Emulation Funds and

Mutual Fund Trading Behaviour

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A dissertation submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

Macquarie Graduate School of Management

Macquarie University

Macquarie Park, Australia

30th August 2013

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Dedication

This dissertation is dedicated to my father, Hong Chen, who has nurtured, encouraged and inspired me throughout my life.

Acknowledgements

There are a number of individuals and organisations whose generous support made this thesis possible. I would like to give special thanks to my supervisors Professor David Gallagher at the Macquarie Graduate School of Management and Professor F. Douglas Foster at the University of Technology, Sydney (previously at the Australian National University) for their invaluable time, guidance and encouragement. Professor Gallagher has been a constant source of expert knowledge, motivation and friendship throughout the course of my doctoral studies, and I deeply appreciate his efforts to nurture an academic environment conducive to fruitful collaboration and research. I am also extremely grateful to Professor Foster for his thought-provoking discussions, honest feedback and the subtle yet highly effective encouragement he provided by way of poignant and often humorous anecdotes. Special mention also goes to Dr. Adrian Lee (UTS), whose technical expertise, practical knowledge, and generosity with his advice inspired me to be a better researcher, and to A/Prof Russ Wermers, who showed me that the stars were not out of reach.

I am also thankful to Professors Mike Aitken and Alex Frino at the Capital Markets Cooperative Research Centre for their leadership and vision in creating and managing the CRC. They have been instrumental in providing the facilities, relationships and opportunities for emerging scholars like myself to engage in industry-relevant and academically significant research. I'd especially like to also thank Dr. George Li for his thoughtful comments and genuine interest in my research.

My industry sponsor, the State Authorities Superannuation Trustee Corporation, has also been indispensable as a source of ideas, resources and data. In particular, I'd like to thank John Livanas and Chris Durack for their leadership and insight into the investment industry, and Martin Drew for his support of rigorous academic research in the commercial space. Lisbeth Rasmussen also deserves special recognition for her endless patience, continuous encouragement, and her generosity in sharing her abundant wisdom.

This doctoral thesis would not have been possible without the financial and administrative support of the Macquarie Graduate School of Management. I would especially like to thank Jennifer Martin and Kerry Daniel for going above and beyond the obligations of their roles to ensure the administration of my program at MGSM went as smoothly as possible.

At times, a thesis dissertation can make you feel like you're the only boat sailing on a dark empty sea, but my fellow PhD candidates have always been there to remind me that I'm not really alone. I'd like to thank Camille Schmidt and Yuki Xi for sharing their parallel journeys with me and offering their companionship, empathy and lunch ideas.

Lastly, I would like to extend my warmest and most sincere gratitude to my family for their unconditional love and support.

Summary

In this dissertation, I examine the efficacy of emulation strategies in both empirical and theoretical contexts, and thoroughly investigate one of the most important underlying factors in determining the effectiveness of emulation funds – the behavioural trading patterns of active fund managers. This research is driven by both increasing commercial interest in emulation products as they become more widespread (a number of providers including MLC, Russell Investments and NAB now offer portfolio emulation products), and a genuine academic interest in understanding the factors that drive their complex investment structures. Furthermore, the high-frequency analysis of active fund manager trading patterns is a significant topic in its own right, and represents an aspect of the fund manager performance literature that has previously been constricted by limited access to high granularity fund-level transactions data.

In the first study, "Does Portfolio Emulation Outperform Its Target Funds?", I find that, while small but economically significant reductions to transaction costs do arise from emulation, the opportunity costs associated with altering the timing of trades significantly outweigh the benefits. The second study, "A Model of Emulation Funds", constructs a model of emulation fund cash flows. This model formalises the interaction between the marginal transaction costs savings and the performance impact of altered trade timing, enables forecasts of emulation fund performance based on forward-looking expectations, and allows numerical optimisation of key emulation fund parameters. The final study, "A Fourfold Pattern to the Art of Active Investing", examines the motivation behind observed trading patterns by mutual fund managers, and provides insight into how we can potentially design a more efficient emulation strategy.

Certification

I hereby declare that, to the best of my knowledge, the research presented in this dissertation is original and my own work, except where due acknowledgement has been made. This dissertation has not been previously submitted, either in part or in its entirety, for the award of a higher degree or qualification at Macquarie University or elsewhere.

Zhe Chen

30th August 2013

Chapter 1: Introduction

It's hard to be a diamond in a rhinestone world – Dolly Parton

1. Objectives

Emulation funds represent one of the latest manifestations of the centralised portfolio management theme. Borrowing from the previous work of centralised portfolio theorists like Rosenberg (1977), DiBartolomeo (1999) and Elton and Gruber (2004), the emulation fund combines their commercially feasible elements into a novel investment paradigm that, until now, has been neglected by academic scrutiny. The purpose of the three papers presented in this thesis dissertation is therefore to analyse, evaluate and characterise the emulation strategy in both empirical and theoretical contexts, and in the process, investigate the behavioural patterns of fund manager trading that impact heavily on emulation fund performance.

Each of the three papers presented will focus on a different dimension of the emulation fund structure. The first paper seeks to analyse a simulated emulation fund using the transactions of a typical large pension sponsor, and provides an overview of the typical outcomes we can expect with this sort of centralised portfolio management strategy. The second paper aims to go deeper and provide a theoretical framework which we can use to characterise emulation funds in a generalised way. This enables us to go beyond the constraints of data availability to model the behaviour of an emulation strategy based on expectations and forecasts. Lastly, the third paper represents an in-depth focus on how the trading behaviours of fund managers reflect their objectives of excess performance generation and risk management. In doing so, I reveal why the opportunity costs associate with the lag structure of emulation funds exist, and provide a foundation for overcoming these challenges.

My hope is that the original research presented in this dissertation will not only enhance our academic understanding of emulation funds, but also provide benefits to both multi-manager investment sponsors and organisations implementing these centralised multi-fund structures. From the perspective of the fund sponsors, this research enables a deeper examination of the emulation investment paradigm and facilitates more effective evaluations of its potential costs and benefits. To the providers of emulation products, this work offers a set of theoretical tools with which to adjust and optimise the strategy for a more profitable outcome.

2. Motivation

The importance of this research is driven by the increasing commercial interest in emulation funds. Since MLC launched the first emulation fund in 2005 as part of a joint venture with Vanguard Investments, a number of other asset managers have followed suit. Vanguard introduced its own version of an emulation fund in 2007, with Russell Investments, State Street Global Advisors, and NAB Custodian Services following suit. Emulation funds hold a fundamental appeal as a means for institutional investors to expand their investment capacity while simultaneously reducing direct management fees and transaction costs. However, to the best of my knowledge, there has been no academic coverage of the space. I seek to address this, then, in this thesis.

In an Australian context, strategies to effectively manage multi-fund assets are especially relevant due to the large pool of superannuation assets that have accumulated since the compulsory "Superannuation Guarantee" scheme was introduced by the Keating government in 1992. The Australian Prudential and Regulatory Authority (APRA) estimates total Australian superannuation assets of $1.40 trillion as of June 2012, with 61.5% of this managed in retail, industry, the public sector and corporate funds[1]. Hence, any incremental benefit in increasing

[1] From APRA's Quarterly Superannuation Performance publication for the June 2012 quarter

effective returns on multi-manager assets would potentially have significant and far-reaching consequences for a large proportion of the Australian public.

Furthermore, my research contributes additional insight into the ongoing academic debate regarding the value added (if any) by mutual fund managers. The motivation here is quite clear – with trillions of dollars invested in actively managed funds and the ready availability of passive alternatives that incur much lower fees, shedding light on this question could potentially have profound impact on the way we manage wealth at individual and institutional levels.

3. Structure and Contents

This dissertation is structured as follows. Chapter 2 provides a review of the current literature that is relevant to the topic of emulation funds. It will broadly focus on the current literature pertaining to the effectiveness of active funds, the benefits of multi-managers, past approaches to centralized portfolio management, and a review of transaction costs.

Chapter 3 presents the first study titled, "Does Portfolio Emulation Outperform Its Target Funds?" This study simulates the outcomes of an emulation framework using the transactions data of a large Australian pension sponsor who currently uses a decentralised funds management structure. This is the first academic paper to look at the efficacy of emulation funds. I use the mechanical application of an emulation algorithm to identify the typical drivers of costs and benefits within the investment structure, and construct characteristics-based sub-portfolios to analyse the effects of emulation across size, price-to-earnings and momentum dimensions. The results show that the opportunity costs associated with internal crossing and delayed trading outweigh the savings in transaction costs. Furthermore, the effect seems to be negatively related with respect to lag structure – shorter delay periods incurred greater underperformance of the emulation fund with respect to the tracking fund. This is due to both a smaller proportion of trade signals being internally offset, and the greater returns gap between stocks that have been recently bought in the underlying funds and those that have been recently sold. Finally, the study shows that emulating trade signals on larger stocks, those with low P/E ratios, and following periods of market contraction is less detrimental to emulation performance.

Chapter 4 generalises the analysis of emulation fund performance by providing a theoretical framework that describes its mechanics. Whereas chapter 3 examined the performance of a particular emulation fund, namely one simulated on the historical trades and holdings of an existing multi-manager portfolio, the paper in chapter 4 enables us to project the performance of a hypothetical emulation fund based purely on the expected values of input parameters. This paper, "A Model of Emulation Funds", identifies the offset ratio (i.e. the proportion of trade signals that can be internally offset by the centralised portfolio manager) as a key factor in determining the magnitude of transaction cost savings relative to the opportunity costs associated with internal offsetting and delayed trading. The chapter then derives the offset ratio as a function of the pre-selected lag period and the expected frequency of underlying trade signals. Finally I show how the model can be applied in a practical context for the purpose of emulation fund optimisation.

Chapter 5 characterises mutual fund trades into the dual objectives of outperforming target benchmarks and controlling portfolio risk, thereby helping to explain stock excess performance patterns post-trade. In the context of emulation funds, this is important for understanding why the lag structure incurs an opportunity cost, while at the same time it provides a foundation for addressing this. As a standalone piece, this chapter "A Fourfold Pattern to the Art of Active Investing" also makes significant contributions to the area of mutual fund trading behaviour. We identify a number of trading behaviours that have been difficult to identify previously, due to limited access to both the trades and holdings of mutual fund managers. My research finds that mutual funds generate excess performance by following analyst recommendations to purchase stocks with subsequent outperformance, and to sell significant underperformers from their underweight positions. Mutual funds simultaneously manage risk by avoiding overexposure to idiosyncratic risk through reduced purchasing of stocks that are already overweight, and trimming down overweight positions that have appreciated significantly. My results are particularly relevant to the design of emulation funds, in that they identify the circumstances under which different lag structures are advantageous.

Finally, Chapter 6 will conclude with an overview of the dissertation and provide concluding remarks and discussions about future research directions.

4. Publications

A number of articles arising from the research contained in this thesis dissertation have either been accepted for publication or are currently under review. These are:

- Chen, Z., Foster, F. D., Gallagher, D. R. & Lee, A. D. 2012. "Does Portfolio Emulation Outperform Its Target Funds?" *Australian Journal of Management*, Volume 38, Issue 2.
- Chen, Z., Foster, F. D., Gallagher, D. R. & Lee, A. D. "A Model of Emulation Funds" Working Paper (Revise and resubmit to *Accounting and Finance*)
- Chen, Z., Foster, F. D., Gallagher, D. R. & Wermers, R. "A Fourfold Pattern to the Art of Active Investing" (Working Paper)

The studies that constitute Chapters 3 and 4 were co-authored with Professor F. Douglas Foster, Professor David Gallagher and Dr. Adrian Lee. The paper constituting Chapter 5 was co-authored with Professors Foster and Gallagher, and Professor Russ Wermers. My co-authors assisted in refining research ideas and editing the final papers, but the research contained therein is original and a significant product of my own effort.

5. Summary

The objective of this thesis dissertation is to deepen our understanding of emulation funds by examining them through both empirical and theoretical perspectives. My motivation is the increasing prominence of centralised portfolio management in the multi-manager funds industry, which is of particular importance in Australia due to the compulsory nature of superannuation contributions. I provide a broad overview of the three papers presented in this dissertation and explain the contribution that each makes to our understanding of emulation funds.

Chapter 2: Literature Review

1. Introduction

In each of the papers presented in the main body of this dissertation, a literature review will be included either as part of the introduction or as a separate section. In this chapter, I provide an overview of the broad academic environment into which my research fits (active funds management and centralised portfolio management), and elucidate areas of research that are relevant to particular aspects of my study (the characterisation of transaction costs).

2. Active Funds Management

At the heart of emulation funds lies the premise that active fund managers provide incremental value to investors over and above that which can be achieved through passive investment. This in itself has been a controversial topic in the academic setting. The performance measurement literature can be broadly broken up into two related areas: Holdings-based approaches (e.g. Jensen (1968), Wermers (2000) and Fama and French (2010)) which attempt to reconstruct the performance of the overall fund using periodic holdings, and trades-based approaches (e.g. Wermers (1999), Pinnuck (2003) and Duan et al. (2009)) that look at the impact of fund manager decisions to reconfigure holdings. Lastly, I present evidence that the granularity of the observation data has a material effect on the measured performance. This is relevant to my study of emulation funds, as the lag structure is typically quite short, and thus requires daily level transactions data to resolve appropriately.

2.1 Holdings-Based Approaches

Fund performance measurement in the academic literature has been typically based on periodic holdings that are disclosed on a monthly or quarterly basis. These studies work on the assumption that changes in holdings are immaterial between reporting dates.

Early studies of mutual fund managers show little evidence of investment skill. Jensen (1968) investigates a sizeable sample (115) of mutual funds between 1945 and 1964, and finds that these fund managers were unable to outperform a buy-the-market-and-hold strategy. In fact, this study finds little evidence to suggest that any individual fund was able to outperform this benchmark in a statistically significant way, even gross of management expenses. Malkiel (1995) confirms Jensen's (1968) result in a more recent 1971 to 1991 setting, concluding that, in aggregate, fund managers have underperformed benchmark portfolios both before and after expenses. Furthermore, while the study finds considerable persistence in performance during the 1970s, this was not evident in the 1980s time period.

In contrast to these historical studies, a number of authors have found superior performance and persistence, at least in a small minority of fund managers. Goetzmann and Ibbotson (1994) use past returns and relative rankings to help predict future ranks and returns, and show that higher-variance funds have a greater incidence of being persistent winners. Furthermore, persistence is evident at intervals from one month to three years. The predictive power of past performance on future risk-adjusted return is confirmed by Elton, Gruber and Blake (1996). Meanwhile, Brown and Goetzmann (1995) suggest that while performance persistence exists in mutual funds, it is mostly due to funds that lag the S&P500. Furthermore, persistence trends appear to be correlated across fund managers, and imply the presence of a common strategy that is not captured by traditional factor bets. The idea that skill is isolated to groups of fund managers in the right-side tail of the returns distribution is supported by the findings of Barras, Scaillet and Wermers

(2010), who suggest that 75% of fund managers do not generate abnormal excess returns net of expenses. Wermers (2000) provides some pre- and post-fee breakdown of fund manager performance. He finds that, on average, stocks held by active fund managers outperform the market by 1.3%. However, this performance is eroded by 0.7% underperformance of non-stock holdings, and 1.6% expenses and transaction costs, leading to a net loss for the investment sponsor.

