weight. This measure does not suffer from any concerns regarding a potential mechanical relation between the variables. Overall, these results can been seen as supporting the behavioral theories on portfolio composition.

Trading volume, also used by Barber and Odean (2008) as a proxy for visibility, does not have a positive effect on portfolio weight. Trading volume can nonetheless also be interpreted as a variable closely related to information uncertainty and mispricing as the information flow into prices is diminished in less traded stocks. The negative relation would, thus, imply a preference for stocks with greater value uncertainty.

Tables 3 also shows other interesting findings. The average weight ($PW_{i,t}$) is higher in stocks with higher past return volatility and earnings volatility—as well as being higher in stocks without analyst coverage. These results are in line with the finding on trading volume. Among the stocks that have analyst coverage, the average weight is higher in stocks that have an average recommendation by analysts that is more favourable as evidenced by the negative and significant coefficient for $Analystrec$. The results imply that shareholders concentrate their holdings in stocks with less coverage and more uncertainty that can be expected to be more severely plagued by information asymmetry as well as being more likely to be mispriced. The results also imply an informational awareness among shareholders, on average, as holdings are more concentrated in stocks with favorable recommendations.

The results pertaining to earnings surprise reported in Table 4 show an interesting pattern where average portfolio concentration is positively related to earnings surprise. Panel A of Table 4 reports the results from univariate regressions of earnings surprise against average portfolio concentration. The results show that the level and direction of earnings surprise is positively related to average portfolio concentration ($PW_{i,t}$) driven by the firms with the highest average portfolio concentration as evidenced by the results in Column (2). The results in Column (2) include two dummy groups for firms falling into the medium (PW_medium) and highest (PW_high) PW groups each year.

The model is also estimated for average portfolio weight estimated across shareholders with an ownership stake above 0.1%.[8] A separate inspection of the relation between

[8] The average portfolio weight when estimated across the largest shareholders is 0.2582, which implies a similar average diversification across the largest investors as across all investors. The standard deviation is somewhat larger across the larger shareholders (0.1856) than across all shareholders (0.1304). The average within-firm standard deviation is 0.0717 for $PW01_{i,t}$.

earnings surprise and the portfolio concentration of the largest shareholders shows if the effect is driven by the portfolio choices of smaller retail investors or institutional investors that can be assumed to be more sophisticated. The results are stronger for average portfolio concentration estimated across all shareholders, which perhaps reflects the liquidity constraints experienced by larger investors. For larger investors, it can feasibly be more difficult to take advantage of mispricing as prices are likely to react to increased buy (sell) volumes. Another reason may be related to the reasoning behind the purchases. While the regressions do control for aspects such as block ownership ($Hfi5$), the average portfolio concentration of large shareholders may nonetheless also more sensitively pick up on other significant variation between firms than time-varying active investment decisions by shareholders. That is, the ownership structure among the largest shareholders is likely to be more static, and thus, the measure would not react as sensitively to firm-specific information. This could explain the results. The measure can also vary due to investment activity in other firms by the largest owners that is non-related to the firm but nonetheless impacts the diversification of its shareholders. The measure is more sensitive since it is calculated over a smaller number of shareholders. Also, larger and more sophisticated investors are more likely to diversify using foreign investments and other instruments than direct equity investments, which means the measure may not to the same extent measure portfolio concentration.

In Panel B of Table 4 other control variables are considered and average portfolio concentration emerges as the only variable with consistently significant predicitive power in Columns (1) and (2) of Panel B in Table 4. The coefficients 0.0552 and 0.0526 imply an approximate increase of 0.7% in abnormal return over the three day estimation window for a one standard deviation increase in $PW_{i,t}$. Once again, the results are stronger when average portfolio concentration is measured across all shareholders. Given the nature and magnitude of the mispricing, it is feasible that the results reflect the ability of smaller investors to speculate on mispriced stocks without having a direct price impact on the stocks through the acquisition of the positions.

The results in Table 6 that display the effect of average portfolio weight on the level of the earnings reaction measured as the absolute value of the three day earnings surprise show a totally different pattern. The magnitude of the earnings reaction is positively related to past return volatility, earnings volatility, share turnover and private ownership while being negatively related to past returns. The results with respect to past earnings volatility and return volatility are in line with expectations as both are proxies of uncertainty. A higher share turnover may also mean the information is to a larger extent priced within the three day window surrounding the announcements. The variable of interest, however, average portfolio weight ($PW_{i,t}$), is not related to the magnitude of the reaction—solely the direction of the reaction—implying it captures information advantage rather than uncertainty.

To assure that the results on average portfolio weight reported in Table 4 are robust, a number of alternate model specifications are estimated. In Table 6, the previous results are firstly replicated in Column (1) to facilitate comparisons. As the effect may be driven by the smallest and most illiquid firms, the same model is estimated excluding these observations. In Column (2), the lowest tercile of firms sorted by market capitalization each year is dropped, and yet, the coefficient for average portfolio weight remains largely unchanged. This coefficient is smaller but continues to be positive and significant. The same applies for Columns (3) and (4) where the quartile with the lowest turnover and highest average bid-ask spreads are excluded from the regressions. In Column (3), the quartile with the lowest turnover ($Turnover$) the previous calendar year is dropped. In Column (4), the firms with the highest average daily closing bid-ask spread during the previous calendar year are dropped. The bid-ask spread is the average relative bid-ask spread calculated as the difference between the ask- and bid price divided by their mid-point using daily closing prices ($BidAsk$).

In Column (5) of Table 6, the one-year lagged earnings surprise is included as a control as there might be autocorrelation in the earnings surprises of some stocks and investors may react to previous announcement returns. This additional control leaves the result intact—in fact, the coefficient increases to 0.0638 and is significant at the 1% level. The sample size is somewhat reduced due to the inclusion of the lagged variable.

Since the results might be affected by outliers in the variables, the model is re-estimated using a sample where the key variables, ABR and PW, are winsorized at a 10% level. That is, 10% of the observations are modified in each tail for both of the variables. The results reported in Column (6) show that the result is not driven by extreme observations within the sample.

Finally, it might also be that the level of portfolio concentration may partly be driven by other firm-level factors than expected earnings surprise. As noted in Grullon et al. (2004) and Bodnaruk and Östberg (2012) for the number of shareholders, the measure may systematically vary across firms due to differences in variables such as size and firm age. That is, larger and older (more visible) firms are expected to have a broader shareholder base. The same could apply to the level of portfolio concentration meaning, for instance, that average portfolio concentration could partly be driven by fluctuations in such firm-level factors. In order to ensure that the results are not driven by other firm characteristics which are not directly related to the perceived mispricing of the firm's earnings, the regressions are also run with a variable where the effect of a number of variables on $PW_{i,t}$ are removed. This involves using the residuals from the regression reported in Table 3 Column (4), denoted excess portfolio weight (RPW_{it}), as the measure of average portfolio concentration. This essentially corresponds to the abnormal variation in the measure (or "excess concentration") where the model in Table 3 Column (4) is used as a predictive regression to determine the expectation. While the measure reduces the sample and introduces some noise given the explanatory power of the regressions used to estimate the residual, the results nonetheless provide additional evidence of the relation between earnings surprise and average portfolio concentration. The key variables RPW and ABR are winsorized as previously by 10% in both tails. The results reported in Column (7) for RPW confirm the positive relationship from the previous tests.

The evidence in Table 6, thus, confirms that the finding is not driven solely by the smallest and most illiquid firms, autocorrelation in earnings surprises, extreme values or spurious correlation.

Table 7 shows the results relating stock price synchronicity to average portfolio weight. Building on the premise in Gul et al. (2010), higher stock price synchronicity, or lower firm-specific return variation, stems from firm-specific information related features. In instances where informed trading is discouraged or there exists limits in the incorporation of firm-specific information into stock prices, prices become more synchronous and less informative. In stocks with greater information asymmetry, it is reasonable to assume that investors have more to gain from analysing the stock and taking active positions—similarly, one would expect less synchronous return patterns. In stocks with higher average porfolio weight, we see a lower synchronicity implying greater idiosynchratic variation in prices. For consistency, the regression is estimated using PW and $PW01$. The regressions are estimated as firm-fixed effects regressions to account for any firm-level differences in synchronicity not accounted for by the controls. If information advantages are a partial driver of portfolio selection, we would expect more concentrated portfolios to be invested in stocks with a larger fraction of firm-specific price variation—i.e. investors expect to be compensated for holding idiosynchratic risk in these stocks. The results support this finding showing that the stocks with higher average portfolio concentration have less syncronous price movements.

4 Discussion and conclusions

Evidence presented by papers studying the portfolio composition of shareholders tell us that individual investors are severely under-diversified (see e.g. Barber and Odean, 2000; Grinblatt and Keloharju; 2000, 2001). As noted in Ivković et al. (2008), there are several feasible and rational reasons why individual investors might choose to concentrate their portfolios. Rational reasoning might be that the fixed costs of trading make it uneconomical to diversify a portfolio with direct investments, or alternatively investors are able to identify stocks with high expected returns. While rational explanations do exist, it might also be the case that the portfolio choices are driven by behavioral biases, such as overconfidence or familiarity.

The level of under-diversification naturally varies across individual investors—and surely so do the reasons for the under-diversification. Thus, it is more interesting to examine the aggregate patterns of under-diversification. If investors on average choose to concentrate holdings in stocks with greater information asymmetry and superior future performance, this has significant implications for price efficiency.

This study examines the average portfolio weight of a stock in the portfolios of its shareholders. The analysis uncovers systematic variation across firms whereby the average portfolio weight of a stock increases with past return volatility, lower trading turnover and is greater in firms that lack analyst coverage. All these results imply a positive relationship with the information asymmetry of stocks. Among stocks with coverage, the portfolio concentration is higher in firms with favorable recommendations among the firms with coverage. This finding suggests that investors on average are, at least to some extent, informed.

A perhaps surprisingly strong finding is that positive earnings surprises are concentrated in stocks with higher average portfolio weight. This simple examination reveals an interesting pattern as average portfolio weight emerges as the only variable with an ability to predict positive earnings surprises. Of course, other motivations may as well influence the average portfolio weight of a stock in the portfolios of its investors, but this robust relationship provides convincing evidence that informational aspects are also at play in determining the aggregate portfolio composition of investors.[9]

[9] It should also be noted that the result is very unlikely to be affected by factors such as insider trading or employee stock-based incentive schemes since the measure is an arithmetic average across all shareholders. The average number of shareholders is 5100 and the results remain robust even when excluding the smallest firms that are also likely to have the most concentrated shareholder bases. Hence, changes among a single investor category, such as insiders, is unlikely to be reflected in the measure.

As a final test, the relationship between stock price synchronicity and average portfolio weight is analysed. Building upon a foundation laid by Roll (1988), this examination extends a growing body of literature providing evidence that is consistent with an information-based interpretation of stock price synchronicity suggesting synchronicity serves as a proxy for the amount of firm-specific information incorporated into share prices (see e.g. Gul et al., 2010 and Morck et al., 2000). The finding is that average portfolio weight is negatively related to stock price synchronicity. This result implies that shareholders concentrate holdings in firms with more firm-specific risk.

There exists mounting evidence that behavioral factors impact and bias the portfolio choices of individuals. While it may well be that some individuals are primarily driven by behavioral biases, the combined evidence in this paper provides compelling evidence that portfolio choices also reflect ability and informational advantage. At the very least, the results show that on average information advantages and informational asymmetry are also related to the under-diversification of investors.

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Table 1

Descriptive Statistics

Table 1 presents descriptive statistics for the variables used in the empiricial analysis. Panel A presents an overview of the variable depicting average portfolio weight (concentration), $PW_{i,t}$. The measure is defined as the equally-weighted average portfolio weight of stock in the portfolios of its shareholders ($PW_{i,t}$). The sample includes 119 firms. The standard deviation is reported for the overall sample as well as between and within firms. The reported between firms standard deviation is the estimated standard deviation of the 119 group means. The within standarard deviation is the average deviation from each firm's average calculated across the unbalanced panels. The explanatory variables in Panel B are defined as follows. The CAPM beta is measured on past year daily returns against a capped market index OMX Helsinki Cap ($Beta$), past 12 month return ($Past\,\mathrm{Re}\,t$) is the cumulative return for the past year, standard deviation of daily returns over past year ($\mathrm{Re}\,tVol$) is calculated on daily raw returns, turnover is the annual trading volume divided by shares outstanding ($Turnover$) and price is measured as the natural logarithm of share price on the 31st of December ($Ln\,\mathrm{Pr}\,ice$). Firm size is measured as the natural logarithm of market capitalization on the 31st of December ($LnMCap$). Earnings volatility is estimated as the standard deviation of the past 5 year earnings before interest and taxes ($EarningsVol$) while operational performance is measured as earnings before interest and taxes over total assets (ROA), and the book-to-market ratio is measured as total assets over market capitalization on the 31st of December each respective year (BM). The ownership measures included as explanatory variables are the extent of block ownership calculated as a Herfindahl index for shareholders that hold at least 5% of the shares outstanding ($Hfi5$), the number of shares held by private shareholder over the number shares held by institutional investors ($\mathrm{Pr}\,ivShare$), and the breadth of the shareholder base measured as the natural logarithm of the number of shareholders covered by the FCSD register ($LnShareh$). Analyst coverage and recommendations are considered with a dummy that equals one for firms with analyst coverage ($Analystdummy$), a variable for the number of analysts following the firm ($Analystcov$), and the consesus analyst recommendation by analysts ($Analystrec$). The measure capturing the consensus analyst recommendation ($Analystrec$) ranges from 1 to 5 where the low values depict the most favorable recommendations. Values between 1-1.49 depict consensus recommendations corresponding to a 'Strong Buy', 1.5-2.49 depict a 'Buy', 2.5-3.49 a 'Hold', 3.5-4.49 an 'Underperform', and 4.5-5 a 'Sell' rating. The analyst coverage and recommendations are taken at year-end each year.

Panel A. Average portfolio weight

Portfolio Weight (PW)	mean	std.dev.
Overall	0.2649	0.1304
Between firms		0.1243
Within firms		0.0431

Panel B. Explanatory variables

Variable	obs	mean	std.dev.	median
Beta	800	0.6064	0.4849	0.4919
EarningsVol	800	5.9379	7.6448	3.4935
LnAge	800	3.433	1.1231	3.6109
ROA	800	8.9139	12.1360	8.5000
PastRet	800	0.2289	0.6542	0.1484
RetVol	800	0.028	0.0172	0.0245
BM	800	0.6866	0.4455	0.6000
Turnover	800	0.4975	0.4931	0.3533
LnPrice	800	1.7847	1.0404	1.8924
LnMCap	800	19.1661	1.7638	19.1624
Hfi5	800	0.1531	0.1629	0.0862
PrivShare	800	0.3083	0.2444	0.2520
LnShareh	800	8.5371	1.2766	8.3854
Analystcov	626	8.1374	7.0681	6.000
Analystrec	626	2.6671	0.7403	2.5700

Table 2

Correlations

Table 2 presents the pairwise correlations between the explanatory variables. All variables are defined as described in Table 1.

	Beta	EVol	LAge	ROA	PRet	RVol	BM	Turno	LPrice	LnMC	Hfi5	Priv	LSha	Acov	Arec
Beta	1.000														
EarningsVol	0.2612	1.000													
LnAge	-0.1594	-0.2331	1.000												
ROA	-0.1142	-0.3585	0.0658	1.000											
PastRet	-0.0497	-0.0587	0.0240	0.2855	1.000										
RetVol	0.2935	0.4942	-0.2165	-0.3656	-0.1093	1.000									
BM	-0.2297	-0.2361	0.0938	-0.3009	-0.2500	-0.0508	1.000								
Turnover	0.5662	0.1484	-0.1185	-0.1635	-0.1516	0.1854	-0.1891	1.000							
LnPrice	0.0569	-0.2583	0.1854	0.3125	0.1485	-0.2835	-0.2718	0.0480	1.000						
LnMCap	0.4011	-0.2944	0.0817	0.2627	0.1220	-0.3484	-0.1500	0.2578	0.5053	1.000					
Hfi5	0.2703	-0.0074	-0.1336	0.0539	0.0682	-0.0085	-0.0411	0.2156	0.1255	0.4546	1.000				
PrivShare	-0.0929	0.2532	-0.0842	-0.0947	-0.0338	0.1923	-0.1066	-0.1465	-0.2475	-0.5111	-0.4525	1.000			
LnShareh	0.4667	-0.0038	0.0591	-0.0635	-0.0761	-0.1407	0.0924	0.3085	0.1182	0.6293	0.1221	-0.1007	1.000		
Analystcov	0.5125	-0.1492	-0.0066	0.0760	-0.0286	-0.1419	-0.0098	0.4266	0.2856	0.8044	0.4458	-0.4315	0.6720	1.000	
Analystrec	-0.1133	0.1048	0.0480	-0.1820	0.0432	0.1363	0.1399	-0.1494	-0.1326	-0.2249	-0.1359	0.2416	0.0103	-0.1199	1.000

Table 3

Determinants of average portfolio weight (PW)

Table 3 displays the results from panel OLS regressions of average portfolio weight ($PW_{i,t}$) against various firm-level determinants. All regressions include industry and year controls. All variables are defined as described in Table 1.

	Table 3. Average Portfolio Weight (PW)				
	(1)	(2)	(3)	(4)	(5)
Beta	-0.0042	-0.0314**	-0.0430***	-0.0407***	-0.0397**
	(0.32)	(2.25)	(2.92)	(2.98)	(2.31)
PastRet	0.0134***	0.0073	0.0088*	0.0105**	0.0117***
	(2.62)	(1.55)	(1.87)	(2.16)	(2.61)
RetVol	0.4025	1.4610***	1.4858***	1.1286**	2.2304**
	(1.59)	(3.04)	(2.89)	(2.52)	(2.58)
Turnover	-0.0301***	-0.0334***	-0.0335***	-0.0343***	-0.0184**
	(3.07)	(3.83)	(3.60)	(3.97)	(2.09)
LnPrice	0.0291***	0.0157***	0.0195***	0.0156***	0.0134***
	(6.99)	(3.59)	(4.08)	(3.41)	(2.67)
EarningsVol		-0.0000	-0.0007	-0.0009	-0.0015**
		(0.07)	(1.04)	(1.49)	(1.97)
LnAge		-0.0001	0.0003	0.0022	0.0016
		(0.03)	(0.07)	(0.57)	(0.42)
ROA		0.0010**	0.0008**	0.0006	0.0014***
		(2.44)	(2.01)	(1.40)	(2.91)
BM		0.0513***	0.0383***	0.0368***	0.0239**
		(3.48)	(2.59)	(2.70)	(1.98)
LnMCap		0.0234***	0.0152**	0.0197***	0.0123*
		(6.48)	(2.24)	(3.06)	(1.91)
Hfi5			0.0490*	0.0488*	0.0742***
			(1.68)	(1.77)	(2.61)
PrivShare			0.0508**	0.0377	0.0686***
			(2.19)	(1.63)	(2.61)
LnShareh			0.0207***	0.0222***	0.0211**
			(2.71)	(3.07)	(2.08)
Analystdummy				-0.0750***	
				(5.93)	
Analystcov					0.0017
					(1.30)
Analystrec					-0.0090*
					(1.67)
Year controls	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes
N	800	800	800	800	626
Adj R^2	0.3766	0.4341	0.4547	0.4978	0.5512

Table 4

Shareholders diversification and earnings surprise

Table 4 displays the results from a regression of cumulative abnormal returns over a three day window surrounding annual earnings announcements (earnings surprise) against average portfolio weight ($PW_{i,t}$, $PW01_{i,t}$) and various firm-level controls. Panel A displays univariate regression results. In Panel B, additional control variables are considered. The alternate portfolio concentration measure that is included ($PW01_{i,t}$) is the average portfolio weight of a stock calculated as an equally-weighted average across all shareholders with an ownership stake that exceeds 0.1% of the shares outstanding. Abnormal returns are calculated as excess returns defined as the difference between daily raw returns and the capped market index OMX Helsinki Cap calculated from one day before to one day after the announcement. All regressions in Panel B include year controls. All variables are defined as described in Table 1.

	Panel A. Univariate regression			
	(1)	(2)	(3)	(4)
PW	0.0303**			
	(2.06)			
PW_medium		0.0060		
		(1.08)		
PW_high		0.0092*		
		1.92		
PW01			-0.0021	
			(0.71)	
PW01_medium				0.0015
				(0.32)
PW01_high				0.0040
				(0.69)
Constant	-0.0016	0.0012	0.0070*	0.0046
	(0.34)	(0.37)	(1.91)	(1.44)
N	1252	1252	1252	1252
R^2	0.0018	0.0008	0.0000	0.0004

	Panel B. Earnings surprise, ABR			
	(1)	(2)	(3)	(4)
EarnVol	0.0003	0.0004	0.0000	0.0000
	(0.65)	(0.56)	(0.06)	(0.04)
PastRet	0.0015	0.0014	0.0024	0.0025
	(0.53)	(0.48)	(0.86)	(0.90)
RetVol	-0.2735	-0.4088	-0.2798	-0.4363
	(1.25)	(1.55)	(1.25)	(1.61)
LnMCap	0.0033	0.0010	0.0028	-0.0001
	(1.19)	(0.17)	(1.00)	(0.01)
Turnover	-0.0004	0.0013	-0.0015	0.0012
	(0.06)	(0.13)	(0.21)	(0.11)
LnPrice	-0.0020	-0.0022	-0.0014	-0.0019
	(0.71)	(0.64)	(0.49)	(0.55)
LnShareh	-0.0064**	-0.0057	-0.0031	-0.0019
	(2.08)	(1.48)	(1.12)	(0.57)
PrivShare	-0.0069	-0.0058	-0.0127	-0.0157
	(0.57)	(0.39)	(0.98)	(0.94)
Analystdummy	0.0017		-0.0018	
	(0.27)		(0.31)	
Analystcov		-0.0029		-0.0036
		(0.74)		(0.91)
Analystrec		0.0003		0.0003
		(0.25)		(0.26)
PW	0.0552**	0.0526*		
	(2.56)	(1.90)		
PW01			0.0238*	0.0306
			(1.70)	(1.60)
Year controls	Yes	Yes	Yes	Yes
N	938	691	938	691
Adj R^2	0.0229	0.0314	0.0229	0.0329

Table 5

Shareholders diversification and level of earnings reaction

Table 5 displays the results from a regression of the absolute value of the cumulative abnormal returns over a three day window surrounding annual earnings announcements (earnings reaction) against average portfolio weight ($PW_{i,t}$, $PW01_{i,t}$) and various firm-level controls. Abnormal returns are calculated as excess returns defined as the difference between daily raw returns and the capped market index OMX Helsinki Cap calculated from one day before to one day after the announcement. All regressions include year controls. All variables are defined as described in Table 1.

	Table 8. Mod Abnormal Returns, $\lvert ABR \rvert$			
	(1)	(2)	(3)	(4)
EarnVol	0.0006*	0.0006	0.0006**	0.0007*
	(1.79)	(1.45)	(1.97)	(1.82)
PastRet	-0.0052***	-0.0043**	-0.0052***	-0.0044**
	(2.68)	(2.04)	(2.71)	(2.16)
RetVol	0.4690***	0.5287**	0.4946***	0.5636**
	(3.04)	(2.38)	(3.11)	(2.45)
LnMCap	0.0018	0.0009	0.0022	0.0017
	(0.87)	(0.19)	(1.05)	(0.36)
Turnover	0.0109**	0.0154**	0.0102**	0.0148**
	(2.16)	(2.17)	(2.00)	(2.05)
LnPrice	0.0002	0.0006	0.0004	0.0007
	(0.13)	(0.27)	(0.23)	(0.33)
LnShareh	-0.0026	-0.0025	-0.0030	-0.0038*
	(1.15)	(0.91)	(1.49)	(1.66)
PrivShare	0.0191**	0.0246**	0.0230**	0.0321***
	(2.11)	(2.24)	(2.38)	(2.60)
Analystdummy	0.0031		0.0022	
	(0.69)		(0.54)	
Analystcov		0.0003		0.0003
		(0.31)		(0.32)
Analystrec		-0.0001		0.0002
		(0.05)		(0.09)
PW	0.0024	-0.0067		
	(0.15)	(0.33)		
PW01			-0.0113	-0.0203
			(1.13)	(1.38)
Year controls	Yes	Yes	Yes	Yes
N	938	691	938	691
Adj R^2	0.0671	0.0810	0.0681	0.0828

Table 6

Robustness tests—shareholder diversification and earnings surprise

Table 6 displays the results from a regression of cumulative abnormal returns over a three day window surrounding annual earnings announcements (earnings surprise, ABR) against average portfolio weight ($PW_{i,t}$) and various firm-level controls. Abnormal returns are calculated as before as simple excess returns defined as the difference between daily raw returns and the capped market index OMX Helsinki Cap calculated from one day before to one day after the announcement. All regressions include year controls. All variables are defined as described in Table 1. To assure the robustness of the results shown in Table 4, the estimations are replicated using slightly altered specifications. To ease comparison, the results from Column (2) in Panel B of Table 4 are re-produced below in Column (1). In Column (2), the observations that correspond to the tercile each year of firms with the lowest market capitalization at December 31st are removed from the sample. In Column (3), the observations with the lowest annual turnover ($Turnover$) from the year preceeding the earnings announcement are removed. In Column (4), the observations with the highest average daily bid-ask spread ($BidAsk$) calculated using closing prices from the year preceeding the earnings announcement are removed. In Column (5), the one year lagged earnings surprise is included as a control variable (ABR_lag1). In Column (6), the variables earnings surprise (ABR) and average portfolio weight (PW) are winsorized at a 10% level in both extremes. In Column (7), the variable PW is replaced with RPW which is the residual from the regression estimated in Table 3 Column (4). The variables ABR and RPW are also winsorized at the 10% level.

	Table 6. Robustness tests						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EarnVol	0.0003	0.0001	0.0005	0.0003	-0.0000	0.0001	-0.0004
	(0.65)	(0.12)	(1.02)	(0.66)	(-0.02)	(0.47)	(-1.26)
PastRet	0.0015	0.0030	0.0005	0.0012	0.0044	0.0013	0.0017
	(0.53)	(1.01)	(0.17)	(0.42)	(1.41)	(0.63)	(0.77)
RetVol	-0.2735	-0.1403	-0.1900	-0.2854	-0.3448	-0.1730	-0.0781
	(-1.25)	(-0.34)	(-0.63)	(-1.05)	(-1.24)	(-1.10)	(-0.36)
LnMCap	0.0033	0.0009	0.0029	0.0013	0.0008	0.0006	-0.0008
	(1.19)	(0.29)	(0.93)	(0.40)	(0.25)	(0.32)	(-0.41)
Turnover	-0.0004	0.0033	-0.0023	-0.0008	0.0053	0.0011	-0.0011
	(-0.06)	(0.37)	(-0.29)	(-0.11)	(0.68)	(0.26)	(-0.25)
LnPrice	-0.0020	0.0007	-0.0009	0.0003	-0.0025	-0.0007	0.0013
	(-0.71)	(0.22)	(-0.24)	(0.09)	(-0.77)	(-0.34)	(0.63)
LnShareh	-0.0064**	-0.0044	-0.0063*	-0.0049	-0.0064*	-0.0029	-0.0006
	(-2.08)	(-1.27)	(-1.77)	(-1.39)	(-1.89)	(-1.47)	(-0.30)
PrivShare	-0.0069	-0.0115	-0.0135	-0.0145	-0.0124	-0.0101	-0.0084
	(-0.57)	(-0.80)	(-1.02)	(-0.99)	(-0.93)	(-1.28)	(-0.96)
Analystdummy	0.0017	-0.0022	0.0006	0.0045	0.0102	0.0021	0.0051
	(0.27)	(0.28)	(0.08)	(0.65)	(1.53)	(0.50)	(1.10)
PW	0.0552**	0.0438**	0.0494**	0.0492**	0.0638***		
	(2.56)	(1.97)	(2.00)	(1.98)	(2.72)		
ABR_lag1					-0.0477		
					(1.13)		
WPW						0.0452**	
						(2.36)	
RPW							0.0525**
							(1.97)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	938	723	786	818	804	938	773
Adj R^2	0.0262	0.0329	0.0208	0.0188	0.0222	0.0211	0.0121

Table 7

The effect of shareholder diversification on stock price synchronicity

Table 7 displays the results from regressions of annual stock price synchronicity against average portfolio weight ($PW_{i,t}$, $PW01_{i,t}$) and various firm-level controls. Stock price synchronicity is measured by first estimating a market model for each fiscal year. Daily stock returns are regressed against the value-weighted, capped market index (OMX Helsinki Cap). Lagged market returns are included to alleviate concerns over potential non-synchronous trading biases. The synchronicity measure is equal to the R^2 of the market model estimated each year. The regressions are firm-fixed effects regression with year-level controls. All variables are defined as described in Table 1.

	Table 7. Stock Price Synchronicity			
	(1)	(2)	(3)	(4)
PastRet	-0.0130**	-0.0123**	-0.0126**	-0.0119**
	(2.38)	(2.20)	(2.27)	(2.08)
RetVol	1.4426***	1.4219***	1.5376***	1.4317***
	(3.95)	(3.07)	(4.14)	(3.12)
Turnover	0.0222***	0.0283**	0.0213***	0.0260**
	(3.37)	(2.54)	(3.40)	(2.44)
LnMCap	0.0491***	0.0528***	0.0478***	0.0495***
	(6.53)	(5.89)	(6.87)	(6.05)
Leverage		0.0182		0.0196
		(0.39)		(0.42)
EarnVol		0.0018**		0.0023***
		(2.45)		(3.08)
BM		-0.0219		-0.0198
		(1.43)		(1.33)
$\text{PW}_{average_{t,t-1}}$	-0.1445*	-0.2263**		
	(1.74)	(2.40)		
$\text{PW01}_{average_{t,t-1}}$			-0.1359***	-0.1574***
			(2.98)	(2.95)
Year controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	848	684	848	684
Adj R^2	0.3212	0.3167	0.3271	0.3116

Essay 2

Does stock market fragmentation harm private investors? A post-MiFID analysis

Does stock market fragmentation harm private investors? A post-MiFID analysis*

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Abstract

This paper studies the impact of market fragmentation on private investors—an investor category with no access to non-public venues. Market fragmentation on a large scale was made possible in Europe by the adoption of the Markets in Financial Instruments Directive (MiFID) in November 2007. I use a unique Finnish data set to measure the trading activity of individuals and estimate the effect of the introduction of multi-market trading on retail investor stock transactions. The evidence suggests that market fragmentation has not hampered market price discovery or liquidity to the extent that it would have affected private investors. While the examination provides no evidence of a harmful effect, increased activity on alternate exchanges does coincide with lower intraday price dispersion and volatility among retail investors, but that effect is trivial in terms of economic magnitude. The results have policy implications regarding the need to additionally regulate these alternate venues.

*JEL Classifications: G12, G14, G18. Keywords: dark pools, price discovery, fragmentation, retail investors, equity market structure.

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1 Introduction

Trading in European equities was transformed with the implementation of the Markets in Financial Instruments Directive ('MiFID') in November 2007. The directive introduced less regulated markets called Multilateral Trading Facilities (MTFs), and also alternative trading venues enabling anonymous and pre-trade unobservable order placements, alongside the regulated exchange markets across all countries of the European Economic Area (EEA).[1] The regulatory changes have resulted in a drastically different post-MiFID trading environment that includes multiple new trading platforms with varying degrees of pre- and post-trade transparency that despite their size are unavailable to all investors. This paper studies the impact that market fragmentation has had on private investors—an investor category with no access to non-public trading venues.

While the broader implications of multimarket trading may be unclear, institutions have nonetheless embraced the new equity trading systems, as evidenced by their rapid growth. The share of turnover in European equities traded on venues with a visible order book was 43.86% in December 2010 according to Thomson Reuters—of which a large share was traded on MTF venues rather than on the traditional regulated exchanges. A considerable share of the total turnover (37.26%) was traded on venues with limited transparency, often called 'dark pools'. This category comprises anonymous trading platforms mostly using transaction prices derived from the primary exchange and some using a hidden order book. In Nordic equities, 62.41% was traded on markets with a visible order book, including MTF venues. The less transparent venues that are entirely unaccesible to private and non-professional investors corresponded to 31.13% of total turnover.[2]

The development has largely been driven by the cost competitiveness of the alternate exchanges. As mentioned in Ready (2013), the change from highly regulated monopolistic markets to multi-market trading has decreased the direct costs of trading by increasing the competition between venues. Also, by simply matching orders internally, investors can avoid the cost of paying two transaction fees to an exchange or external dark-pool operator. In an examination on the expectations from MiFID, Degryse (2009) argues that increased competition leads to more liquidity, reflected in lower spreads and greater market depth.

Despite such benefits as the significant decrease in trading costs, the market devel-

[1]MiFID is an EU law aimed at harmonising the regulation for investment services. An overview of the relevant regulation is provided in Section 2. See Degryse (2009) and Gresse (2012) for additional information.

[2]Monthly statistics available at Thomson Reuters Monthly Market Share Reports webpage.

opment has also received a fair share of critisism. In a hearing on the review of MiFID, the European Commission remarked that the increased use of dark pools raises concerns regarding price discovery on public exchanges.[3] Duncan Niederauer, chief executive of NYSE Euronext, argues that dark pool venues serve an important function for investors trading large blocks of securities, but they should not account for a substantial portion of overall equity volume. He claims that price discovery deteriorates and private investors are put at a disadvantage as information is increasingly kept outside public view (Financial Times, 2012). The chief executive of OMX Helsinki echoes his concerns. He warns that the increasing amounts of turnover that are being routed to venues with limited or no transparency hamper the market. He posits that price discovery suffers as trading becomes thin (Talouselämä, 2012).

The critique often stems from a concern that market fragmentation hampers price discovery on the main exchange as informed trades migrate to anonymous venues (Ye, 2011; Barclay et al., 2003). As noted in Boehmer and Wu (2013), informed traders often have incentives to trade in a way that minimizes information leakage, and therefore, information is not impounded into prices instantaneously. However, the prediction that market fragmentation weakens price discovery is not entirely clear. As stated in Zhu (2013), dark pools offer potential price improvements but at the risk of no execution of the submitted trade. Trades are mostly executed at prices derived from the main exchange. Investors do not know whether there are counterparties available, which can lead to a delayed execution time and an unfavorable price development in the underlying stock price. As informed traders tend to trade in the same direction, they face a higher execution risk in the dark pool in comparison to uninformed traders. Zhu (2013) shows that exchanges are more attractive to informed traders while dark pools are better suited for trading in more liquid stocks with lower price uncertainty and intra-day volatility.[4]

Regarding the implications for liquidity, Hendershott and Mendelson (2000) and Degryse et al. (2008) find that the introduction of a dark pool venue that derives its price from the main market generates liquidity by inducing some investors to submit orders that otherwise would not have submitted. However, if the dark pool venue attracts uninformed order flow, the liquidity on the main exchange ultimately suffers. This follows from there being less uninformed traders present on the exchange that previously could compensate for losses generated when trading against informed traders. The presence of less uninformed traders discourages some investors from trading on the main exchange—thus, the

[3]The concerns are being addressed in MiFID II. The new directive is expected to adopt caps on the volume that can be traded on dark pools under the existing transparency waivers.

[4]The empirical findings in Ready (2013) and Buti et al. (2011b) support the predictions of Zhu (2013).

presence of dark pool venues may deteriorate the liquidity on the main exchange.

The prediction that exchanges attract informed traders can, under certain conditions, mean that adding an anonymous dark pool venue alongside an exchange improves price discovery (Zhu, 2013). The implications for private investors are nonetheless not necessarily favorable. On average, this prediction would imply that private investors, confined to trading on the exchange, are more likely to be trading against an informed party—as pointed out in Hendershott and Mendelson (2000) and Degryse et al. (2008) with regards to any investor type, private or other, trading on the main exchange. Thus, it would follow that private investors, being less informed on average, are disadvantaged on a market with improved price discovery but reduced liquidity. Overall, the prior papers provide multiple predictions that can be interpreted in different ways with regards to private investor stock transactions. The empirical outcome, thus, emerges as a separate research question to be adressed in this paper.[5]

I examine the implications of stock market fragmentation in Finnish equities on private investor transactions. This is enabled by the unique Finnish data set that covers the stock transactions of all domestic private investors surrounding the introduction of MTF and dark pool (DP) venues. My findings contribute to our understanding of the importance of investor protection for non-professional investors and fair access to information by examining the effect that the market structure in the current regulatory setting has had on the least informed investor category. Second, this paper contributes to the growing literature on trading dynamics in fragmented markets. Using data from the Finnish Central Securities Depository, I am able to observe the transactions of all private investors active on the stock market. Private investors are arguably the most vulnerable market participants as they have no access to the alternate venues as well as having the highest cost and inconvenience of acquiring information on a post-trade basis. The empirical examination evaluates the effect of dark pool and MTF trading on the intra-day price volatility and transaction prices of private investors.

The results suggest that market fragmentation has not disadvantaged private investors. While the intra-day price volatility of private transactions has increased since November 2007, it appears to have resulted from overall changes in market conditions rather than the introduction of multi-market trading per se. Higher levels of dark pool or MTF trading coincide with lower volatility and dispersion in the price of buy- and sell side transactions of private investors—the result being more consistent for dark pool than MTF trading. The impact on daily price deviation is less conclusive. However, across

[5]MTFs are less likely than dark pools to impact price discovery as they have pre-trade transparency. MTFs nonetheless impact the liquidity on the main exchange. Thus, I consider both in this paper.

all model specifications, the economic magnitude of the effect is negligible even when statistically significant.

The negative relation between intra-day price volatility among private investors supports the idea that dark pool trading is best suited and more prevalent in shares with lower execution risk—that is, more liquid shares with low price volatility, as shown in Ready (2013) and Buti et al. (2011a, 2011b). Also, the average prices obtained by private investors do not appear to have been adversely affected by dark pools volumes even if the share of uninformed institutional investors on the main exchange would have been affected. For private investors with limited or no access to alternate venues, the results are encouraging. They mean that private investors are marginally, if at all, affected by the liquidity drainage. It is feasible to assume that institutional investors are unlikely to route orders to the extent that the liquidity on the primary market suffers and execution risk rises. Deteriorating price discovery on the primary market increases execution risk, which means that informed traders will ultimately revert to the exchange if pricing suffers. The results in this study provide no evidence that primary market price discovery has been affected by the market fragementation enabled by the MiFID—at least not to the extent that private investors would be disadvantaged.

The remainder of this paper is organized as follows. Section 2 provides an overview of off-exchange trading venues and relevant earlier research. Section 3 describes the data and presents the empirical methodology as well as the results. Section 4 provides some additional tests examining off-exchange trading. Section 5 discusses the results and concludes the paper.

2 An overview of off-exchange trading

This section provides an overview of the MiFID and presents earlier papers on market fragmentation and its implications.

The adoption of MiFID introduced a number of new trading platforms in Europe. While it should be noted that alternative trading mechanisms already existed, they previously mainly consisted of the possibility to negotiate larger trades in the upstairs trading room of brokerage firms rather than execute them on the exchange.[6] Thus, market fragmentation on a large scale is a recent phenomenon in Europe and has, therefore, not previously been perceived as a central regulatory concern.

[6] See Booth et al. (2002) for a study of the upstairs market on the Helsinki stock exchange. Madhavan and Cheng (1997) study the U.S. market.

The MiFID allowed the creation of new trading platforms and specified the rules that govern them.[7] Firstly, the MiFID defines the terms Regulated Markets and MTFs. Regulated Markets (RM) are multilateral systems with the highest transparency and regulation requirements and are open to all investors. Multilateral Trading Facilities (MTF) are operated by an investment firm or a market operator bringing together trading interests in accordance to non-discretionary (i.e. public) rules. According to MiFID, investment banks may also act as Systematic Internalizers (SI), which deal on own account by executing client orders outside a regulated market or MTF. Regulated markets, MTFs and systematic internalizers are all subject to transparency requirements, albeit to a varying degree. In the case of large or illiquid transactions, transparency waivers exist for MTFs and SIs but specific requirements need to be met on a transaction basis.

Dark pool trading facilities match anonymously large and small orders and have considerable self-regulatory power despite having grown large in size. They are classified in two categories: 1) dark pools operated by broker dealers or investment banks (called crossing networks), and 2) dark pools operated as MTFs. Crossing networks do not have to comply with MiFID pre-trade transparency requirements, or with other rules imposed on RMs and MTFs such as the obligation to treat investors equally, to provide fair access to the trading platform and market surveillance, and to operate a non-discretionary execution system. Dark pools operated as MTFs are regulated but they benefit from some pre-trade transparency waivers—for instance, in the case of larger orders. However, in all cases, investment firms responsible for executing the orders decide themselves whether the submission to the dark pool complies with the order handling and best execution obligations to which they are subject (e.g. regarding the various waivers). The current framework arguably provides a fairly high degree of self-regulation. The caveats are expected to be adressed in the revised version of the directive.[8]

With regards to pricing and order execution, most existing dark pools passively, and anonymously, match buyers and sellers at exchange derived prices, such as the midpoint of the exchange bid and ask price or a lagged average thereof. However, some dark pools execute orders by price and time priority without disclosing the order book to market

[7]For a more detailed description see Boskovic et al. (2009) and MEMO/11/716 published by the European Commission. This overview provides a brief summary of the relevant content in the aforementioned publications.

[8]There exists differences in terminology and practice when comparing the U.S. and Europe. In the U.S., dark pools are more explicitly captured by current law (see Boskovic et al., 2009). Essentially, they do not have to display public quotes if the venues are below a certain trading volume threshold. The SEC 2010 Concept Release on Equity Market Structure nonetheless also displayed concerns on the effect of undisplayed liquidity on market quality and fair access to all sources of liquidity.

participants.

The motivations for trading over dark pool venues are related to cost efficiency and/or anonymity. The main drawback pertains to execution risk. If an order is not filled, the investor has to submit it to an exchange for execution—and because of the time delay, the price is likely to have moved in an unfavorable direction. A regulated exchange displays the bid and ask prices and executes orders submitted at either level. In a dark pool, if one places an order on the heavier side of the market with more orders, the execution probability is low.

The model in Zhu (2013) builds on the difference in execution probability between informed and liquidity traders. Since the orders of informed traders are more likely to be correlated, they suffer a greater execution risk in dark pools pushing them to trade on exchanges. This should decrease the noisiness of orders on exchanges, and thus, increases their order informativeness. Zhu's model predicts that as informed traders flock to the exchange, order informativeness increases, and so does the price impact of trades on the exchange. Contrary to widespread media critique, this would imply that market fragmentation in its current form would not result in deteriorated price discovery on the primary exchanges.

In a different model, Ye (2011) focuses on the decision of a single informed trader and finds that as the insider's information advantage increases, a larger fraction of the orders are directed to the dark pool. Hence, dark pool volume is expected to be greater in stocks with higher degrees of adverse selection or informational asymmetry. This result is in line with the findings in Barclay et al. (2003) who compare the price impact of trades, as a measure of informativeness, of anonymous trades over a dark pool (electronic crossing network) with nonanonymous dealer trades. They find that dark pool trades have a greater permanent price impact.[9] The model by Ye (2011) does, however, not consider the impact of informed traders gradually shifting to the dark pool on order execution probability.

Degryse et al. (2009) and Hendershott and Mendelson (2000) make two predictions with regards to the impact of market fragmentation on market quality. The papers show that the introduction of a dark pool venue that derives its prices from the main market generate orders that otherwise would not have been submitted. This has the positive

[9] Reiss and Werner (2004) find that uninformed dealer trades (also measured by price impact) are more likely to be routed to anonymous brokered markets. However, unlike Barclay et al. (2003), they consider a brokered anonymous market explaining the result with dealers pricing "adverse selection". In today's regulatory setting, investors can trade fully anonymously using electronic venues without having to resort to dealers.

effect of generating liquidity. However, if the dark pool attracts uninformed trades, in line with the prediction by Zhu (2013), the effect on the main exchange may be that liquidity declines as uninformed order flow no longer exists to compensate the potential losses faced when trading against informed traders. This follows as some investors are now less inclined to trade. On an empirical note, both predict that volumes in dark pools increase as bid-ask spreads increase.

Buti et al. (2011a) also consider a limit order book market and predict the opposite in terms of spreads. They find that the market share of the dark pool is higher when primary market depth is high and spreads are narrow. The intuition builds on traders optimally trading off the execution risk and the midquote price in the dark pool against trading opportunities on the exchange. For stocks with higher depth at the inside or narrower spread, an order submitted to the limit order book has to be more aggressive to gain priority and, thus, the alternative of a midquote execution becomes relatively more attractive. Glukhov (2007) models optimal trade execution on trading costs and execution probability predicting that dark pool volumes should decrease in the presence of greater price variation—whether it be event driven or trade flow driven.

In terms of prior empirical work, Gresse (2006) finds that spreads are negatively related to dark pool executions. Ready (2013) finds that dark pools execute most of their volume in liquid stocks with low spreads and a high share volume. He finds that dark pools capture a lower fraction of volume for stocks with higher levels of adverse selection—which is consistent with the prediction from Zhu (2013), but inconsistent with the prediction from Ye (2011). The finding in Ready (2013), with regards to spreads, is consistent with the predictions from Zhu (2013) and Buti et al (2011a). Buti et al. (2011b) also find that dark pool volumes are concentrated in liquid stocks with high depth, low intraday volatility, low order imbalances and lower absolute returns—and when comparing like-for-like, dark pool activity appears to improve market quality measures such as spread, depth and short-term volatility.

Based on the earlier research, I would expect a possible impact on private investors to come from liquidity drainage to alternate venues or a shift in the share of other uninformed traders on the exchange. The dynamics that drive execution risk in the dark pools nonetheless limit the harmful effect on the primary exchange as institutional investors are likely to re-route trades back to the exchange if market quality begins to suffer. Given these dynamics, the effect on private investors emerges as a separate empirical question.

To the extent of my knowledge, this paper is the first one to examine the impact of market fragmentation on a specific investor category. If dark pool venues impact the share of informed traders on the main exchange (either by predominantly attracting informed trades or uninformed institutional trades), it is possible that private investors are adversely affected even if other investors, also trading on the main exchange, are not. This follows from the differences in sophistication, and venue access, across different investor categories. The effect could also emerge as a result of the liquidity implications of multi-market trading. The unique Finnish FCSD data containing all the private stock transactions makes this examination possible.

3 Data and empirical analysis

3.1 Data sources and Sample

A central part of the empirical investigation involves observing the daily stock transactions of private investors. To obtain the daily stock transactions of private individuals, I use the unique shareholder register of publicly listed Finnish firms upheld by Euroclear Finland Ltd. Euroclear is responsible for maintaining the Finnish Central Securities Depository (FCSD) legal liability accounts—a data source also employed by Grinblatt and Keloharju (2000, 2001).

The Finnish FCSD shareholder register contains entries of all transactions in the shares of publicly traded Finnish firms from the 2nd of January 1995 and onwards, as well as the balance of the register as of the 1st of January 1995 for every Finnish investor. The dataset enables the identification of the buy and sell transactions of each individual investor that has participated in the Finnish stock market within the sample period with the exception of foreign holdings as they are summed under nominee-registered shareholdings. The data set includes information on each share transaction for individual investors—including the ISIN number of the stock, the date of the transaction, type (buy/sell), price and quantity traded. The intra-day timing of the transactions is not observed.

The empirical investigation includes daily data on stock transactions over the period 1 May 2007 to 9 October 2009. The data period covers the introduction of fragmented trading that followed the implementation of the MiFID on 1st November 2007 and spans until 9th October 2009 when central counterparty (CCP) clearing was introduced on the Helsinki Stock Exchange. With the introduction of CCP clearing the individual stock market transactions can no longer be estimated from the Finnish Central Securities Depository (FCSD) legal liability accounts as the change involved netting daily transactions (on an investor level) into single inputs in the accounts rather than including separate transactions individually. Hence, the data period ends in October 2009. A 6 month period prior to the implementation of MiFID is included for comparative purposes.

The daily data on dark pool and MTF trading activity comes from the Thomson Reuters Equity Market Share Reporter (EMSR) covering all venues trading Finnish equities. The data includes daily volume, turnover and number of shares traded across all of the different trading venues covering all stocks listed on OMX Helsinki. The fraction of total daily turnover (euros), volume (shares) and number of trades is measured separately over the MTF and dark pool venues. The MTF category includes all venues in the data set that are categorised as multilateral trading facilities comprising a total of 9 venues. I examine all the venues separately to complete the classification based on venue names and codes. The dark pool (DP) category includes all over-the-counter, off-order-book and dark pool venues that have traded Finnish equities.[10] A marginal fraction of trades categorised as 'Other' are not considered in the examination as they are trivial in magnitude. The Thomson Reuters EMSR data set is available as of January 2008. Stock price data have been extracted from Thomson Reuters Datastream.

Figure 1 illustrates the trading across the various venues during the sample period. The daily variation in turnover across the dark pool (henceforth denoted DP) and MTF venue categories is considerable. The daily observations are presented in equally-weighted and value-weighted terms for the Finnish sample. The equally-weighted measures are the average daily fractions of DP and MTF turnover measured across all the equities (EW_MTF and EW_DP in Figure 1). The value-weighted measures are the total daily euro turnover in Finnish equities traded on DP and MTF venues divided by the total euro turnover across all venue types.

I consider the aggregated turnover in MTF and DP venue categories rather than on individual underlying venues due to the low activity levels on several of the underlying market places when measured continuously on a daily level. Furthermore, since the transparency of single trades may vary even on a venue-level, it is difficult to differentiate the expected price impact of market fragmentation depending on the venue within the DP or MTF categories.

The descriptive statistics for the daily fractions in terms of volume, turnover (euros) and trades across the DP and MTF venues are presented in Panels A, B and C of Table 1. The equally-weighted measure is once again an average of the daily fractions across

[10] The MTF category covers BATS, Burgundy, Chi-X, Equiduct, EuroTLX, NYSE Arca Europe, Quote MTF, TOM and Turquoise. The OTC category includes trades reported on Euronext Paris OTC, Irish Stock Exchange OTC, Markit Boat, Milan OTC, Oslo Stock Exchange OTC and Xetra OTC.

all equities traded on the OMX Helsinki Stock Exchange (HEX). In the value-weighted measures, the daily observations are weighted by their respective turnover in euros or number of trades as a fraction of the total turnover or sum of trades—i.e. the fractions correspond to the total market wide level of turnover and trades in these venue types.

As market fragmentation is closely related to the level of institutional interest and trading activity in a stock, the levels of DP and MTF trading are also closely correlated with turnover (and firm size). Therefore, the measures are also reported separately for 4 different subgroups. In the first category, all observations are included. In the second category, only observations with a daily euro turnover exceeding the first quartile ($>Q_1$) are included. In the second category, only observations with a daily turnover exceeding the second quartile ($>Q_2$), that is the median turnover, are included. In the fourth category, only observations in the highest turnover quartile are included ($>Q_3$). The measures are estimated separately for HEX trades in Panel A, DP trades in Panel B and MTF trades in Panel C. The tables show that the level of market fragmentation is highest in the stocks with the highest turnover. While the regulated market (HEX) dominates in terms of trades, the share of DP turnover is nonetheless 15.6% within the highest turnover category of stocks. The fraction of trades is nonetheless only 2.85%, implying that a large share of the turnover comes from larger block trades—in spirit with the motivations outlined by MiFID as arguments for allowing DP trading. The objective has been to alleviate the price impact from larger trades by allowing alternate trading mechanisms.

The share of MTF trading is smaller in magnitude. For the whole sample, the share of MTF turnover is less than 1%. For the most liquid stocks, the share is 3.14%—unlike with DP trades, the MTF trades are more comparable to regular exchange trades in size.

In Table 2, additional descriptive statistics are reported on firm-level to illustrate the daily variation in market fragmentation across the stocks. The standard deviation between firms is calculated as the standard deviation of the average estimates on firm-level. The within-firm measures are the average firm-level standard deviation of the measure. The table shows that there is considerable variation in the measures on a daily level, also within firms. On single days, the share of HEX trades can be considerably lower than suggested by the market-wide measures. The minimum level of HEX trades is as low as 26.68%.

In subsequent regressions, only those observations are considered where the fraction of HEX volume is below 0.9. Since the aim of the investigation is to examine the impact of market fragmentation on private investor stock transactions, it is reasonable to restrict the sample to observations where trading has in fact been fragmented.

3.2 Methodology and results

To assess the impact of the introduction of MiFID, I begin by running a firm-fixed effects regression of the intra-day price volatility of private investor transactions against a dummy for the period after the implementation of the new rules and a constant. That is, the dummy equals one for observations on and after November 1, 2007. The intra-day volatility is normalized by the average price of the transactions during that day ($Std/Price_{avg}$). This is done separately for buy and sell transactions. The same is done with price deviation measured as the difference between the daily maximum price and the daily minimum price normalized by the average daily price ($MaxMin/Price_{avg}$). Once again, this is estimated and regressed separately for buy and sell transactions.

Finally, I also estimate the daily price change with respect to the average purchase or sell price of private investors ($\Delta Price_t$). That is, the relative difference between the daily close price and the average transaction price ($Price_{avg}$). This is also estimated for buy and sell transactions separately—a positive price change would imply an initial profit for the buy transactions made that day and a 'loss' in price appreciation realized by the private investors that have sold shares during that day. That is, a positive price deviation is good in terms of buy- but bad in terms of sell trades. The measure is the following: $\Delta Price_t = Close_t/Price_{avg,t} - 1$

This value is included to test for potential impacts on private investor transaction prices on the regular exchange caused by DP or MTF trading. If DP trading (the primary suspect based on prior literature) were to affect the primary market, one would expect it to impact the realized transaction prices of market participants confined to trading on the regulated exchange. Since most DP venues do require post-trade transparency, one would expect the information to be incorporated from other venues by the end of the trading day. Thus, the mispricing is expected to be corrected in the closing price.

I motivate the measure with the results in Chordia et al. (2005) who point out that price discovery occurs mainly within a trading day, and Boehmer and Kelley (2009) who also find evidence in this direction. Hence, I would expect all relevant information to be incorporated in the closing price. This includes information from trades in dark pools that predominantly are bound by post-trade transparency requirements. The longest lag in post-trade transparency requirements is 3 days (i.e. upon settling). However, using a 3 day price deviation is not possible since the return over a 3 day period is driven more by other information (and trade flow) than information from dark pools with a 3-day transparency waiver. Hence, I only consider one day price change. The measure, thus, captures deviation in average private investor transaction price from the fundamental price. New information may have arrived after many of the trades included in calculating the average across private investor transactions, but this cannot be assumed to be positive or negative on a systematic basis. The measure, thus, captures a deviation from fundamental value and is included to capture a possible harmful effect that DP or MTF trading can have on private investors transaction prices.

The measure is comparable to two different intra-day measures used to capture the relative efficiency of transaction prices: 1) the pricing error as suggested in Hasbrouck (1993), and 2) the absolute value of intraday return autocorrelations—as both measures are computed from intraday transactions (or quote data) and capture temporary deviations from a random walk (see Boehmer and Kelley 2009). However, since I am only interested in the transactions by private investors, the relevant intraday transactions do not necessarily follow each other in order (i.e. multiple transactions are likely to be missing in between trades when the trading parties have been institutions). The underlying assumption that an efficient price process implies that prices (quote midpoints) follow a random walk can nonetheless be extended to this setting. On a daily level, the expected price deviation, $\Delta Price_t$, can be expected to be equal to zero—unless fragmented trading is causing systematic intraday pricing errors in the transaction prices of uninformed investors.

I run the regressions using daily data of a 6 month period before and after the implementation of the MiFID. The estimated firm fixed effects model is the following:

$$y_{i,t} = c_i + \beta MiFID_{i,t} + \epsilon_{i,t}$$
$$\text{where } y_{i,t} = Std_{i,t}/Price_{avg},\ \ MaxMin_{i,t}/Price_{avg},\ \ \Delta Price_{avg}$$

To assure that the results are not driven by extreme observations resulting from independent events or erroneous inputs in the FCSD files, I exclude the observations that exceed the 95th percentile in terms of daily price deviation ($MaxMin/Price_{avg}$). I also exclude observations with daily stocks returns below the 5th percentile or above the 95th percentile to assure that days with extreme events are not driving my results (as extreme events might impact intraday pricing, volatility and market fragmentation levels). The restrictions are applied in all subsequent regressions.

The results from the regressions are reported in Table 3. The results indicate that the daily volatility and dispersion in transaction prices is greater in the post-MiFID period. Both buy and sell transactions provide similar inferences. The coefficients 0.0021 and 0.0022 for the normalized daily standard deviation are sizable with respect to the average prior to the directive. In terms of pricing, the daily price deviation has not changed in buy transactions. The price deviation for sell transactions has decreased, which indicates a favorable effect. This suggests that price discovery has not deteriorated as a result of the change in trading rules.