In an out-of-sample context, Cuthbertson, Nitzsche and O'Sullivan (2008) find a relatively small number of top performing mutual funds possess stock picking ability, but conversely, the bottom performing managers actually have "bad skill". The study finds persistence among losers but not winners. Pinnuck (2003) also shows that stocks held by Australian fund managers do realise abnormal returns, which is consistent with the hypothesis that they have some stock selection ability.

A number of alternative techniques have been used to discern whether active fund managers are truly skilled. For example, Kosowski, Timmermann, Wermers and White (2006) uses bootstrap analysis to find that a sizeable minority of fund managers is able to stock-pick well enough to cover their costs and earn persistent, superior alphas. Fama and French (2010) add to this by also utilising bootstrap simulations to demonstrate non-zero alphas in both tails of the fund manager returns distribution. However, the authors conclude that most fund managers and unskilled in this context and underperform the market portfolio after fees. Meanwhile, Cremers and Petajisto (2009) develop a measure of tracking error called Active Share, which predicts fund manager performance. Funds with the highest Active Share persistently beat their benchmarks, while those with the lowest Active Share underperform.

In contrast to these studies, a number of papers claim that the observed abnormal performance is an artifact of factor exposures that have not been adequately controlled for. Carhart (1997) demonstrates that persistence in equity mutual funds is driven by common factors in stock returns and investment expenses. Specifically, the "hot hands" effect (i.e. short term persistence in superior performance) can be almost entirely explained by the one-year momentum effect. The only persistence that remains unexplained lies in the strong underperformance of the worst funds. Berk and Green (2004) confirm the persistent underperformance in the worst performing funds once momentum is adequately controlled for. More recently, Busse, Goyal and Wahal (2010) show that average alpha of active fund managers is statistically indistinguishable from zero. Furthermore, while they find modest evidence of persistence in three-factor models, there is little to none in four-factor models, which indicates once again that momentum is responsible for much of the persistent outperformance in three-factor models.

There is also a temporal dimension to views about the investment skill of active fund managers, both in terms of the observation period and the historical period examined. Bollen and Busse (2004), for example, show that persistence of superior performance is observable over short intervals (i.e. from one quarter to the next) but disappears over longer measurement periods. Furthermore, the literature suggests that overall levels of fund manager skill are changing. Barras et al. (2010) demonstrate that a significant proportion of funds appeared to be skilled prior to 1996, while almost none were by 2006.

Overall, the holdings-based evidence for fund manager skill is mixed. While there is some evidence to suggest that managers are able to outperform their benchmarks gross of fees, detractors have attributed this to inadequate controls for factor risk (predominantly the momentum factor). The general consensus, however, is that only a very small group of fund managers, if any, are able to outperform their benchmarks well enough to cover the management fees that they charge. This has important implications for emulation funds. Since the trade signals from underlying managers can be acquired cheaply, an emulation fund is effectively able to implement management with pre-fee performance, and potentially produce superior outcomes to the underlying portfolio.

2.2 Trades-Based Approaches

Alternatively, a number of papers have also examined fund manager performance from a trades-based perspective. Due to the difficulty in acquiring proprietary trade-level data, these studies typically extrapolate inferred trades from changes in periodically disclosed fund manager holdings. Again, there are conflicting viewpoints regarding whether fund managers possess superior skill.

The trades-based approach to fund manager performance evaluation is motivated by findings such as those by Chen, Jegadeesh and Wermers (2000), which show that, while stocks widely held by funds do not outperform their peer stocks, those that are purchased have significantly higher returns than those that are sold across size and value-growth characteristics. Chen et al. (2000) also find that growth funds exhibit better stock selection than income funds. However, overall persistence in stock picking skill is weak. This is consistent with an earlier study by Wermers (1999) which documents herding behaviour by fund managers in small stocks and in trades by growth-oriented funds. In the subsequent 6 months to trading, stocks that are bought by herding fund managers outperform those that they sell by 4%. The superior trading skill of active fund managers has also been documented in out-of-sample studies. For example, Pinnuck (2003) shows that in the Australian market, stocks bought by fund managers realised abnormal returns, while those that they sold did not.

Research also suggests that fund manager skill, if it exists, is not evenly distributed across stock characteristics. Duan et al. (2009) find that mutual fund managers are able to stock-pick high idiosyncratic volatility stocks but not those with low idiosyncratic volatility. This is complemented by the findings of Chen, Comerton-forde, Gallagher and Walter (2010) who reveal significant stock selection skill in Australian small-cap managers.

A number of longer-term studies, however, contradict this result. Over 1-year horizons, Brown et al. (2007) find that stocks that are heavily bought as a result of herding after analyst recommendations tend to underperform peer stocks, while those that are heavily sold as a consequence of herding earn positive excess returns. Similarly, Dasgupta et al. (2011) demonstrate that persistent institutional trading negatively predicts long-term returns – stocks that are sold consistently outperform those that are bought. Incidentally, the study also finds that the effect is most concentrated within small stocks.

As in holdings-based fund performance research, the trend seems to be that fund manager skill, if it had existed in the past, is decreasing. Duan et al. (2009) show that stock-picking ability significantly declined after the extensive growth of the active fund manager industry in the late 1990s.

The trades-based approaches to performance measurement provide a number of related conclusions that seem broadly consistent within the literature. Firstly, herding by fund managers after analyst recommendations is an important factor in driving stock price movements after concentrated trading. Secondly, as a consequence of herding, stocks that fund managers buy tend to initially outperform those that they sell. However, this relationship is reversed over observation periods greater than one year. Lastly, the heterogeneous performance of bought versus sold stocks appears to be concentrated in securities with smaller market capitalisation. Since emulation funds by their nature alter the timing of when trade signals are executed, the time structure of how trades-based excess returns are generated may potentially have adverse effects on the emulation portfolio. In particular, I would anticipate an opportunity cost in the short-term returns gap between bought and sold stocks, the magnitude of which is currently unknown. As part of this thesis, I seek to characterise and quantify these short-term returns, and thus contribute to understanding this aspect of fund manager performance.

2.3 Impact of Data Granularity

Access to high granularity data is a significant obstacle associated with academic research into the proprietary activities of fund managers. Academics typically rely on the returns data or periodic holdings disclosures mandated by government authorities to evaluate the effectiveness of active fund managers. However, a number of studies have demonstrated potential inaccuracies with using extrapolated data.

Returns data typically provide the monthly returns of a fund but do not reveal its cross-sectional holdings. Elton, Gruber and Blake (2011) show that cross sectional analysis of holdings in conjunction with fund returns produce much more accurate predictions of future alpha than time series regression on fund returns alone. They also suggest that the frequency of holdings data is positively related to the accuracy of the forecasts. In addition, Kothari and Warner (2001) use simulated fund manager trading to show that standard measures of performance may be unable to detect abnormal performance where profit opportunities are short-lived and concentrated in a few quarters.

Perhaps the most significant recent work in this field is a study by Puckett and Yan (2011), who examine the intra-quarter returns of funds between mandated reporting periods. The authors find that, on average, fund managers generate statistically significant abnormal returns in intra-quartile periods, and that these returns are typically missed by traditional holdings and trades based approaches. Puckett and Yan (2011) also show that this short-term timing skill is heterogeneous across their fund manager sample, and persistent for at least a year. These results highlight the importance of the inter-day data I use in this dissertation to accurately assess the expected outcomes of operating an emulation fund.

3. The Multi-Manager Investment Paradigm

Emulation funds fit within the multi-manager research space. Their effectiveness is contingent on the assumption that, not only does diversified investment through constituent managers bring additional benefits over investing in any one particular underlying fund manager, but there are also efficiencies in centralising this approach. In the following section, I will examine the literature that analyses the incremental advantages of multi-fund investment, as well as the existing studies into centralised multi-manager frameworks.

3.1 Multi-manager Funds

The popularity of multi-manager funds rests on two main premises. Firstly, by investing in a group of underlying fund managers, the multi-manager is able to diversify the idiosyncratic risk associated with the investment processes of any individual manager. Secondly, the multi-manager may be able to select a portfolio of superior underlying funds relative to the fund evaluation capabilities of an uninformed investment sponsor.

As with creating a portfolio of stock holdings, individual fund managers bear idiosyncratic risk factors that can be diversified through proper portfolio construction. Lhabitant and Learned (2002) analyse the effects of diversification, and find that a combination of five to 10 different managers is sufficient to achieve the majority of diversification benefits. This is confirmed by Brands and Gallagher (2005), who find that on average, six constituent managers provide optimal net benefits. They argue that adding additional funds beyond this point is actually detrimental to the skewness and kurtosis of the overall fund returns. Gallagher and Gardner (2005) also explore the dangers of over-diversification and its potential to dilute excess returns.

Multi-manager funds typically charge an additional level of fees on top of those charged by the underlying fund manager. Hence, as Brown, Goetzmann and Liang (2004) show, individual hedge funds will tend to generate superior performance relative to funds-of-funds, in terms of both after-fee returns and Sharpe ratio. However, where there is significant ability on the part of the multi-fund manager to select skilled underlying funds, these additional fees may be justified. Ang, Rhodes-Kropf and Zhao (2008) argue that funds-of-funds should be benchmarked against the active fund manager universe on the whole, rather than just the funds that have been selected into the multi-manager portfolio. They find evidence to suggest that when evaluated in this context, multi-fund managers are, in fact, able to deliver incremental value to the uninformed fund sponsor.

3.2 Centralised Portfolio Management

As the latest manifestation of the centralised portfolio management theme, emulation funds build upon a substantial body of research in attempting to address the perceived inefficiencies of a decentralised multi-manager approach to investment management. The main criticism of the decentralised approach is the presence of redundant trading. Specifically, this is defined as the execution of opposed transactions (i.e. buying and selling) by different constituent managers, which incur transaction costs without changing the net position of the overall portfolio. Centralising the trading process represents a means of eliminating redundant trading while preserving the underlying active exposure.

Rosenberg (1977), an early proponent of centralised portfolio management, suggests that constituent managers should provide explicit numerical forecasts on stock returns to the central manager. The central manager then performs trading, based on a consensus of such forecasts. However, this could not be realistically implemented at the time since fund manager forecasts were highly qualitative and could not be readily translated into solid numerical data. These and other difficulties were recognized by Sharpe (1981). To address these shortcomings, DiBartolomeo (1999) proposed a management structure where underlying fund managers ran paper portfolios and submitted their trades to the central manager. These trade signals were then used to generate the numerical forecasts required for Rosenberg's (1977) model.

In reality, fee structures are often linked to funds under management – hence fund managers are often reluctant to disclose proprietary forecasts. To circumvent this problem, Elton and Gruber (2004) offer an alternative solution where underlying managers share only partial portfolio level information with the central manager, but not individual security forecast. Nevertheless, these arrangements require significant cooperation between the constituent funds and the central portfolio manager. Emulation funds are innovative in this regard as they do not directly affect the regular activities of the underlying fund. Instead, they utilise trade signals that are already available to the multi-fund manager.

4. Transaction Costs

One of the main attractions of emulation funds is the potential transaction cost savings captured via the internal crossing mechanism. Previous literature on brokerage commission and price impact indicates that these trade cost components have material consequences on the net performance of a fund. Each trade that a fund manager executes on-market attracts both implicit and explicit transaction costs. Explicit costs are commissions charged by the broker, while implicit costs include the market impact of a trade and the bid-ask spread. This section provides an overview of these costs across different international markets and time periods, and allows us to infer the magnitude of potential savings we can expect from an emulation fund.

4.1 Brokerage Commissions

Brokerage varies across international markets but has generally been decreasing. Using U.S. mutual fund data between 1995 and 2006, Chalmers, Edelen and Kadlec (2000) find brokerage commissions to average 0.53% of assets under management annually, with a substantial degree of variation across fund groups. Goldstein, Irvine, Kandel and Wiener (2009) calculate commissions on a per trade basis using order level data of NYSE listed stocks between January 1999 and December 2003. They find the average commission on a single trade to be 0.11% of trade value. For comparison, they report the standard full-service institution commission as of 2007 in Europe at 0.15% (electronic execution is 0.05%). Commissions tend to be higher in Australia. Based on Australian equity and superannuation funds data between July 1995 and March 2001, Parwada (2003) estimates brokerage to be 0.20% of trade value in 2000, with an additional stamp duty of 0.15% (this was abolished after 30th June 2001).

4.2 Price Impact

There are a number of differing approaches to measure the price impact of trades in the literature. In general, implicit transaction cost associated with the bid-ask spread and market impact tends to be more substantial than the brokerage commission. Chiyachantana, Jain, Jiang and Wood (2004) find that price impact accounts for 0.45% of the trade price in the bull market of 1997 to 1998 and 0.37% in the bear market of 2001, based on a "decision price" benchmark (previous day close-to-trade price difference). The authors also identify a declining trend in market impact costs, citing Perold and Sirri's (1998) price impact estimate of 0.99% in the 1987 to 1991 period. This is supported by Domowitz, Glen and Madhavan (2001) who examine 42 international markets with a VWAP based benchmark between September 1996 and December 1998 and find average market impact costs of 0.46% of trade value.

In Australia, (Aitken and Frino, 1996) show that execution costs associated with purchases average 0.27%, while sells incur no execution costs. Comerton-Forde, Fernandez, Frino and Oetomo (2005) observe a similar disparity between purchases and sales, noting the open-to-trade price impact of buys to be 0.34%, while only 0.16% on the sell side. The magnitude of these figures is consistent with the finding of Gallagher and Looi (2003) for Australia, where they estimated the price impact cost of a round trip trade package at 0.27% in the period 1994 – 2001.

5. Summary

The effectiveness of emulation funds is predicated on a number of prior conditions. Firstly, it is necessary to assume that fund managers are able to outperform their passive benchmarks at least before fees. My research finds some support for this in the literature from both holdings and trades perspectives. Secondly, there must be additional payoffs to holding a portfolio of funds, rather than directly investing in any individual fund. I provide evidence to show that, indeed, there are diversification benefits associated with multi-manager investing, and furthermore, multi-fund managers are able to provide incremental value to uninformed investors by selecting funds with superior performance. Lastly, I examine the literature on transaction costs and show that there are potentially material savings if one can reduce the volume of on-market trading through centralised portfolio management.

Chapter 3: Does Portfolio Emulation Outperform Its Target Funds?

Pages 25-72 of this thesis have been removed as they contain published material. Please refer to the following citation for details of the article contained in these pages.

Chen, Z., Foster, F. D., Gallagher, D. R., & Lee, A. D. (2013). Does portfolio emulation outperform its target funds? Australian Journal of Management, 38(2), 401-427.

DOI: 10.1177/0312896212455933

Chapter 4: A Model of Emulation Funds

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20 February 2013

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Abstract

Emulation funds are a potentially cost-effective way for multi-manager funds to improve their investment performance by delaying and netting trade signals from underlying managers. We develop a model to represent the expected sources of differential performance in an emulation fund relative to its underlying multi-manager portfolio. The model formalises the expected interaction between potential savings and opportunity costs, and allows us to observe complexities in the emulation process that are hidden without a benchmark. Finally, the functional representation of the model allows sensitivity analysis of the emulation fund to key parameters, and enables us to determine theoretically optimal lag periods.

JEL classification: G23

Keywords: Multi-manager, fund-of-funds, transaction costs, emulation funds

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The authors gratefully acknowledge the assistance and support of an anonymous pension fund sponsor. The Capital Markets CRC Limited is also a sponsor of this research.