It should, however, be noted that in these first regressions, I do not correct for potential differences in overall market conditions. Since the market deteriorated considerably in 2008 due to the onset and spread of the subprime crisis, it is reasonable to question whether the two periods (6 months before 1 November 2007 and 6 months after 1 November 2007) are comparable.[11] That is, since the market volatility or uncertainty may have changed. Therefore, the regressions are also estimated using a 2 month window before and after the implementation of MiFID and the results do not change. This, however, does not fully adress the problem—nor is it optimal since the growth of DP and MTF trading took some time after the initial implementation of the new rules and year-end effects could also distort the results when using the 2 month estimation period.

Therefore, I proceed by estimating a daily firm-fixed effects regression of the same dependent variables ($Std/Price_{avg}$ and $MaxMin/Price_{avg}$ and $\Delta \Pr ice_t$) against the daily level of DP and MTF trading in the underlying stock for which the dependent variables are estimated and a number of control variables. The sample period begins 1 January 2008 and ends 9 October 2009. I consider the fraction of DP volume (DP_Volume_Frac) and DP trades (DP_Trades_Frac). For the MTF venues, I only consider the fraction of volume (MTF_Volume_Frac) since the fraction of volume is highly correlated with the fraction of trades in this case. The correlation coefficient in this case is 0.9287. The other pairwise correlations as reported in Panels C, D of Table 2 and are all significantly lower. The models are estimated for buy and sell transactions, separately. I include return related controls that feasibly could affect the buy and sell transactions of private investors. The control variables are the natural logarithm of total daily euro turnover ($LnTurno$) as a measure of liquidity, the fraction of individual investor transactions (Buy or Sell) as a fraction of the total number of transactions ($PrivBuy\_Frac$ and $PrivSell\_Frac$) to measure the activity of professional investors, and stock return on day t ($Stockret_t$) to account for events or information flow that same day. I also include one day lagged stock return ($Stockret_{t-1}$) to account for contrarian effects. The estimated firm fixed effects model is the following (estimated as previously separately for buy and sell transactions):

$$
\begin{aligned}
y_{i,t} = c_i + DP\_Volume\_Frac_{i,t} + DP\_Trades\_Frac_{i,t} + MTF\_Volume\_Frac_{i,t} +& \\
LnTurno_{i,t} + Priv\_Frac_{i,t} + Stockret_t + Stockret_{t-1} + \epsilon_{i,t}& \\
\text{where } y_{i,t} = Std_{i,t}/Price_{avg},\ \ MaxMin_{i,t}/Price_{avg},\ \ \Delta \Pr ice_{avg}&
\end{aligned}
$$

[11]See Eichengreen et al. (2012) for a description of the subprime crisis and its spread.

Panel A of Table 4 shows the results for the regressions estimated using buy transactions by private investors. The results indicate that DP- and MTF trading have a significant negative effect on the intraday price volatility and dispersion of buy-side transaction prices. The average daily volatility measured across the entire sample is 0.0096. The coefficient, -0.0029, implies a -0.0004 change in daily volatility for a one standard deviation increase in the fraction of DP Volume. In terms of DP trades, the change is also -0.0004 for a one standard deviation increase in DP trading. The economic magnitude of a one standard deviation increase in MTF volume is approximately the same. So, while the variation does seem to have a significant effect, it is negligible in terms of economic magnitude.

For daily price deviation ($\Delta Price_t$), only DP trading appears to have a significant effect—in this case, a -0.0005 change for a one standard deviation increase in the fraction of daily DP trades. The fraction of DP trades is the variable that one would expect to have the largest impact on price discovery as it captures the magnitude of trades routed outside the main exchange meaning a greater fraction of information (in terms of trades) outside the primary venue. With block trades, one would expect the price to be derived from the exchange—the reason for doing the trade outside the exchange is merely cost efficiency and smaller price impact by not crowding one side of the market. The information value of the execution price is perhaps of lesser value in this case as is significance of the liquidity effect. However, while the variable (DP_Trades_Frac) is significant, it is not significant in terms of economic magnitude.

In Panel B of Table 4, we see the results from the sell side transactions. The results are fully in line with the findings in Panel A. While the variables capturing market fragmentation are significant, they nonetheless only have a marginal economic impact on the trade performance of private investors.

As a final test to assure that the exceptional market conditions in 2008 are not driving my results, I re-run the previous regressions using two alternate specifications. Firstly, I include monthly time-dummies to capture any independent variation in the levels of intraday volatility or price uncertainty that may have been caused by the events during the subprime crisis. I also re-run the regressions reported in Table 4 using a sub-sample starting in January 2009. The results are reported in Panels A and B of Table 5. For buy transactions, the levels of DP trading continue to have a significant effect but the coefficients are even smaller than in the previous specifications when time-dummies are included. Based on the results of the empirical investigation, it is impossible to conclude that market fragmentation would have hurt private investors.

The other investor categories not covered by this examination are far more likely to have access to the alternate venues if they so desire. For institutional investors, it can also be assumed to be significantly easier to acquire the post-trade data on off-market transactions making them far less vulnerable to any hazardous effects of multimarket trading. Thus, it appears that the regulation change has not had a detrimental effect on the market—not even with the current regulatory framework.

4 Some additional tests

This section provides results of some additional empirical examinations that shed light on the drivers of multi-market trading and its impact on private investors stock transactions.

Buti et al. (2011b) find, that for a given stock, dark pool volumes are concentrated in liquid stocks with high depth, low intraday volatility, low order imbalances and lower absolute returns. Their results contradict the predictions in Ye (2011) who models the decision of a single informed trader and finds that as the insider's information advantage increases, a larger fraction of his orders are directed to the dark pool. That is, the level of dark pool volume is expected to be greater in stocks with higher degrees of adverse selection or informational asymmetry. The results in this paper are more in line with the prediction that trading on these venues is concentrated in liquid stocks with lower execution risk—and in this case, the re-routing of trades would not be expected to have a significant price impact on the transactions of investors confined to the primary exchange, as shown by the results.

To confirm that this is in fact the mechanism driving the degree of market fragmentation, I run a daily firm level fixed-effects panel regression with monthly time dummies of the determinants of DP and MTF trading. The daily levels of DP and MTF trading (DP_Volume_Frac, DP_Trades_Frac, MTF_Volume_Frac) are as previously defined. The explanatory variables are the daily high price divided by the daily low price on the primary exchange over all investor categories ($HighLow$), the closing bid-ask spread measured as the difference between the closing ask and sell divided by their average ($BidAsk$), past ten day return volatility ($10DayVola$), the daily stock return (Ret), the absolute value of the daily return ($AbsRet$), the natural logarithm of the daily euro turnover ($LnTurno$), the fraction of private individual sell transactions as a fraction of the total ($PrivSell\_Frac$), the fraction of private individual buy transactions as a fraction of the total ($PrivBuy\_Frac$), and the difference in buy and sell private interest measured as the absolute value of the difference between $PrivSell\_Frac$ and

$PrivBuy\_Frac$ ($Diff\_BuySell$).[12] The regressions are estimated for the ten largest firms on the Helsinki Stock Exchange in terms of market capitalization to assure a fairer comparison in terms of institutional interest (foreign and domestic) and information availability (e.g. analyst coverage) and information asymmetry. Based on the earlier research, I would expect firm-level variation in drivers such as execution risk or liqudity to affect the level of DP and MTF trading.

The results in Table 6 show that the share of DP volumes are larger when liquidity is higher measured as the natural logarithm of daily euro turnover. The results also confirm that DP volumes are concentrated in stocks with less intra-day volatility as evidenced by the negative coefficients for maximum daily deviation in price ($HighLow$), return (Ret) and absolute value of the daily return ($AbsRet$). The coefficient for past 10 day return volatility is positive. This, however, may reflect days following events or news announcements when institutional trading interest can be expected to increase–which naturally would coincide with higher trade volumes outside the primary exchange.

The variables estimating private investor dominance and order inbalance on the primary market ($PrivBuy\_Frac$, $PrivSell\_Frac$, $Diff\_BuySell$) are not statistically significant. This suggests that the proportional presence of institutional order flow to the primary exchange is not affected by the presence of DP venues. That is, there is no systematic relation between the level of institutional activity on the primary exchange and activity on alternate venues. In terms of MTF trading, only the maximum intra-day price deviation on the primary market has a statistically significant impact. While this could suggest that important information (in terms of order flow) is not as readily available to all market participants when information uncertainy is accentuated (large price deviations occur), the results in the previous specifications nonetheless show that MTF trading does impact market quality measures such as intra-day volatility or price deviation among private investors.

Finally, I also examine the difference in average daily transaction prices across the venues with average daily private investors prices. For the alternate venues, I can only estimate a value-weighted average price from the daily euro turnover and volume. Thus, the averages strongly reflect larger blocks that have been traded or periods during the day when trading has been more active. As DP trading has largely comprised of larger blocks (as evidenced by the disparity in terms of fraction of turnover versus fraction of trades), the value-weighted average nonetheless fairly accurately reflects the average price on these

[12] The pairwise correlations for the explanatory variables range between -0.2825 for $PrivBuy\_Frac$ and $LnTurno$ and 0.7646 for $PrivBuy\_Frac$ and $PrivSell\_Frac$. The correlations should not be a significant source of concern in this estimation.

venues. In Table 7, I report descriptive statistics for the daily relative price difference. The differences are defined as (for DP buy trades):

$$Diff\_Buy\_Priv - DP_{VW} = \frac{(Average\_BuyPrice\_Private - DP\_BuyPrice_{VW})}{Average\_BuyPrice\_Private}$$

The price difference for the other venues and when using private sell transactions are also defined as above. The difference is also calculated using the value-weighted average HEX price across all investor categories. The statistics show that private buy prices are on average lower than value-weighted transaction prices on the other venues. The differences are statistically significant as evidenced by the t-tests in Panel B. The results also show that private investors' sell transactions are on average at a higher price than the value-weighted transaction prices at the alternate venues—and once again, the differences are statistically significant.

It should be noted that the measures are not fully comparable since the alternate measure are value-weighted and therefore reflect transactions that have required greater market depth at the executed price. This is also evident in the fact that the value-weighted HEX transaction price estimated across all investor categories trading on the HEX is inferior to the average private buy and sell transactions of private investors. Calculating the value-weighted private investor price would excessively capture single large trades (e.g. trades of more sophisticated private investors not necessarily representative of the category) and, thus, not capture the prices obtained by private investors as a category. It can nonetheless be stated that the results provide no indication that private investors are put at a disadvantage because information is kept out of public view due to multimarket trading.

5 Discussion and concluding remarks

Less regulated market venues have become an established and integral part of equity market structure. The benefits of increased competition and lighter regulation on markets used solely by professional investors are obvious. They reduce the trading costs for institutional and professional traders by cutting out the number of intermediaries necessary to trade in equities. Since every market participant is not guaranteed or given equal access to the less regulated venues, it might be tempting to require regulators to impose additional regulation or demand more consolidation. However, this should not be done without understanding how the current regulatory framework has affected different investor categories and dimensions of price discovery.

This paper examines the effect of DP and MTF trading on private investors using data from the Finnish Central Securities Depository. The results challenge the claim that market fragmentation is harmful for price discovery. While the intra-day price volatility of private transactions has increased since November 2007, this appears to have resulted from overall changes in market conditions rather than the introduction of multi-market trading per se. Increases in DP or MTF trading coincide with lower volatility and dispersion in the price of buy- and sell side transactions of private investors. The impact on daily price deviation is less conclusive. However, across all model specifications, the economic magnitude of the effects is negligible even when significant. The results support the idea that DP trading is best suited and prevalent in more liquid shares with low price volatility. From an institutional investor point of view, in these conditions, the execution risk faced by investors trading in dark pools is smaller. The mechanism also assures that the impact on price discovery is limited as informed traders continue to be active on the lit markets despite the access to other markets. The examination provides no evidence that private investors, the most vulnerable of all investor categories, would have been harmed by volumes leaking to other venues.

Firstly, as most venues rely on quotes from the primary market to determine the execution prices, it places significant restrictions on the extent that price discovery on the main exchange can deteriorate before institutional investors re-route their trades back to the primary exchange. As prices diverge from fundamental values, informed traders are increasingly likely to direct their orders to an exchange with an order book. Within the category of venues that use a lit order book, it is clear that the pricing stays consistent across the venues so not to enable near-arbitrage opportunities to institutional investors active on all of them.

In conclusion, the findings support the claim that traders use dark pools to primarily to save transaction costs or minimize the price impact of larger orders rather than to minimize the price impact of their trades by hiding the direction of the flow. Fragmented trading should not directly be associated with poorer market quality or increased short-term volatility based on the impact it has had on private investor transactions.

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Figure 1

Figure 1 displays the daily variation in trading across the different trading venues.The equally-weighted measures (EW_MTF, EW_DP) are an average of the daily fractions across all equities traded on the Helsinki Stock Exchange over MTFs and dark pools, DPs. In the value-weighted measures, the daily observations are weighted by their respective turnover in euros or number of trades as a fraction of the total turnover or sum of trades. The data is from the Thomson Reuters Equity Market Share Reporter database. The MTF category includes all venues that are categorised as multilateral trading facilities. This category comprises of 9 venues (BATS, Burgundy, Chi-X, Equiduct, EuroTLX, NYSE Arca Europe, Quote MTF, TOM and Turquoise). The DP category includes all dark pool venues that have traded Finnish equities (Euronext Paris OTC, Irish Stock Exchange OTC, Markit Boat, Milan OTC, Oslo Stock Exchange OTC and Xetra OTC) over the sample period. The Thomson Reuters EMSR data is available as of January 2008.

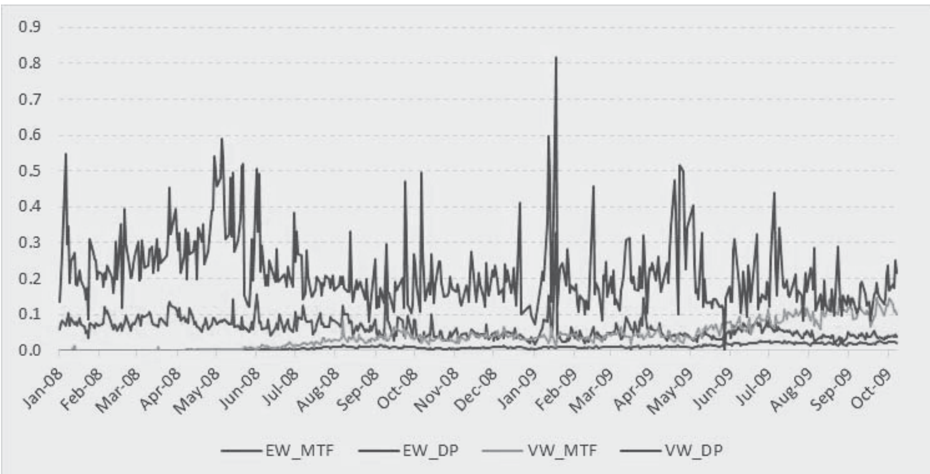

Table 1

Overview of volume and trade fragmentation across venues

Table 1 presents an overview of average daily trading volume across the different venue categories. The equally-weighted measures are an average of the daily fractions across all equities traded on the Helsinki Stock Exchange. In the value-weighted measures, the daily observations are weighted by their respective turnover in euros or number of trades as a fraction of the total turnover or sum of trades. The measures are estimated separately for 4 different subgroups. In the first category, all observations are included. In the second category, only observations with a daily euro turnover exceeding the first quartile ($>Q_1$) are included. In the second category, only observations with a daily turnover exceeding the second quartile ($>Q_2$), that is the median turnover, are included. In the fourth category, only observations in the highest turnover quartile are included ($>Q_3$). The measures are estimated separately for HEX trades in Panel A, DP trades in Panel B and MTF trades in Panel C.

Panel A. Share of Helsinki Stock Exchange (HEX)					
	Equally-weighted daily average			Value-weighted daily average	
	HEX Volume	HEX Turnover	Hex Trades	HEX Turnover	Hex Trades
Full sample	0.9090	0.9076	0.9623	0.5962	0.8614
$>Q_1$	0.8803	0.8786	0.9511	0.5960	0.8606
$>Q_2$	0.8358	0.8337	0.9341	0.5952	0.8419
$>Q_3$	0.7597	0.7577	0.9015	0.5718	0.8394

Panel B. Share of OTC venues			
	Equally-weighted average		
	DP Volume	DP Turnover	DP Trades
Full sample	0.0593	0.0593	0.0157
$>Q_1$	0.0781	0.0781	0.0202
$>Q_2$	0.1073	0.1072	0.0257
$>Q_3$	0.1519	0.1519	0.0285

Panel C. Share of MTF venues			
	Equally-weighted average		
	MTF Volume	MTF Turnover	MTF Trades
Full sample	0.0086	0.0086	0.0158
$>Q_1$	0.0114	0.0114	0.0210
$>Q_2$	0.0168	0.0167	0.0309
$>Q_3$	0.0314	0.0314	0.0574

Table 2

Descriptive statistics

Panel A of Table 2 presents descriptive statistics for the daily observations of trading across the venue categories as fractions of the total daily volume and trades across all venues. The categories are defined as in Table 1. The standard deviation between firms is calculated as the standard deviation of the average estimates on firm-level. The within-firm measure is the average firm-level standard deviation of the measure. In the regressions, only observations are considered where the fraction of HEX volume is below 0.9. In Panel B, the restrictions are applied as described in Section 3. That is, the observations that exceed the 95th percentile in terms of maximum spread between maximum and minimum transaction prices normalized by the average daily price ($MaxMin/Price_{avg}$) are excluded. Also, the observations below the 5th and above the 95th percentile in terms of daily stock returns are excluded. In Panel C and Panel D, the correlations of the explanatory variables of the Buy and Sell Trade regressions are reported.

Panel A. Trading across venues

	Mean	Std. Dev.	Min.	Max.
HEX Volume	0.7088	0.1668	0.0037	0.9989
Between Firms		0.0809		
Within Firms		0.1601		
HEX Trades	0.8939	0.0866	0.2668	0.9974
DP Volume	0.1923	0.1512	0	0.9974
Between firms		0.0380		
Within firms		0.0749		
DP Trades	0.0356	0.0403	0	0.7315
MTF Volume	0.0325	0.0439	0	0.9938
Between firms		0.0201		
Within firms		0.0389		
MTF Trades	0.0598	0.0760	0	0.4439
Number of observations:	11 170			
Number of firms:	88			

Panel B. Main variables		
	Mean	Std. Dev.
Std_Buy/Price	0.0096	0.0057
MaxMin_Buy/Price	0.0349	0.0120
ΔPrice_Buy$_t$	0.0006	0.0142
Std_Sell/Price	0.0114	0.0107
MaxMin_Sell/Price	0.4148	0.4778
ΔPrice_Sell$_t$	-0.0006	0.0199
PrivTrades_Buy	131.8734	216.1325
PrivBuy_Frac	0.3574	0.3163
PrivTrades_Sell	104.5568	160.9091
PrivSell_Frac	0.3046	0.3663
LnTurno	14.2701	2.5973
Stockret$_t$	-0.0010	0.0197
Stockret$_{t-1}$	-0.0006	0.0287
Number of observations:	23 081	
Number of firms:	119	

Panel C. Buy trade correlations							
	PrivBuy	LnTurno	Sret_t	Sret_{t-1}	DP_Vol	DP_Trad	MTF_Vol
PrivBuy_Frac	1.0000						
LnTurno	-0.6530	1.0000					
Stockret_t	-0.0111	-0.0166	1.0000				
Stockret_{t-1}	-0.0021	0.0055	0.0313	1.0000			
DP_Volume_Frac	0.0091	0.0798	-0.0030	0.0208	1.0000		
DP_Trades_Frac	0.0146	-0.1545	-0.0128	-0.0193	0.2058	1.0000	
MTF_Volume_Frac	-0.2554	0.2608	0.0285	0.0054	-0.2614	-0.1216	1.0000

Panel D. Sell trade correlations							
	PrivSell	LnTurno	Sret_t	Sret_{t-1}	DP_Vol	DP_Trad	MTF_Vol
PrivSell_Frac	1.0000						
LnTurno	-0.5037	1.0000					
Stockret_t	0.0477	-0.0047	1.0000				
Stockret_{t-1}	0.0283	-0.0113	0.0450	1.0000			
DP_Volume_Frac	-0.3280	0.4983	-0.0181	-0.0309	1.0000		
DP_Trades_Frac	-0.1729	0.1966	-0.0020	-0.0042	0.3636	1.0000	
MTF_Volume_Frac	-0.2041	0.4001	0.0094	0.0071	0.1242	0.0145	1.0000

Table 3

Impact of MiFID on private investor stock transactions

Table 3 presents results of firm level fixed-effects panel regressions of the normalized daily standard deviation in price ($Std/Price_{avg}$), normalized difference in daily maximum and minimum price ($MaxMin/Price_{avg}$), daily difference in average private investor price and daily close price ($\Delta Price_t$) against a dummy measure for days following the implementation of MiFID and a constant. The average private investor price and corresponding deviation measures are calculated for buy and sell trades separately and the results are reported separately for the regressions. Panel A reports the results for the buy trade measures. Panel B reports the results for the sell trade measures. Coefficients marked with ***, ** or * are significant at the respective thresholds of 1%, 5% or 10%. Robust t-statistics based on standard errors using Huber-White sandwich estimators are shown in parentheses.

Panel A. Buy trades			
	Std/Price_{avg}	$\text{MaxMin/Price}_{avg}$	ΔPrice_t
$\text{MiFID}_{i,t}$	0.0022***	0.0082***	0.0001
	(22.01)	(23.52)	(0.47)
Constant	0.0075***	0.0271***	0.0007***
	(123.73)	(122.97)	(4.78)
R^2	0.0377	0.0452	0.0000
Obs	9 173	9 173	9 173

Panel B. Sell trades			
	Std/Price_{avg}	$\text{MaxMin/Price}_{avg}$	ΔPrice_t
$\text{MiFID}_{i,t}$	0.0021***	0.0076***	-0.0004*
	(26.67)	(28.18)	(-1.84)
Constant	0.0072***	0.0255***	-0.0005***
	(150.21)	(150.76)	(-3.92)
R^2	0.0379	0.0466	0.0006
Obs	12 688	12 688	12 688

Table 4

Daily market fragmentation of trading volume and private investor stock transactions

Table 4 presents results of a firm level fixed-effects panel regression of the normalized daily standard deviation in price ($Std/Price_{avg}$), normalized difference in daily maximum and minimum price ($MaxMin/Price_{avg}$), and daily difference in average private investor price and daily close price ($\Delta Price_t$) against measures capturing daily variation in the level of market fragmentation of trades and various control variables. The DP and MTF categories are defined as in Table 1. The control variables are the natural logarithm of daily euro turnover ($LnTurno$), the fraction of individual investor transaction (Buy or Sell) as a fraction of the total number of transactions ($PrivBuy\_Frac$ and $PrivSell\_Frac$), stock return on day t ($Stockret_t$) and one day lagged stock return ($Stockret_{t-1}$). Coefficients marked with ***, ** or * are significant at the respective thresholds of 1%, 5% or 10%. Robust t-statistics based on standard errors using Huber-White sandwich estimators are shown in parentheses.

Panel A. Buy trades			
	$Std/Price_{avg}$	$MaxMin/Price_{avg}$	$\Delta Price_t$
DP_Volume_Frac	-0.0029***	-0.0139***	-0.0017
	(-5.96)	(-8.28)	(-1.29)
DP_Trades_Frac	-0.0088***	-0.0320***	-0.0115***
	(-5.37)	(-5.57)	(-2.81)
MTF_Volume_Frac	-0.0083***	-0.0290***	0.0005
	(-5.36)	(-5.58)	(0.13)
LnTurno	0.0008***	0.0047***	-0.0006*
	(8.49)	(13.52)	(-1.92)
PrivBuy_Frac	0.0048***	0.0300***	-0.0264***
	(6.52)	(10.27)	(-5.42)
$Stockret_t$	-0.0067**	-0.0149	0.0097
	(-2.21)	(-1.39)	(1.16)
$Stockret_{t-1}$	-0.0003	-0.0007	-0.0200***
	(-0.15)	(-0.09)	(-3.24)
R^2	0.0193	0.0711	0.0417
Obs	6 213	6 213	6 213

Panel B. Sell trades			
	Std/Price$_{avg}$	MaxMin/Price$_{avg}$	ΔPrice$_t$
DP_Volume_Frac	-0.0025***	-0.0114***	-0.0000
	(-7.33)	(9.84)	(-0.02)
DP_Trades_Frac	-0.0101***	-0.0355***	0.0060**
	(-8.80)	(-9.28)	(2.58)
MTF_Volume_Frac	-0.0053***	-0.0197***	-0.0063**
	(-5.49)	(-5.74)	(-2.96)
LnTurno	0.0008***	0.0041***	0.0000
	(11.40)	(17.23)	(0.24)
PrivSell_Frac	0.0025***	0.0211***	0.0068***
	(3.71)	(9.09)	(4.22)
Stockret$_t$	-0.0189***	-0.0564***	0.3179***
	(8.11)	(-7.23)	(65.11)
Stockret$_{t-1}$	-0.0060***	-0.0209***	0.0095***
	(-3.91)	(3.82)	(2.60)
R^2	0.0094	0.0532	0.3658
Obs	11 170	11 170	11 170

Table 5

Daily market fragmentation of trading volume and private investor stock transactions

Table 5 presents results of a firm level fixed-effects panel regression of the normalized daily standard deviation in price ($Std/Price_{avg}$), normalized difference in daily maximum and minimum price ($MaxMin/Price_{avg}$), and daily percentage difference in average private investor price and daily close price ($\Delta Price_t$) against measures capturing daily variation in the level of market fragmentation of trades and various control variables. The MTF and DP categories are defined as in Table 1. The control variables are the natural logarithm of daily euro turnover ($LnTurno$), the fraction of individual investor transaction (Buy or Sell) as a fraction of the total number of transactions ($PrivBuy\_Frac$ and $PrivSell\_Frac$), stock return on day t ($Stockret_t$) and one day lagged stock return ($Stockret_{t-1}$). Panel A shows the results for Buy trades. Panel B shows the results for Sell trades. The table reports results for firm fixed effects regressions that also control for monthly effects and for a sub-sample starting in January 2009. Coefficients marked with ***, ** or * are significant at the respective thresholds of 1%, 5% or 10%. Robust t-statistics based on standard errors using Huber-White sandwich estimators are shown in parentheses.

Panel A. Buy trades						
	Firm and month-year fixed effects			Sample 1/2009-		
	Std/P_{avg}	MaxMin/P_{avg}	ΔPrice$_t$	Std/P_{avg}	MaxMin/P_{avg}	ΔPrice$_t$
DP_Vol_Frac	-0.0024***	-0.0119***	-0.0019	-0.0011	-0.0071***	-0.0030
	(-5.45)	(-7.79)	(-1.46)	(-1.55)	(-2.81)	(-1.32)
DP_Trad_Frac	-0.0041***	-0.0140***	-0.0092**	-0.0099***	-0.0339***	-0.0096
	(-2.86)	(-3.00)	(-2.32)	(-5.06)	(-4.57)	(-1.45)
MTF_Vol_Frac	0.0002	0.0076	-0.0184***	-0.0231***	-0.0860***	-0.0214***
	(0.13)	(1.19)	(-3.04)	(-9.87)	(-10.57)	(-3.33)
LnTurno	0.0013***	-0.0064***	-0.0002	0.0014***	0.0066***	-0.0002
	(12.41)	(17.19)	(-0.61)	(8.99)	(11.61)	(-0.50)
PrivBuy_Frac	0.0033***	0.0242***	-0.0278***	0.0004	0.0104***	-0.0391***
	(5.01)	(9.19)	(-5.18)	(0.40)	(2.86)	(-8.77)
Stockret$_t$	-0.0023	0.0053	0.0082	-0.0135***	-0.0344**	0.0227*
	(-0.82)	(0.55)	(0.98)	(-2.97)	(2.23)	(1.70)
Stockret$_{t-1}$	0.0006	0.0046	-0.0240***	0.0025	0.0007	-0.0279***
	(0.29)	(0.71)	(-3.90)	(0.72)	(0.06)	(-2.82)
R^2	0.0941	0.1817	0.0905	0.0327	0.0899	0.0586
Obs	6 216	6 216	6 216	2 704	2 704	2 704

Panel B. Sell trades						
	Firm and month-year fixed effects			Sample 1/2009-		
	Std/P$_{avg}$	MaxMin/P$_{avg}$	ΔPrice$_t$	Std/P$_{avg}$	MaxMin/P$_{avg}$	ΔPrice$_t$
OTC_Vol_Frac	-0.0021***	-0.0099***	-0.0001	-0.0017***	-0.0082***	-0.0024**
	(-6.63)	(-9.16)	(-0.15)	(-3.24)	(-4.78)	(-2.21)
OTC_Trad_Frac	-0.0048***	-0.015***	0.0031	-0.0061***	-0.0194***	0.0029
	(-4.53)	(-4.42)	(1.36)	(-3.73)	(-3.54)	(0.80)
MTF_Vol_Frac	-0.0000	0.0005	0.0015	-0.0211***	-0.0801***	0.0039
	(-0.01)	(0.08)	(0.56)	(-13.65)	(-15.40)	(1.19)
LnTurno	0.0011***	0.0055***	-0.0001	0.0013***	0.0058***	-0.0004*
	(15.50)	(21.07)	(-0.94)	(12.69)	(16.08)	(-1.66)
PrivSell_Frac	0.0025***	0.0208***	0.0074***	0.0003	0.0105	0.0079***
	(2.87)	(7.10)	(4.78)	(0.43)	(3.55)	(4.46)
Stockret$_t$	-0.0160***	-0.0445***	0.3167***	-0.0314***	-0.0314***	0.3262***
	(-7.11)	(-6.06)	(65.42)	(-2.75)	(-2.75)	(50.27)
Stockret$_{t-1}$	-0.0037***	-0.0120***	0.0087**	-0.0042	-0.0042	-0.0046
	(-2.80)	(-2.63)	(2.40)	(-0.56)	(-0.56)	(-0.91)
R^2	0.0716	0.1515	0.3784	0.0244	0.0779	0.4089
Obs	11 170	11 170	11 170	4 732	4 732	4 732

Table 6

Determinants of DP and MTF trading

Table 6 presents results of a daily firm level fixed-effects panel regression with month-year time dummies of DP and MTF trading against a set of explanatory variables. The daily levels of DP and MTF trading (DP_Volume_Frac, DP_Trades_Frac, MTF_Volume_Frac) are as previously defined. The explanatory variables are the percentage difference between the daily high and the daily low price on the primary exchange ($HighLow$), the closing bid-ask spread measured as the difference between the closing ask and sell divided by their average ($BidAsk$), past ten day return volatility ($10DayVola$), the daily stock return (Ret), the absolute value of the daily return ($AbsRet$), the natural logarithm of the daily euro turnover ($LnTurno$), the fraction of private individual sell transactions as a fraction of the total ($PrivSell\_Frac$), the fraction of private individual buy transactions as a fraction of the total ($PrivBuy\_Frac$), and the difference in buy and sell private interest measured as the absolute value of the difference between $PrivSell\_Frac$ and $PrivBuy\_Frac$). The regressions are estimated for the ten largest firms on the Helsinki Stock Exchange in terms of market capitalization. Coefficients marked with ***, ** or * are significant at the respective thresholds of 1%, 5% or 10%. Robust t-statistics based on standard errors using Huber-White sandwich estimators are shown in parentheses.

	Determinants of DP and MTF trading			
	DP_Volume_Frac	DP_Volume_Frac	DP_Trades_Frac	MTF_Volume_Frac
HighLow	-1.1379***	-1.1763***	-0.1420***	0.0950***
	(-8.67)	(-8.78)	(-7.27)	(4.99)
BidAsk	3.6726**	3.7680**	0.1417	-0.2003
	(2.49)	(2.55)	(0.50	(-0.75)
10DayVola	0.0002*	0.0002	-0.0000	0.0001
	(1.72)	(1.44)	(-1.00)	(2.73)
Ret	-0.2009***	-0.2211***	-0.0096	0.0162
	(-3.23)	(-3.05)	(-0.88)	(1.49)
AbsRet	-0.4028***	-0.3999***	-0.0036	-0.0501
	(-3.16)	(-3.06)	(-0.18)	(-2.43)
LnTurno	0.1155***	0.1168***	0.0024***	-0.0101
	(17.00)	(16.83)	(3.00)	(-12.06)
PrivSell_Frac		0.0651		
		(1.21)		
PrivBuy_Frac		0.0738		
		(1.59)		
Diff_BuySell		-0.0746		
		(-1.43)		
R^2	0.1969	0.1964	0.0716	0.6557
Obs	3 275	3 275	3 275	3 275

Table 7

Difference in average private investors price and prices on alternate venues

Table 7 shows descriptive statistics for differences in the daily buy and sell price of private investors on the Helsinki Stock Exchange and average value-weighted prices on the DP and MTF venues. The difference between average private investor price and value-weighted HEX price across all investor categories is also reported for comparative purposes. Panel A reports the descriptive statistics for the daily relative differences with respect to the average private price ((average private price - average value-weighted DP/MTF/HEX price) / private price). The measures are calculated separately for buy and sell transactions. Panel B reports simple t-test results to test if the differences are equal to zero, i.e. prices do not differ across the venues or investor categories. In Panel B, the same data restrictions are applied as in the previous regressions. That is, the observations that exceed the 95th percentile in terms of maximum spread between maximum and minimum transaction prices normalized by the average daily price ($MaxMin/Price_{avg}$) are excluded. Also, the observations below the 5th and above the 95th percentile in terms of daily stock returns are excluded.

Panel A. Descriptive statistics on relative price differences

	Mean	Median	25th perc	75th perc	StDev
Diff_Sell_Priv-DP$_{VW}$	0.0015	0.0012	-0.0044	0.0072	0.0274
Diff_Sell_Priv-MTF$_{VW}$	0.0015	0.0012	-0.0011	0.0038	0.0067
Diff_Sell_Priv-HEX$_{VW_ALL}$	0.0018	0.0011	-0.0009	0.0038	0.0085
Diff_Buy_Priv-DP$_{VW}$	-0.0026	-0.0017	-0.0082	0.0035	0.0275
Diff_Buy_Priv-MTF$_{VW}$	-0.0018	-0.0013	-0.0041	0.0010	0.0069
Diff_Buy_Priv-HEX$_{VW_ALL}$	-0.0012	-0.0007	-0.0032	0.0013	0.0078

Panel B. T-tests on relative price differences

	Mean	t-stat
Diff_Sell_Priv-DP$_{VW}$	0.0009***	4.5831
Diff_Sell_Priv-MTF$_{VW}$	0.0014***	20.8109
Diff_Sell_Priv-HEX$_{VW_ALL}$	0.0016***	37.6530
Diff_Buy_Priv-DP$_{VW}$	-0.0026***	-10.3045
Diff_Buy_Priv-MTF$_{VW}$	-0.0017***	-19.3169
Diff_Buy_Priv-HEX$_{VW_ALL}$	-0.0016***	-30.1760

Essay 3

Firm Expansion and Stock Price Momentum

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Firm Expansion and Stock Price Momentum*

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Abstract. We document a significant and robust connection between firm-level asset changes and return momentum. Momentum profits are large and significant for firms that have experienced large asset expansions or contractions, whereas they otherwise are small and often insignificant. The interaction pattern is not subsumed by previously documented drivers of momentum and shows up in market states where prior literature has documented an absence of momentum profits. Furthermore, we find a positive time series relationship between aggregate asset growth (AG) and return momentum, and the effect of aggregate AG is stronger than that of variables related to business cycles and investor sentiment. While most existing models of firm investment and momentum cannot explain our results, recent real options models appear to hold the most promise.

JEL Classification: G12

1. Introduction

Few stock market anomalies have received such vast attention among researchers as the momentum effect first documented by Jegadeesh and Titman (1993). Still, after almost two decades of its initial discovery, the momentum anomaly remains an intellectual curiosity: a simple trading strategy that buys stocks with the highest returns over the past 3–12 months and sells stocks with the lowest returns over the same horizon produces profits that remain large after standard adjustments of risk (see, e.g., Fama and French, 1996). The prevalence and robustness of the momentum effect justify the abundance of theoretical and empirical research

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that has been directed at uncovering the underlying reasons for the large payoffs from the trading strategy.[1]

In this article, we investigate the role of firm-level asset expansion as a source of momentum profits. Our article is motivated by the growing literature that models the relation between firm-level investment decisions and expected returns.[2] Although existing studies do not formally model the ability of asset expansion to predict momentum profits, they make indirect predictions about the impact of changes in firms' asset bases on expected return momentum. Given the interactions implied by prior literature, the question that emerges is how the different predictions are supported by data. To the best of our knowledge, our article is the first to explicitly study the interaction between firm-level asset changes and momentum effects.

Our analysis shows that the momentum effect is closely connected to the investment behavior of firms. We show that large changes in the asset base of a firm enhances short-term stock return momentum even when controlling for previously documented firm-level drivers of momentum. Our results reveal a momentum pattern where profits from the strategy are essentially confined to firms that have experienced a large contraction or expansion in their total assets. The strong empirical evidence in our article has significant implications for models aiming to uncover the sources of momentum profits or model the relation between firm-level investments and expected returns.

Existing theoretical investment-based asset pricing models imply various underlying structures in momentum profits that incorporate asset growth (AG). Our results are most closely related to the investment-based asset pricing models by Berk, Green, and Naik (1999) and Hackbarth and Johnson (2012). In the model of Berk, Green, and Naik (1999), momentum profits arise due to slow changes in firms' asset bases resulting in staleness in expected returns that lead to momentum. Our main empirical result—that momentum is driven by rapid rather than slow changes in firms' assets—does not seem compatible with this theoretical prediction. On the other hand, our interaction pattern is notably supported by the recent model of Hackbarth and Johnson (2012). They propose a different underlying

[1] Barberis, Shleifer, and Vishny (1998); Daniel, Hirshleifer, and Subrahmanyam (1998); and Hong and Stein (1999) among others, present behavioral explanations for momentum. On the other side of the spectrum, Berk, Green, and Naik (1999); Johnson (2002); and Sagi and Seasholes (2007) introduce theoretical models that predict price momentum without appealing to behavioral arguments.

[2] Relevant papers within this strand of literature include Berk Green, and Naik (1999); Gomes, Kogan, and Zhang (2003); Zhang (2005); Chen, Novy-Marx, and Zhang (2010); as well as Hackbarth and Johnson (2012).

dynamic that considers the impact of cross-firm heterogeneity in investment flexibility on expected returns. They show that a distinguishing feature of firms with more investment flexibility is that their risk falls, on average, as profitability declines and as operating leverage increases. However, for firms with less investment flexibility, risk rises as profitability declines and as operating leverage increases. Their model implies that return autocorrelations should be U-shaped conditional on lagged operating variables which translates into enhanced momentum returns for firms with large expected changes to their asset base—that is, firms near the exercise of expansion or contraction options. The extremes comprise a significant share of firms that subsequently experience extreme changes in their asset bases. Fama and French (2006) provide evidence from univariate regressions that lagged growth shows strong power to forecast AG up to 3 years ahead. This implies that realized AG can be seen as a good proxy for expected growth—thus, linking our results to the model of Hackbarth and Johnson (2012). Although their model does not explicitly take on the interaction between momentum and realized AG, it nevertheless implies an autocorrelation pattern that closely conforms with our findings.

Other models show a less direct link between firm-level AG and return momentum. Chen, Novy-Marx, and Zhang (2010) propose a new three-factor model, where one of the factors is an investment-based factor that is closely connected to the *AG* variable that we use. We show that although their model decreases the overall magnitude of momentum profits, it nonetheless fails to explain the differences in profits across AG groups. Johnson (2002) presents a theoretical model of momentum, where a firm's log price to dividend ratio is convex with respect to expected growth rates, implying that stock returns are more sensitive to changes in expected growth when expected growth is high. We show, however, that the interaction between AG and momentum is not driven by within-group differences in expected growth rates, measured as in Liu and Zhang (2008) by the momentum portfolios' factor loadings on the growth rate in industrial production.

Our results are also connected to those of Cooper, Gulen, and Schill (2008) who examine the cross-sectional relation between firm-level AG and future returns. They show that firms with high lagged AG rates display anomalously low returns relative to standard adjustments for risk. However, they do not investigate the connection between AG and return momentum. We extend their results by showing that in addition to predicting the magnitude of future returns, AG is also a strong and independent predictor of future return autocorrelation. The combined evidence on the strong forecasting ability of AG on returns provides valuable insights into the complex linkages between risk and investment.

Summing up, existing theoretical and empirical models provide contradictory and incomplete predictions regarding the interaction of AG and momentum. By documenting a strong and robust interaction between AG and return momentum, our results have implications for models studying the impact of investments and disinvestments on risk. The value and investment premiums have previously been linked to investment-based mechanisms. Linking the momentum premium and investment can thus potentially give rise to a unified framework simultaneously explaining the economic drivers behind the different risk premiums, and thus provide a more comprehensive explanation of stock returns.

In the first step of our analysis, we divide the stocks into 10 groups based on their past AG rates using the intersection of Center for Research in Security Prices (CRSP) and Compustat firms during a sample period of 40 years. We follow the momentum strategy of Fama and French (2008) and assign the stocks within the AG groups into five portfolios based on their 11-month past returns. Then, we study the returns of a monthly strategy that buys (sells) the prior 11-month winners (losers) within each of the groups. These independent double sorts reveal a strong interaction between firm asset expansion and momentum: momentum payoffs are large for firms that have either contracted or expanded heavily, whereas they are small for firms that have not had large changes in their asset bases. In particular, for firms that, on average, show a lagged AG rate close to zero, the equal-weighted 5–1 momentum payoff is 0.26% per month and statistically insignificant. Moving up along the AG deciles, the momentum profits show an almost monotonically increasing pattern. For firms with the largest past AG rates, the momentum profit is 1.52% per month and highly statistically significant. Furthermore, within decile 1, where firms, on average, have contracted by 10%, the monthly average momentum payoff is 1.03% and statistically significant.

We control for a set of previously identified drivers of momentum.[3] The positive relationship between AG and momentum remains strong when we control for market value of equity (MV), book-to-market (BM), share turnover, return volatility, and credit rating. We also take into account the criticism by Bandarchuk and Hilscher (2013), who document that several momentum strategies enhance profits simply by trading in stocks with more extreme returns. However, we find that asset expansion is a significant

[3] Hong, Lim, and Stein (2000) show that momentum profits are higher for small stocks; Daniel and Titman (1999) and Sagi and Seasholes (2007) show that momentum effects are largest for stocks with low BM ratios; Lee and Swaminathan (2000) find that momentum is concentrated in high turnover stocks; Zhang (2006) find that momentum is strongest in stocks with high informational uncertainty proxied by variables such as return volatility; and Avramov *et al.* (2007) find that momentum is confined to stocks with low credit quality.

predictor of momentum returns even when controlling for the level of past returns. These results imply that our cross-sectional determinant is highly robust in comparison to many of the previously documented drivers of momentum profits.

We also study the time series pattern of momentum profits by creating a quarterly measure of aggregate AG across firms. Chordia and Shivakumar (2002) and Cooper, Gutierrez, and Hameed (2004) have documented that the momentum effect is dampened during recessions and after periods of negative market returns. These findings are exactly what we would expect based on our cross-sectional results since average firm expansion is smaller during these periods. Thus, if AG interacts with momentum, we expect the average firm to show lower momentum profits during recessions and after periods of negative market returns. On the other hand, firms that show large asset expansions in these market states should still show economically significant momentum profits. Our empirical results provide support for this claim. To deepen our understanding of the time series interaction, we assign our sample quarters into four groups based on the magnitude of the aggregate AG rates in the previous quarter, and study the quarterly momentum returns during these market states. The results display a dramatic pattern: in periods characterized by low aggregate AG rates, the momentum profits correspond approximately to 0.18% per month. When aggregate AG increases, the average momentum returns increase monotonically. In periods of high aggregate AG rates, the average momentum profits reach their highest level at 1.74% per month. As a final test, we regress quarterly momentum profits on lagged aggregate AG rates while simultaneously controlling for other time series determinants of momentum profits. The results indicate that AG emerges as one of the strongest time series determinants of momentum profits.

Finally, we contrast our findings with the behavioral models of momentum presented in Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998). We argue that these models do not seem fully compatible with our results. We also investigate the post-earnings-announcement drifts (PEADs) within our AG groups. Hirshleifer (2001) emphasizes that if the behavioral biases postulated by Barberis Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) are at play, we should observe particularly strong PEADs in the groups of stocks that show strong momentum. Our results do not provide much evidence that the PEADs are concentrated among firms that have experienced large asset reductions or expansions. This implies that the large momentum returns in extreme AG groups are not driven by the same psychological biases that have been used to explain drifts after earnings announcements.

Taken together, our results provide strong evidence that balance sheet AG is one of the key drivers of stock price momentum. Although our results show that momentum returns are closely linked to firm-level investment, we nonetheless acknowledge that return momentum may also arise in part from other unrelated drivers of returns. Asness, Moskowitz, and Pedersen (2012) examine macroeconomic and liquidity risk indicators in an attempt to explain the momentum returns found across various asset classes. However, for equities, it seems natural to consider the momentum implications of systematic risk as a function of firm characteristics. Although developing a new theoretical model is beyond the scope of this article, we conclude that any theory that attempts to explain stock price momentum should also be consistent with the empirical facts linking investment and future returns.

The outline of the article is as follows. The next section describes our data and presents results from the cross-sectional tests and from the time series tests. We begin by examining the effect of AG on momentum and then test the robustness of the interaction when controlling for the previously documented firm-specific and time series drivers of the return pattern. The Section 3 relates our results to existing risk-based and behavioral explanations of momentum. The Section 4 concludes.

2. Interaction between AG and Momentum

This section presents our main empirical findings. We begin by describing the data set used in our main tests. Then, we document the cross-sectional relationship between AG and momentum. Thereafter, we turn our attention to the time series relationship of AG and momentum profits.

2.1 DATA

We use New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ firms that have data available on the CRSP stock return database and Compustat annual industrial files from 1964 to 2006. To minimize potential backfilling and survival biases, we follow earlier research and require that a firm must be listed on the Compustat files 2 years before we begin calculating the firm-specific variables. Furthermore, we include only ordinary common equity (CRSP share codes 10 or 11) in our sample. To ensure that the accounting variables are in the investors' information set when the portfolios are formed, we follow the timing convention used in earlier studies. That is, the accounting variables for fiscal year ending in calendar year t are matched with portfolios that are formed at the end of June in year $t+1$.

Following Cooper, Gulen, and Schill (2008), we use a comprehensive measure of investment capturing all components of growth in the balance sheet as our test variable. Our *AG* variable is defined as the yearly percentage change in total balance sheet assets (Compustat data item 6). For a given firm *i*, the *AG* variable that is matched with returns from July of year $t+1$ to June of year $t+2$ is given by

$$AG_{i,t} = \frac{AT_{i,t} - AT_{i,t-1}}{AT_{i,t-1}}, \tag{1}$$

where AG_i is the AG for firm *i*, and AT_i is the value of the firm's total assets.

As in Fama and French (2008), our portfolio sorts pertaining to stock price momentum are based on a $J/K/L$ strategy, where $J = 11$, $K = 1$, and $L = 1$. That is, we sort stocks into groups based on the magnitude of their returns during a formation period of 11 months. To mitigate the effects of short-horizon negative return autocorrelation (Jegadeesh, 1990) and bid–ask bounces, we skip 1 month between the formation and holding periods. The resulting momentum portfolios are held for 1 month; thereafter, the sorting procedure is repeated. We also document the robustness of our results by extending the holding period to $L = 3$ and $L = 6$.

To allow for a meaningful comparison of the momentum effect within the different AG groups, we use the same prior return breakpoints within each AG group in sorting stocks into momentum portfolios. We use the NYSE prior return breakpoints to assign a stock to a portfolio.[4]

To ensure that tiny and illiquid stocks do not drive our results, we exclude from our main tests stocks whose MV at the end of each June falls below the 20th percentile of market cap of NYSE stocks. This excludes from our main sample the stocks that Fama and French (2008) define as microcaps. In our setup, including the microcaps would distort the equal-weighted momentum returns because prior losers within the lowest AG group consist predominately of stocks with a very low market capitalization. These firms then dominate the equal-weighted momentum returns in the lowest AG group. However, because the momentum effect is negative for the very smallest firms (Hong, Lim, and Stein, 2000), this leads to a negative equal-weighted momentum profit within the lowest AG decile. We are therefore motivated to have a screen for MV to mitigate the effect that the very smallest firms have on our results. Nevertheless, we also document that our results hold

[4] Using prior return breakpoints constructed from all stocks in our sample does not change our conclusions. The prior (2–12) NYSE return breakpoints, the NYSE market equity breakpoints, and data on the Fama–French factors are obtained from Kenneth French's homepage.

qualitatively within the groups of microcaps, small stocks (having MVs between the 20th and 50th NYSE percentiles) and large stocks (having MVs above the 50th NYSE percentile).

2.2 UNIVARIATE SORTS ON AG AND PRIOR RETURNS

We begin our analysis by documenting descriptive statistics for AG deciles and for five momentum portfolios in isolation. First, we investigate 10 portfolios based on univariate sorts on AG. Then, we move our analysis to five portfolios based on univariate sorts on prior returns.

At the end of each June, using the screen for MV detailed above, we sort our sample of stocks into 10 portfolios based on their AG rates during the previous year. These portfolios are held for the subsequent 12 months, and then they are rebalanced. The sample period for the holding period returns is from July 1968 to June 2006.

Panel A of Table I, Upper Panel, shows results for the AG deciles. Consistent with Cooper, Gulen, and Schill (2008), the average monthly holding period returns decrease as we move from the low to the high AG groups. However, in contrast to Cooper, Gulen, and Schill (2008), the negative relationship between AG rank and holding period returns is not monotonic.[5] For the equal-weighted (value-weighted) portfolios, the mean raw return difference between the extreme low and high AG portfolios is 0.66% (0.53%) per month, with a Newey–West (1987) *t*-statistic of 4.24 (3.02). Adjusting the 1–10 hedge portfolio returns with the Fama–French (1993) three-factor model drives down the alpha on the equal-weighted 1–10 spread to 0.45% per month. The corresponding spread between value-weighted portfolios is 0.30%. Both return differences are significant at the 5% level. The table also shows the time series averages of value-weighted AG rates and BM ratios for the portfolios. By construction, the average AG rates increase as we move along the AG deciles. The last row displays descriptive statistics on the time series averages of value-weighted past returns of the stocks included in the portfolios.

Table I, Middle Panel, documents results for five portfolios sorted on the past 11-month returns using NYSE prior (2–12)-return breakpoints, with a 1-month lag between the formation and holding periods. The holding period is 1 month, resulting in an 11–1–1 strategy. The numbers confirm the

[5] Similar to our results, Chan *et al.* (2008) document that when small stocks are excluded from the analysis, the AG effect shows up only in the decile of stocks with the highest AG rates. Using all stocks without any screens for size, we are able to replicate the monotonic negative relationship between AG rates and portfolio returns, as in Cooper, Gulen, and Schill (2008).

Table I. Portfolios sorted on past AG and past returns

Panel A shows descriptive statistics for 10 portfolios sorted on the yearly percentage change in balance sheet total assets (Compustat data item 6), denoted AG. We exclude stocks with a MV that at the end of June each year falls below the 20th percentile of market capitalization of NYSE stocks. The sample period for the holding period returns is from July 1968 to June 2006. The reported equal- and value-weighted portfolio returns are average monthly holding period returns (HPRet (EW), HPRet (VW)). The significance of the mean raw return difference between the extreme low and high AG portfolios (1–10) is estimated with a Newey–West (1987) *t*-statistic. The Fama–French (1993) three-factor alphas (FF3) are estimated to evaluate the return difference between the portfolios 1 and 10. The standard deviation of equal-weighted returns (Std (EW)) and average market shares (Market share) are reported for each decile. Descriptive statistics are reported for the time series averages of value-weighted past returns (PastRet, measured from months 2 to 12 prior to portfolio formation), BM, and lagged AG rates (AG). Panel B documents results for five portfolios sorted on past 11-month returns using NYSE prior (2–12) return breakpoints, with a 1-month lag between the formation and holding periods. The holding period is 1 month. Panel C reports a time series average of the cross-sectional correlations between the relevant firm-specific variables *AG*, *BM*, shares traded divided by shares outstanding (*Turnover*), idiosyncratic volatility calculated relative to the Fama–French (1993) three-factor model (*IVOL*) and market capitalization (*Size*).

Panel A. Portfolios sorted on AG—20% screen for size

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	1–10	*t*	FF3	*t*
HPRet (EW)	1.25	1.30	1.32	1.24	1.25	1.22	1.22	1.11	1.00	0.59	0.66	[4.24]	0.45	[3.06]
HPRet (VW)	1.17	1.20	1.07	1.02	1.00	0.99	1.07	0.87	0.88	0.64	0.53	[3.02]	0.30	[1.99]
Std (EW)	6.1	5.0	4.7	4.5	4.7	4.8	5.1	5.4	6.2	7.2				
Market share	5.6	8.5	10.8	11.5	12.4	12.7	12.3	10.0	9.4	6.9				
AG (VW)	−9.7	0.1	3.4	6.1	8.7	11.6	15.2	20.5	30.7	88.7				
BM (VW)	0.7	0.8	0.7	0.7	0.6	0.6	0.5	0.5	0.4	0.4				
PastRet (VW)	10.3	11.1	11.8	12.3	11.6	11.9	11.0	11.8	12.4	12.6				

Panel B. Portfolios sorted on past returns—20% screen for size

	P1	P2	P3	P4	P5	P5–P1	*t*	FF3	*t*
HPRet (EW)	0.66	1.01	1.11	1.27	1.56	0.90	[4.17]	1.14	[4.87]
HPRet (VW)	0.62	0.89	0.82	1.02	1.33	0.71	[2.90]	0.90	[3.45]
Std (EW)	7.3	5.3	4.8	4.7	5.8				
Market share (%)	10.9	20.3	23.0	24.1	21.7				
AG (VW)	25.2	16.2	14.2	13.9	17.9				
Past return (2–12) (VW)	−25.5	−4.6	9.3	24.6	56.7				

Panel C. Correlations between firm-specific variables

Series	*AG*	*BM*	*Turnover*	*IVOL*	*Size*
AG	1	−0.15	0.13	0.15	−0.01
BM		1	−0.06	−0.09	−0.09
Turnover			1	0.50	−0.08
IVOL				1	−0.21
Size					1

momentum anomaly in our sample. The holding period equal-weighted (EW) return spread between past winners and losers is 0.90% per month and statistically significant. Controlling for the Fama–French factors exaggerates the momentum anomaly; the spread in three-factor alphas (FF3) is 1.14%, with a t-value close to 5. The same conclusion applies to value-weighted (VW) returns, even though the momentum effect is slightly reduced.

2.3 THE CROSS-SECTIONAL INTERACTION BETWEEN AG AND MOMENTUM

We now turn our attention to the profitability of momentum strategies within the AG deciles. At the end of June each year, stocks are sorted into 10 groups based on their AG rates in the previous year. Then within each AG decile, we rank stocks at the end of each sample month based on their past 11-month returns (excluding the month preceding the first holding period month) and then group these stocks into five portfolios based on the NYSE prior return breakpoints. This results in a 10x5 independent sort on AG rates and past returns.

We first concentrate on the 11–1–1 momentum strategy. Panels A.I and A.II of Table II, displays average EW returns and average VW returns, respectively, on the five portfolios sorted on past returns. We also report the average return on the 5–1 hedge portfolio that takes a long position in past winners and a short position in past losers for each AG group.

The momentum profits within the AG groups reveal two distinctive patterns. First, momentum seems to be concentrated among firms that have either experienced asset contraction (AG decile 1, where firms, on average, have experienced a negative AG rate of 10%; see Table I, Panel A) or large asset expansion (AG deciles 7–10). In particular, firms in deciles 2 and 3, where the AG has been close to zero, do not show a reliable momentum effect. Second, moving from AG decile 2–10, the average momentum profits for equal-weighted portfolios increase almost monotonically, from 0.26% to 1.52% (0.02–1.34% when returns are value weighted). Furthermore, 5 out of the 10 VW and 3 out of the 10 EW raw momentum profits are insignificant, and these insignificant profits are concentrated in the low AG groups. The FF3-adjusted momentum profits are generally significant.[6]

[6] The results conditioned on annual accounting data imply, in line with previous studies, that we match accounting data for fiscal years ending in calendar year t with returns from July of $t+1$ to June of $t+2$. In an unreported test of robustness, we shorten the lag between the holding period and the conditioning variable by redoing the sorts using quarterly accounting data from Compustat. We confirm that the results are qualitatively unchanged from the sorts based on annual data.