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1. Introduction

In this study we develop and analyse a model for the process by which an emulation fund generates differential gross returns relative to its target portfolio. The model provides a number of analytical advantages over simulation alone. These include formalising the expected interactions between cost and benefit drivers in the emulation process, identifying complexities that are not consistent with expected model outcomes, enabling the forecast of emulation fund performance based on forward looking expectations rather than historical data, and allowing numerical optimisation of the exogenously determined emulation parameters. An emulation fund is a multi-manager investment strategy relying on delegated portfolio management services, whereby the fund-of-funds uses the trade signals of its constituent fund managers to coordinate a separate portfolio that tracks the holdings of the underlying portfolio. A key feature of emulation funds is that trade signals are followed on a delayed basis to prevent competition for market volume with the underlying active fund managers. Commercial emulation funds rebalance using weekly or fortnightly snapshots of the aggregated underlying portfolio. However, we use a continual rolling window in this paper to smooth discrepancies across using different start dates for a fixed window. The lag enables opposing market signals, within the delay period, to be offset against each other, and results in potential transaction cost savings. However, the altered timing of the trade signals introduces potential opportunity costs arising from adverse market price movements in the delay period.

Large institutional investors (e.g. pension funds and sovereign wealth funds) typically employ multi-manager investment organisations to manage their assets. The delegation of stock-picking decisions to multiple fund managers in a decentralised framework (i.e. constituent fund managers do not actively communicate with one another) also helps to mitigate manager-specific risk (Elton and Gruber, 2004, Brands and Gallagher, 2004, Sharpe, 1981). However, the use of underlying active fund managers may introduce an additional level of management fees (Brown et al., 2004, Ang et al., 2008), and ostensibly results in some degree of trading redundancy, whereby constituent fund managers execute trades on opposite sides of the market within a short period of time. Hence, transaction costs are incurred with little change in exposure to the underlying stock in the context of the overall portfolio position. Emulation strategies seek to address both these issues by (1) allowing the multi-manager investor to negotiate very low additional fees with the underlying fund manager to use their trade signals indirectly[11], and (2) internally offsetting opposing order signals. Emulation funds are also purported to deliver capital gains tax savings through their reduced turnover relative to the underlying multi-manager portfolio. However, due to the idiosyncratic nature of each investment service provider's tax structure, we leave this issue to be researched in a later study. Given the recent growth and interest in emulation products, the topic of emulation funds is increasingly relevant to large multi-manager funds.

Commercial interest in emulation funds as a low cost method of extending investment capacity has been primarily driven by the pursuit to reduce transaction costs (and taxes), which are both well observed and significant. For example, studies on brokerage commissions have found these costs to range from 0.11% of trade value in the US and 0.15% in Europe (Goldstein et al., 2009). In Australia, brokerage rates have fallen significantly over the past fifteen years. In our representative sample of active Australian equity fund manager trades, we observe a steady decline in commissions paid per trade from 0.36% in 1996 to 0.16% in 2010. On-market trading also incurs substantial price impacts, which have been found to be as high as 0.46% (Domowitz et al., 2001). Conceptually, emulation strategies are appealing as they are meant to reduce on-market trading, thereby lowering transaction costs. However, there is little academic research that investigates the effect of opportunity costs associated with altered trade timing. Accordingly, this paper seeks to account for this effect by incorporating this into our model.

[11] We have been told in interviews with senior investment executives that reusing a fund manager's trade signals is typically costs around 0.10% of funds under management per year.

While it is possible to simulate emulation funds ex-post based on historical trade flow (see Chen, Foster, Gallagher and Lee (2012)), there are a number of limitations with this approach. The primary concern of this paper is to address the “black box” characteristic of analysis based solely on simulation using limited historical data. By introducing a structured framework, however, we are able to decompose the process of fund emulation into individual theoretical components, which lead to further avenues of enquiry and a more generalisable understanding of emulation fund mechanics. Hence, by developing a model that can be calibrated on sample data, we are able to generalise trends and infer emulation fund performance in a way that is not restricted by the availability of trade level data. Furthermore, an intuitive model provides a benchmark for comparison against empirically simulated results, and enables us to identify and quantify unexpected sources of volatility in the emulation fund. Such a model also allows us to determine the proportion of trades that can be internally offset as a function of the delay period and the trade frequency of the underlying security. Finally, from an implementation point of view, the model can be used to optimise the delay period, which represents the lag between receiving a trade signal from the underlying fund, and implementing that signal in the emulation fund.

We use the model to show that the potential costs and savings of an emulation fund are strongly related to the proportion of trades that can be internally crossed (the offset ratio). Further, the main determinants of this offset ratio are the chosen delay period and the frequency of trading of underlying stock holdings. We find that the model has the most explanatory power with respect to the most heavily traded stock groups: large-cap stocks, moderate growth and style neutral stocks, and stocks with relatively neutral past period historical returns. Incidentally, for the multi-fund manager data we used to simulate an emulation fund, we find that stock prices tend to immediately increase following buy trade signals, and immediately decrease after sell signals. Hence, short timing delays in exploiting the fund manager trade signals results in a significant opportunity cost, which in the majority of instances, outweighs the commission and price impact savings from internal crossings.[12] The model reflects our expectation that both the lag period and a security's expected trade density have a positive (but marginally diminishing) relation to a security's expected offset ratio, and this is confirmed by the empirical analysis. We also consider the implications from the model for the required potential savings, relative to potential costs, that enable a profitable emulation strategy to be engineered, and thereby derive the conditions that must be met to compute the optimal lag period.

2. Background

Chen, Foster, Gallagher and Lee (2013) is the only paper that has directly addressed the topic of emulation funds. In that case study, the authors simulate an emulation fund using trade level data, and show that the hypothetical emulation fund, on average, underperforms its target fund, primarily due to the opportunity cost of delayed trading outweighing the benefits of reduced transaction costs. This paper innovates on the Chen et al. (2013) study in a number of ways. Formulating a model enables us to compare our expectations of how an emulation fund will perform to how it actually does perform. In doing so, we better understand where our assumptions about trading signal patterns hold, and where unexpected sources of risk arise. In addition, a continuous multifactor model provides transparency to the mechanism through which an emulation fund accrue differential returns to its tracking fund, and allows projections of expected costs and savings based on beliefs regarding future trading patterns. At the same time, the model allows us to analyse the sensitivity of emulation performance to key parameters.

Emulation funds represent a new and largely unexplored form of multi-manager investment. They share risk-moderating and transaction cost-saving characteristics with other multi-manager portfolio structures, and through examining these alternative structures, we can gain some insight into the mechanisms that drive emulation fund costs and savings. However, because emulation

[12] Note that this does not take into consideration the payment of management fees to active fund managers, which is not covered in this study. In addition, tax implications are also beyond the scope of this research.

funds have a unique system for altering the timing of trades, there remains a gap in understanding. This is the gap which this paper seeks to address.

The key advantage of multi-manager investment is diversification of manager-specific risk. Indeed, Lhabitant and Learned (2002) and Brands and Gallagher (2005) show that significant reductions in manager-specific risk can be achieved with five to ten different fund managers. Beyond this, adding more underlying funds may be detrimental to the skewness and kurtosis of portfolio returns (Brands and Gallagher, 2005) and may decrease potential alpha (Gallagher and Gardner, 2005). However, there has been little work on the level of trading redundancy that multi-manager frameworks exhibit.

There is also interest in determining whether multi-managers generate value beyond that created by their constituent managers. Emulation funds represent a plausible example of this approach, as they take the trade signals of the underlying managers to exogenously create capacity (with the creation of an auxiliary, internally administered fund) with much lower fees and potential transaction cost savings. Multi-managers charge additional fees that represent the cost of maintaining an additional level of management and reporting activities. (Brown et al., 2004) find that within the fund-of-hedge-funds environment, individual hedge funds tend to dominate fund-of-funds in terms of both after-fee return and Sharpe ratio. However, Ang et al. (2008) argue that the fees charged by funds-of-hedge-funds are justified because the correct benchmark should be the direct returns of an uninformed investor in the underlying hedge fund pool, rather than of the constituent funds. This takes into consideration the value of fund research services that multi-managers provide. Nevertheless, emulation funds are advantageous in this context, as the fees paid to the underlying managers in using their signals are usually much lower than the fees paid for direct management[13], and hence espouse a new dimension to cutting the costs of multi-manager investing.

Concerns about trading redundancy are a significant driver of research in centralised multi-manager investment strategies, and are a key motivator for the development of emulation funds. Redundant trades occur when independently managed constituent managers execute trades on the same underlying security, but on opposite sides of the market almost coincidentally. These trades incur transaction costs, but may provide very little additional net return to the overall portfolio. Approaches designed to address this problem can be broadly classified into three categories: inventory funds, explicit forecast models, and paper portfolios.

An inventory fund acts as a 'buffer' between the trades of the individual managers and the market. Orders entered by the constituent managers are executed against the inventory fund, which periodically rebalances by routing orders to the market. As in emulation funds, offsetting trades within a predetermined period of time are netted. A variation of this is to structure the inventory fund so that it tracks a market index within a specified band and rebalances when active manager trades push its index tracking beyond an acceptable tolerance range. These market index funds essentially contribute a passive investment component to the overall portfolio, and may take the place of other passive market investments. In either case, inventory funds delay the execution of trade signals from the underlying managers. However, this delay is typically much longer than is the case for emulation funds. Ferguson (1978) presents a case against market index inventory funds by arguing that if managers are knowledgeable, the offsetting mechanism will remove many valuable trades. On the other hand, if managers are not knowledgeable, a simple passive index fund should outperform a portfolio of active managers, net of fees. This argument is also pertinent to the case of emulation funds. (Wagner and Zipkin, 1978) examine real and

[13] From interviews with senior investment personnel at a major superannuation fund, we found that active management fees for direct funds management range between 30 and 70 basis points of funds under management per annum. We were told anecdotally that, in contrast, active fund managers typically charged 10 basis points for the additional use of their trade data in existing emulation strategies.

simulated inventory funds using US data and show cost savings of 0.8% of assets under management over a six month period (assuming total transaction costs of 1.5%). However, transaction costs have fallen significantly since the 1970s and there appears to be a notable lack of recent research.

A seminal paper by Rosenberg (1977) proposes a more active approach to centrally managed multi-manager structures, and specifies that constituent managers provide explicit numerical forecasts on stock returns. A central fund manager then trades, based on a consensus of these forecasts. At that time, the primary drawback of the model was that many fund managers were highly qualitative and thus could not readily provide detailed numerical data. Sharpe (1981) recognised these difficulties and discusses a number of other issues involved in constructing and managing a portfolio of funds. DiBartolomeo's (1999) extension on Rosenberg's (1977) model introduces a paper portfolio system where individual fund managers submit their trades to the central manager, who then uses these trades to generate the numerical forecasts required for Rosenberg's model.

Both Rosenberg's (1977) and DiBartolomeo's (1999) approaches require considerable cooperation between the constituent fund managers and the central manager. However, this may not be feasible. In a commercial setting, fund managers are often reluctant to disclose alpha forecasts for both privacy and economically-sensitive (i.e. intellectual property) reasons. Elton and Gruber (2004) address this problem by assuming only partial information sharing between the underlying managers and the central decision maker — namely, that each fund manager will only share information about the portfolio, and not forecasts about individual securities. Nevertheless, these centralised portfolio approaches require a fundamental shift in information flows.

Emulation funds differ from Rosenberg's (1977) and DiBartolomeo's (1999) approaches in two ways. First, the abovementioned structures are designed to replace the existing multi-manager framework. In contrast, emulation funds merely provide additional capacity, while maintaining the incumbent arrangements with the underlying fund managers. Second, emulation funds only use trade signals after the underlying fund manager has exploited them. Hence, an emulation fund does not require cooperation from the underlying fund managers beyond contractually attaining their permission to use their trade signals. Emulation funds represent a compromise between traditional decentralised multi-manager investing and the centralised investment structures proposed by Rosenberg (1977), diBartolomeo (1999), and Elton and Gruber (2004). Emulation funds are a simplification of these past approaches: they extend investment volume without changing the existing management arrangements, and the consequences are purely incremental. However, concerns regarding the extent to which the anticipated performance drivers in emulation funds (i.e. potential transaction cost savings and opportunity costs of delayed trade timing) affect their overall investment outcome remain unresolved. Our research attempts to fill this gap in the existing literature.

3. The Model

The emulation algorithm inputs trade signals from the target fund managers with information specifying timing, side (i.e. to buy or sell) and volume. The internal logic of the algorithm then computes the lags and offsets, and outputs a sequence of trade signals to be implemented on the emulation fund. For simplicity, we assume that the emulation fund receives trade signals from the underlying fund managers at particular frequencies with uniform distribution (we find that this assumption does not significantly impact the modelled rate of trade signal offsetting). These trade signals represent when fund managers execute purchase or sell orders that change their own directly-managed holdings. Trade efficiencies associated with emulation funds may arise when conflicting trade signals (i.e. a buy signal and a sell signal) arrive from different underlying fund managers within a short period of each other — this is the delay period. When this happens, the conflicting signals are internally offset so that only the net signal is offset and is executed on the emulation fund at the end of the delay period. Figure 1 provides an example of the offsetting process. The offset ratio (*OR*) describes the proportion of trade signals (weighted by the nominal value of each signal) that is internally offset in the emulation fund. Section 3.1.1 describes this in more detail.

The offset ratio (OR) influences a number of cost and saving drivers within the emulation structure. The four fundamental performance factors that account for the relative return difference between an emulation fund and its underlying tracking fund are: Brokerage commissions (C), price impact (PI), the opportunity costs associated with internal crossing (X) and those associated with delayed execution (D). *The* model represents the interaction between these factors and an offset ratio (OR) parameter, which refers to the portion of the order that is internally crossed. Intuitively, we would expect reductions in commission and price impact, as well as the opportunity costs of internally crossing trades (which reduces the crystallisation of trade gains or losses) to be positively associated with the OR while the opportunity cost of delayed execution is negatively associated. The model is specified on a per-security basis. We describe the expected profit ($\pi_{i,m,L}$) from an emulation strategy as:

$$\begin{aligned} E(\pi_{i,m,L}) = E(OR_{i,m,L})\left(C_{i,m} + E(PI_{i,m}) - E(X_{i,m,L})\right) \\ - \left(1 - E(OR_{i,m,L})\right)E(D_{i,m,L}) \end{aligned} \quad (1)$$

Here, i is a unique security identifier, m denotes a specific market side (either buys or sells) and L denotes the lag period. Hence, the profit in the strategy arises from the proportion of total transaction costs $\left(C_{i,m} + E(PI_{i,m})\right)$ that can be internally offset $\left(E(OR_{i,m,L})\right)$, minus the proportion of all crystallised gains $\left(E(X_{i,m,L})\right)$ that are eliminated with internal offsetting, and the opportunity cost of executing the proportion of trade volume that is not offset $\left(1 - E\left(OR_{i,m,L}\right)\right)$ and executed on a delayed basis $(E(D_{i,m,L}))$.

Expression (1) reflects our expectation that, as more trade signals are internally offset (i.e. $OR_{i,m,L}$ increases), we would realise a greater proportion of total potential reductions in commission ($C_{i,m}$) and price impact ($PI_{i,m}$). At the same time, the opportunity cost of internally offsetting crossed trades ($X_{i,m,L}$) at an intermediate price, rather than executing these trades at differing market prices, will also increase. Conversely, the $OR_{i,m,L}$ negatively affects the delayed execution opportunity cost ($D_{i,m,L}$), since a smaller proportion of total trade signals require delayed on-market execution if more of these signals are internally offset. We explore each of these parameters in further detail in the following sections.