Table II. Momentum within AG groups

Panel A (I and II) presents average returns on portfolios sorted independently on balance sheet AG and past return. At the end of June each year, stocks are sorted into 10 groups based on their AG rates in the previous year. Within each AG decile, stocks are ranked at the end of each sample month based on their past 11-month returns, excluding the month preceding the first holding period month. The stocks are then grouped into five portfolios based on the NYSE prior return breakpoints. The momentum strategy (P5–P1) involves buying the past winner portfolio (P5) and selling the past loser portfolio (P1). The holding period is 1 month. The table shows the average monthly portfolio returns during the holding period as well as the average momentum strategy returns on the 5–1 hedge portfolio. The corresponding momentum profits adjusted with the Fama–French (1993) three-factor model are also reported. Newey and West (1987) *t*-values are reported in brackets. Only stocks with a MV that at the end of June exceeds the 20th NYSE size percentile are included in the analysis. Panel B.I presents the 5–1 raw momentum returns as in Panel A, but without any screens for firm size. Average raw momentum returns using longer holding periods of 3 and 6 months are reported in Panel B.II. The sample is from July 1968 to June 2006. Panel C studies the impact of excluding firms with an S&P Long-Term Domestic Issuer Credit Ratings lower than B from the sample. The sample is from July 1986 to June 2006.

	Past return groups								
AG	P1	P2	P3	P4	P5	P5–P1	*t*	FF3	*t*
Panel A.I. Momentum within AG groups—equal-weighted returns									
Low	0.62	1.20	1.25	1.45	1.65	1.03	[4.51]	1.36	[5.65]
2	1.19	1.15	1.31	1.35	1.44	0.26	[0.96]	0.43	[1.59]
3	1.25	1.29	1.16	1.37	1.60	0.34	[1.30]	0.52	[1.92]
4	1.01	1.12	1.21	1.18	1.54	0.52	[2.18]	0.80	[2.92]
5	1.05	1.14	1.16	1.30	1.59	0.53	[2.09]	0.86	[3.33]
6	1.13	1.03	1.17	1.28	1.48	0.35	[1.42]	0.57	[2.21]
7	0.86	1.00	1.08	1.37	1.67	0.81	[3.59]	1.00	[3.95]
8	0.54	0.94	1.04	1.24	1.60	1.06	[4.35]	1.36	[5.36]
9	0.34	0.64	0.91	1.22	1.68	1.34	[5.06]	1.64	[6.10]
High	−0.13	0.44	0.50	0.86	1.39	1.52	[5.68]	1.83	[6.39]
Panel A.II. Momentum within AG groups—value-weighted returns									
Low	0.60	1.15	1.09	1.32	1.39	0.78	[2.94]	1.19	[4.22]
2	1.22	1.01	1.09	1.36	1.24	0.02	[0.05]	0.12	[0.36]
3	1.29	1.37	0.87	1.15	1.44	0.15	[0.42]	0.23	[0.60]
4	1.03	0.96	0.98	0.99	1.28	0.25	[0.74]	0.67	[1.95]
5	1.18	0.95	0.84	1.01	1.45	0.27	[0.84]	0.54	[1.70]
6	0.73	0.84	1.07	1.03	1.22	0.50	[1.77]	0.64	[2.07]
7	0.62	1.05	0.82	1.14	1.44	0.81	[2.92]	1.00	[3.43]
8	0.25	0.77	0.72	0.95	1.40	1.15	[3.82]	1.43	[4.59]
9	0.28	0.41	0.65	1.00	1.54	1.27	[4.28]	1.50	[4.45]
High	−0.16	0.35	0.61	0.62	1.18	1.34	[4.33]	1.71	[5.28]

Table II. (Continued)

Panel B. Robustness tests

	I. No screen for size				II. 20% screen for size				
	11–1–1					11–1–3		11–1–6	
AG	P5–P1	*t*	P5–P1	*t*	AG	P5–P1	*t*	P5–P1	*t*
Low	−0.19	[−0.76]	0.65	[2.12]	−23.0	0.82	[3.35]	0.57	[2.38]
2	0.27	[1.16]	0.92	[3.19]	−6.2	0.31	[1.21]	0.27	[1.13]
3	0.09	[0.44]	−0.02	[−0.06]	−0.5	0.36	[1.50]	0.33	[1.47]
4	0.57	[3.06]	0.42	[1.30]	3.1	0.68	[2.88]	0.74	[3.15]
5	0.85	[4.10]	0.26	[0.83]	6.2	0.42	[1.72]	0.38	[1.61]
6	0.69	[3.32]	0.39	[1.28]	9.4	0.40	[1.66]	0.33	[1.46]
7	0.73	[3.59]	0.79	[3.12]	13.3	0.76	[3.36]	0.56	[2.49]
8	1.01	[4.80]	1.00	[3.33]	18.9	0.86	[3.66]	0.78	[3.58]
9	1.39	[6.86]	1.49	[5.44]	29.8	1.22	[4.86]	0.99	[4.17]
High	1.39	[5.75]	1.24	[4.26]	96.9	1.30	[5.04]	1.12	[4.54]
Weighting	EW		VW			EW		EW	

Panel C. Impact of credit rating, July 1986 June 2006

	20% screen for size							
	11–1–1							
AG	P5–P1	*t*	P5–P1	*t*	P5–P1	*t*	P5–P1	*t*
Low	1.00	[3.04]	1.02	[2.92]	0.62	[1.82]	0.67	[1.79]
2	0.00	[0.00]	0.07	[0.20]	0.20	[0.46]	0.29	[0.65]
3	0.30	[0.85]	0.28	[0.79]	0.24	[0.62]	0.20	[0.54]
4	0.42	[1.18]	0.38	[1.07]	0.24	[0.54]	0.18	[0.42]
5	0.61	[1.58]	0.64	[1.68]	0.63	[1.25]	0.74	[1.53]
6	−0.11	[−0.32]	−0.08	[−0.25]	0.32	[0.69]	0.34	[0.78]
7	0.57	[1.80]	0.61	[2.02]	1.17	[2.41]	1.33	[2.85]
8	0.68	[2.11]	0.62	[1.92]	1.16	[2.52]	1.05	[2.33]
9	1.16	[2.91]	1.10	[2.86]	1.46	[2.94]	1.30	[2.78]
High	1.25	[3.40]	1.21	[3.33]	1.86	[3.55]	1.80	[3.43]
Sample	Rated and unrated		Rated and unrated excluding rated below B		Only rated		Only rated excluding rated below B	

In the results above, we have omitted stocks from our analysis that fall below the 20th NYSE market cap percentile. Panel B.I of Table II, replicates

(continued)

the results in Table II, Panel A without any screen for size. To preserve space, we report only the 5–1 raw momentum spreads and their t-values.

A marked difference between the EW and VW portfolio returns emerges when we include microcaps in the analysis. The EW momentum spread for decile 1 is negative, albeit insignificant, whereas the corresponding VW spread is positive and highly significant. As previously mentioned, the reason for this discrepancy is that the past loser portfolio in the lowest AG deciles contains a disproportionately large amount of microcaps. Hong, Lim, and Stein (2000) document that, within the lowest NYSE/AMEX size decile, momentum profits are negative. Thus, the EW returns for the lowest AG deciles in our Table II, Panel B.I reflect this pattern in the data. The VW returns that control for this size effect confirm the earlier results from Table II, Panel A. That is, the momentum profits are large in magnitude and significant in the negative AG growth deciles and increase across the positive AG deciles. Thus, our main results in Table II, Upper Panel, do not appear to be driven by the screen for market capitalization that we have used.

The results in Table II, Panel A are based on a holding period of 1 month. However, as it is also customary to study momentum profits on portfolios that are held for longer periods, we replicate the results in Table II, Panel A using holding periods of 3 and 6 months. Following Jegadeesh and Titman (1993), we construct portfolios with overlapping holding periods. For example, when a holding period of 3 months is used, we have three observations on a given portfolio for any given month. The portfolio return for that month is then calculated as an equal-weighted average of the portfolio constructed that month and the portfolios constructed in the two previous months.

Table II, Panel B.II shows that our conclusions are not materially affected with a longer holding period.[7] For holding periods of 3 and 6 months, the highest momentum returns show up in the high AG decile. However, the large momentum profits for AG decile 1 that were evident for the 1-month holding period appear to have dissipated quicker than the profits in the other deciles.

Avramov *et al.* (2007) document that distressed firms with a low credit rating tend to show the highest momentum profits. Recall that AG decile 1 consisted of firms that, on average, have experienced asset contractions. Hence, a potential concern is that our lowest AG decile mainly consists of distressed firms with a low credit rating, and these firms are driving the momentum profits that we have documented. To mitigate this concern, we collect Standard and Poor's (S&P) Long-Term Domestic Issuer Credit

[7] To conserve space, we only report EW returns throughout the rest of our article. VW returns produce similar results and are available upon request.

Ratings from Compustat for firms included in our sample. Due to the non-availability of S&P ratings in the early part of the sample, our sample begins in July 1986. The first column in Table II, Panel C replicates the results in Table II, Panel A.I for this shorter sample and displays the momentum profits across the AG groups using all rated and unrated firms while applying the 20% screen for size. The mean momentum profit in decile 1 between July 1986 and June 2006 is 1.00% ($t = 3.04$), and the momentum profits across the AG deciles show qualitatively the same pattern as in the full sample. Next, we drop all firms that have a credit rating lower than "B" at the time of portfolio formation, implying that we drop firms that fall below the lowest tercile of credit ratings assigned by S&P. With this filter, the mean momentum profit within decile 1 increases slightly to 1.02% ($t = 2.92$). The remaining columns show the results when we apply our portfolio sorts to only those firms that have a credit rating ("Only rated") and then dropping firms rated below B ("Only rated, excluding rated below B").[8] Among the rated firms, the mean momentum profit for AG decile 1 is 0.62% ($t = 1.82$), and the exclusion of low-rated firms increases the profit slightly to 0.67% ($t = 1.79$). Thus, while rated firms show a relatively smaller momentum effect in AG decile 1 than firms in the unrestricted sample, the high momentum profit in the low AG decile does not appear to be driven by distressed firms having a low credit rating.

2.4 CONTROLLING FOR PREVIOUSLY DOCUMENTED DRIVERS OF MOMENTUM

Prior literature has documented several firm-specific characteristics that appear to be connected to the magnitude of momentum profits. For example, Jegadeesh and Titman (1993) and Hong, Lim, and Stein (2000) show that the returns on small firms exhibit larger momentum effects than the returns on large firms. Daniel and Titman (1999) and Sagi and Seasholes (2007) document that momentum seems to be concentrated within the group of firms having low BM equity ratios. Lee and Swaminathan (2000) find that firms with high trading volumes show relatively larger momentum, whereas the results in Zhang (2006) and Arena, Haggard, and Yan (2008) indicate that momentum profits are high among firms with high past return volatility. Furthermore, Avramov *et al.* (2007) report that momentum seems to be concentrated in firms that have high credit risk. In what follows, we show

[8] On average, 51% of firms in our sample have a credit rating at the time of portfolio formation, implying that we lose about half of the stocks in our portfolios. The lower level of portfolio diversification is also reflected in the relatively smaller t-statistics obtained for this sample.

that the momentum profits within the AG groups are not driven by the previously documented interaction variables.

To purge the effect of the control variables, we start with independent three-way portfolio sorts. First, we sort our sample of stocks into three groups based on the magnitude of the control variable. Then, in an independent sort, we arrange the stocks into three groups based on their AG rates. Each stock is then allocated to one of the nine resulting control variable/AG groups. Finally, within each of the nine groups, we rank stocks at the end of each sample month based on their past 11-month returns (excluding the month preceding the first holding period month) and then group these stocks into five portfolios based on the NYSE prior return breakpoints. This allows us to study the returns on the 11–1–1 momentum strategies while simultaneously controlling for a given control variable and AG rates. If, for example, the interaction between AG and momentum were simply driven by the fact that high AG firms are characterized by low BM ratios, we would not expect to find a spread in momentum profits between high and low AG firms when BM ratios are held relatively constant.

A detailed description of our portfolio sorts and the included variables can be found in the online Appendix (available as supplementary data). To obtain a sufficient number of stocks in each of the independently sorted 45 portfolios, we use all the stocks in our sample without applying a screen for MV. We report EW returns and corresponding *t*-statistics from a 5–1 strategy that buys the prior winner portfolio and shorts the prior loser portfolio for each control variable/AG bin. The results using VW returns, which downsize the possible dominance of microcaps in some portfolios, are qualitatively the same. These results, and some further robustness checks, are presented in the online Appendix (available as supplementary data). The results from the portfolio sorts are reported in Table III, Panel A.

To control for MV, we independently sort the stocks into three size and AG groups at the end of each June. Following Fama and French (2008), the size breakpoints are defined as the NYSE 20th and 50th percentiles of market cap for NYSE stocks. Then, within each of the nine size/AG groups, we study the monthly average return on the 11–1–1 momentum strategy. Table III, Panel A.I shows the results for each size/AG bin. The last row of the panel displays the difference in momentum profits between high and low AG groups within each size group. For all size groups, the high AG group displays the largest momentum profits.[9]

[9] The difference in momentum profits between high and low AG groups is significant within microcaps and large stocks but insignificant within the group of small stocks. The low AG group within small stocks contains a subgroup of stocks with a large negative AG

Table III. Controlling for other drivers of momentum

Panel A presents average monthly momentum returns from July 1968 (July 1986 when controlling for credit ratings) to June 2006 within AG groups while controlling for other firm-specific variables. First, stocks are sorted into three groups based on the magnitude of the control variable. Then in an independent sort, stocks are arranged into three groups based on their balance sheet AG rates. Finally, within each of the nine AG/control variable groups, stocks are ranked on their past 11-month returns (excluding the month preceding the first holding period month) into five portfolios based on the NYSE prior return breakpoints. In Panel AI, the size breakpoints are defined as the 20th and 50th percentiles of market capitalization for NYSE stocks. In Panel A.II, book value is calculated as in Davis, Fama, and French (2000) and divided by the MV at the end of June in year t to obtain BM ratios. Negative book values are excluded. In Panel A.III, trading volume is the average daily turnover (number of shares traded/number of shares outstanding) within the 11-month portfolio formation period. NASDAQ stocks are excluded. Idiosyncratic volatility (Panel A.IV) is relative to the Fama–French (1993) three-factor model using daily returns within the 11-month formation period. In Panel A.V, S&P Long-Term Domestic Issuer Credit Ratings are used as a control variable. In contrast to the previous sorts, past 11-month return breakpoints are calculated within each credit rating/AG group. Panel B reports firm-level Fama–MacBeth (1973) regressions of monthly stock returns on lagged empirical determinants of cross-sectional returns and on terms that capture how the different control variables interact with momentum. In the regression results, we apply the 20% screen for size to the stocks in our sample. In specifications that include turnover, NASDAQ stocks are excluded, and the sample starts from start from July 1986 when credit rating is included. Newey–West (1987) t-statistics are given in brackets.

Panel A. Three-way independent portfolio sorts—equal-weighted returns

	I. Size			II. BM			III. Turnover			IV. Idiosyncratic volatility			V. Credit rating		
	Micro caps	Small stocks	Big stocks	High BM	Med BM	Low BM	Low TO	Med TO	High TO	Lov IVOL	Med IVOL	High IVOL	High CR	Med CR	Low CR
Low AG	0.04	1.04	0.09	0.21	0.15	0.36	0.04	0.76	0.88	0.46	1.02	−0.78	−0.13	−0.04	1.13
	[0.19]	[4.57]	[0.30]	[0.90]	[0.72]	[1.62]	[0.13]	[3.04]	[3.46]	[3.14]	[4.99]	[−2.21]	[−0.47]	[−0.13]	[1.92]
Med AG	0.96	0.74	0.26	0.58	0.78	0.92	0.86	0.59	1.14	0.38	0.99	0.99	0.12	0.78	1.59
	[5.44]	[3.49]	[1.10]	[3.08]	[4.35]	[4.50]	[4.32]	[2.65]	[4.99]	[3.23]	[5.64]	[3.39]	[0.46]	[2.12]	[2.58]
High AG	1.26	1.32	1.12	1.20	1.12	1.59	0.94	1.18	1.51	0.86	1.51	1.15	0.42	0.89	2.95
	[6.35]	[5.57]	[4.40]	[4.78]	[5.75]	[8.02]	[4.34]	[5.41]	[6.21]	[5.36]	[7.38]	[3.43]	[1.36]	[2.24]	[4.69]
Spread in momentum (EW)	1.22	0.28	1.03	0.99	0.97	1.23	0.91	0.42	0.63	0.40	0.49	1.94	0.55	0.93	1.82
	[6.56]	[1.53]	[4.49]	[3.99]	[4.74]	[6.68]	[3.49]	[1.95]	[3.06]	[2.64]	[2.88]	[5.64]	[2.55]	[3.05]	[2.67]

(continued)

Table III. Continued

Panel B. Firm-level Fama–MacBeth (1973) regressions							
	1	2	3	4	5	6	7
Intercept	2.559	2.446	2.558	2.554	2.395	1.558	1.577
	[4.04]	[3.98]	[4.06]	[4.07]	[3.91]	[1.43]	[1.76]
AG	−0.003	−0.002	−0.003	−0.003	−0.003	−0.003	−0.003
	[−3.60]	[−2.64]	[−3.60]	[−3.40]	[−3.11]	[−1.68]	[−2.11]
MV	−0.080	−0.075	−0.080	−0.080	−0.074	−0.031	−0.038
	[−2.15]	[−1.98]	[−2.15]	[−2.17]	[−1.95]	[−0.46]	[−0.64]
BM	0.178	0.165	0.181	0.194	0.195	0.082	0.062
	[2.31]	[2.34]	[2.37]	[2.27]	[2.38]	[0.82]	[0.58]
ret11	0.009	0.009	0.008	0.008	0.010	0.009	0.010
	[5.28]	[5.35]	[4.83]	[3.94]	[4.17]	[2.87]	[2.35]
IVOL	−0.218	−0.163	−0.211	−0.208	−0.153	−0.044	−0.043
	[−2.01]	[−1.70]	[−1.95]	[−1.95]	[−1.59]	[−0.31]	[−0.33]
TO		−0.660			−0.636		0.090
		[−3.05]			[−2.32]		[0.34]
CR						−0.265	−0.300
						[−1.37]	[−1.45]
ret11 × AG			0.005	0.04	0.006	0.004	0.008
			[2.86]	[2.22]	[2.89]	[2.12]	[2.72]
ret11 × BM				−0.132	−0.122		0.211
				[−1.43]	[−1.00]		[0.95]
ret11 × TO					−0.553		0.061
					[−1.56]		[0.16]
ret11 × CR						0.764	0.661
						[1.50]	[1.44]

Within the group of large stocks, only the high AG group shows a reliable momentum effect.

Next, in Panel A.II of Table III, we control for BM and find that the high AG groups once again show the highest momentum profits, and all of the differences in momentum profits between high and low AG groups are significant. Similarly, the portfolio sorts with asset turnover in Table III, Panel A.III show that the high AG stocks show higher momentum profits than low AG stocks within each turnover group.[10] In controlling for idiosyncratic volatility (IVOL), we calculate the measure relative to the Fama–French (1993) three-factor model for each stock in the sample using daily returns within the 11-month portfolio formation period. As observed from Table III, Panel A.IV the AG interaction with momentum is still significant when controlling for lagged return volatility.

We conclude the portfolio sorts by controlling for credit risk in Panel A.V of Table III, Following Avramov *et al*. (2007), we collect S&P Long-Term Domestic Issuer Credit Ratings from Compustat and match these credit ratings with the stocks in our sample. Restricted by the availability of credit ratings from Compustat, our portfolio sorts start from July 1986. The results confirm that the AG interaction survives even when controlling for credit rating. Within each credit rating group, the differences in momentum profits between high and low AG groups are positive and statistically significant.

2.4.a. *Fama–MacBeth regressions*

The portfolio sorts indicated that the effect that AG has on momentum profits survives the inclusion of the control variables. However, there are some shortcomings with the robustness tests in the previous section. In essence, we would like to know the marginal significance of AG for momentum profits with respect to the previously documented interaction variables. Unfortunately, the universe of NYSE/AMEX/NASDAQ stocks with available historical accounting data in Compustat is not sufficiently large to evaluate the joint effect of the control variables on the AG–momentum relationship through four- or five-way portfolio sorts.

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rate. Due to the U-shaped AG–momentum relationship, demonstrated in Upper Panel of Table II, firms that have experienced a large asset contraction tend to display high price momentum. This drives up momentum profits within the low AG groups. Using value-weighted returns, the difference is significant within each size group.

[10] As in Lee and Swaminathan (2000), we exclude NASDAQ stocks from our sample due to the double counting of dealer trades and report results only for the NYSE/AMEX sample.

To circumvent the problem, we run firm-level Fama–MacBeth (1973) regressions of monthly stock returns on empirical determinants of cross-sectional returns and on terms that capture how the variables interact with momentum. The full cross-sectional model that we estimate each sample month is given by

$$\begin{aligned} r_{i,t} = {} & b_0 + b_1 AG_i + b_2 \log(MV_i) + b_3 \log(BM_i) + b_4 ret11_i + b_5 IVOL_i \\ & + b_6 TO_i + b_7 CR_i \\ & + b_8 (ret11_i \times AG_i) + b_9 (ret11_i \times \log(BM_i)) \\ & + b_{10} (ret11_i \times TO_i) + b_{11} (ret11_i \times CR_i) + e_{i,t}. \end{aligned} \tag{2}$$

The dating conventions follow our previous definitions. The monthly returns from July in year t to June in year $t+1$ are matched with the AG rate (AG) measured during the fiscal year ending in calendar year $t-1$. The log MV of equity, MV, is measured at the end of June in year t. Log BM equity, BM, is based on accounting data from the fiscal year ending in calendar year $t-1$, whereas the MV in the denominator is from June in year t. The variable $ret11$ is the lagged 11-month return used in our earlier portfolio sorts, measured from month $t-2$ to $t-12$. The average turnover (TO) and idiosyncratic volatility ($IVOL$) are measured over the same period as the lagged 11-month return. CR is the most recent credit rating assigned to the firm.[11] The coefficients for the interaction terms, b_8–b_{11}, measure how the past return interacts with the control variables. If, for example, b_8 is positive and significant, a higher AG rate increases the effect that lagged past returns have on holding period returns, that is, there is a stronger price momentum effect when the change in total balance sheet assets is large.

In the regression results reported below, we apply the 20% screen for size to the stocks in our sample and exclude stocks with a negative BM ratio. As in the portfolio sorts, we exclude NASDAQ stocks from our sample when the turnover variable is included. Furthermore, the sample starts from July 1986 for the estimations that contain the credit rating variable. The standard errors are based on Newey–West (1987) estimates.

Regression models with interaction variables are potentially plagued by multicollinearity. We find the largest correlation between the past returns and the interaction term between log MV and past returns (the average correlation between $ret11$ and $ret11 \times \log(MV)$ is 0.99), the second largest average absolute correlation is between past returns and their interaction

[11] We linearly transform the 22 credit rating groups to a scale from -1 to 1, where -1 denotes the firms with the highest credit rating ("AAA"), and 1 denotes the firms with the lowest rating ("D").

with IVOL (0.92). Thus, we exclude the size and volatility interactions from our model above. The correlations between the other variables are considerably lower.

Table III, Panel B, columns 1 and 2 show the results without interaction variables. The signs of the parameter estimates do not produce any surprises relative to prior literature. Consistent with Cooper, Gulen, and Schill (2008), lagged AG shows up with a negative and highly significant coefficient. Furthermore, BM and lagged 11-month returns display significantly positive coefficients, whereas the coefficient for MV is negative. These results are perfectly in line with the well-documented value, momentum, and size effects. As in Ang *et al.* (2006), the sign of *IVOL* implies that higher idiosyncratic volatility is associated with lower returns. In the NYSE/AMEX sample (column 2), high turnover is associated with significantly lower returns.[12]

Next, we investigate the results from regressions that include the interaction terms. Specification 3 adds the interaction between AG and past returns to our baseline model presented in column 1. The coefficient for the interaction term is positive and significant ($t = 2.86$). Including the interaction between past returns and BM ratio (specification 4) does not drive away the significance of the AG interaction. Indeed, the significance of the AG interaction remains high ($t = 2.22$), whereas the BM interaction is insignificant ($t = -1.43$). Column 5 further demonstrates the robustness of the AG interaction: the interaction remains significant even when the specifications control for the interaction of past returns with turnover.

The two remaining specifications control for the interaction between credit rating and past returns. Recall that in these tests, our sample length is cut in half, and our regressions begin from July 1986. Results from specification 6 reveal that the credit rating interaction, while having the right sign relative to portfolio sorts, does not reach statistical significance ($t = 1.50$). The AG interaction, on the other hand, remains significant, with a t-value of 2.12.

Finally, in specification 7, we test for the significance of the AG interaction while simultaneously controlling for the previously documented drivers of momentum. From these results, AG emerges as the variable with the strongest amplifying effect on return momentum. The AG interaction displays a t-value of 2.72, whereas the other interactions are rendered insignificant.

[12] A similar pattern has been documented, among others, by Datar, Naik, and Radcliffe (1998) and Lee and Swaminathan (2000).

As a whole, our results thus far indicate that firm-level AG is connected to the profitability of momentum strategies. More significantly, when we control for a set of previously documented drivers of momentum, AG emerges as the strongest and most significant interaction variable that predicts the magnitude of the momentum effect.

2.4.b. *Controlling for dispersion in past returns*

Bandarchuk and Hilscher (2013) present a critique of previous studies that have relied on double sorts to document how momentum profits vary with various firm characteristics. Their critique is based on the observation that firms with extreme characteristics have more extreme past returns. Because momentum profits across portfolios increase with extreme past returns, the previously documented interaction patterns merely emerge as a result of differences in the dispersion of past returns across the portfolios. For example, firms with high turnover display more dispersion in past returns than firms with low turnover. Thus, it is not *ex ante* surprising that momentum strategies within high turnover groups produce larger profits than momentum strategies within low turnover groups. The authors subsequently show that most of the previously documented momentum interactions appear to only capture the effect that extreme past returns have on momentum profits.

We are sympathetic to the concern raised by Bandarchuk and Hilscher (2013). We note, however, that the Fama–MacBeth regressions in the previous subsection suggest that our AG interaction is not merely driven by differences in past returns across the AG groups. The estimated interaction coefficients control, to some extent, for the spread in past returns: they measure the magnitude at which the sensitivity of holding period returns to a fixed change in past returns varies across the AG spectrum. Nevertheless, to alleviate any remaining concerns, we present in our online Appendix (available as supplementary data) results from a further robustness test that directly controls for the dispersion of past returns within AG deciles. The results, based on benchmark-adjusted momentum returns (as in Daniel *et al*., 1997), demonstrate that the interaction between AG and momentum is not explained by a larger dispersion in formation period returns in the extreme AG deciles.

2.5 TIME SERIES EVIDENCE

The previous sections indicated that firm-level balance sheet AG is a strong cross-sectional determinant of momentum profits. We now turn our attention to the time series of momentum profits.

2.5.a. *Momentum profits during different business cycle periods*

Chordia and Shivakumar (2002) document a business cycle pattern to momentum profits where momentum profits are positive during expansionary periods but negative (though insignificant) during recessions. Our cross-sectional evidence that price momentum is connected to firm expansion is consistent with this finding. During expansionary periods, firm-level expansion is likely to be larger than during recessions.[13] If momentum is connected to firm expansion, we would expect the average firm to show higher momentum profits during periods that are associated with higher AG rates. Furthermore, even if momentum profits on aggregate are lower in recessions due to weaker firm expansion, we would nevertheless expect firms expanding heavily to show positive momentum profits during recessionary periods as well. We now document that this is indeed the case.

Panel A of Table IV, documents the momentum profits during the different business cycle periods. We categorize the holding period months from July 1968 to June 2006 as expansionary or contractionary months based on the classifications made by the National Bureau of Economic Research (NBER). Altogether, there are 391 months that are classified as expansions and 65 months classified as recessions. To investigate the significance of momentum profits in the two economic states, we regress the time series of our 5–1 momentum portfolio returns on an expansionary dummy variable and a contractionary dummy variable without an intercept. The estimated coefficients for the two dummy variables capture the mean momentum profits in the two states.

The first row, labeled "all stocks", shows the aggregate 5–1 momentum profits for all stocks in our sample. The mean momentum returns in the two periods follow the same pattern as in Chordia and Shivakumar (2002): momentum profits are larger in expansions (mean $= 0.96\%$, $t = 4.20$) than in recessions (mean $= 0.54\%$, $t = 0.85$).