3.1 Offset Ratio

The offset ratio $OR_{i,m,L}$ is the proportion of trade signal volume on security i and market-side m that can be eliminated for on-market trading through an L-day delay period. Where the timing and volume of each trade is known explicitly (e.g. ex-post analysis), this ratio can be computed through an iterative application of the offset function. That is, for each trade signal x in a security-specific trade sequence, we identify the specific percentage volume of that signal that can be offset as follows:

$$OR_{i,m,L_x} = \frac{min\ (V_x, \sum_{y=1}^{N_{L_x}} V_{x+y}^{-})}{V_x} \tag{2}$$

V_x	Trade volume of trade signal x
V_{x+y}^{-}	Trade volume of a transaction signal subsequent to x, on the opposite market

side and executed by a different manager

N_{L_x} The number of same security trades on the opposite market side within transaction x's offset window

In Equation (2), the left hand side denotes the offset ratio associated with x, a trade signal on security i, market side m and within an emulation framework with lag period L. The numerator in the right hand side is the entire volume of trade signal x if it is completely offset by subsequent crossed volume, or as much volume as can be crossed within the L day lag window. This is expressed as a proportion of the entire volume of x. Note that in practical application, an iterative procedure is applied to prevent double offsetting.[14] Thus, the V_{x+y}^{-} term is updated to the post-offset volume after each offset event.

Where the expected trade density is known but individual trades cannot be inferred, we use an algebraic formulation of $OR_{i,m,L}$, incorporating the expected trade density and the lag period in the emulation structure. This lends the additional advantage of being a continuous differentiable function with respect to key emulation parameters. Hence, the model is not restricted by the availability of historical data and can be analysed for a range of hypothetical scenarios. The offset ratio function is based on the notion that the proportion of trade signal volume that can be crossed out depends on (a) the collision rate $CR_{i,m,L}$ (which represents the probability that a buy (sell) trade signal will occur within L days of another manager's sell (buy) trade signal on the same security) and (b) the overlap ratio VR (which is the expected proportion of trading that we expect to offset, given two trades are already within *L* days of each other).

We need to make a number of assumptions about the nature of the projected trade signals on market side m. In the simplest case, we assume that the timing of all trades on the opposite market side m^{-} follow a uniform distribution $\mathcal{U}_i$, that both buy and sell side trade signals lie in

[14] For example, in a buy-sell-buy trade sequence of equal volumes, we must ensure that the sell does not offset against both buys, as this would incorrectly inflate our offset ratio.

the same range (i.e. the domain of $\mathcal{U}_i$) and that all funds that buy security s also sell it, and vice versa. Hence, the probability of a trade signal lying within L days of subsequent offsetting signal is expressed as:

$$E\left(CR_{i,m,L}\right) = 1 - \lim_{P\to\infty}\left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)} \tag{3}$$

$CR_{i,m,L}$	The collision rate of signals for security i on the m market side
P	Period over which trade density is measured
L	Trade delay period
td	Trade density on the opposite market side, expressed as the number of trade signals over period P
f	Total number of funds that traded in security i.

Appendix 2 provides the formal derivation of expression (3). Note that in this specification, the collision rate is not static, given an expected trade density td, but is asymptotic to the true collision rate for large values of *P*.

In reality, there are a number of effects that a uniformly distributed pattern of trade signal arrival does not take into consideration. First, institutional trades tend to be auto-correlated due to fund managers trading on short-lived information and exhibiting herding behaviour (Hirshleifer, Subrahmanyam and Titman, 1994, Kothari and Warner, 2001, Brown et al., 2007). Hence, institutional trade imbalance[15] is expected to lean towards the traded side (i.e. positive institutional trade imbalance following institutional buying, and negative institutional trade imbalance following institutional selling) in the period following the trade. Second, the total volume of trading by institutional investors is elevated in the period following other institutional

[15] Defined by $\frac{V_b-V_s}{V_b+V_s}$ where V_b is the volume of buys executed by mutual funds and V_s is the volume of sells executed by fund managers on any particular day.

trade, leading to non-uniformity in absolute trade density. Lastly, in securities where the trade density is high, one trade signal may offset against multiple subsequent signals on the opposite market side. We do not take multiple-signal offsetting into consideration in our basic model, but we do investigate what divergences this causes between the model and the simulated results in section 3.2.

Next, we estimate the expected proportion of trade volume that overlaps when two trade signals are crossed. This is equivalent to twice the overlapping volume divided by the total volume of the two trade signals:

$$VR = \frac{2 \cdot min(V_1, V_2)}{V_1 + V_2} \tag{4}$$

The overlap ratio depends on the distribution of typical trade sizes. Kyle and Obizhaeva (2011) note that after adjusting for trade activity, order size distributions across stocks in different volume and volatility groups closely resemble a log-normal. In this study, we do not calculate the order statistics of lognormal distributions as this is a non-trivial problem[16]. Instead, we use repeated two-signal sampling of a 1-year segment of our data to establish an approximate overlap ratio (VR) of 0.5 (i.e. given two trades drawn at random, the smaller volume is half the size of the greater volume). We acknowledge that this is parametrically insensitive to variations in the mean and standard deviation of trade volume distributions across securities but, as shown in section 3.2, the overall overlap ratio does not seem to vary significantly with time.

Combining the collision rate with the overlap ratio, the expected offset ratio is given as:

$$E\left(OR_{i,m,L}\right) = 0.5 \cdot \left(1 - \lim_{p \to \infty} \left(\frac{P - L}{P}\right)^{2 \cdot E(td) \cdot P \cdot \left(\frac{f-1}{f}\right)}\right) \tag{5a}$$

[16] For example, see Nadarajah (2008)

Figure 3 illustrates model forecasts of offset ratios as a function of realistic values of the delay period (L) and expected trade density ($\mathrm{E(td)}$), and demonstrates the need for longer (shorter) delay periods for less (more) frequently traded stocks to achieve a substantial internal crossing. We assume the number of underlying funds (f) supplying trade signals to the emulation fund remains constant. Since we do not account for a signal offsetting against multiple signals on the opposite market side (i.e. one large buy trade offsets against multiple smaller sell signals), we expect some model prediction error of the offset ratio for larger values of lag days and higher expected trade densities. We provide an example below of how this model can be used to infer the $\mathrm{OR_{s,m,L}}$ given the expected number of trades on either market side over a hypothetical period of trading and specified lag period.

Assume in the coming 100-day period that we expect 20 buy side trade signals and 25 sell side trade signals from four separate fund managers about security x. Let the lag period be five days. Then, the buy side offset ratio, by substituting $\mathrm{L} = 5$, $\mathrm{n} = 25$, $\mathrm{P} = 100$, is calculated as:

$$E\left(OR_{s,buy,5}\right) = 0.5 \cdot \left(1 - \lim_{p\to\infty} \left(\frac{P-5}{P}\right)^{2\cdot\frac{25}{100}\cdot P\cdot\left(\frac{4-1}{4}\right)}\right) = 0.423 \qquad (5b)$$

Similarly, the offset ratio for sell side signals, where we substitute $\mathrm{n_{\overline{m}}} = 20$, is:

$$E\left(OR_{s,sell,5}\right) = 0.5 \cdot \left(1 - \lim_{p\to\infty} \left(\frac{P-5}{P}\right)^{2\cdot\frac{20}{100}\cdot P\cdot\left(\frac{4-1}{4}\right)}\right) = 0.388 \qquad (5c)$$

3.2 Brokerage Commission

The brokerage is usually computed as a fixed percentage of trade value, though this may vary between security classes and brokers. Where the commission rate is not explicitly known, it may be proxied by the weighted mean commission rate from historical data. The model assumes that the commission structure is proportional and does not contain a fixed component; an x% reduction in on-market trade volume is expected to result in an x% reduction in paid commissions.

3.3 Price Impact

We use prior-day close prices to benchmark trade prices and determine historical price impact. This is used as an indication of the expected price impact on trades. The price impact calculation follows from Comerton-Forde et al. (2005), Chiyachantana et al. (2004), (Keim and Madhavan, 1996) and Chan and Lakonishok (1995). Chiyachantana et al. (2004) refers to this as the decision price measure and uses an approximation of the market price when the trade decision is made by the fund manager. The expected price impact on trade signal x is a hypothetical price impact should it be executed on-market.

The expected price impact of trade signal x is calculated as a weighted aggregate of the individual price impacts of the constituent trades within the underlying trade package:

$$E(PI_x) = \begin{cases} ln\left(\frac{\sum_{x' \in x} w_{x'} P_{x'}}{P_x \sum_{x' \in x} w_{x'}}\right) + \varepsilon \; for \; buy \; trade \; signals \\ -ln\left(\frac{\sum_{x' \in x} w_{x'} P_{x'}}{P_x \sum_{x' \in x} w_{x'}}\right) + \varepsilon \; for \; sell \; trade \; signals \end{cases} \quad (6)$$

$w_{x'}$ Trade value (price × volume) of individual trade x' within the trade package

$P_{x'}$ Trade price of individual trade x' within the trade package x

P_x Closing price on day prior to initiating trade day

In the buy side case, the numerator within the natural log function represents the total cash flow (less commissions) involved in the trade package (if we assume trade signal volume as the weighting factor), while the denominator is the hypothetical cost of the package if it had been fully executed at the decision price. Our approach differs slightly from the original Chiyachantana et al. (2004) measure in that we do not subtract the market price movement in the trade package period. This allows us to fully preserve the differential returns of the emulation fund relative to the tracking fund. The previous day close price was also chosen as the benchmark price since both our performance metrics (close-to-close returns and characteristics-based alpha) are close price based.

In an ex-ante context, the expected price impact on a hypothetical trade signal is taken as the mean weighted expected price impact of historic on-market trading of that stock on the particular market side:

$$E(PI_{i,m}) = \frac{\sum_{x \in i,m} w_x E(PI_x)}{\sum_{x \in i,m} w_x} \tag{7}$$

3.4 Internal Crossing Opportunity Cost

When crossed trade signals are offset in the emulation fund, we forgo the crystallisation of gains or losses that arise through execution at differing market prices. The internal crossing opportunity cost ($X_{i,m,L}$) is therefore the opportunity cost of eliminating exposure to market price shifts, and is measured as the log difference in the benchmark prices on buy and sell signal days. We use a benchmark price (in this case, the previous-day close price) rather than the actual trade price, since the price impact is computed separately.

If we assume that fund managers have short-term trade timing ability, then our expectation is that prices on traded securities will move in favour of the trade direction (i.e. prices will increase after institutional purchases, and decrease after institutional sales) immediately after the trade. While there will naturally be a significant degree of variance in price paths following trading, we define a "characteristic" price path function $\rho_{i,m}(t)$, which represents the ability of fund managers to anticipate favourable price movements in particular stocks. Empirically, this is defined by the weighted mean price movement following trading on a particular stock (Equation (8)).

$$\rho_{i,m}(t) = \frac{\sum_{x\in i,m} w_x \left(\frac{P_{x+t} - P_x}{P_x}\right)}{\sum_{x\in i,m} w_x} \tag{8}$$

If we assume, as in Equation (3), that trade signals on the opposite market side are uniformly distributed following an initial institutional trade signal, then the expected price movement between the initial trade and a subsequent offsetting trade within L lag days is given by:

$$X_{i,m,L} = \frac{\sum_{t\in[1,L]} \rho_{i,m}(t)}{L} \tag{9}$$

3.5 Delayed Execution Opportunity Costs

An inherent feature of emulation funds is the requirement to delay the exploitation of trade signals by a predetermined number of days. This is to ensure that on-market trading performed by the emulation fund does not compete with the underlying active funds for market volume. When a trade cannot be fully offset within the delay period, it must be executed at a subsequent market price to ensure tracking of the target fund. This leads to an opportunity cost in deliberately mistiming the trade, given by $\rho_{i,buy}(L)$ for buy side signals and $-\rho_{i,sell}(L)$ for sell side signals. In an aggregate sense, the absolute values of $\rho_{i,buy}(L)$ and $\rho_{i,sell}(L)$ are not important for our analysis. Rather, it is the difference between them (i.e. $\rho_{i,buy}(L) - \rho_{i,sell}(L)$) which is of main significance. If this value diverges positively from 0, then we expect greater opportunity costs associated with delayed trade execution. On the other hand, if the value diverges negatively from 0, then we would expect delayed trade execution to improve trading returns. Moreover, convergence to 0 in the long-term would indicate that fund managers neither add nor subtract long-term value in their trading.

4. Data, Calibration and Simulations

The aim of this section is to assess the accuracy of the model and demonstrate its strengths and weaknesses against empirical analysis across different types of securities. Since expectations data are not readily available, we use observed historical trading data as a proxy for expectations:

$$E\left(OR_{s,m,L}\right) = \overline{OR}_{s,m,L} + \varepsilon_1 \tag{10}$$

$$E\left(PI_{s,m,L}\right) = \overline{PI}_{s,m,L} + \varepsilon_2 \tag{11}$$

$$E\left(X_{s,m,L}\right) = \bar{X}_{s,m,L} + \varepsilon_3 \tag{12}$$

$$E\left(D_{s,m,L}\right) = \bar{D}_{s,m,L} + \varepsilon_4 \tag{13}$$

This gives an empirical form of:

$$\begin{aligned} E\left(\pi_{s,m,L}\right) = \left(\overline{OR}_{s,m,L} + \varepsilon_1\right)\left(C_{s,m,L} + \left(\overline{PI}_{s,m,L} + \varepsilon_2\right) + \left(\bar{X}_{s,m,L} + \varepsilon_3\right)\right) \\ + \left(1 - \left(\overline{OR}_{s,m,L} + \varepsilon_1\right)\right)\left(\bar{D}_{s,m,L} + \varepsilon_4\right) \end{aligned} \tag{14}$$

In the following sections, we generate model estimates for each of the performance drivers using our sample of multi-manager data, and compare the output results to those computed by a simulated emulation fund that uses actual recorded trades as hypothetical trade signals. The simulation algorithm iteratively applies Equation (2) to compute the specific offset ratio on individual offsetting events, and uses this to determine commission and price impact savings. Both of these factors are assumed, on average, to scale linearly with reductions in on-market traded values on an individual trade signal basis. Internal crossing opportunity costs are determined individually in each instance of offsetting trade as the sell signal price minus the buy signal price. Trade signals that are not fully offset are executed at a delayed point in time; the difference between benchmark prices on the original signal date and the hypothetical delayed execution date are used to compute the delayed execution cost. The model provides projected estimates specific to each security and market side; we present these in an aggregated context to provide an overall perspective on the model's performance. For robustness, we compare the accuracy of the model results to the simulation on a variety of security sub-portfolios partitioned by size, style and return characteristics.

4.1 Data

The data used to compare the model with a simulated emulation fund come from the Australian Equities component of a major Australian superannuation fund. Contained within the data set are daily aggregated transactions that include the trade price, volume, fund manager identifier and broker identifier over the period 2005 to 2009 inclusive. The multi-fund portfolio includes all major fund styles, and no emulation strategy is currently utilised by the superannuation fund. Statistics for this data set are summarised in Figure 4. This institutional trades data set is supplemented by stock price data from the SIRCA Australian Equities Tick History (AETH) database, market capitalisation and dividend payment data from the SIRCA Share Price and Price Relative (SPPR) database, and earnings data from Aspect Huntley.

4.2 Simulation Method

The simulation is executed with a procedural algorithm that iterates through a list of trade signals from the tracking portfolio fund managers (i.e. their daily trades). The algorithm delays these trade signals for a specified lag period, over which time the signal may be partially or fully offset against opposing signals from other constituent funds. Outstanding volume at the end of the lag window is executed on the following day at an inferred market price.

4.2.2 Transaction Cost Savings

The two transaction costs we look at are brokerage and price impact. Brokerage commissions are known explicitly from the daily trades data – hence, commission savings are calculated pro rata according to the offset ratio. The price impact measure we use follows from the widely used open-to-trade method in prior literature (e.g. Comerton-Forde et al. (2005), Chiyachantana et al. (2004) and Keim and Madhavan (1996)). This is defined as:

$$PI_{open} = \sum_{i}^{N} w_i \left(\frac{P_i - OP_1}{OP_1} - \frac{M_i - M_1}{M_1}\right) \tag{15}$$

Trade packages have been deconstructed into their N constituent trades. w_i is the volume weighting of each trade in the package, P_i is the trade price of trade i in the package, OP_1 is the opening on the first day of the trade package, M_i is the value of the market index on the day of trade *i* and M_1 is the value of the market index on the day of the first trade in the package. The simulation uses the underlying assumption that price impact scales down linearly with the offset ratio.

4.2.3 Timing-related Opportunity Costs

There are two opportunity costs associated with altering the timing of trades in the emulation fund relative to the tracking portfolio. When two trade signals on the same underlying security are offset in the emulation fund, we forgo the crystallisation of either a gain or a loss from the difference in their on-market trade prices. Where a gain was made in the tracking portfolio, each unit of volume that is offset incurs an opportunity cost associated with internal crossing (x) equivalent to:

$$x_i = x_j = \frac{P_b - P_s}{2} \tag{16}$$

P_b is the benchmark price of the day of the buy order and P_s is the benchmark price on the day of the sell order. The total cost of internal crossing attributable to each of the crossed trades is:

$$X_i = X_j = x_i \cdot argmin(V_i, V_j) \tag{17}$$

Here, $\mathrm{argmin}(V_i, V_j)$ represents the crossed volume between two opposing trade signals with volumes V_i and V_j.

The second opportunity cost arises from the delayed execution of trade signals from the tracking portfolio that have not been internally offset in the emulation fund. This results from the price movement in the lag period between when the trade is executed in the tracking portfolio and when it is emulated. The simulated delayed execution opportunity cost (D) is hence:

$$D_i = \begin{cases} P_{i+n} - P_i \; if \; buy \\ P_i - P_{i+n} \; if \; sell \end{cases} \tag{18}$$

4.3 Offset Ratio Modelling

We first examine the model's projected offset ratio compared to the measured offset ratio in the simulated fund. The model is calibrated on the same data as those used for the simulation, but uses only aggregated statistics concerning the trades (i.e. trade density), while the simulation processes every single trade signal. Figure 5 shows a comparison between the offset ratio (OR_L) predicted by the model, and that derived through simulation on the same data over five, 10 and 20 days. The model appears to be quite accurate over the shorter delay windows, but underestimates the projected OR_L more significantly over 20 days. There are two short-term deviations from our assumption about normally distributed trade signals that could possibly affect the projected offset ratio: the skewed trade imbalance following institutional trades, and the elevated levels of both institutional buying and selling. While we do observe these effects[17], the fact that the model-projected offset value over five days closely matches the offset value observed through simulation indicates that the rate of offsetting is not greatly affected by the combination of these two factors.

At longer delay periods, the model underestimates the simulated offset ratio more substantially. We believe this is primarily caused by the model ignoring crossing events where a trade signal offsets against multiple signals on the opposite market side. As expected, this effect occurs more commonly as the lag period (L) increases. Overall, the model's offset ratio projections appear to be very accurate for emulation strategies with a 5-day lag period, and do a reasonably good job of modelling OR_L for 10-day lags. Over longer lag windows, a more sophisticated model of multiple trade offsetting needs to be considered. However, since current commercial emulation strategies primarily operate with short five to 10 day lags, our simple 2-trade crossing model appears to be sufficient in this context.

[17] In the five days after a fund manager trades, the institutional buy (sell) side trade imbalance, excluding other trades by that manager, is 7.71% (5.55%) away from the long-term equilibrium imbalance in the buy (sell) direction. In the same 5 day period, institutional sell (buy) activity decreased (increased) by 0.62% (4.98%) following an institutional buy (sell).

4.4 Performance Drivers Modelling

Next, we compare the model predictions for each of the performance drivers against the results from our simulated emulation fund. Panels A, B and C of Figure 6 show a side-by-side comparison of each of the four performance drivers for five, 10 and 20 lag days. The modelled commission savings turn out to be slightly lower than the true savings, which reflects the model's underestimation of the simulated offset ratio. On the other hand, the model significantly overestimates both the price impact savings and the internal crossing opportunity costs. The former observation suggests that in the simulated emulation fund, trade signals with relatively low price impact are more likely to be internally offset. This may be due to the presence of contrarian trading patterns — e.g. if a fund manager buys when other managers are selling, then those buy signals would incur relatively low or even negative price impacts. The emulated signals would also have a greater probability of being offset, by definition, since there is elevated institutional supply of that stock. This view is supported by the presence of both growth and value managers in the data sample. The latter observation, that the modelled internal crossing opportunity costs are greater than those seen in the simulation, in conjunction with the observed tendency for $\rho_{i,buy}(t) - \rho_{i,sell}(t) > 0$ for small values of t, suggests that offsetting events tend to occur close to each other rather than spread out through the lag period. Finally, the delayed execution opportunity cost appears to be underestimated by the model over five days, closely estimated over 10 days and overestimated over 20 days. Since the modelled offset ratio underestimates the simulated offset ratio, this implies that with a corrected OR, the model would generally tend to slightly underestimate the true delayed execution opportunity cost. This suggests that stocks that are less likely to be offset (e.g. small-cap stocks with lower trade densities) incur greater than expected opportunity costs associated with delayed execution of trade signals, and confirms previous observations that fund managers exhibit greater stock selection ability in small stocks (Chen et al., 2010). We also observe that opportunity costs associated with delayed trading seem to decrease with longer lag periods. This implies that $\rho_{i,buy}(t) - \rho_{i,sell}(t)$ converges for larger values of t, and indicates that longer lag periods result in a more profitable emulation strategy.

From a practitioner's point of view, the model demonstrates that the opportunity costs of delayed trading are at least as significant as the transaction cost savings. While trading efficiency and transaction cost reduction are often touted as the selling points of an emulation fund, the actual cost savings from reduced turnover is bounded by the maximum value of market impact and brokerage. On the other hand, both the opportunity cost of internal crossing and the opportunity cost of delayed execution are dependent on the structure of $\rho_{i,buy}(t)$ and $\rho_{i,sell}(t)$, which are potentially unbounded. Empirically, the effects of these post-trade price movement functions are much more significant than the transaction cost savings and, at least over short lag periods, adverse to overall performance.

In general, the model shows some discrepancy in predicted and actual factor performance as computed by the simulated emulation algorithm, particularly in price impact reduction and internal offsetting opportunity cost. However, the model effectively projects both commission savings and the delayed execution opportunity cost (which has the most significant influence on overall emulation performance).

4.5 Model Robustness

We test the model against simulated emulation sub-portfolios constructed along market capitalisation, book-to-market and historical returns characteristics. Results are summarised in figure 7. For 5 and 10-day lags, the model forecasts within 0.30% of simulated outcomes for all stocks ranked between 1 and 300 in size (Figure 7, Panel A). Stocks ranked below 300 exhibit large errors in the forecasted performance relative to simulation, and cannot be reliably modelled. Over a 20-day lag, the model forecasts simulated emulation performance within 0.15% for stocks ranked down to 200 in size. However, accuracy significantly drops for smaller stocks (forecasting errors of 1.27% and 1.68% for stocks ranked in 201 to 300 and 300+ respectively). Along the value-growth dimension, the model appears to be more accurate forecasting emulation performance on stocks in the high market-to-book (i.e. growth) end of the spectrum compared to the low market-to-book (i.e. value) end (Figure 7, Panel B). We also note that over the 20-day lag period, the model tends to underestimate performance relative to simulation for growth stocks, and overestimate performance (and much more significantly so) for value stocks. The model is also less effective for forecasting performance in stocks with very negative prior-year returns, and to a lesser extent, those with very positive prior-year returns (Figure 7, Panel C). A comprehensive breakdown of the model's predicted results against results simulated directly from the data and analyses across market capitalization, book-to-market ratio and momentum can be found in the online supplement[18].

The forecasting accuracy of the model is also a function of the lag length employed. There appears to be a lower margin of error in the offset ratio prediction (Figure 5) for shorter lags compared to longer ones. This may be a product of the model's implicit assumption that offsetting only occurs in independent, opposed signal pairs (i.e. a buy and a sell). In reality, the offsetting process happens continuously where one signal (e.g. a buy) may be offset against multiple opposing signals (e.g. several sells). As the lag period is increased, the frequency of these complex, multi-signal interactions also increases, which leads to the model underestimating the simulated offset ratio. However, the model's overall predictive accuracy actually increases as the lag period lengthens up to 20 days. This is a product of the model producing greater underestimation bias on commission savings and internal crossing opportunity costs as the lag period lengthens, but an opposite effect in the errors associated with the delayed execution opportunity cost – the model underestimates this cost with 5 and 10 days but overestimates it with the 20-day lag. The net result is that errors cancel each other out with the 20-day lag

[18] https://dl.dropboxusercontent.com/u/37092/ChenGallagherFosterLee2012_Supp.docx

window. The errors between the model and the simulated emulation fund are 0.08%, 0.07% and 0% for 5, 10 and 20 lag days respectively. We suggest that this model should be applied with caution for emulation portfolios with lag periods longer than 20-days, since we expect the error on the predicted offset ratio to be exacerbated by the longer lag.

5. Model Applications

Having established that the model provides a fair representation of the differential performance an emulation fund generates relative to its tracking fund (in the stocks that constitute the majority of trading), we look at practical applications of this model to potential real-world scenarios. We do this in two ways: in section 5.1, we assume that the short-term price evolution of a stock subsequent to purchase is not significantly different from the price movement of a stock subsequent to sale. Hence, we only look at savings generated by the internal crossing mechanism. In section 5.2, we add a price evolution model based on empirical observations about how prices evolve subsequent to being traded by mutual fund managers.

5.1 Offset Ratio Optimisation

We first assume that purchased stocks exhibit short-term price movement patterns that are not significantly different to sold stocks after they are traded by mutual fund investors. This is generally the assumption implicit in the justification of commercial emulation products[19]. Under this condition, the expected value of timing opportunity costs (i.e. $E(X_{i,m,L})$ and $E(D_{i,m,L})$) is zero. Equation (1) hence simplifies to:

$$E(\pi_{i,m,L}) = E(OR_{i,m,L})\left(C_{i,m} + E(PI_{i,m})\right) \quad (19)$$

[19] From the marketing content of an emulation portfolio provider

That is, the profit from the emulation strategy arises purely as a linear proportion of the offset ratio. The offset ratio, in turn, is a function of the predetermined lag period and the expected trade density (equation (5)). We can therefore show using partial derivatives of equation (5) with respect to the lag period and the expected trade density that the expected payoff from emulation increases with longer lags and higher trade densities, but these exhibit rapidly diminishing marginal returns.

We first examine the partial derivative of $E(OR_{i,m,L})$ with respect to L (Equation (20)).

$$\frac{\partial E(OR_{i,m,L})}{\partial L} = \lim_{P\to\infty}\left(2 \cdot E(td) \cdot \left(\frac{f-1}{f}\right) \cdot \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)-1}\right) \tag{20}$$

We note that $\frac{\partial E(OR_{i,m,L})}{\partial L}$ is strictly positive – hence the offset ratio (and marginal profit from emulation) monotonically increases with the lag period. However, Figure 8 Panel A shows that the marginal benefit of increasing the lag rapidly diminishes with the size of the lag, particularly for stocks with high trade density.

A similar trend occurs when we examine the partial derivative of $E(OR_{i,m,L})$ with respect to $E(td)$ (Equation (21)).

$$\frac{\partial E(OR_{i,m,L})}{\partial E(td)} = -1 \cdot \lim_{P\to\infty}\left(P \cdot \left(\frac{f-1}{f}\right) \cdot log\left(\frac{P-L}{P}\right) \cdot \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}\right) \tag{21}$$

Again, the function is monotonically increasing with respect to the expected trade density, but marginal improvements to the expected offset ratio rapidly diminish with a larger flow of trades. While multi-fund managers cannot directly control the volume of trading each constituent fund executes, the issue of trade density becomes pertinent should the multi-fund manager decide to include additional funds in the investment strategy. The inclusion of additional underlying funds not only increases the expected trade density, but also the value of f – the number of funds. However, the effect of increasing f is deemed to be marginal for most large multi-fund managers since $\frac{f-1}{f}$ diminishes rapidly as f increases. In the base case where the post-trade performance of buys and sells are homogenous, increasing the lag period or adding additional fund managers to the tracking portfolio always improves the return outcome of the emulation fund relative to the tracking portfolio.

5.2 Lag Period Optimisation with Heterogeneous Post-Trade Price Movement

The simulation shows that the post-trade price movement function of purchased stock differs from that of sold stocks – mutual funds tend to buy stock that outperform sold stock in the short term subsequent to trading. To model this, we introduce the post-signal price movement function ($\rho_{i,m}(L)$), which describes the evolution of stock prices immediately after they are traded by a mutual fund. i denotes the specific stock being traded and m the side of the market (either buy or sell) We can substitute $\frac{P_{i,m}(L)}{L}$ for $E(X_{i,m,L})$ if we assume that offsetting trades are uniformly distributed across time, and we can also substitute $\rho_{i,m}(L)$ for $E(D_{i,m,L})$, since delayed execution occurs at the end of the lag period. Hence, the marginal payoff of emulation becomes:

$$E(\pi_{i,m,L}) = \begin{cases} E(OR_{i,m,L})\left(C_{i,m} + E(PI_{i,m}) - \dfrac{P_{i,m}(L)}{L}\right) - \left(1 - E(OR_{i,m,L})\right)\rho_{i,m}(L) \; if \; m \; is \; buy \\ E(OR_{i,m,L})\left(C_{i,m} + E(PI_{i,m}) + \dfrac{P_{i,m}(L)}{L}\right) + \left(1 - E(OR_{i,m,L})\right)\rho_{i,m}(L) \; if \; m \; is \; sell \end{cases} \tag{22}$$

In the context of maximising returns in the emulation fund relative to its tracking fund, the optimal lag period should be specific to each security and is dependent on the expected trade density of that security and the structure of its post-signal price movement function ($\rho_{i,m}(L)$). Combining the buy and sell sides, the payoff from emulating a particular stock i is given by:

$$E(\pi_{i,L}) = E(OR_{i,L})\left(2C_i + E(PI_{i,buy}) + E(PI_{i,sell}) - \frac{P_{i,sell}(L) - P_{i,buy}(L)}{L}\right) + \left(1 - E(OR_{i,L})\right)\left(\rho_{i,sell}(L) - \rho_{i,buy}(L)\right) \tag{23}$$

Here, we assume that both the volume of trading and the brokerage commissions are symmetrical for buys and sells. Note that $P_{i,m}(L)$ is the integral of $\rho_{i,m}(L)$. The ideal lag period thus dependent on the difference between the structure of buy-side post-trade price movement function and the sell-side function. Figure 9 provides an application of Equation (23) on the "average" stock (with weighted mean characteristics of all stocks). The underlying data suggests that buys outperform sells in the short term, but this trend reverses between 50 and 100 days post-trade. A proposed emulation portfolio emulating this particular stock is therefore expected to generate negative marginal returns using a short lag period, but positive marginal returns with a very long lag period (in our example 100 trade days). Given the large degree of variation occurs between the post-trade price movements of different stocks, the model would be useful in determining whether a long lag is optimal (as in the example provided), a short lag is optimal (e.g. if buys tend to outperform sells), or some intermediate lag period (e.g. if the buy-minus-sell returns difference initially diverges after trade and then subsequently converges).