The remaining rows in the table show the mean profits of the momentum portfolios within 10 AG groups. The numbers demonstrate that, during recessions, AG groups 2–7 show average momentum profits that are close to zero and even negative, whereas firms that expand heavily in recessions have positive momentum profits. In particular, groups 9 and 10, with the largest AG rates, show large average monthly momentum profits of 1.05 and 1.40%, respectively. However, these profits are not significant, with

[13] We confirm this statement by collecting quarterly AG data from Compustat and calculating the cross-sectional average AG rates for each quarter during our sample period. During recessions, as defined by the NBER, the time series mean of the average AG rate is 2.4% per quarter, whereas it is 3.9% during expansions.

Table IV. Momentum profits conditioning on market states

Panel A groups the holding period months in expansionary and contractionary months based on the classifications made by the NBER. The table reports, for these two states of the economy, the average profits on 5–1 momentum strategies that use all stocks in the sample (applying a 20% screen for market capitalization) and on the momentum strategies within 10 AG groups. To assess the market state in Panel B, we use the lagged 12-month cumulative returns on the CRSP value-weighted market index. If the 12-month lagged return on the index is positive (skipping 1 month before the holding period), a holding period month is classified as an UP month, otherwise it is classified as a DOWN month. Panel B also reports the results for the DOWN market momentum profits when January 2001 is excluded from the sample (labeled DOWN*). In Panel C, the monthly sentiment index constructed by Baker and Wurgler (2006, 2007) is used to classify the sample months into pessimistic and optimistic periods. A moving average of the sentiment values is calculated for the 3 months prior to the holding period. If this average sentiment level falls within the bottom 33% of all months, the holding period month is classified as pessimistic, otherwise it is optimistic. The sample is from July 1968 to June 2006. Newey–West (1987) *t*-statistics are in brackets.

	A.				B.						C.			
	Expand	*t*	Contract	*t*	UP	*t*	DOWN	*t*	DOWN*	*t**	Optimistic	*t*	Pessimistic	*t*
All stocks	0.96	[4.20]	0.54	[0.85]	1.19	[5.80]	−0.02	[−0.02]	0.37	[0.64]	1.13	[4.04]	0.45	[1.02]
Low AG	1.08	[4.29]	0.75	[1.15]	1.35	[5.60]	0.02	[0.04]	0.28	[0.45]	1.22	[4.27]	0.70	[1.40]
2	0.29	[1.04]	0.04	[0.05]	0.65	[2.68]	−0.99	[−1.36]	−0.54	[−0.80]	0.43	[1.28]	−0.15	[−0.29]
3	0.53	[2.29]	−0.80	[−0.77]	0.88	[3.69]	−1.35	[−1.72]	−1.05	[−1.34]	0.43	[1.31]	0.16	[0.31]
4	0.61	[2.37]	−0.01	[−0.01]	0.92	[3.80]	−0.73	[−1.08]	−0.38	[−0.61]	0.89	[3.22]	-0.09	[−0.18]
5	0.60	[2.13]	0.13	[0.17]	0.83	[3.10]	−0.40	[−0.69]	−0.07	[−0.13]	0.83	[2.49]	−0.03	[−0.06]
6	0.44	[1.66]	−0.21	[−0.33]	0.69	[2.81]	−0.75	[−1.22]	−0.51	[−0.87]	0.61	[1.96]	−0.18	[−0.34]
7	0.99	[3.94]	−0.23	[−0.38]	1.15	[4.79]	−0.26	[−0.42]	0.08	[0.15]	0.90	[3.03]	0.67	[1.62]
8	1.16	[4.48]	0.43	[0.73]	1.35	[5.11]	0.13	[0.23]	0.46	[0.96]	1.09	[3.35]	0.93	[2.18]
9	1.39	[4.93]	1.05	[1.37]	1.77	[7.00]	0.00	[0.01]	0.42	[0.68]	1.64	[4.93]	0.69	[1.46]
High AG	1.54	[5.55]	1.40	[1.52]	1.69	[5.99]	0.97	[1.29]	1.52	[2.23]	1.78	[5.07]	1.03	[2.24]
N	391		65		346		110		109		300		150	

respective t-values of 1.37 and 1.52. The lack of statistical significance is likely to be due to the low number of months that are classified as recessions. Nevertheless, the high point estimates of momentum profits within the extreme AG groups provide further support for our claim that firm-level expansion is an important driver of momentum.

2.5.b. *Momentum profits following up and down markets*

Cooper, Gutierrez, and Hameed (2004) document that momentum profits are significant only when the lagged 1- to 3-year stock market returns have been positive. This empirical finding appears to be related to our results. Following up markets, managers are likely to invest more due to better access to capital.[14] This leads to larger firm expansion and, consistent with our cross-sectional results, to larger momentum effects.

Panel B of Table IV, presents the momentum profits for the AG groups in up and down markets. We use 12-month cumulative returns on the CRSP value-weighted market index as a proxy for market returns. If the 12-month lagged return on the index has been positive (skipping 1 month between the formation and holding period), we classify a holding period month as an UP month. Otherwise, the month is classified as a DOWN month. In total, 346 months are UP months, and 110 are DOWN months.

We confirm that the results in Cooper, Gutierrez, and Hameed (2004) hold for our sample. For a momentum strategy involving all stocks (first row), the payoff in UP months is a highly significant 1.19% per month ($t = 5.80$). In DOWN months, the unconditional strategy essentially yields zero profits, with a mean of −0.02%. Examining the momentum profits within the AG groups, the returns in UP markets reveal that the extreme AG groups once again show up with the highest profits. However, in DOWN markets, only AG decile 10 displays a relatively high average momentum profit of 0.97%, albeit with an insignificant t-value of 1.29. The rest of the AG deciles show momentum payoffs that range from −1.35% (decile 3) to 0.13% (decile 8).

Despite the high 0.97% per month time series mean of the DOWN market momentum profits in AG decile 10, the insignificance of the payoff might raise the question if the AG/momentum interaction survives in DOWN

[14] In an unreported test, we regress quarterly average AG rates on lagged 12-month market returns and a constant. The t-statistic for the lagged market return is 3.28, and the r^2 from the regression is 10%. The correlation between lagged market returns and the quarterly AG rate is 0.32. Furthermore, the average quarterly AG rate following 12-month DOWN markets is 2.80%, whereas it is 4.32% following 12-month UP markets.

markets. We believe, however, that the results in Table IV, Panel B are broadly in line with our earlier findings. First, the momentum profits generally show an increasing pattern from AG decile 3 to decile 10. Second, it is a well-documented fact that volatility tends to be high in down markets. The standard deviation of monthly momentum returns within decile 10 is 10.3% in DOWN months, whereas it is only 4.9% in UP months. The high volatility coupled with a low number of DOWN observations leads to a lack of statistical significance. Third, one single month, January 2001, seems to have been devastating for momentum strategies. During this month, the unconditional 5–1 momentum strategy lost −42.1%. We do not wish take a strong position on whether this observation is an outlier (a random event distorting our statistical inference).[15] For completeness, Panel B of Table IV, also shows the results for the DOWN month momentum profits, where January 2001 is excluded from our sample. In this case, the mean momentum profit for AG decile 10 is 1.52% per month (compared to 0.97% when January 2001 is included) and statistically significant ($t = 2.23$), despite the low number of observations. In unreported results, we furthermore test that when we include all DOWN months, the median momentum profit for decile 10 is 1.61%, and 60% of the monthly momentum profits are positive. In UP months, the median is also 1.61%, and 63% of the monthly momentum profits are positive. Thus, correcting for one single extreme return, firms that have experienced the largest asset expansions appear to provide similar momentum profits in both UP and DOWN markets.

2.5.c. *Momentum profits following periods of low and high sentiment*

Building on the behavioral theory proposed by Daniel, Hirshleifer, and Subrahmanyam (1998), Antoniou, Doukas, and Subrahmanyam (2010) argue that market-wide investor sentiment should be connected to aggregate momentum profits. Using different proxies for sentiment, they find support for this hypothesis: momentum profits are high after periods of optimistic

[15] Using data on 10–1 momentum portfolio returns from Kenneth French's homepage, we find that January 2001 marks the third-largest loss that has occurred on a simple momentum strategy since 1927. The 10–1 momentum loss in this month was −60.4%. The two other outliers occurred in August 1932 (−83.2%) and September 1939 (−89.7%). This largest loss in 1939 occurred after a 12-month UP market, which indicates that these observations are pure outliers and may not be connected to lagged market states. Furthermore, the behavioral theories that motivate the use of lagged market returns as a conditioning variable for momentum profits do not predict that momentum profits should be negative when investor overconfidence decreases.

sentiment and insignificant after periods of pessimistic sentiment. In what follows, we show that the AG/momentum interaction shows up in both pessimistic and optimistic market states.

We use the monthly sentiment index constructed by Baker and Wurgler (2006, 2007) to classify our sample months in pessimistic and optimistic periods.[16] Following Antoniou, Doukas, and Subrahmanyam (2010), we calculate a moving average of the sentiment values for the 3 months prior to the holding period. If this average sentiment level falls within the bottom 33% of all months, we classify the holding period month as pessimistic. The rest of the sample months are classified as optimistic months.

The first row in Panel C of Table IV replicates the result in Antoniou, Doukas, and Subrahmanyam (2010): for the unconditional 5–1 momentum strategy, profits are high and significant following optimistic periods (mean = 1.13%, $t = 4.04$) but insignificant after pessimistic periods (mean = 0.45%, $t = 1.02$). However, despite this insignificance of unconditional momentum profits, firms with high asset expansion still display reliable momentum profits even after periods of pessimistic sentiment. AG decile 10 shows up with a mean momentum profit of 1.03% ($t = 2.24$). On the other hand, firms with medium asset expansion (deciles 2–6) display mean momentum profits that are close to zero. Thus, even though pessimistic investor sentiment appears to have a dampening effect on the magnitude of momentum profits, it does not significantly affect the interaction between AG and momentum.

2.5.d. *Momentum profits conditioned on aggregate AG*

We have thus far provided evidence indicating that the interaction between AG and momentum survives in various market states, where prior research has documented an absence of momentum profits. We now provide further evidence on the time series dimension, in support of our premise that AG is an independent driver of momentum. If firm-level AG is connected to the magnitude of momentum profits, we would expect the magnitude of unconditional momentum profits to be lower in periods of low aggregate AG and higher in periods of high aggregate AG. Thus, using aggregate firm expansion as a conditioning variable, we expect to find a similar spread in unconditional momentum profits across these market states, as we found in the momentum portfolios that were conditioned on firm-level AG.

[16] The sentiment index is available from Jeffrey Wurgler's homepage, http://pages.stern.nyu.edu/~jwurgler/.

We collect quarterly balance sheet total assets using the intersection of all firms included in the CRSP and Compustat quarterly databases. For each firm, we calculate the annual AG rates using formula (3) below:

$$AG_{i,t}^{quarter} = \frac{AT_{i,t}^{quarter} - AT_{i,t-4}^{quarter}}{AT_{i,t-4}^{quarter}}, \tag{3}$$

where $AT_{i,t}^{quarter}$ denotes total balance sheet assets for firm i during the fiscal quarter ending in calendar quarter t.[17] Then, for each quarter t, we take an average over all firms for which the AG rates are available. This produces a measure of aggregate average AG for a given calendar quarter.

$$AG_{t}^{quarter} = \frac{1}{N}\sum_{i=1}^{N} AG_{i,t}^{quarter} \tag{4}$$

Our aim is to study unconditional momentum profits conditioned on low and high aggregate AG rates. To this end, we use returns on 10 momentum portfolios that include NYSE, AMEX, and NASDAQ stocks and are formed on NYSE prior (2–12) return decile breakpoints. These portfolio returns are available from Kenneth French's homepage. We calculate quarterly momentum returns by compounding the monthly returns on the loser and winner portfolios over the quarters and then calculating the difference between the compounded winner and loser portfolio returns. We match the quarterly AG rates $AG_{t}^{quarter}$ with the subsequent 10–1 quarterly momentum returns measured during quarter $t+1$. Then, we sort our time series of quarterly aggregate AG rates into four groups based on their magnitudes and study the resulting momentum profits within each of these four market states. Our sample consists of 152 quarterly observations, and each AG group contains 38 observations.

Panel A of Table V, presents the mean quarterly momentum returns and their corresponding t-statistics when the returns are conditioned on aggregate AG. To allow for an easier comparison with our earlier results, the last column shows the quarterly mean returns transformed to a monthly basis.[18] The results display a dramatic pattern. During periods of low aggregate AG, momentum returns are small and insignificant. The quarterly mean is 0.55%

[17] Note that we use quarterly AG rates calculated on a yearly basis (i.e., growth measured over four quarters) to remove predictable seasonal variation that might arise if we used quarter-to-quarter changes. The quarter-to-quarter AG rates show some signs of seasonality; a nonparametric Kruskal–Wallis test for the equality of quarterly medians of the AG rates rejects the null at a 5% level of significance.

[18] That is, the approximate monthly return is given by $r^{month} = 100\times((1 + r^{quarter}/100)^{1/3} - 1)$.

Table V. Momentum profits conditioned on aggregate average AG

Table V examines momentum profits using aggregate firm expansion as a conditioning variable. For each firm, the annual AG rate is calculated from the balance sheet total assets during the fiscal quarter ending in calendar quarter t relative to the total assets in quarter $t-4$. Then, an average is taken for each quarter t over all firms for which the AG rates are available. We obtain quarterly returns on 10 momentum portfolios. The quarterly momentum return is the return difference between the winner and loser portfolios. The AG rates at time t are matched with the 10–1 momentum returns during quarter $t+1$. Then, the time series of aggregate AG rates are sorted into four groups based on their magnitudes allowing us to study the resulting momentum profits within each of these four market states. Panel A presents the mean quarterly momentum returns and their corresponding t-statistics when the returns are conditioned on aggregate AG. The last column shows the quarterly mean returns transformed to a monthly basis. In Panel B, we regress the quarterly 10–1 momentum returns on one-quarter lagged aggregate AG rates and other variables that have previously been shown to predict momentum payoffs. The variables are a recessionary dummy as defined by the NBER, lagged market sentiment, lagged 12-month market return, and the square of lagged market returns. Model 5 restricts the sample to those observations when the lagged market return has been positive.

Panel A. Quarterly momentum profits across periods of low and high aggregate AG rates

Aggregate AG	P10–P1	t	P10–P1^{month}
Low	0.55	[0.27]	0.18
2	2.13	[1.05]	0.71
3	4.50	[4.28]	1.48
High	5.30	[4.28]	1.74
High–Low	4.76	[1.97]	

Panel B. Time series regressions

Model	1	2	3	4	5
Intercept	−1.85	−0.87	−1.22	1.24	3.55
	[−0.73]	[−0.33]	[−0.51]	[0.46]	[1.54]
$AG_{t-1}^{quarter}$	0.30	0.26	0.26	0.14	0.22
	[2.45]	[2.11]	[2.20]	[1.12]	[2.82]
recdummy		−2.63			
		[−0.73]			
sentiment$_{t-1}$			1.01		
			[1.46]		
market$_{t-1}$				0.28	−0.16
				[3.45]	[−1.08]
market$_{t-1}^2$				−0.01	0.00
				[−3.51]	[0.21]

(corresponding approximately to 0.18% per month), with an insignificant t-statistic of 0.27. As aggregate AG increases, momentum profits follow the same trend and show a monotonically increasing pattern. During periods characterized by the highest aggregate AG rates, the momentum profits reach their highest level; the quarterly mean is 5.30% (corresponding approximately to 1.74% per month) and highly significant ($t = 4.28$). The difference between quarterly momentum profits in high and low aggregate AG periods is 4.76%, with a corresponding t-statistic of 1.97.

In Table V, Panel B, we perform time series regressions to further evaluate the relationship between aggregate AG and momentum profits. The dependent variable is the quarterly 10–1 momentum payoff, whereas the explanatory variables are the one-quarter lagged aggregate AG rate and other variables that have previously been shown to predict momentum payoffs. The first model uses the lagged AG rate as a sole explanatory variable. The results confirm the finding in Panel A: higher lagged aggregate AG rates are connected with larger momentum profits. The coefficient for $AG_{t-1}^{quarter}$ is 0.30 and statistically significant with a t-statistic of 2.45. Following Chordia and Shivakumar (2002), model 2 adds a dummy variable, capturing recessions, to the specification. We code a quarter as recessionary if at least 2 out of 3 months within the lagged quarter are classified as recessionary by the NBER. As expected, the point estimate of the dummy variable is negative (−2.63), implying that momentum payoffs are smaller in recessions. The coefficient is, however, not statistically significant ($t = -0.73$). Furthermore, controlling for recessions does not diminish the significance of lagged AG rates.[19]

Antoniou, Doukas, and Subrahmanyam (2010) show that lagged sentiment levels predict future momentum returns. Therefore, in model 3, we control for the lagged sentiment level, defined as in Table IV. Although sentiment is positively related to momentum profits, the relationship is not statistically significant. On the other hand, the effect of lagged AG remains significant.

Cooper, Gutierrez, and Hameed (2004) document a nonlinear relationship between lagged market returns and momentum profits: momentum profits increase with lagged market returns but decrease with the square of lagged market returns. In model 4, we control for these effects using the lagged 12-month cumulative returns on the CRSP value-weighted market index as a proxy for market returns. The results show that in this specification, the

[19] We also estimate model 2 using a contemporaneous dummy variable that captures whether the holding period quarter is recessionary. The results remain robust.

lagged AG rate loses its significance ($b = 0.14$, $t = 1.12$). However, we note that, at least in our sample, extreme downside returns are driving the significance of the specification used by Cooper, Gutierrez, and Hameed (2004). Excluding 3% of the lowest market returns from our sample (4 out of 152 observations) makes both the lagged market return and its square insignificant. Furthermore, as Antoniou, Doukas, and Subrahmanyam (2010) note, during these extremely adverse market conditions, momentum strategies cannot easily be implemented due to increased volatility and reductions in liquidity. To study the interaction between AG and momentum in "normal" market states, model 5 uses the same specification as model 4 but excludes all negative market observations from the sample. The number of excluded negative market returns is 38, leaving us with 114 observations that are used to estimate model 5. In this specification, lagged AG emerges as a highly significant predictor of momentum profits ($t = 2.82$), whereas the lagged market return and its square become insignificant, with respective t-values of -1.08 and 0.21. Overall, while momentum payoffs are better forecasted by lagged market returns than by lagged AG rates when all sample points are considered, this relationship between the two explanatory variables is not robust when we control for a few extreme observations or when we study only UP market states. Specifically, in UP market states, the forecasting power of AG strongly dominates that of lagged market returns.

3. Discussion

Having established the interaction between AG and momentum, we now discuss how our results relate to existing explanations of momentum.

3.1 RELATION TO INVESTMENT-BASED ASSET PRICING

A growing literature studies the relation between optimal investments and expected returns. Most of the literature concentrates on theoretically modeling the relation between firm-level decisions, investment, and the average return patterns related to BM and market capitalization.[20] A common prediction in the literature is that firms that invest more should have lower expected returns relative to firms that invest less. However, most of the theoretical models do not explicitly predict that firms that experience

[20] See, for example, Gomes, Kogan, and Zhang (2003); Carlson, Fisher, and Giammarino (2004); Zhang (2005); and Cooper (2006).

large asset changes, either through investment or disinvestment, should show large momentum profits.[21]

An investment-based framework that explicitly studies momentum effects is Berk, Green, and Naik (1999). In their model, persistence in a firm's assets and systematic risk leads to persistence in expected returns at longer horizons. Contrarian effects at shorter horizons arise because of shocks to the composition of a firm's assets. If slow turnover in firms' assets were the driving force behind momentum, we would expect to see the strongest momentum effects in firms that have not rapidly changed their asset bases. However, our results point to an opposite conclusion. Firms that have experienced rapid shocks to their assets during the previous year, as measured by AG, display the strongest momentum effects.

3.1.a. *The impact of real options on autocorrelations*

Hackbarth and Johnson (2012) propose a theoretical model that implies a return structure more compatible with our results. Their framework builds on the impact of cross-firm heterogeneity in investment flexibility on expected returns. Their model assumes that the relationship between realized profitability shocks and expected returns is dependent of the investment and disinvestment options available to the firm. As a result of the real options, risk exhibits a concave region followed by convex region with respect to profitability where the slope in the middle section may have either sign. The effect of good (bad) news on expected returns is nonetheless always more positive (negative) near the exercise of the firm's real options. The momentum implication of the model is that return autocorrelations should be U-shaped conditional on relevant lagged operating variables. With respect to changes in the asset base of firms, the model predicts enhanced momentum returns for firms near the exercise of expansion or contraction options.[22] The intuition is that following positive productivity shocks, the firm's risk rises due to more valuable expansion options. On the other hand, when profitability declines, the firm's risk declines due to more valuable contraction options. The model can easily be applied to explain

[21] Such momentum profits could occur if, for example, optimal investment had the tendency to increase the autocorrelation in stock returns, or if the group of firms that are characterized by the largest investment/disinvestment were to show the largest spreads in expected returns.

[22] Also using real option-type models, Sagi and Seasholes (2007) and Garlappi and Yan (2011) similarly predict enhanced momentum profits in restricted samples of stocks. They predict enhanced returns in firms with more growth options and in distressed firms with disinvestment options. The model derived by Hackbarth and Johnson (2012) considers both types of real options resulting in a prediction that is supported by our empirical findings.

return momentum since profitability or productivity shocks are arguably associated with realized returns in the cross-section. Our findings provide support for the model if one assumes that firms near the exercise of their options comprise a significant share of firms that have experienced extreme changes in their asset bases. Fama and French (2006) provide evidence from univariate regressions that lagged growth shows strong power to forecast AG up to 3 years ahead. This implies that realized AG can be seen as a good proxy for expected growth—thus, linking our results to the model of Hackbarth and Johnson (2012). Unlike Berk, Green, and Naik (1999), their model thus implies an autocorrelation pattern that supports our findings.

3.1.b. *Controlling for profitability*

Chen, Novy-Marx, and Zhang (henceforth CNZ, 2010) propose a new factor model derived from investment-based asset pricing. Their model consists of the market factor, an investment factor, and a return on assets (ROA) factor, resulting in a model for expected returns given below:

$$E[R_i^e] = \beta_{i,MKT}E[R_{MKT}^e] + \beta_{i,INV}E[R_{INV}] + \beta_{i,ROA}E[R_{ROA}], \tag{5}$$

where $E[R_{INV}]$ is the expected premium on a portfolio long in low investment stocks and short in high investment stocks, and $E[R_{ROA}]$ is the expected premium on a portfolio long in stocks with high returns on assets and short in stocks with low returns on assets. They hypothesize that when holding investment-to-assets constant, firms with a high expected ROA should earn higher returns than firms with a low expected ROA. Furthermore, they argue that sorts based on past returns are likely to generate an implied sort on expected ROA because past winners (losers) are more likely to have experienced a positive (negative) shock to their earnings. Consequently, the different factor loadings that winners and losers have on the ROA factor can potentially explain part of the momentum anomaly. CNZ show that their new factor model produces substantially smaller momentum alphas than the Fama–French (1993) three-factor model or the Capital Asset Pricing Model (CAPM).

The results in CNZ are connected to our results in the sense that their model contains an investment-based factor that empirically appears to give a reasonable description of the returns on momentum portfolios. Although their theoretical framework does not explicitly predict that firms that invest more should show a stronger return momentum, it could be that the winner and loser portfolios in the more extreme AG groups show a wider dispersion in their CNZ factor loadings. It is also plausible that the spread in firm profitability, measured by ROA, is larger within the more extreme AG groups. Next, we examine whether the CNZ model explains the momentum/AG interaction.

For each of the AG groups, we regress the time series of the equal-weighted 5–1 momentum returns on a constant, the market factor, and the two CNZ factors. Data on the CNZ factors are available from January 1972.[23] Table VI, Panel A reports the raw returns on the momentum portfolios, the CNZ alphas, and the corresponding *t*-statistics. The raw momentum profits show the familiar increasing pattern as we move from AG group 2 to 10. Turning to the CNZ alphas, our results confirm that their factor model substantially decreases abnormal profits from momentum strategies. For example, the CNZ adjustment cuts down the raw momentum profit in AG group 10 from 1.53% to 0.93% per month. Still, abnormal momentum returns within AG groups 8–10 are large (ranging from 0.75% to 1.02% per month) and statistically significant.

Next, we perform a test where we control more directly for the effects of firm profitability. At the end of June each year, we rank firms in three groups based on their AG rates in the fiscal year ending in the previous calendar year. Since we are interested in studying the robustness of the positive interaction between AG and momentum, we exclude AG decile 1 from these sorts.[24] Then, at the beginning of each month, we independently rank firms in three groups based on their quarterly ROAs. ROA is defined as the firm's most recently reported quarterly income before extraordinary items (Compustat item IBQ) divided by the total assets (ATQ) of the firm in the previous quarter. Based on the group ranks, we form nine AG/ROA groups. Finally, within each of the nine groups, we study 5–1 momentum profits using five portfolios sorted on the past 11-month returns within groups where AG and profitability are held relatively constant. The holding period is 1 month. In line with our previous results, we apply the 20% screen for MV. To ensure that we have sufficiently many firms with quarterly accounting data, we start the sample from July 1980.

The results are displayed in Table VI, Panel B. When ROA is held relatively constant, the raw 5–1 momentum profits are largest for the high AG groups. For example, for firms that have a high ROA, the difference in monthly raw momentum profits between the high and low AG groups is 0.84% per month (*t*-value 2.84). The same strong pattern can also be found

[23] We thank Long Chen for providing us with the CNZ factors.

[24] Since the first AG decile displays a strong momentum effect, including firms from this decile in our sorts would drive up the momentum profits in the lowest AG tercile, thus distorting our inferences.

Table VI. Momentum profits when controlling for profitability

Panel A examines momentum profits across AG deciles when controlling for the Chen, Novy-Marx, and Zhang (2010) factors. For each AG group, we regress the time series of the equal-weighted 5–1 momentum returns on a constant and the CNZ factors. The sample starts from January 1972. Panel A reports the raw returns on the momentum portfolios, the CNZ alphas, and the corresponding *t*-statistics. In Panel B, we rank firms at the end of June each year in three groups based on their past AG rates. We apply a 20% screen for size (based on NYSE breakpoints) and exclude firms falling within the lowest decile of AG rates. Then, at the beginning of each month, we independently rank firms in three groups based on their quarterly ROAs. ROA is defined as the firm's most recently reported quarterly income before extraordinary items (Compustat item IBQ) divided by the total assets (ATQ) in the previous quarter. We form nine AG/ROA groups. Finally, within each group, we rank stocks at the end of each sample month based on their past 11-month returns, and then group these stocks into five portfolios based on the NYSE prior return breakpoints. The Panel B reports the average winner-minus-loser returns and their corresponding *t*-statistics. We start the sample from July 1980.

Controlling for Chen, Novy-Marx, and Zhang factors and for ROA								
A. Raw returns and CNZ alphas on 5–1 momentum portfolios					B. Three-way independent portfolio sorts			
AG	P5–P1	*t*	CNZ	*t*		Low ROA	Med ROA	High ROA
Low	1.05	[4.30]	0.64	[1.88]	Low AG	0.62	0.00	0.29
2	0.34	[1.21]	−0.32	[−0.94]		[1.72]	[0.00]	[1.05]
3	0.39	[1.58]	0.04	[0.14]	Med AG	0.39	0.40	−0.08
4	0.53	[2.06]	0.27	[0.63]		[1.07]	[1.35]	[−0.23]
5	0.57	[2.08]	0.21	[0.53]	High AG	0.97	0.84	1.13
6	0.30	[1.18]	0.03	[0.09]		[2.69]	[2.52]	[3.82]
7	0.81	[3.37]	0.47	[1.34]				
8	1.09	[4.35]	0.75	[2.00]	Spread in raw	0.35	0.84	0.84
9	1.36	[4.85]	1.02	[2.65]	momentum returns	[1.23]	[2.81]	[2.84]
High	1.53	[5.36]	0.93	[2.27]				
					Spread in	0.01	0.89	1.07
					CNZ alphas	[0.04]	[2.87]	[3.25]

in the medium ROA group. The pattern in the low ROA group is, however, weaker and the difference in momentum profits does not reach statistical significance.

For all of the ROA groups, the last row in Table VI, Panel B shows the difference between the winner-minus-loser CNZ alpha for the high AG group and the winner-minus-loser CNZ alpha for the low AG group. If the CNZ factors were to explain the difference between momentum returns in high and low AG groups, then we would expect to see an insignificant alpha. However, this is not the case for the medium and high ROA groups. We conclude that the CNZ model provides, at best, only a partial explanation as to why firms with large asset base changes show a stronger return momentum.