We note that it may also be desirable to minimise the tracking error between the emulation fund and the target portfolio; this preferences shorter lag periods. The idiosyncratic risk tolerance of the multi-manager fund manager is not incorporated into our model.

6. Conclusions

At the most basic level, our model formalises the interaction between potential transaction cost savings and the opportunity costs associated with internal offsetting and delayed trade timing. This provides both predictive and explanatory advantages over observing simulation output. From a forecasting point of view, we can estimate the reduction in turnover based purely on expected trade signal density and a predefined lag period. This, in turn, allows us to make estimates about the performance of a proposed emulation fund based on historical observations of transaction costs and post-trade price movements. From an explanatory point of view, our model — in conjunction with simulation — enables us to evaluate our hypotheses about the underlying statistical processes that drive emulation funds, and hence reveal where intuitive assumptions hold and where they break down.

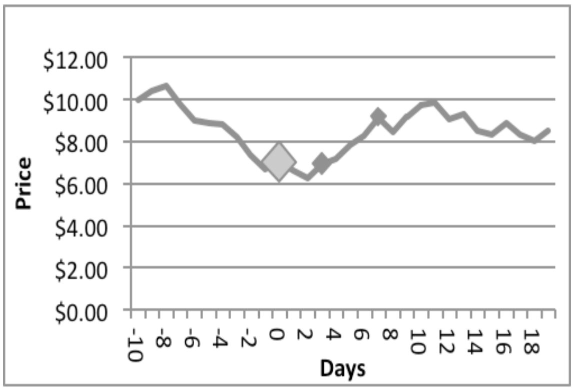
Importantly, the model highlights aspects of the emulation process which we may not have thought to investigate in a pure simulation setting. For example, the observed price impact saving determined in the simulation is much lower than that predicted by the model — indicating that low price impact trade signals are more likely to be internally offset in the emulation fund. Merely observing the level of price impact saving itself would not have allowed us to reach a similar conclusion. Furthermore, having the model as a benchmark enables us to determine that infrequently traded stocks have a greater than expected opportunity cost to delayed trading, and hence are likely to be more skilfully traded. This suggests that these stocks should be emulated with shorter lags or excluded from the emulation fund altogether.

When tested against simulation, we show that the model does reasonably well at forecasting both the offset ratio and overall performance for shorter lag periods (i.e. less than 10 lag days). Hence, by examining the functional representation of the model, we can actually determine the sensitivity of the offset ratio to changes in lag period and trade density. In particular, we observe that the marginal benefit to increasing the lag period, when the lag period is already greater than seven days, is extremely low, even for securities with very low trade signal densities in our data sample. From a practitioner's point of view, this allows us to compare the potential opportunity costs determined by the post-trade price movement function (i.e. $\rho_{i,m}(L)$) to the potential savings arising from higher levels of internal trade signal offsetting. Where the post-trade price adjustment functions of individual stocks can be reasonably estimated, we can also use the model to infer the optimal lag structure of the emulation fund on a stock-by-stock basis.

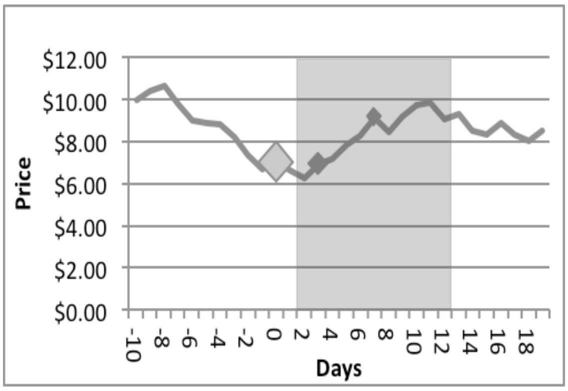
Finally, we note that the outcomes of emulation also depend on factors other than those that have been addressed here. These include the tax consequences of administering the emulation fund, active management fees, and implementation issues such as brokerage, risk and cash flow management in the emulation fund. These topics would provide rich avenues for future research.

7. Appendices

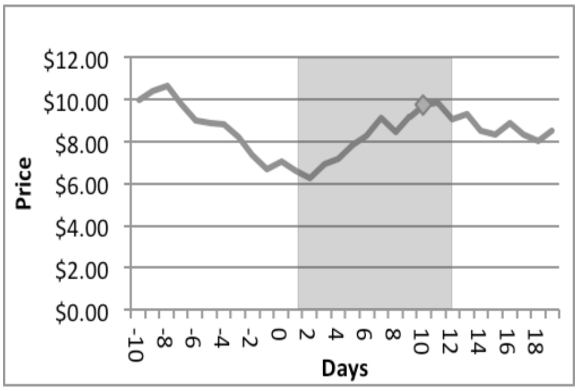
Figure 1: Example of the trade signal offsetting process (from Chen et al. (2013)).



A. Assume the following trade sequence:
1. Manager X issues buy signal for x100 on day 0
2. Manager Y issues sell signal for x30 on day 3
3. Manager Z issues sell signal for x20 on day 7



B. Offset subsequent sell signals (x30 and x20) against the initial buy signal, which in this case is lagged for 10 days.



C. Execute residual buy volume on-market at the end of the lag delay period (x50).

Appendix 2: Explanation and derivation of the collision rate equation

Assume sell side trade signals are drawn from a uniform distribution with range P. P represents the total period of observation from which trades can be drawn:

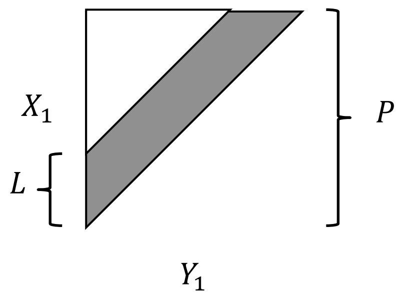
$$Y_1 \sim \mathcal{U}_s(0, P)$$

Further assume that a buy side signal (X_1) is drawn from the same range and distribution as sell side signals. The collision rate is the probability that X_1 is within distance L of Y_1 for $L \geq 0$:

$$CR_{X_1,Y_1} = P(|X_1 - Y_1| \leq L)$$

$$= P(X_1 - Y_1 \leq L \mid X_1 \geq Y_1) \cdot P(X_1 \geq Y_1) + P(Y_1 - X_1 \leq L \mid Y_1 \geq X_1) \cdot P(Y_1 \geq X_1)$$

Since the two sides are symmetrical, we can simply solve for $P(X_1 - Y_1 \leq L \mid X_1 \geq Y_1)$. The figure below graphically characterises the distributions of X_1 and Y_1 on orthogonal axes, and the grey area represents the region where $0 \leq X_1 - Y_1 \leq L$:



Hence:

$$P(X_1 - Y_1 \leq L \mid X_1 \geq Y_1) = \frac{\mathrm{P}^2 - (P - L)^2}{P^2} = \frac{L(2P - L)}{P^2}$$

$$\therefore CR_{X_1,Y_1} = \frac{L(2P - L)}{P^2}$$

We take the n^th power of the base probability, where n is the number of opposed trade signals. Since signals issued by the same fund manager are excluded from offsetting, we scale the number of trade signals on the opposite market side by $\frac{f-1}{f}$, where f is the number of managers that participated in trading the particular security.

Hence, for n signals on the opposite market side:

$$CR_{X_1,Y_1..Y_n} = 1 - \left(1 - \frac{L(2P-L)}{P^2}\right)^{n\left(\frac{f-1}{f}\right)} = 1 - \left(\frac{P-L}{P}\right)^{2\cdot n\left(\frac{f-1}{f}\right)}$$

Finally, we formulate this equation with n as a stochastic variable with respect to an expected trade density td (i.e. $td \sim n/P$). Since the trade density assumes that P is unbounded, we must take the limit of P as it approaches infinity. Indeed, the function is non-stationary when taking small values of P, but asymptotic as P increases:

$$CR_{L,td} = 1 - \lim_{P\to\infty} \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}$$

For practical purposes, we can achieve an arbitrary degree of accuracy for the projected collision rate by using a sufficiently large value of P.

Figure 3: Plot of the expected offset ratio function with realistic value ranges for the lag period and expected trade density. The expected offset ratio function is given by:

$$E\left(OR_{i,m,L}\right) = 0.5 \cdot \left(1 - \lim_{p\to\infty} \left(1 - \frac{L(2P-L)}{P^2}\right)^{E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}\right)$$

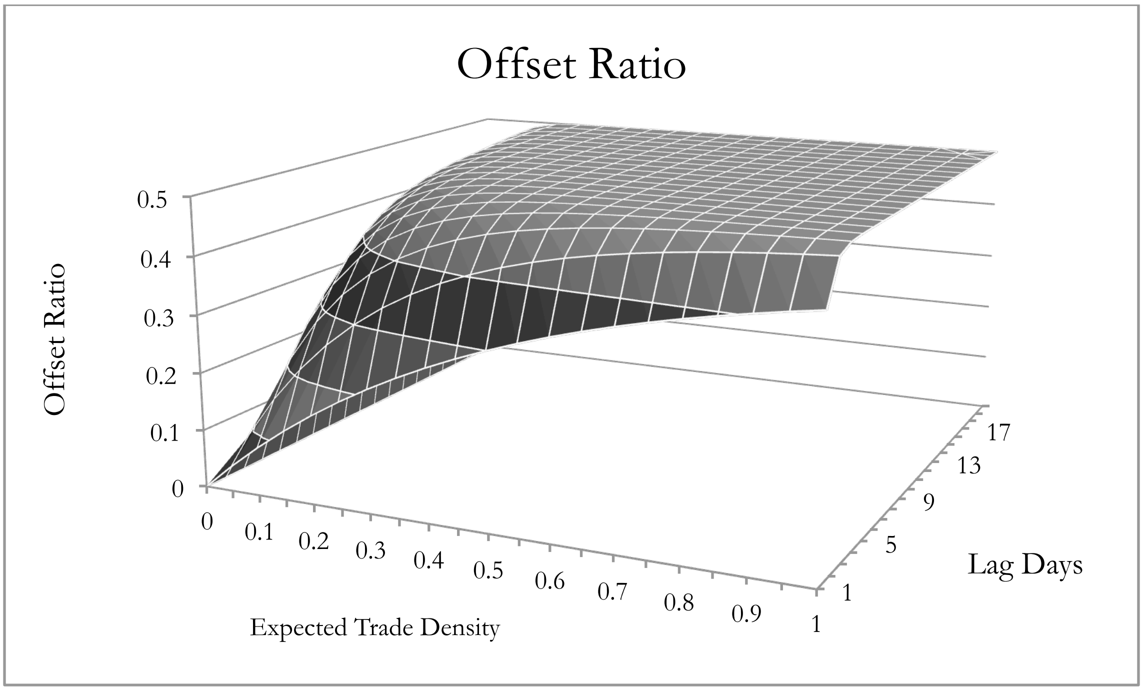

Offset Ratio
0.5
0.4
0.3
0.2
0.1
0
Offset Ratio
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Expected Trade Density
1
5
9
13
17
Lag Days

Figure 4: Descriptive statistics of the dataset. Trade packages are determined from individual trades by aggregating successive trades executed by a single manager on one side of the market. These packages must be unbroken by any trade by that manager on the opposite market side or contain a gap in trading of five days or longer. See Chan and Lakonishok (1995) for further details on the trade packaging method. Data for this table are entirely sourced from our sample multi-manager.

	2005	*2006*	*2007*	*2008*	*2009*	*All Years*
Multi-manager Composition						
Enhanced Passive	4	4	4	4	4	4
Growth	1	1	1	2	2	2
Long/Short	1	1	1	2	2	2
Style-Neutral	1	1	2	3	3	3
Value	3	3	4	5	5	5
Total	**10**	**10**	**12**	**16**	**16**	**16**
Total trades						
Buy	4,137	5,669	5,746	8,272	9,097	32,921
Sell	3,640	4,892	6,112	7,630	8,650	30,924
Total trade packages						
Buy (% in parentheses)	1,392	1,980	2089	2691	3073	11,225
Sell (% in parentheses)	1,431	1,753	2188	3048	3528	11,948
Total Fund Value ($m)	6,782.2	8,153.4	9,084.3	8,010.7	8,351.7	
Annual Turnover (%)	37.88	41.14	38.58	50.83	46.71	
Unique Securities Traded	155	165	215	220	248	332

Figure 5: Comparison of aggregated offset ratios predicted by the model and those observed in the ex-post simulated emulation fund. The offset ratio represents the proportion of traded value that can be internally crossed (and hence removed from on-market trading) in the emulation fund relative to the target fund. The x-axis represents the three lag periods that were used for both the model and the simulated fund.

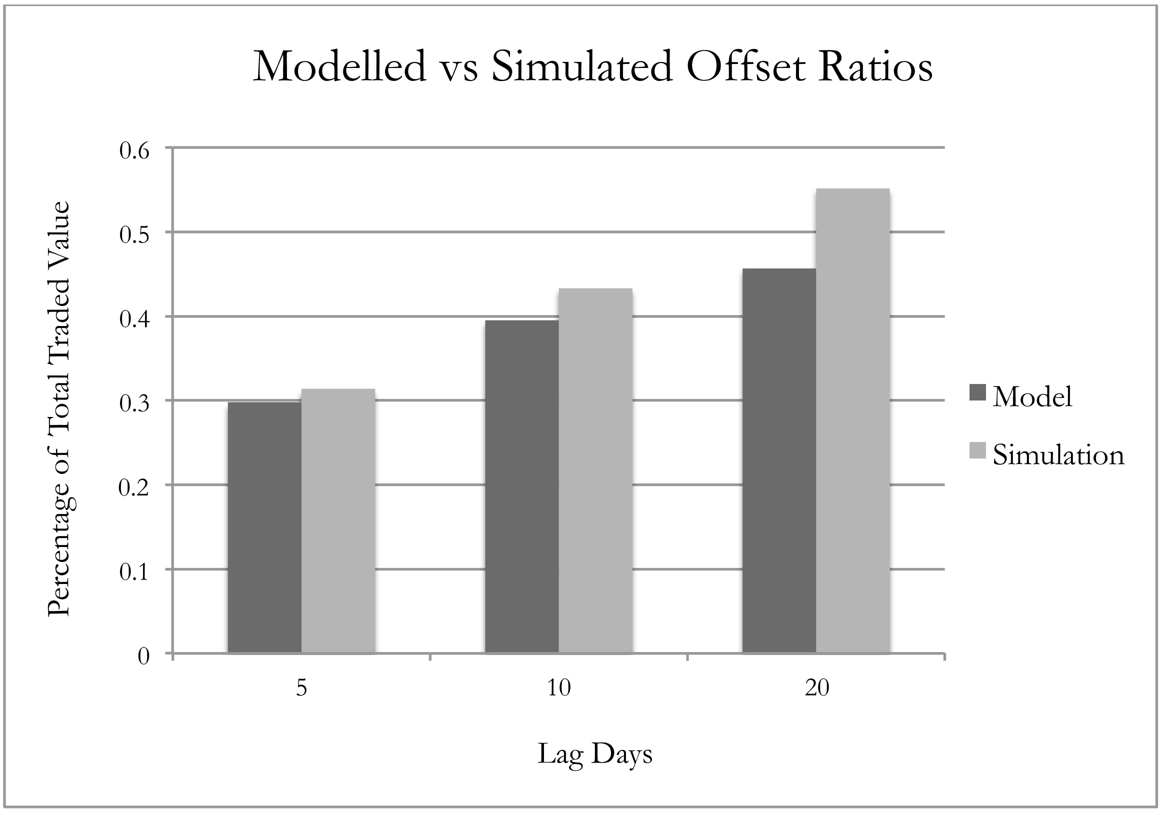


Figure 6: Individual performance drivers as forecasted by the model compared to those observed in the simulated emulation fund. Results are aggregated on a trade-value weighted basis across the observation period. We present results for emulation funds with five, 10 and 20-day lag periods. Note that commissions and price impacts are presented as savings, which create positive cash flows to the emulation fund, while internal crossing and delayed execution represent costs. The total relative returns represent the aggregated costs and benefits, with positive values representing excess performance and vice versa. Performance is measured as a proportion of total traded value – i.e. if the commission saving is reported as 0.05% in the simulation, it means that the total benefit arising from commission savings is 0.05% of the total traded value (buys plus sells).

Lag Days		*5*			*10*			*20*	
	Model	*Simulation*	*Model - Simulation*	*Model*	*Simulation*	*Model - Simulation*	*Model*	*Simulation*	*Model - Simulation*
Commission Savings	0.04%	0.05%	-0.01%	0.05%	0.06%	-0.01%	0.06%	0.08%	-0.02%
Price Impact Savings	0.04%	0.02%	0.02%	0.05%	0.01%	0.03%	0.05%	0.02%	0.03%
Internal Crossing Opportunity Cost	0.12%	0.08%	0.04%	0.18%	0.13%	0.05%	0.22%	0.15%	0.07%
Delayed Trading Opportunity Cost	0.39%	0.45%	-0.05%	0.36%	0.36%	-0.01%	0.30%	0.28%	0.02%
Total Impact	-0.43%	-0.47%	0.03%	-0.44%	-0.42%	-0.02%	-0.41%	-0.33%	-0.08%

Figure 7: Summary of model accuracy relative to a simulated emulation portfolio using subportfolios of different stock size (Panel A), market-to-book ratio (Panel B) and prior 1-year return (Panel C). Positive outcomes represent where the model/simulation outperforms the target fund; negative outcomes represent underperformance.

Panel A: Size

	Lag Days								
	5			*10*			*20*		
Size Rank	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*
1 - 20	-0.30%	-0.50%	0.19%	-0.29%	-0.47%	0.18%	-0.21%	-0.31%	0.11%
21 - 50	-0.41%	-0.51%	0.10%	-0.38%	-0.42%	0.03%	-0.27%	-0.24%	-0.03%
51 - 100	-0.53%	-0.37%	-0.16%	-0.46%	-0.39%	-0.07%	-0.46%	-0.38%	-0.08%
101 - 200	-0.53%	-0.38%	-0.15%	-0.47%	-0.25%	-0.22%	-0.57%	-0.42%	-0.15%
201 - 300	-0.98%	-1.18%	0.20%	-0.84%	-0.56%	-0.28%	-0.90%	0.38%	-1.27%
301 +	-0.60%	-3.58%	2.98%	-0.49%	-4.92%	4.43%	-1.11%	-2.79%	1.68%

Panel B: Market-to-Book

	Lag Days								
	5			*10*			*20*		
Market-to-Book	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*
Highest M/B	-0.19%	0.28%	-0.47%	-0.13%	0.43%	-0.56%	-0.37%	0.60%	-0.96%
2	-0.56%	-0.69%	0.13%	-0.61%	-0.56%	-0.04%	-0.71%	-0.51%	-0.19%
3	-0.50%	-0.50%	0.00%	-0.29%	-0.20%	-0.09%	-0.18%	0.11%	-0.28%
4	-0.39%	-0.33%	-0.07%	-0.29%	-0.17%	-0.12%	-0.24%	0.01%	-0.25%
5	-0.49%	-0.53%	0.04%	-0.46%	-0.39%	-0.07%	-0.26%	-0.60%	0.33%
6	-0.26%	-0.30%	0.04%	-0.32%	-0.30%	-0.03%	-0.30%	-0.06%	-0.24%
7	-0.45%	-1.36%	0.91%	-0.52%	-1.55%	1.04%	-0.59%	-1.76%	1.17%
8	-0.63%	-0.69%	0.06%	-0.51%	-0.51%	-0.01%	-0.58%	-1.06%	0.48%
9	-0.24%	0.64%	-0.88%	-0.39%	0.19%	-0.57%	-0.76%	-1.20%	0.45%
Lowest M/B	-0.34%	-4.21%	3.87%	0.14%	-5.43%	5.57%	-0.74%	-5.99%	5.25%

Panel C: Momentum

	Lag Days								
	5			*10*			*20*		
Prior 1-year return	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*	*Forecast*	*Actual*	*Forecast - Actual*
Lowest Pr1yr	-0.24%	-2.11%	1.87%	0.11%	-2.46%	2.57%	0.23%	-2.81%	3.04%
2	-0.41%	0.54%	-0.95%	-0.25%	0.10%	-0.35%	-0.17%	0.56%	-0.72%
3	-0.39%	-0.40%	0.01%	-0.35%	-0.35%	-0.01%	-0.25%	-0.10%	-0.15%
4	-0.34%	-0.27%	-0.08%	-0.33%	-0.47%	0.14%	-0.32%	-0.51%	0.19%
5	-0.38%	-0.56%	0.19%	-0.41%	-0.42%	0.02%	-0.35%	-0.63%	0.27%
6	-0.31%	-0.67%	0.36%	-0.27%	-0.38%	0.11%	-0.20%	-0.50%	0.30%
7	-0.38%	-0.56%	0.18%	-0.35%	-0.32%	-0.03%	-0.32%	-0.32%	0.00%
8	-0.42%	-0.50%	0.08%	-0.39%	-0.34%	-0.05%	-0.31%	-0.15%	-0.16%
9	-0.57%	-0.51%	-0.06%	-0.53%	-0.82%	0.30%	-0.58%	-0.39%	-0.19%
Highest Pr1yr	-0.73%	-0.36%	-0.37%	-0.67%	-0.20%	-0.46%	-0.75%	1.01%	-1.77%

Figure 8: Partial derivatives of the expected offset ratio equation, given by:

$$E(OR_{i,m,L}) = 0.5 \cdot \left(1 - \lim_{p\to\infty} \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}\right)$$

Panel A plots the partial derivative of this with respect to the lag days L, with realistic value ranges for the lag period and expected trade density:

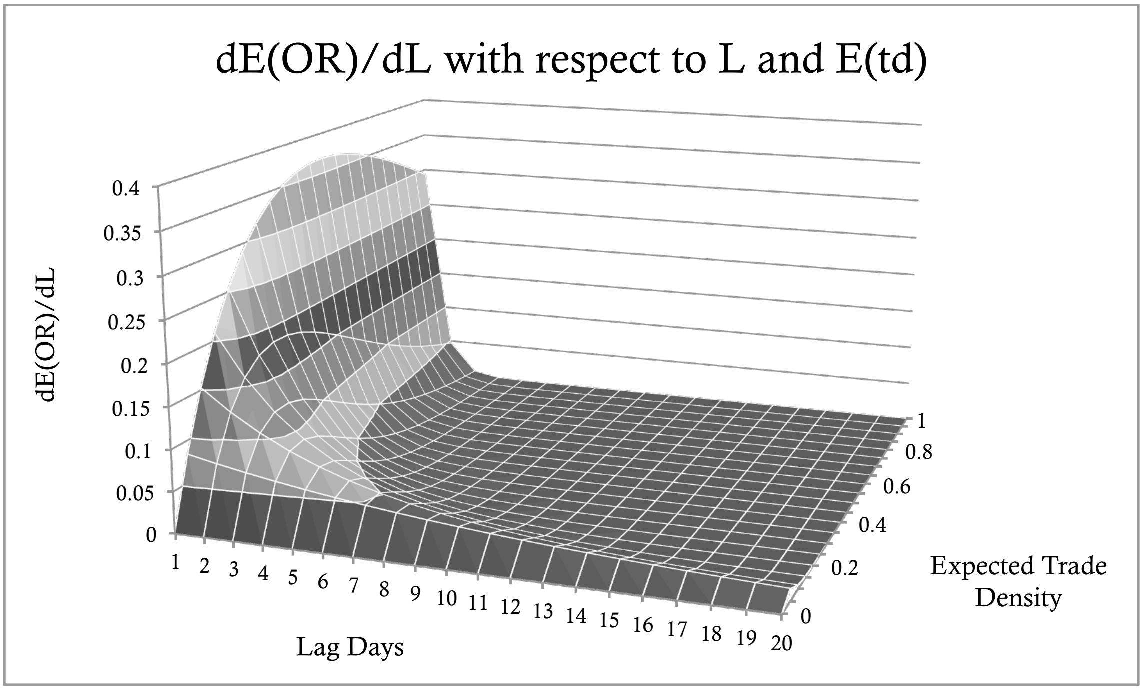
$$\frac{\partial E(OR_{i,m,L})}{\partial L} = \lim_{P\to\infty} \left(2 \cdot E(td) \cdot \left(\frac{f-1}{f}\right) \cdot \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)-1}\right)$$

Panel B plots the partial derivative of the expected offset ratio equation with respect to the expected trade density $\mathrm{E(td)}$, for realistic value ranges for lag period and expected trade density:

$$\frac{\partial E(OR_{i,m,L})}{\partial E(td)} = -1 \cdot \lim_{P\to\infty} \left(P \cdot \left(\frac{f-1}{f}\right) \cdot log\left(\frac{P-L}{P}\right) \cdot \left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}\right)$$

We use $f = 12$ for the purposes of creating the graphs below as this was the mean number of individual fund managers that traded each stock on a trade-value weighted basis:

Panel A



Panel B

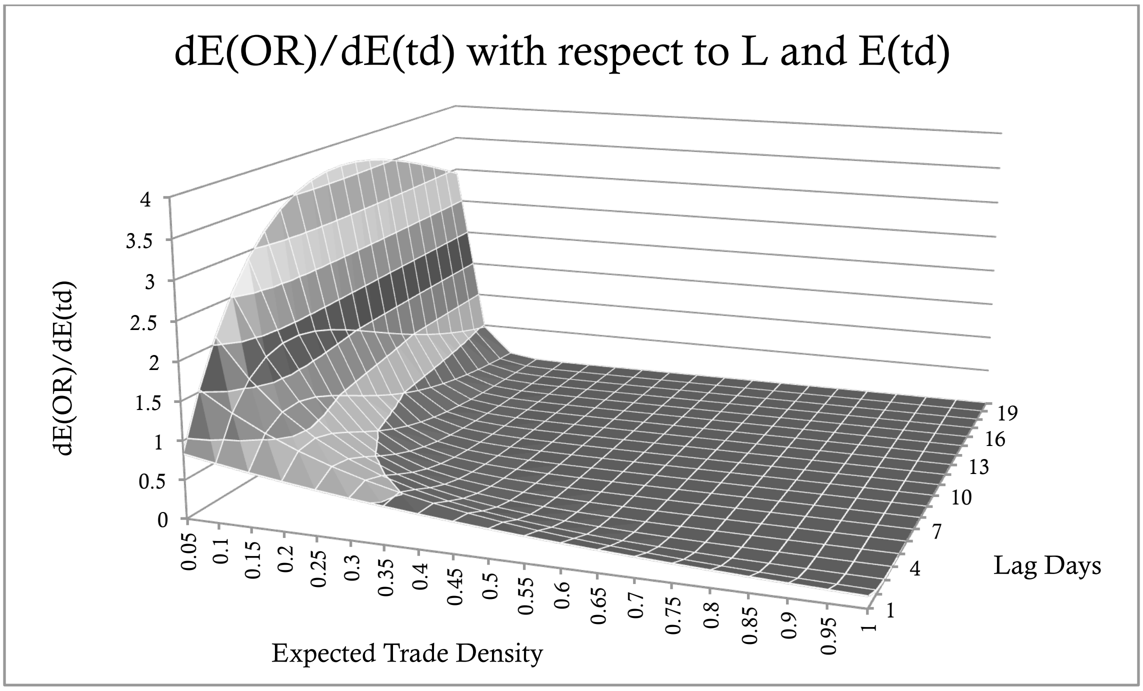


Figure 9: Application of the model for lag period optimisation. The model is specified as:

$$E(\pi_{i,L}) = E(OR_{i,L})\left(2C_i + E(PI_{i,buy}) + E(PI_{i,sell}) + \frac{P_{i,sell}(L) - P_{i,buy}(L)}{L}\right) + \left(1 - E(OR_{i,L})\right)\left(\rho_{i,sell}(L) - \rho_{i,buy}(L)\right)$$

The expected offset ratio is given by the following equation:

$$E(OR_{i,L}) = 0.5 \cdot \left(1 - \lim_{p\to\infty}\left(\frac{P-L}{P}\right)^{2\cdot E(td)\cdot P\cdot\left(\frac{f-1}{f}\right)}\right)$$

Input variables are based on observations in the mutual fund trade dataset to provide realistic estimates of emulation performance.

L	*5*	*10*	*20*	*50*	*100*
$\boldsymbol{E(td_i)}$	0.05	0.05	0.05	0.05	0.05
$\boldsymbol{f}$	8	8	8	8	8
$\mathbf{E(OR_{i,L})}$	17.72%	29.16%	41.31%	49.37%	49.99%
$\mathbf{C_i}$	0.15%	0.15%	0.15%	0.15%	0.15%
$\mathbf{E(PI_{i,buy})}$	0.10%	0.10%	0.10%	0.10%	0.10%
$\mathbf{E(PI_{i,sell})}$	0.02%	0.02%	0.02%	0.02%	0.02%
$\boldsymbol{\rho_{i,buy}(L)}$	0.30%	0.52%	0.93%	2.60%	6.62%
$\boldsymbol{\rho_{i,sell}(L)}$	0.06%	0.19%	0.58%	2.57%	7.53%
$\mathbf{\frac{P_{i,buy}(L)}{L}}$	0.15%	0.28%	0.50%	1.26%	2.94%
$\mathbf{\frac{P_{i,sell}(L)}{L}}$	0.03%	0.08%	0.23%	1.04%	3.04%
$\boldsymbol{E(\pi_{i,L})}$	**-0.14%**	**-0.17%**	**-0.14%**	**0.08%**	**0.72%**

Chapter 5: A Fourfold Pattern to the Art of Active Investing

Pages 117-162 of this thesis have been removed as they contain published material. Please refer to the following citation for details of the article contained in these pages.

Chen, Z., F. D. Foster, D. R. Gallagher, and R. Wermers, 2014, A fourfold pattern to the art of active investing, Working paper (UNSW Business School, UNSW Australia).

Chapter 6: Conclusions and Future Research Directions

In this dissertation, I present three articles related to the evaluation and analysis of emulation fund performance. The first paper analyses the outcomes of a simulated emulation fund, while the second paper generalises the analysis framework with a model representation of cost and savings drivers within an emulation framework. The third paper directly examines trading patterns and outcomes of mutual fund managers, which have a direct impact on the opportunity costs associated with the internal crossing and lagged trading mechanics of emulation funds. The combination of these approaches constructs a multifaceted understanding of emulation fund performance.