3.2 CONTROLLING FOR EXPECTED GROWTH RISK AND MACROECONOMIC VARIABLES

Finally, to assure that the interaction between AG and momentum is not a manifestation of some of the previously suggested explanations for the momentum and AG anomalies, we test for expected growth risk and macroeconomic risk exposure as suggested by Johnson (2002) and Cooper and Priestley (2011), respectively. The unreported results from these robustness tests and more detailed descriptions of the estimations are available in the online Appendix (available as supplementary data).

In the first test, we consider the theoretical model by Johnson (2002) where a firm's log price to dividend ratio is convex with respect to expected growth rates. This convexity implies that the prices of stocks with high expected growth are more sensitive to changes in expected growth than prices of firms with low expected growth, and as a consequence, growth rate risk rises with expected growth rates. If exposure to growth rate risk is positively priced, then expected returns should also rise with growth rates. Firms with poor past performance are likely to have had negative growth shocks, whereas firms with good past performance are likely to have had positive growth shocks. Consequently, due to their higher expected growth rates, past winners are riskier and should have higher expected returns than past losers, leading to momentum. Insofar as firms that have experienced high AG in the past are affected more than firms with lower AG by the growth rate risk as defined in Johnson (2002), the convexity of the log price to dividend ratio in Johnson's model could provide a rationale for the momentum interaction that we document.

As the expected growth risk appearing in Johnson's model is unobservable, we follow the methodology in Liu and Zhang (2008) to operationalize our tests. We estimate the loadings on growth rate in industrial production (MP) for our 50 momentum portfolios controlling for the other Chen, Roll, and Ross (1986; henceforth CRR) factors.[25] If, as argued by Liu and Zhang

[25] We thank Laura Xiaolei Liu and Lu Zhang for making the data on the CRR factors publicly available. The factors include unexpected inflation (UI), change in expected inflation (DEI), the term premium (UTS), and the default premium (UPR).

(2008), the MP factor summarizes aggregate changes in expected growth, and if growth-related risk were more important within the high AG groups thus driving their higher momentum profits, then we would expect to see a larger spread in MP loadings between past winners and losers in the high AG groups than in the low AG groups. However, the spreads in factor loadings between past winners and losers do not follow the same pattern as the momentum profits along the AG ranks. It appears that expected growth risk does not provide a satisfying explanation for the interaction between AG and momentum.

Next, we test whether the higher momentum profits in high AG groups can be explained by macroeconomic risk exposure. Cooper and Priestley (2011) document that the average return difference between low and high AG portfolios is, to a large extent, captured by the factor loadings that these portfolios have on the macroeconomic CRR factors. The result implies that firms that invest more also have lower systematic risk translating into lower average expected returns. Although theory is silent about why systematic risk spreads between prior winners and prior losers should be larger among firms that have invested more, one can still hypothesize that more dynamic firms, characterized by high levels of investment, have better possibilities to choose from a wide variety of investment projects that have different exposures to systematic risk. This could lead to a wider spread in expected returns within the high AG groups, manifesting itself in stronger apparent return momentum than within the less extreme AG groups.

Our test setup follows Griffin, Xiuqing, and Spencer (2003) and Liu and Zhang (2008). We first estimate risk premiums for the five CRR factors. We then use these risk premiums together with the factor loadings on our 5–1 momentum portfolios to calculate the momentum profits that are predicted by these portfolios' macroeconomic risk exposures.

We find that although the macroeconomic risk model indeed predicts higher momentum returns in the high AG groups, it still fails to provide a full explanation of the interaction between AG and momentum. It also fails miserably in explaining the high momentum returns in AG group 1. Full details of these estimations and results are in the online Appendix (available as supplementary data).

3.3 RELATION TO BEHAVIORAL THEORIES

We conclude with a brief overview of how our results reconcile with existing behavioral explanations for momentum. In short, we do not believe that current behavioral theories can fully account for our results. We refer the reader to our online Appendix (available as supplementary data) for a thorough discussion of this theme.

A number of papers, among them Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998), have argued that momentum profits arise because investors are plagued by systematic cognitive biases when they have to interpret the implications of new information. Furthermore, the behavioral biases that drive momentum should be more important for stocks with high information uncertainty than for stocks with low uncertainty. Thus, it could be that the interaction between AG and momentum is produced by the possibility that firms having experienced large changes to their asset bases are characterized by more value uncertainty and, consequently, by stronger momentum. We note, however, that we control in Section 2.4 for MV, BM, turnover, and return volatility, and find that the interaction between AG and momentum remains robust. All of these variables have been used as proxies for information uncertainty in earlier literature (Daniel and Titman, 1999; Jiang, Lee, and Zhang, 2005; Zhang, 2006). The robustness of the AG/momentum interaction in stocks otherwise classified as having low information uncertainty leads us to believe that information uncertainty is not the sole driving force behind our results.

Neither do our time series tests of momentum profits described in Section 2.5 lend direct support to the possibility that current behavioral-based theories would fully explain our results. If the slow market response to information is due to psychological biases, such as overconfidence, then the mechanisms that result in momentum should largely be confined to periods of high investor overconfidence. We find that even though pessimistic investor sentiment appears to have a dampening effect on the magnitude of momentum profits, the interaction between AG and momentum remains robust when controlling for investor sentiment.

In our online Appendix (available as supplementary data), we also investigate the PEADs within the AG deciles. As noted by Hirshleifer (2001), the behavioral models mentioned above use exactly the same arguments for explaining momentum as they do for explaining the PEADs. Consequently, if magnified psychological biases were driving the high momentum returns in the extreme AG groups, we would also expect the returns on a PEAD strategy to be at their highest in those groups. However, our results, reported in the Appendix, do not provide strong evidence that returns on PEAD strategies are concentrated in the extreme AG deciles. This leads us to believe that cognitive biases among investors cannot fully explain our findings; rather, some other mechanisms seem to be at play.

4. Conclusions

In this article, we establish a significant and robust connection between firm-level asset changes and stock price momentum. AG retains its predictive ability when controlling for previously documented cross-sectional predictors of momentum and its predictive power often dominates that of other variables. Momentum profits are statistically significant and economically meaningful among firms that have experienced large asset expansions or contractions, but they are small and often insignificant among firms that have not experienced a drastic change in their asset bases. Our cross-sectional analysis shows that firm-level AG rates are not only predictors of future abnormal returns as in Cooper, Gulen, and Schill (2008) but also strong predictors of short-term return momentum.

In addition to the cross-sectional evidence, we document a positive time series relation between AG and price momentum, showing that average momentum returns increase almost monotonically with aggregate AG. The interaction between AG and momentum persists in various market states where prior literature has documented an absence of momentum profits. Furthermore, the results indicate that the time series effect of aggregate AG subsumes the explanatory power of previously documented determinants of momentum related to the business cycle and aggregate investor sentiment. This finding provides strong complementary evidence to support our view that AG is an important determinant of the momentum effect.

The results have implications for the existing theories aiming to explain stock price momentum. We argue that most of the existing theoretical literature does not offer clear answers as to why firm investment, measured by AG, should be connected to return momentum. We subject our results to several robustness tests and find that the interaction between AG and momentum cannot be fully explained by pricing factors derived from investment-based asset pricing, by expected growth risk, or by macroeconomic risk exposures. Furthermore, we argue, based on our results controlling for the effects of information uncertainty and investor overconfidence that the behavioral theories of Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) cannot fully account for the interaction between AG and momentum. Our results on the PEADs within the AG deciles also suggest that the interaction between AG and stock price momentum may not originate solely from a systematic failure of information to flow correctly and completely into stock prices.

Our empirical results do, however, produce a pattern aligned with theoretical predictions of the model by Hackbarth and Johnson (2012). Even though the aim of our article has not been to offer a formal test of their model, our independent empirical results nevertheless suggest that a real options framework, such as the one considered by Hackbarth and Johnson (2012), can be fruitful for understanding asset return dynamics. This is important, because the cross-sectional return premiums uncovered in the literature appear to be linked to each other. Cooper, Gulen, and Schill (2008) have linked AG to an investment premium, whereas our results show that AG is linked to the momentum premium. Furthermore, the results in Asness, Moskowitz, and Pedersen (2012) indicate an underlying common structure for the momentum premium and the value premium in that they are negatively correlated. A promising avenue for future research would thus be to analyze AG in a real options framework, and see to what extent the momentum premium, the value premium, and the investment premium can be linked to AG within a unified model.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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Essay 4

Influential ownership and capital structure

Influential ownership and capital structure*

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Abstract

This paper explores the relation between ownership structures and capital structures in Russia – an economy with a state-run banking sector, weak corporate governance, and highly concentrated ownership. We find that firms with the state as controlling shareholder have significantly higher leverage than firms controlled by domestic private controlling shareholders other than oligarchs. Both firms controlled by the state or oligarchs finance their growth with more debt than other firms. Profitability is negatively related to leverage across all types of controlling owners indicating a preference for internal funding over debt. The results indicate that firms with owners that have political influence or ties to large financial groups enjoy better access to debt.

Key words: capital structure, ownership structure, state ownership, oligarchs, political connections, Russia.

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1. Introduction

The institutional setting and firm-specific characteristics have been shown to impact the choice of capital structure. Growing firms and economies are often equity financed, whereas more mature firms and economies rely more on bank financing when they have a need for external financing (Shleifer and Vishny, 1997). Debt finance seems to be most common for firms with tangible assets (e.g., Rajan and Zingales, 1995). Firms' access to external capital to finance growth may be limited when investors' rights are poor (e.g., La Porta *et al*., 1998). In despite of its exceptional institutional setting with multiple potentially relevant characteristic features, there appears to be little systematic evidence on how the institutional environment has affected the capital structures of Russian firms.

We attempt to explore three central aspects in relation to capital structure that are characteristic features of the Russian market: namely, high ownership concentration (Guriev and Rachinsky, 2005), high frequency of politically connected firms (Faccio, 2006), and weak legal investor protection (e.g., Shleifer and Vishny, 1997). We aim to answer two fundamental questions. Firstly, how are publicly traded Russian firms financed? Secondly, to what extent do firms with controlling owners that have political influence or economic influence through ties to large financial-industrial groups enjoy better access to external debt capital?

Corporate ownership concentration in Russia is among the highest in the world (Guriev and Rachinsky, 2005) and the transparency of ultimate control structures is typically low (Chernykh, 2008). In Russia, the 22 largest oligarchs control about 40 % of sales in a large sample of Russian firms (Guriev and Rachinsky, 2005). The term oligarch denotes an owner with sufficient wealth and strategic ownership to have significant economic and thus also political influence.[1] The state controls 37 % of Russian traded firms (Chernykh, 2008). While state-controlled firms' may have easier access to debt financing through state banks, Guriev and Rachinsky (2005) argue that oligarch-controlled firms may have better access to capital than other privately controlled firms through internal finance within the oligarch-controlled financial conglomerates. Moreover, Faccio (2006) argues that politically powerful owners may get preferential treatment from government-controlled banks. Taken together, we would expect firms with strong political and economic ties to have better access to debt financing. Such financing benefits could also be associated with a lower average cost of capital and consequently higher firm value.

Using a sample of 95 Russian listed firms over the period 2000-2004, we find that traditional determinants and ownership variables impact capital structures. Firm profitability is significantly negatively related to debt financing. This result indicates that many profitable Russian firms rely less on debt financing and more on less expensive internal funds.

The governance structure and reporting practices also help explain the level of debt financing. When the state is the controlling shareholder, firms have significantly more debt in their capital structures than firms with domestic private controlling shareholders other than oligarchs. Firms with controlling shareholders that are either foreign or oligarchs do not have debt levels that are significantly different from other privately controlled firms. The results on ownership structures suggest that Russian firms

[1] In line with Guriev and Rachinsky (2005), the term oligarch is not used to imply a legal, economic or moral judgment on Russia's richest businessmen, but merely as a term for referring to Russian industrial tycoons.

do not have equal access to external capital. Moreover, after controlling for ownership characteristics, we do not find that firm size is associated with higher debt levels in cross-sectional tests. Regarding reporting practices, we find that firms reporting financial statements according to Russian statutory accounts have significantly lower levels of long-term debt. Taken together, firms with controlling ownership by the state as well as firms issuing financial statements prepared according to international standards employ significantly more debt financing.

We also explore how firms' growth opportunities are related to capital structures. Equity financing is typically preferred when the firm has limited collateral to back credit and when near-term cash flows cannot service large debt payments (e.g., Shleifer and Vishny, 1997). To measure how firms finance their growth, including the need to expand their long-term operating assets, we relate the firm's market-to-book ratio of equity to leverage. Contrary to expectations, we find a positive and significant relation between the market-to-book measure of growth and debt financing. Moreover, the market-to-book ratio is significantly positively related to leverage in firms with the state or an oligarch as controlling shareholder, while we find no such relation in firms with other control structures. One explanation for the positive relation is that high market-to-book firms with powerful owners may have better access to external capital due their influential owners. Another explanation would be that high market-to-book firms simply have lower risk premiums and therefore better access to external capital. However, the latter explanation cannot be the whole reason since we do not find that higher valuations would be associated with higher leverage in firms without influential owners.

As a positive development, the use and maturity of financial debt have increased significantly during the study period. The increase in the use of financial debt, and long-term financial debt in particular, indicate that the market for external capital has developed.

The results in this paper are related to several strands in the literature. Our paper adds to the studies that analyze the impact of the costs and benefits of political power on firm productivity (Guriev and Rachinsky, 2005) and valuations (Faccio, 2006; Maury and Liljeblom, 2009) in Russia. We also add to the small number of studies focusing on traditional determinants of capital structure in Russia (Ivashkovskaya and Solntseva, 2007; Delcoure, 2007). More generally, our paper adds to the studies analyzing capital structures in emerging markets (e.g., Booth *et al*., 2001).

The paper proceeds as follows. Section 2 briefly describes the Russian institutional setting, and discusses the relation between influential owners and capital structure decisions. Section 3 describes the data and presents descriptive statistics. Section 4 presents regression results. Section 5 concludes the paper.

2. Influential owners and capital structure

2.1. Overview of ownership and banking in Russia

Russian firms have undergone significant changes in their corporate governance structures since the privatization began in the early 1990s. The aim of the privatization was to move away from bureaucratic control and to enable more efficient private ownership (Boycko *et al*., 1995). Various privatization options were available for Russian firms, which moved former state property into the hands of managers, employees, and outside shareholders to various degrees (see Brunswick UBS equity guides for these options). The subsequent sales of blocks of state holdings in large Russian firms also enabled increases in the concentration of private ownership. However, concentrated control together with weak legal shareholder protection often leads to minority shareholder expropriation -- as was the case in Russia especially in the 1990s (e.g., Black *et al*., 2000; Filatotchev *et al*., 2001). An efficient corporate governance system is likely to arise with some form of concentrated private ownership coupled with efficient enforcement of legal investor rights (e.g., Shleifer and Vishny, 1997; La Porta *et al*., 2000). In Russia, the latter was initially disregarded.

Chernykh (2008) traced the ultimate ownership and control rights in Russian firms for the year 2003 and found that the Russian state effectively controls about 38 % of publicly traded firms. Moreover, pyramid ownership structures and golden shares are often used by the state to maintain control. In addition to extensive state control, Guriev and Rachinsky (2005) estimate that the 22 largest private owners, or so-called oligarchs, in Russian industry control around 40 % of the sales and employment in a large sample of both listed and unlisted firms. Guriev and Rachinsky (2005) consider ownership concentration in Russia to be among the highest in the world. Guriev and Rachinsky (2005) and Gorodnichenko and Grygorenko (2008) argue that oligarch-controlled firms may obtain performance advantages compared with other privately controlled firms due to lower separation of ownership and control, better protection against the grabbing hand of the state, better control of hold up problems due to their often vertically integrated group structures, and better access to capital from within their group as well as to external capital. Summing up, the continued strong presence of the Russian state as well as powerful private individuals characterizes the ultimate control in Russian traded firms.

The Russian government plays a central role in the Russian banking sector both via direct ownership and through regulatory bodies. Based on data on the ten largest banks in Russia, La Porta *et al*. (2002) find that the state owns about one-third and exercises control over approximately 50% of the banking assets. Vernikov 2007 reports that official Russian sources put the total share of the public sector in banking at 33-34%. However, he suggests that official sources understate state holdings. The actual figure is likely to be higher as the four biggest state-owned banks themselves are reported to control 40.7% of Russia's total banking assets.[2] Using cross-country analysis, La Porta *et al*. (2002) find support for the view that state ownership of banks politicizes resource allocation and generally lowers efficiency. Vernikov (2007) also notes that Russia differs from most other transition economies in that the banking industry is largely in the hands of Russian domestic owners with only a very small share under foreign control. The power of the Russian state exceeds its ownership interests in the largest banks since the state is the regulator through the Central Bank, the largest creditor, and controls most insolvency proceedings (see also, Tompson, 1997, 2002). Thus, firms with significant ownership interests by the Russian state are likely to be in an advantageous position in terms of access to debt financing compared to other firms.

[2] The four biggest banks are all state-controlled. They are Sberbank; Vneshtorgbank group which includes VTB, its retail subsidiary Bank VTB 24, and Promstroybank; Gazprombank; and Bank Moskvy.

2.2 Influential owners and access to external finance

Large Russian firms are typically politically connected (Faccio, 2006), and oligarch owners as a group have considerable political power and vast economic influence (Guriev and Rachinsky, 2005). While Freeland (2005) characterizes the relationship between the political elite in Kremlin and most oligarchs as highly interrelated in the 1990s, Glaeser *et al*. (2003) argue that President Putin's rise to power lead to a reduction in the oligarchs' high political influence (see also, Maury and Liljeblom, 2009). However, the oligarch-controlled firms may still enjoy significant advantages in their access to debt capital compared to other private firms. Faccio (2006) note that politically connected firms may get preferential treatment from government-owned banks, though lending by government banks mostly benefits large state-owned companies themselves (see Claessens and Perotti, 2007). In addition, oligarch-controlled firms may obtain better access to debt financing due to oligarchs' affiliations with financial-industrial groups (e.g., Guriev and Rachinsky, 2005; Perotti and Gelfer, 2000). One can also draw a comparison to Chang and Hong (2000) who argue that Korean companies affiliated with corporate groups can utilize the group's reputation to enhance the access to external finance. Similarly Manos *et al*. (2007) find that group affiliated firms in India enjoy exceptional access to government and foreign loans. In summary, firms with significant ownership interests by the government and firms with political and group connections such as those controlled by oligarchs are likely to enjoy better access to debt markets than other firms.

Influential owners can also affect the relative importance of traditional theories of capital structure. Firstly, the pecking order theory suggests that firms prefer internal financing in the form of retained earnings as it involves no direct costs. Debt is the secondary choice as it involves lower costs than the most expensive type of financing, equity. The differences in the cost of financing stem from asymmetric information. A negative relation between profitability and leverage that has been found in empirical studies (e.g., Rajan and Zingales, 1995; Booth *et al*., 2001; Nivorozhkin, 2005) is often viewed as support for the pecking order theory. When firms in developing economies use debt, they tend to use more short-term debt than firms in developed economies (Delcoure, 2007). Moreover, firms in developing economies often have to rely on expensive equity financing due to underdeveloped bond markets and poor institutions governing the banking industry (Delcoure, 2007; Shleifer and Vishny, 1997). Assuming state-owned and oligarch-owned companies have improved and less costly access to debt financing, one would expect them to utilize more debt than other firms on average.

According to the trade-off theory, each firm has an optimal capital structure that stems from the tradeoff between the benefits of tax deductibility of interest rate costs and the higher bankruptcy risk from debt. Political contacts by owners may affect this balance since they may face lower tax liabilities in the first place (Faccio, 2006; Manos *et al*., 2007). In Russia, such lower tax liabilities could pertain to oligarchs particularly in the Yeltsin era during which oligarchs enjoyed tremendous political influence (e.g., Guriev and Rachinsky, 2005). After the political regime shift in year 2000, we would expect the tax deductibility of interest rate costs to play a larger role again, which would favor the use of debt in oligarch-controlled firms.

The agency theory of capital structure (e.g., Jensen and Meckling, 1976) predicts lower debt levels in growth firms due to the risk of agency conflicts between debt and equity holders and the risk of underinvestment due to debt payments in early stages. This stems from the inflexible relationship between regular annual debt payments and future cash flows that are difficult to predict for a growth firm. The increased possibility of risk shifting to the detriment of creditors in growth firms, which correspondingly raises the cost of debt, makes debt a less attractive alternative. Generally, Shleifer and Vishny (1997) note that growing firms and economies tend to rely more on equity than debt. In a weak institutional environment, politically connected firms with growth opportunities may be able to access external debt capital on more favorable terms than other firms, which would reduce the relevance of the prediction of agency theory. In addition, large shareholders who may also be connected to creditors may on average reduce such agency conflicts.

Politically influential owners may also have an impact on the importance of other traditional determinants of capital structure such as asset tangibility and firm size – this is particularly true in developing markets (Rajan and Zingales, 1995, 2003). Berger and Udell (1995) claim that firms who have close relationships with their creditors may be required less physical collateral. More generally, Rajan and Zingales (1995) argue that asset tangibility as a proxy for collateral may matter less in bank-oriented markets than in market-oriented ones. If we extend these arguments to ownership, politically influential owners may reduce the sensitivity of debt financing to the size of the physical collateral. The argument that larger firm size is associated with lower probability of default may also be affected by owner characteristics. For Japanese firms, Hoshi *et al.* (1990) argue that firms tied to a main bank may face lower cost of financial distress. Similarly, politically connected ownership may replace the significance of firm size as a guarantee for stability and thus limit its role as a determinant of capital structure. For example, government bailouts in politically connected firms may reduce the default risk in small firms (see Faccio *et al*., 2006).

3. Summary of research focus

Our principal interest is determining whether firms with powerful owners have superior access to debt financing on a market with weak institutions governing debt and equity markets. Firstly, we assess the direct impact of politically and economically influential owners such as the state and the oligarchs on firms' leverage ratios. Secondly, we compare the relevance of traditional determinants of capital structure in firms with influential owners and firms without such owners.

3. Data

3.1. Sample and data sources

We use accounting, ownership, and market data from several editions of the Russian Equity Guide by Brunswick UBS.[3] The guides include historical accounting and ownership data, as well as key performance and valuation ratios. Ownership data has also been obtained from Skrin (a database containing Russian public companies).

The sample period begins in year 2000, motivated by the change in the political regime in the beginning of year 2000. The change in the institutional power balance combined with the exceptional situation on the credit market following the default of government bonds in 1998 motivates our focus on year 2000 and onwards.

[3]We use guides titled 2002/2003, 2004/2005, 2005/2006, and 2006.

The sample consists of publicly traded companies on the Russian Trading System (RTS) and Moscow Interbank Currency Exchange (MICEX). We focus on publicly traded companies due to three main reasons. Firstly, most of the companies are considerable in size and have a substantial impact on the Russian economy (e.g., Kuznetsov and Muravyev, 2001). Secondly, ownership and accounting data are easier to obtain and far more comparable in quality. Finally, the firms' access to external finance is more comparable when focusing on mid- and large-cap companies. The average market capitalization is USD 3025 million (median USD 512 million).

The accounting and ownership information has been obtained from an independent and established third party institution, Brunswick UBS. The figures are reported in nominal US dollars (year-end exchange rates for the balance sheet and year-average rates for the income statement). The problem with including data from multiple sources stems from differences in currency conversion, comparability across years as well as inflationary accounting and consolidation practices. Firms can report in dollars, roubles, or real roubles (Brunswick UBS Russian Equity Guide 2004) and different versions of historical statements do appear. Thus, it is better to use data from a source that aims to provide consistent and comparable data across all firms. The sample consists of firms listed during the period 2000-2004. Firms that have been de-listed or introduced during the period are included. The final sample consists of a panel of 95 firms with 368 firm-year observations.

3.2. Definitions of leverage

The ambiguity in prior research regarding capital structures may be partially due to the difficulties in measuring leverage and the explanatory variables (e.g., Harris and Raviv, 1991). We consider multiple definitions for leverage -- partially to illustrate the dominant types of debt in Russia. Three different definitions will be considered using book values and market values. The broadest definition of leverage is total liabilities to total assets. It is the most common definition in previous research (see Frank and Goyal, 2004). We use two variables for total debt: (1) Total Debt / Total Assets (TD/TA), and (2) Total Debt / Enterprise Value (TD/EV). Throughout the study, 'Total Assets' denotes the value of the firm at book value, whereas 'Enterprise Value' denotes the market value of the firm. The market capitalization figures in the enterprise value are based on year-average prices.[4]

Total debt does not provide a good indicator of whether the firm is at risk of default in the near future, nor does it only reflect interest cost liabilities as it includes items such as accounts payable. They may be used for transaction purposes rather than financing, thus overstating financial leverage (Bevan and Danbolt, 2002). Therefore, 'Financial Debt' that only considers interest bearing debt is included: (1) Financial Debt / Total Assets (FD / TA), and (2) Financial Debt / Enterprise Value (FD / EV).

Long-term debt (LTD) with a maturity exceeding one year is regarded separately to assess the definitional sensitivity discussed by Bevan and Danbolt (2002). This split-up is interesting in developing markets where short-term debt tends to be important. Long-term debt (LTD) consists of long-term financial debt and other long-term liabilities.

[4] For some firm-years that we could not obtain average stock prices, we use prices from August for the relevant year.

3.3. Explanatory variables

To define profitability, we use the ratio of income before interest, tax, depreciation, and amortization to total assets. The natural logarithm of sales is used as a proxy for firm size. Tangibility is measured by the proportion of tangible fixed assets to total assets. In addition to debt financing, firms can use trade credit – especially when debt financing is unavailable or expensive. The fourth explanatory variable is thus net trade credit to total assets. This variable is only used in regressions where the definition of the dependent variable debt excludes operative leverage such as trade credit. The market-to-book ratio (M/B) is used as a proxy for growth opportunities.

The ownership structure of firms is included in the main model through ownership dummies. Three dummies are included: oligarch, state, and foreign. Other private ownership is the control group in the regression models. Ownership data published in the Brunswick UBS equity guides and by Skrin are used as raw data.[5] To identify oligarch ownership, we use information on private oligarchs in Guriev and Rachinsky (2005), "Moscow's Group of Seven" (1996), and Barnes (2003). The oligarch ranking in Guriev and Rachinsky (2005), as they note, is generally consistent with various other rankings.[6] Our definition is also consistent with Maury and Liljeblom (2009). If the firm has a controlling shareholder with at least 20 % of votes, it is identified as state-owned, oligarch-owned, foreign-owned, or privately owned following the ultimate controlling owner definition used in La Porta *et al*. (1999). A controlling shareholder that is not identified as being the state, an oligarch, or a foreign owner is identified as a privately

[5] The aim is to utilize year-end ownership figures.

[6] To be included in their list of the 22 largest Russian oligarchs, it is required that total annual sales revenues controlled by a particular group of shareholders are above $700 million or the total employment controlled by the group is above 20,000 people.

controlled firm. The few companies that do not have a controlling shareholder with at least 20 % of votes are identified as having dispersed ownership. Private control and dispersed ownership are combined due to the limited amount of observations with dispersed ownership. The 20 % voting control, which has been used in La Porta *et al.* (1999) and Perotti and Gelfer (2001), can be viewed as a threshold that gives the shareholder significant power to control the management.

The remaining dummy variables control for industry, accounting standards and time effects. Industry effects are controlled for by including industry dummies as industries may by virtue be subject to varying risks and volatilities or may be growing at a different pace. The industry classification is based on the classification in the Brunswick UBS equity guides: auto, consumer, metals, telecom, power, oil & gas, and other. In addition, we use a dummy variable that indicates reporting according to Russian Statutory Accounting (RSA). This is done to control for differences in asset valuation and profit measurement.[7] A time dimension is included by adding a time dummy for each year following year 2000. This is also used to control for a tax reform in 2002 whereby the corporate tax rate was cut but at about the same time tax law enforcement was also considerably increased, which had the consequence of raising the effective tax rate for firms (see Desai *et al.*, 2007). Ceteris paribus, we would expect this to increase the attractiveness of debt finance due to the tax shelter provided by interest rate payments.

3.4. Model

Regressions are performed using an ordinary least squares (OLS) regression model. We use standard errors that control for within-cluster (firm) correlation and

[7] See Russian Equity Guides by Brunswick UBS for an overview of accounting practices in Russian firms.

heteroscedasticity to relax the independence assumption required by the OLS estimator to being just independence between clusters (firms).[8] Summing up, the leverage model we employ takes the following form (see Table 1 for detailed variable descriptions):

$$\frac{D_{i,t}}{V_{i,t}} = \alpha_0 + \beta_1(profit_{i,t}) + \beta_2(trade\ debt_{i,t}) + \beta_3(size_{i,t}) + \beta_4(collateral_{i,t}) + \beta_5(M/B_{i,t})$$
$$+ \beta_6(ownership_{i,t}) + \beta_7(RSA_{i,t}) + \beta_8(year\ dummies) + \beta_9(industry\ dummies) + \varepsilon$$

where

profit = EBITDA / total asset; *trade debt* * = trade credit / total assets,

size = ln (sales); *collateral* = fixed assets / total assets (tangibility), *M/B* = market cap of equity / book value of equity; *ownership* = ownership type (1 for each), *RSA* = 1 for the accounting standard RSA; *year dummies* = 1 for each year after 2000,[9] and *industry dummies* = 1 for industry groups.

* included when definition of D excludes trade credit

The model is used on the entire sample as such to determine the significance of ownership structure while controlling for traditional capital structure determinants within the Russian institutional context. Secondly, the model is used on sub-samples to evaluate the significance of traditional capital structure determinants depending on the type of controlling owner.

[8] Some previous studies have employed a censored Tobit model due to several observations with zero indebtedness. These studies also find that the results on the determinants of leverage are very robust to the estimation technique used (Rajan and Zingales, 1995; Bevan and Danbolt, 2002). We do not use a censored Tobit due to the problems relating to panel data analysis and due to the previous findings on the robustness of various methods. Moreover, zero debt observations only represent 0.0%-7.5% of the observations in our sample depending on the measure of gearing.

[9] By including year dummies, we have also considered the impact of the tax reform in 2002 that reduced the value of tax shields. The change in the corporate tax rate was not found to reduce the use of leverage as indicated by the insignificant year dummy for 2002 (though not reported in the tables).

3.5. Descriptive statistics

The descriptive statistics for the 95 major Russian firms are displayed in Table 2. Panel A shows that the average Russian listed firm has a total non-equity liabilities to total assets ratio of 40.0 %, whereas the corresponding figure using market values amounts to 36.1 % (Panel B). A mean debt ratio of 40.0 % may appear quite high. It is, however, worthwhile to notice that a considerable fraction of net liabilities are made up of payables, which is a non-interest bearing operating debt. The financial debt amounts to 17.1 % of assets (Panel A), while the figure is 13.8 % as of the market value of the firm. Panels A and B also show that total long-term liabilities amount to 16.2 % of total assets, or 13.4 % of the market value of the firm.

Our leverage ratios for Russia differ from, e.g., data on a large sample of UK firms in Bevan and Danbolt (2002), who report total liabilities amounting to 49 % of total assets. With similar sized US companies in 2001, the ratio of debt to net worth equaled 59 % using market values (Federal Deposit Insurance Corporation). In sum, Russian companies appear to employ significantly less debt than their Western peers.

The descriptive statistics for the explanatory variables, displayed in Panel C of Table 2, reveal considerable variety among the sample firms. The mean return on assets of 17 % is very close to the average figure of 16 % reported by Rajan and Zingales (1995) for UK companies during 1988-1990. The variation in our return-on-assets variable is nevertheless large. The variation in trade credit is large as well, ranging from -40.6 % to 36.4 %, with a mean of -0.7 % in proportion to total assets. The figure for total sales, measured in million USD, averages 2023. The mean ratio of asset tangibility equals 60.7 %, and the market-to-book ratio is on average 1.05.

Interesting changes in the composition and the level of debt occur over the period 2000-2004, as shown in Panel A of Table 3. The development is particularly clear when one decomposes financial debt into short-term and long-term financial debt. The use of debt has increased during the period 2000-2004, particularly the use of financial debt. Long-term financial debt has increased considerably during the period. In 2000, it should be noted that the interest-bearing financial debt consisted mostly of short-term financial debt. For the same year, short-term financial debt as a percentage of total assets equals on average 5.3 %. The total financial debt ratio measured 10.0 % -- leaving 4.7 % of assets as long-term financial debt. Over the period, short-term financial debt and long-term financial debt diverge. By 2004, the level of the financial-debt ratio is 23.2 %, the short-term financial debt ratio equals 9.7 %, and the long-term financial-debt ratio amounts to 13.5 %. The increase in the use of long-term financial debt indicates that the market for external capital has developed over the period.

Panel B of Table 3 displays the composition of debt by the type of controlling shareholder. Interestingly, the Russian state-controlled firms have the highest levels of long-term financial debt to total assets (LTD_fin/TA) of all controlling shareholder types and oligarch-controlled firms appear highly debt-financed across all debt types. Perhaps more importantly, the firms that have private controlling shareholders that are neither foreigners nor oligarchs tend to have significantly lower long-term debt ratios (LTD/TA). Non-oligarch controlled firms (with private Russian owners) may thus have lower access to external long-term debt capital (see also Guriev and Rachinsky, 2005).

4. Regression results

4.1. The impact of influential owners on capital structure

Table 4 relates politically powerful controlling ownership by oligarchs and the Russian state to leverage ratios. Panel A of Table 4 shows that state-controlled firms employ significantly more debt in their capital structures than firms with domestic non-oligarch controlling owners. The coefficient for the state controlling shareholder dummy is economically significant and equals 0.10 using financial debt to total assets as the leverage ratio (column 2) and it is statistically significant at the 5% level. Panel A of Table 4 also shows that the coefficient for the dummy for oligarch control is positive and equals 0.04 in column 2, although the coefficient is not statistically significant at conventional levels. The positive coefficient support the higher than average leverage ratios for oligarch-controlled firms reported in Table 3. Panel A of Table 4 also shows that the coefficients for controlling foreign owners change sign between specifications and is statistically unrelated to leverage ratios, which as a whole indicates that foreign and non-oligarch privately controlled firms do not employ different leverage levels. Furthermore, Panel B of Table 4 shows that the relation between the type of controlling ownership and leverage ratios is less clear when leverage is measured using market value of equity. However, the market value of equity tends to be affected by the governance structure and owner types of firms (e.g., Maury and Liljeblom, 2009), which makes leverage ratios for firms with various controlling owner types less comparable. Taken together, after controlling for traditional determinants of capital structure, we conclude that firms employed by the state tend to employ significantly more debt than firms with domestic nonoligarch controlling shareholders.[10]

While Table 4 explored the direct impact of controlling owner types on capital structure, Table 5 focuses on the relative importance of various variables used as determinants of capital structure in previous literature in different controlling owner categories. The coefficient for firm size is negatively related to leverage in state-controlled firms (column 1) and oligarch-controlled firms (column 2), while the coefficient is positive in other firms. Moreover, the coefficient for firm size is significantly different between oligarch-controlled firms and other privately controlled firms.[11] The results for firm size suggest that influential owners can substitute for the importance of the size effect as a determinant for debt capacity. The variable tangibility measured as fixed assets to total assets is positively related to leverage in firms with oligarch and other controlling shareholders (though not statistically significantly), whereas tangibility is significantly negatively related to leverage in state-controlled firms (significant at the 5% level). The coefficient of tangibility is significantly different between the state-controlled and group "other firms".[12] Thus, the collateral value of fixed assets does not explain higher debt levels in state-controlled firms.

[10] As a robustness test, we re-run the regressions by excluding observations in each variable that represent the three highest and three lowest values in each explanatory variable excluding dummy variables. The results from the reduced sample confirm the findings in Table 4; and the relations are even stronger using this reduced sample. In particular, the ownership dummies obtain increased statistical significance levels. The state dummy is systematically positive and highly significant.

[11] We obtain this result by including an interaction variable between the oligarch dummy and the size variable to the basic model used in Table 5 for a sample of oligarch-controlled and "other firms". The interaction variable has a *t*-statistics of -1.88.

[12] This result is obtained by including an interaction variable between the state dummy and the tangibility variable to the basic model used in Table 5 for a sample of state-controlled and "other firms". The interaction variable has a *t*-statistics of -3.28.

Furthermore, Table 5 shows that our proxy for growth opportunities, the market-to-book ratio of equity, is significantly positively related to leverage in firms with the state and oligarchs as the controlling shareholder (significant at the 1% level), while the growth measure is statistically unrelated to leverage in the group "other firms". The results for the market-to-book ratio indicate that growth opportunities have a significantly different relation with leverage whether the firm has politically and economically influential owners such as oligarchs or the state or not.[13] This result could mean that firms with a need to expand long-term operative assets to support growth have better access to debt only if they have strong owners.

4.2. Traditional determinants of capital structure

Table 4 shows that firm profitability is negatively related to leverage. The coefficient for profitability using financial debt to total assets as the dependent variable equals -0.185 and -0.289 (significant at the 1% level), using book values and market values, respectively. Moreover, profitability is significantly negatively related to the different measures of leverage in the firm-level fixed-effects model in Table 6. To explore whether the negative relation is a short-term effect, we also relate lagged profitability to leverage. We still find a negative relation to leverage when we lag profitability (not reported in the tables).[14] The overall negative relation between

[13] We estimated the significance between groups by including an interaction variable between the oligarch dummy and the growth variable to the basic model used in Table 5 for a sample of oligarch-controlled and "other firms". The interaction variable has a *t*-statistics of 1.63. Likewise, we estimated the significance between groups by including an interaction variable between the state dummy and the growth variable to the basic model used in Table 5 for a sample of state-controlled and "other firms". This interaction variable has a *t*-statistics of 3.28.
[14] The significance of profitability as an explanatory variable is somewhat lower when it is lagged by one year, though it remains statistically significant and negative for four out of the six definitions for gearing in Table 4.

profitability and leverage suggests that internal financing through retained earnings plays an important financing role.

The variable size is negatively related to leverage in the cross-sectional regressions in Table 4, although only statistically significantly so for the financial debt-to-total assets measure. In the fixed-effects specification in Table 6, the size variable is positively related to all leverage ratios, which suggests that size does also have an independent effect. Taken together, firms size, as measured by the logarithm of sales, does not have a strong independent effect after controlling for owner and other firm characteristics in the cross-sectional model, whereas increases in size is significantly associated with increases in leverage ratios in the firm-level fixed-effects model.

Tangibility defined as fixed assets to total assets is positively related to leverage using long-term debt, although the coefficient is statistically insignificant (columns 3 and 6 of Tables 4 and 6). Tangibility consistently takes a negative sign when we use total debt to total assets (column 1 in Tables 4 and 6), which indicates that firms with more collateral value rely less on trade debt. The fact that we do not generally find a statistically significant positive impact of tangibility on long-term debt suggests that other factors such as an influential owner may substitute for physical collateral as a guarantee for stability as shown in Table 5.

Our measure of growth opportunities, the market-to-book ratio, is significantly positively related to leverage using book values (Panel A of Table 4). The coefficient ranges from 0.049 to 0.061 depending on the specification and it is significant at the 1% level. These results imply that firms with more growth opportunities employ higher debt levels in their balance sheets. Table 5 also showed that the positive relation occurs significantly so only in firms with influential owners. Furthermore, Panel B of Table 4 shows that the market-to-book ratio is significantly negatively related to leverage using market values. Such a negative relation, also reported by Rajan and Zingales (1995), may arise due to the fact that a higher market valuation results, by definition, in lower leverage. The results using a firm-level fixed-effects specification (Table 6) are in line with the OLS results in Table 4.

Table 4 shows that firms reporting according to Russian statutory accounts (RSA) employ significantly less debt in their capital structures than firms reporting in accordance with IAS or US GAAP (columns 3 and 6). The coefficient for RSA is economically significant and equals -0.11 using long-term debt to total assets and long-term debt to enterprise value (significant at the 1% level). The fixed-effects specification in Table 6 measuring changes in reporting practices also shows a negative relation for RSA and leverage ratios. The obtained negative relation is interesting since one could expect the opposite because asset valuation according to RSA on average measures below that of international accounting standards (see, e.g., Brunswick UBS Russian Equity Guides). In sum, reporting according to international accounting standards seems to have a positive impact on leverage after controlling for owner and firm characteristics.

When operating debt is excluded from the definition of leverage, the coefficient for trade debt is typically negatively related to leverage in both the cross-sectional and fixed-effects models (Tables 4 and 6). This implies that firms with more trade debt have lower levels of financial debt in their capital structures. In general, the problems relating to informational asymmetries and an underdeveloped capital market are likely to be reflected in considerable use of operating debt (see also Delcoure, 2007).

5. Conclusions

The Russian institutional environment is characterized by a largely state-run and concentrated banking sector, high ownership concentration, and weak investor protection. The state (e.g., Chernykh, 2008) and the so-called oligarchs (Guriev and Rachinsky, 2005) have a dominant and influential position. In this paper, we focus on how politically and economically influential owners impact firms' access to debt financing.

Using a sample of 95 major Russian traded firms over the period 2000-2004, we find that firms with the state as controlling shareholder use significantly more debt financing than firms with domestic private controlling shareholders not affiliated with the oligarchs. Higher growth opportunities are associated with higher debt financing in firms with either an oligarch or the state as controlling shareholder, while other firms do not appear to finance growth opportunities with debt capital. Furthermore, we find that more profitable firms across different controlling owner types use less external debt financing than less profitable firms, which would indicate a preference for internal financing.

The significance of traditional determinants of capital structure also varies across different types of controlling owners. Firm size, for instance, appears to be negatively related to the level of debt in oligarch- and state-controlled companies, whereas the relation is positive for other companies, as one would expect. In terms of the role of collateral, the results show a negative and significant relation between asset tangibility and leverage in state-controlled companies while this relation is positive, though not statistically significant, in other firms. The results illustrate the relative importance of ownership characteristics as a determinant of capital structures in Russian firms.

The results indicate that Russian firms do not have equal access to debt financing to finance their operations and growth. Both state and oligarch controlling owners appear to have better possibilities to optimize firms' capital structures than do firms without such owners. Improvements in legal investor protection as well as improved transparency are likely to contribute to a better access to external financing.

Unequal access to external funding is not without consequence as poor corporate governance reduces much needed access to external finance. Historically, the relatively high cost of external financing has made internal financing the primary alternative. For example, Guriev *et al*. (2004) report that out of the 78% of Russian firms that made investments in 2002, only 21% financed their investments with bank loans -- and only 0.7 percent by issuing stock. Earlier, the situation was even less encouraging. For the 1990s, Judge and Naoumova (2004) report that only five percent of funds were raised from banks and only one percent from equity finance in larger Russian firms with more than 200 employees. The statistics give support to the pecking-order theory implying that equity financing is indeed the most expensive source of funding. While firms with politically and economically influential owners have superior access to debt finance, other firms are on average forced to rely on more expensive funding to finance growth or alternatively restrict growth. This type of inequality impacts the development of the economy by making it skewed towards certain sectors and leaving it underdeveloped in others. This reinforces the already dominant status of Russia's financially and politically influential groups.

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Table 1. Variable definitions

Descriptions of the main variables used in the analysis.

Variable	Description
Total debt (TD) / Total assets (TA)	Total non-equity liabilities / Book value of total assets. Source: Brunswick Warburg Russian Equity Guides.
Financial debt (FD) / Total assets	Financial interest-bearing debt / Book value of total assets. Source: Brunswick Warburg Russian Equity Guides.
Long-term debt (LTD) / Total assets	(Long-term financial debt + other long-term debt) / Book value of total assets. Source: Brunswick Warburg Russian Equity Guides.
Total debt / Enterprise Value (EV)	Total non-equity liabilities / Market value of total assets. Source: Brunswick Warburg Russian Equity Guides.
Financial debt / Enterprise Value	Financial interest-bearing debt / Market value of total assets. Source: Brunswick Warburg Russian Equity Guides.
Long-term debt / Enterprise Value	(Long-term financial debt + other long-term debt) / Market value of total assets. Source: Brunswick Warburg Russian Equity Guides
Profitability	Equals EBITDA over total assets. Source: Brunswick Warburg Russian Equity Guides.
Trade debt	Trade credit divided by total assets. Equals (payables - receivables) over total assets. Source: Brunswick Warburg Russian Equity Guides.
Size	Log(sales). Equals the logarithm of sales. Source: Brunswick Warburg Russian Equity Guides.
Tangibility	Equals fixed assets divided by total assets. Source: Brunswick Warburg Russian Equity Guides.
M/B	Market value of a firm's equity divided by the book value of a firms' equity. Market capitalization is measured as year-average. Source: Brunswick Warburg Russian Equity Guides.
Oligarch	Equals one if a firm in a particular year is controlled by an oligarch or a holding company controlled by a oligarch with at least 20 % of the votes and otherwise zero. Ownership is measured at the end of the year. Source: Brunswick Warburg Russian Equity Guides, Skrin.ru, Guriev and Rachinsky (2005).
State	Equals one if a firm in a particular year is controlled by the state or a state-owned holding company with at least 20 % of the votes and otherwise zero. Ownership is measured at the end of the year. Source: Brunswick Warburg Russian Equity Guides, Skrin.ru.
Foreign	Equals one if a firm in a particular year is controlled by a foreigner or a foreign held company with at least 20 % of the votes or otherwise zero. Ownership is measured at the end of the year. Source: Brunswick Warburg Russian Equity Guides, Skrin.ru.
RSA	Equals 1 if the accounts are prepared according to Russian Statutory Accounts and zero if the accounts are prepared according to IFRS or US GAAP. Source: Brunswick Warburg Russian Equity Guides.
Industry dummies	Industries are Auto, Consumer, Metals, Telecom, Power, Oil & Gas and Other industries. A dummy is included for each but Other industries. Source: Brunswick Warburg Russian Equity Guides.
Year dummies	Dummy variables for years 2000-2004.

Table 2. Summary statistics

This table presents means, standard deviations, minimums, and maximums for the various definitions of leverage and the explanatory variables. The sample consists of 95 Russian listed firms with 368 firm-year observations during the time period 2000-2004. Variable definitions are presented in Table 1.

	Mean	St. dev.	Min.	Max.
Panel A: Leverage using book value				
Total debt	40.0%	19.1%	4.3%	94.9%
Financial debt	17.1%	14.7%	0.0%	91.3%
Long-term debt	16.2%	14.0%	0.0%	65.4%
Panel B: Leverage using market value				
Total debt	36.1%	19.2%	5.3%	91.9%
Financial debt	13.8%	10.8%	0.0%	51.6%
Long-term debt	13.4%	11.5%	0.0%	59.8%
Panel C: Explanatory variables				
Profitability	17.0%	12.7%	-12.9%	94.9%
Trade credit	-0.7%	9.1%	-40.6%	36.4%
Log(sales)	6.42	1.43	3.12	10.44
Tangibility	60.7%	18.5%	7.2%	90.4%
M/B	1.05	1.00	0.04	5.81

Table 3. The composition of debt by year and type of controlling owner

This table displays the annual levels of leverage measured at book value for each year within the sample period 2000-2004. The different leverage measures are included to illustrate the change that has occurred in capital structure and in the composition of debt within the period (Panel A). For clarity, the table only includes the measures at book value. The sample consists of 95 Russian publicly traded firms with 368 firm-year observations during 2000-2004. The variables are the same as the measures used in the regressions: total debt to total assets (TD/TA), financial debt to total assets (FD/TA), long-term debt to total assets (LTD/TA). In addition, financial debt has been split into long-term and short-term financial debt, LTD_fin/TA and STD_fin/TA, respectively. This split is done to further illustrate the change in the composition of debt. Panel B illustrates the capital structures for the firms by controlling shareholder type.

Year	Observations	TD/TA	FD/TA	STD_fin/TA	LTD_fin/TA	LTD/TA
Panel A. Leverage ratios by year						
2000	68	38.7 %	10.0 %	5.3 %	4.7 %	11.2 %
2001	77	37.8 %	15.2 %	6.5 %	8.7 %	14.2 %
2002	72	37.1 %	16.4 %	6.4 %	9.9 %	16.4 %
2003	80	41.1 %	19.6 %	8.2 %	11.3 %	18.3 %
2004	71	45.1 %	23.2 %	9.7 %	13.5 %	20.0 %
Panel B. Leverage ratios by controlling owner type						
Oligarch	120	43.8 %	19.2 %	10.3 %	8.9 %	18.4 %
State	181	38.9 %	16.4 %	5.0 %	11.3 %	16.9 %
Foreign	13	35.8 %	18.8 %	12.5 %	6.3 %	12.7 %
Other private	54	41.6 %	16.3 %	9.3 %	6.7 %	11.0 %

Table 4. Regression results

The table presents coefficient estimates from regressions of leverage on profitability, trade debt, size, tangibility, market-to-book, and controlling owner types. The coefficients are estimated using an OLS regression model with industry and time dummies. A control variable for the accounting standard is also included. The sample consists of 95 Russian publicly traded firms with 368 firm-year observations during 2000-2004. Variables are defined in Table 1. TD refers to total non-equity capital, FD to financial (interest bearing) debt and LT to long-term debt. TA stands for total assets at book value, whereas EV stands for enterprise value that is the value of all assets at market value. Robust standard errors that control for firm-level clustering are in parentheses below the coefficient estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Panel A. Leverage using book values			Panel B. Leverage using market values		
	(1)	(2)	(3)	(4)	(5)	(6)
	TD/TA	FD/TA	LTD/TA	TD/EV	FD/EV	LTD/EV
Constant	0.867***	0.216*	0.081	0.735***	0.266***	0.168**
	(0.140)	(0.117)	(0.082)	(0.082)	(0.075)	(0.065)
Profitability	-0.325***	-0.289***	-0.050	-0.216***	-0.185***	-0.057
	(0.119)	(0.076)	(0.059)	(0.076)	(0.053)	(0.043)
Trade		-0.057	0.022		-0.164	-0.079
debt		(0.149)	(0.098)		(0.102)	(0.073)
Size	-0.025	-0.021*	-0.004	-0.017	-0.019**	-0.007
	(0.020)	(0.012)	(0.011)	(0.012)	(0.008)	(0.010)
Tangibility	-0.410***	-0.005	0.102	-0.100*	0.111*	0.157**
	(0.088)	(0.088)	(0.080)	(0.056)	(0.066)	(0.065)
M/B	0.063***	0.055***	0.049***	-0.093***	-0.026***	-0.022**
	(0.016)	(0.011)	(0.014)	(0.014)	(0.008)	(0.009)
Oligarch	0.053	0.042	0.014	-0.030	-0.001	-0.015
	(0.043)	(0.036)	(0.030)	(0.026)	(0.028)	(0.023)
State	0.095**	0.100**	0.063*	0.058*	0.041	0.044
	(0.046)	(0.040)	(0.034)	(0.029)	(0.033)	(0.029)
Foreign	-0.019	0.023	-0.064	0.031	-0.003	-0.046
	(0.063)	(0.072)	(0.078)	(0.030)	(0.031)	(0.031)
RSA	-0.111**	-0.027	-0.112***	-0.103***	-0.028	-0.113***
	(0.045)	(0.029)	(0.024)	(0.027)	(0.020)	(0.019)
R^2	0.44	0.36	0.38	0.60	0.35	0.45

Table 5. Regression results by owner types

The table presents coefficient estimates from regressions of leverage on profitability, trade debt, size, tangibility, market-to-book for sub samples based on controlling owner types (state, oligarch, and other types). The category "other firms" in column 3 includes primarily nonoligarch private controlling shareholders. The dependent variable is defined as financial (interest bearing) debt / total assets. The coefficients are estimated using an OLS regression model with industry and time dummies. A control variable for the accounting standard is also included. The total sample consists of 95 Russian publicly traded firms during 2000-2004. Variables are defined in Table 1. Robust standard errors that control for firm-level clustering are in parentheses below the coefficient estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10%, respectively.

	State-controlled firms	Oligarch-controlled firms	Other firms
	(1)	(2)	(3)
Constant	0.539***	0.330**	-0.061
	(0.136)	(0.132)	(0.209)
Profitability	-0.520***	-0.170	-0.166
	(0.146)	(0.111)	(0.111)
Trade	-0.282**	-0.153	0.046
debt	(0.109)	(0.146)	(0.229)
Size	-0.025	-0.031**	0.032
	(0.015)	(0.015)	(0.047)
Tangibility	-0.212**	0.124	0.013
	(0.096)	(0.136)	(0.194)
M/B	0.074***	0.054***	0.003
	(0.010)	(0.018)	(0.021)
RSA	-0.078***	-0.002	-0.008
	(0.027)	(0.052)	(0.087)
Observations	181	120	67
R^2	0.60	0.40	0.34

Table 6. Regression results using firm fixed effects

The table presents coefficient estimates from regressions of leverage on profitability, trade debt, size, tangibility, market-to-book. The coefficients are estimated using a firm-level fixed-effects regression specification. Time dummies are included in the models. The sample consists of 95 Russian publicly traded firms with 368 firm-year observations over the period 2000-2004. Variables are defined in Table 1. TD refers to total non-equity capital, FD to financial (interest bearing) debt and LT to long-term debt. TA stands for total assets at book value, whereas EV stands for enterprise value that is the value of all assets at market value. Dummy variables for controlling owner types are included but not displayed. Standard errors are in parentheses below the coefficient estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Panel A. Leverage using book values			Panel B. Leverage using market values		
	(1)	(2)	(3)	(4)	(5)	(6)
	TD/TA	FD/TA	LTD/TA	TD/EV	FD/EV	LTD/EV
Profitability	-0.342***	-0.249***	-0.115*	-0.199***	-0.131***	-0.090**
	(0.053)	(0.053)	(0.062)	(0.051)	(0.040)	(0.043)
Trade debt		-0.250***	-0.069		-0.297***	-0.161**
		(0.079)	(0.092)		(0.060)	(0.063)
Size	0.128***	0.086***	0.057**	0.070***	0.054***	0.034*
	(0.023)	(0.023)	(0.027)	(0.022)	(0.017)	(0.018)
Tangibility	-0.543***	-0.193***	0.026	-0.142**	-0.000	0.027
	(0.060)	(0.059)	(0.069)	(0.058)	(0.045)	(0.048)
M/B	0.011	0.022**	0.010	-0.119***	-0.035***	-0.032***
	(0.010)	(0.010)	(0.011)	(0.009)	(0.007)	(0.008)
RSA	-0.192***	-0.174***	-0.221***	-0.138***	-0.108***	-0.138***
	(0.029)	(0.029)	(0.033)	(0.028)	(0.022)	(0.023)
R^2	0.41	0.38	0.23	0.55	0.33	0.24

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SALLA PÖYRY

ESSAYS ON FINANCIAL MARKET FRICTIONS AND IMPERFECTIONS

The fundamental function of financial markets is to channel funds within an economy. To efficiently do so, financial markets need to generate asset prices that consistently incorporate all available information and reflect all non-diversifiable dimensions of risk. While perhaps elegant, perfect market functionality and efficiency can nonetheless be seen as an unattainable ideal. Financial market imperfections, such as those generated by asymmetric information or transactions costs, can easily distort the underlying financial market mechanisms.

The research questions that are addressed in this thesis are all related to phenomena that have been associated with, or explained by, financial market frictions or imperfections. This thesis consists of four separate essays that examine questions that would be irrelevant in a perfect market – that is, in a world with no predictability of returns, informational advantages or institutional weaknesses. At least, they would be irrelevant when considering the perfect market setting as described by financial economists up until the mid- 1980s. While the guiding principles may have been somewhat updated, it is nonetheless important to stress that recent findings do not necessarily conflict with the view that markets are reasonably efficient or driven by rational market forces.

The first essay of this thesis examines the under-diversification of investors and its sources using data from the Finnish Central Securities Depository (FCSD) legal liability accounts. That is, is under-diversification rational and driven by informational advantages, or the result of the behavioral biases of investors? The former source relies on market inefficiency to justify its existence whereas the latter is an imperfection in itself. In the second essay, I examine the impact of market fragmentation on private investors using the same data source. It examines whether market functionality deteriorated for private investors as a result of a regulatory change (MiFID I) that enabled market fragmentation on a large scale, but did not guarantee equal access to all market venues across all investor types.

In the third essay, we explore and document a novel and robust connection between firm-level asset changes and return momentum using US stock data. The momentum anomaly is one of the most robust documented return anomalies and is recognized as one of the biggest challenges to asset pricing research. While the existing theoretical literatures on risk-based or behavioral models do not offer a clear explanation to our empirical results, recent real options models appear to hold the most promise.

In the last paper, we explore the relation between ownership structures and capital structures in Russia. This is a market plagued by severe institutional imperfections and inefficiencies.

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