In Chapter 3, I presented the paper, "Does Portfolio Emulation Outperform Its Target Funds?", in which I simulate an emulation fund based on the daily Australian equity trades of a large pension fund manager. While I do find reduced transaction costs in the emulation fund relative to the target portfolio, I reveal hidden costs associated with the internal crossing and delayed execution of trade signals. These consist of foregoing crystallisation of profits from on-market trading and the loss of trade timing ability on short-lived information. In general, these opportunity costs outweigh the savings in brokerage commission and market impact from reduced on-market trading. Using lag periods of up to 20 days, I conduct both a cross-sectional examination of emulation funds based on stock portfolio with particular style characteristics, and longitudinal analysis with respect to changing market conditions. I find advantages to selectively emulating subsets of stocks – in general, emulation of trade signals on large and style neutral stocks result in better outcomes than on smaller stocks or those with heavy growth or value characteristics. Furthermore, emulation funds are more effective during periods of market distress; underperformance in my simulated emulation fund was greatest during the growth period prior to the Global Financial Crisis and the recovery period after. In this first paper, I find little evidence that the application of a straightforward emulation strategy will lead to improved performance before fees and taxes.

Being a case study, there are a number of constraints that limited the scope of the paper which constitutes Chapter 3. Firstly, the breadth of my experiment was limited by the representativeness of my sample. While I show that average returns in my sample of fund managers generally match those in the wider fund manager universe, the selection criteria used by the pension fund to hire these managers may have favoured particularly biases in the decision-making process of fund managers in my sample. Secondly, I deliberately omitted the treatment of taxes due to their idiosyncratic nature with respect to the setup of the multi-fund manager. However, tax savings could potentially have a large influence on the final outcome of the emulation fund. Furthermore, I also did not quantify management fee savings, again due to the idiosyncratic nature of these costs with different funds.

The article in Chapter 4, "A Model of Emulation Funds", addresses the shortcomings of the study in Chapter 3 by developing a generalised theoretical framework of performance drivers within emulation funds. This model takes, as its inputs, expectations of transaction costs, trade signal frequency and the lag structure, to forecast the expected outcomes of implementing an emulation fund. By taking expectations data rather than actual historical trades, we remove the restriction of being limited only to events for which we have observations. Examining the partial derivatives of this model, I am able to show how the lag periods affect the proportion of trade signals from underlying funds that can be internally offset, and in turn, calculate transaction cost savings and timing-related opportunity costs. I also derive minimum boundary conditions that must be satisfied in order for any emulation strategy to be successful, and finally, I compute the optimum lag structure. Having a model framework for describing the performance characteristics of an emulation fund confers a number of advantages over simulation alone. It formalises the interaction between the marginal transaction cost savings and the performance impact of altered trade timing, it enables the forecast of emulation fund outcomes based on expected trading patterns, and it allows the numerical optimisation of key emulation fund parameters.

One of the main weaknesses of the model derived is that it depends on my conjecture of how stock prices moved after a security was bought or sold. This was based on previous observations that prices tended to adjust to a new equilibrium level after trading occurred. Although we had some indication that bought stocks tended to outperform sold stocks in the short period after trading, what we needed was a much more comprehensive characterisation of the opportunity cost associated with the tracking error between the emulation fund and the aggregated underlying portfolio being emulated. Furthermore, as with the paper in Chapter 3, I did not address savings in management costs or taxes. Another aspect of emulation funds that is open to further research is in tracking error risk (i.e. the volatility in the difference of returns between the emulation fund and its tracking fund) and in the cash flow management side of operationally maintaining this centralised management strategy.

Chapter 5 focuses on the nature of the underlying trades which an emulation fund tracks. This is important for understanding why an opportunity cost arises through altering the timing of trades, and provides a foundation for the design of an emulation strategy that mitigates the timing-related opportunity cost. This paper, titled, "A Fourfold Pattern to the Art of Active Investing", examines the way in which mutual funds use their buying and selling decisions to meet their objectives to generate excess performance and to manage portfolio risk. I show that mutual funds generate excess returns on their purchases, in part by following analyst recommendations, and manage risk by preferentially purchasing in current underweight positions rather than overweight ones. However, my results suggest that when mutual funds do extend positions that are already overweight, they tend to be confident in the stock generating subsequent excess returns. Mutual funds enhance excess performance on the sell side by cutting underperforming stock in underweight positions – this has the effect of removing stock with low anticipated future performance (due to short-term alpha momentum), and confers a tax-loss benefit. On the other hand, mutual funds exhibit a strong tendency to trim overweight positions that have significantly appreciated in the prior quarter. This appears to be for the purpose of controlling the exposure of the portfolio to idiosyncratic risk, but it incurs a significant opportunity cost in the excess returns that sold outperformers continue to generate post-sale.

My results in Chapter 5 indicate that purchased stocks outperform sold stocks only over short post-trade durations. This explains why an emulation fund running a short lag incurs timing-related opportunity costs to its performance. However, over longer periods, stocks sold for the purpose of trimming risk (i.e. the sale of outperforming overweight positions) incur an opportunity cost that is greater than the alpha generated by informed purchasing activities. This results in a net negative trading difference that an emulation fund, with the right lag strategy, could potentially exploit.

The two main gaps in my coverage of emulation funds are the treatment of tax and the structuring of management fees. Emulation affects tax in two ways. Firstly, it results in the foregone crystallisation of profits and losses through on-market trading that would have occurred in the tracking portfolio. Secondly, because turnover is reduced, the effective holding period increases and this could have capital gains tax implications. The fees in running an emulation fund are also typically much lower than those in running directly managed funds. Since the multi-fund manager usually has a proportion of his/her funds directly invested with the underlying manager, the additional fee paid to reuse their trade signals is usually either much lower or non-existent. These fee savings could potentially have a significant impact too, on the net outcomes of running an emulation portfolio.

The aim of this dissertation is to provide empirical analyses and theoretical models around the topic of emulation funds that might be useful to both investment sponsors and multi-fund managers seeking to run an emulation fund, as well as to improve our academic understanding of these investment structures. The simulated emulation fund presented in Chapter 3 informs our expectations about the potential outcome from a typical multi-fund manager, while Chapter 4 expands and generalises our analysis through parametric modelling. In Chapter 5, I take a detailed view of the way mutual funds meet investment objectives through their trading patterns, in order to better understand the nature of the trades being emulated. The content in these chapters provides not only insight into the mechanics and potential outcomes of emulation funds, but also builds the foundation for designing an intelligent, effective emulation fund with real-world application potential.

References

A

Ainsworth, A., Gallagher, D. R. & Gardner, P. 2007. Performance Evaluation and the Potential Biases in Fund Manager Return Databases. *JASSA,* Winter, 21-27.

Aitken, M. J. & Frino, A. 1996. Execution Costs Associated with Institutional Trades on the Australian Stock Exchange. *Pacific-Basin Finance Journal,* 4, 45-58.

Aitken, M. J., Muthuswamy, J. & Wong, K. L. 2001. The Impact of Brokers' Recommendations: Australian Evidence. *Working Paper, SIRCA.*

Alexander, G. J., Cici, G. & Gibson, S. 2007. Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds. *Review of Financial Studies,* 20, 125-150.

Ang, A., Rhodes-Kropf, M. & Zhao, R. 2008. Do Funds-of-Funds Deserve Their Fees-on-Fees? *NBER Working Paper*, 1-32.

B

Barras, L., Scaillet, O. & Wermers, R. 2010. False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas. *Journal of Finance,* 65, 179-216.

Ben-David, I. & Hirshleifer, D. 2012. Are Investors Really Reluctant to Realize Their Losses? Trading Responses to Past Returns and the Disposition Effect. *Review of Financial Studies,* 25, 2485-2532.

Bennett, S., Gallagher, D. R., Harman, G., Warren, G. J. & Xi, L. 2013. Alpha Generation in Portfolio Management: Long-Run Australian Equity Fund Evidence. *Working Paper*, 1-44.

Berk, J. B. & Green, R. C. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy,* 112, 1269-1295.

Bernhardt, D. & Miao, J. 2004. Informed Trading When Information Becomes Stale. *Journal of Finance,* 59, 339-390.

Bollen, N. P. B. & Busse, J. A. 2004. Short-Term Persistence in Mutual Fund Performance. *Review of Financial Studies,* 18, 569-597.

Brands, S. & Gallagher, D. R. 2004. Risk and Return Properties of Fund-of-Funds. *JASSA,* Autumn, 33-40.

Brands, S. & Gallagher, D. R. 2005. Portfolio Selection, Diversification and Fund-of-Funds: A Note. *Accounting & Finance,* 45, 185-197.

Brown, N. C., Wei, K. D. & Wermers, R. 2007. Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices. *Working Paper*, 1-70.

Brown, P., Chappel, N., Da Silva Rosa, R. & Walter, T. 2006. The Reach of the Disposition Effect: Large Sample Evidence Across Investor Classes. *International Review of Finance,* 6, 43-78.

Brown, S., Goetzmann, W. & Liang, B. 2004. Fees-on-Fees in Funds-of-Funds. *Journal of Investment Management,* 24, 39-56.

Brown, S. J. & Goetzmann, W. N. 1995. Performance Persistence. *Journal of Finance,* 50, 679-698.

Busse, J. A., Goyal, A. & Wahal, S. 2010. Performance and Persistence in Institutional Investment Management. *Journal of Finance,* 65, 765-790.

C

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance,* 52, 57-82.

Chalmers, J. M. R., Edelen, R. M. & Kadlec, G. B. 2000. Transaction-Cost Expenditures and the Relative Performance of Mutual Funds. *SSRN Electronic Journal*, 1-42.

Chan, L. K. C. & Lakonishok, J. 1995. The Behavior of Stock Prices Around Institutional Trades. *Journal of Finance,* 50, 1147-1174.

Chen, C., Comerton-Forde, C., Gallagher, D. R. & Walter, T. S. 2010. Investment Manager Skill in Small-Cap Equities. *Australian Journal of Management,* 35, 23-49.

Chen, H.-L., Jegadeesh, N. & Wermers, R. 2000. The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers. *Journal of Financial and Quantitative Analysis,* 35, 343-368.

Chen, Z., Foster, F. D., Gallagher, D. R. & Lee, A. D. 2013. Does Portfolio Emulation Outperform Its Target Funds? *Australian Journal of Management,* 38, 401-427.

Chiyachantana, C. N., Jain, P. K., Jiang, C. & Wood, R. A. 2004. International Evidence on Institutional Trading Behavior and Price Impact. *Journal of Finance,* 59, 869-898.

Cici, G. 2012. The Prevalence of the Disposition Effect in Mutual Funds' Trades. *Journal of Financial and Quantitative Analysis,* 47, 795 - 820.

Cohen, R., Coval, J. & Pastor, L. 2005. Judging Fund Managers by the Company They Keep. *Journal of Finance,* 60, 1057-1096.

Comerton-Forde, C., Fernandez, C., Frino, A. & Oetomo, T. 2005. How Broker Ability Affects Institutional Trading Costs. *Accounting & Finance,* 45, 351-374.

Cremers, K. J. M. & Petajisto, A. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. *Review of Financial Studies,* 22, 3329-3365.

Cuthbertson, K., Nitzsche, D. & O'sullivan, N. 2008. UK Mutual Fund Performance: Skill or Luck? *Journal of Empirical Finance,* 15, 613-634.

D

Daniel, K., Grinblatt, M., Titman, S. & Wermers, R. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance,* 52, 1035-1058.

Dasgupta, A., Prat, A. & Verardo, M. 2011. Institutional Trade Persistence and Long-Term Equity Returns. *Journal of Finance,* 66, 635-653.

Dibartolomeo, D. 1999. A Radical Proposal for the Operation of Multi-Manager Investment Funds. *Northfield Information Services*, 1-15.

Domowitz, I., Glen, J. & Madhavan, A. 2001. Liquidity, Volatility and Equity Trading Costs Across Countries and Over Time. *International Finance,* 4, 221-255.

Duan, Y., Hu, G. & Mclean, D. 2009. When Is Stock Picking Likely to Be Successful? Evidence from Mutual Funds. *Financial Analysts Journal,* 65, 1-12.

E

Edelen, R. 1999. Investor Flows and the Assessed Performance of Open-End Mutual Funds. *Journal of Financial Economics,* 53, 439-466.

Elton, E. J. & Gruber, M. J. 2004. Optimum Centralized Portfolio Construction with Decentralized Portfolio Management. *Journal of Financial and Quantitative Analysis,* 39, 481-495.

Elton, E. J., Gruber, M. J. & Blake, C. R. 1996. The Persistence of Risk-Adjusted Mutual Fund Performance. *The Journal of Business,* 69, 133-157.

Elton, E. J., Gruber, M. J. & Blake, C. R. 2011. Holdings Data, Security Returns, and the Selection of Superior Mutual Funds. *Journal of Financial and Quantitative Analysis,* 46, 341-367.

F

Fama, E. F. & French, K. R. 2010. Luck versus Skill in the Cross-Section of Mutual Fund Returns. *Journal of Finance,* 65, 1915-1947.

Ferguson, R. 1978. Do Market Inventory Funds Really Make Sense? *Financial Analysts Journal*, May-June, 38-45.

Fong, K., Gallagher, D. R. & Lee, A. D. 2008. The State of Origin of Australian Equity: Does Active Fund Manager Location Matter? *Australian Journal of Management,* 32, 503-524.

Frazzini, A. 2006. The Disposition Effect and Underreaction to News. *Journal of Finance,* 61, 2017-2046.

G

Gallagher, D. R. & Gardner, P. 2005. Portfolio design and challenges inherent in multiple manager structures. *JASSA,* Summer, 20-25.

Gallagher, D. R. & Jarnecic, E. 2004. International Equity Funds, Performance and Investor Flows: Australian Evidence. *Journal of Multinational Financial Management,* 14, 81-95.

Gallagher, D. R. & Looi, A. 2003. An Examination of the Market Impact Costs of Active Australian Equity Managers. *Working Paper*, 1-35.

Goetzmann, W. N. & Ibbotson, R. G. 1994. Do Winners Repeat? Patterns in mutual fund return behaviour. *Journal of Portfolio Management,* Winter, 9-18.

Goldstein, M. A., Irvine, P. J., Kandel, E. & Wiener, Z. 2009. Brokerage Commissions and Institutional Trading Patterns. *Review of Financial Studies,* 22, 5175-5212.

Grinblatt, M. & Han, B. 2005. Prospect Theory, Mental Accounting, and Momentum. *Journal of Financial Economics,* 78, 311-339.

Grinblatt, M. & Keloharju, M. 2001. What Makes Investors Trade? *Journal of Finance,* 56, 589-616.

Gruber, M. J. 1996. Another Puzzle: The Growth in Actively Managed Mutual Funds. *Journal of Finance,* 51, 783-810.

Henderson 2012. Prospect Theory, Liquidation, and the Disposition Effect. *Management Science,* 58, 445-460.

H

Hirshleifer, D., Subrahmanyam, A. & Titman, S. 1994. Security Analysis and Trading Patterns When Some Investors Receive Information Before Others. *Journal of Finance,* 49, 1665-1698.

J

Jackson, A. R. 2005. Trade Generation, Reputation, and Sell-Side Analysts. *Journal of Finance,* 60, 673-717.

Jensen, M. C. 1968. The Performance Of Mutual Funds In The Period 1945-1964 *Journal of Finance,* 23, 389-416.

Jin, L. & Scherbina, A. 2011. Inheriting Losers. *The Review of Financial Studies,* 24, 786-820.

K

Kacperczyk, M. & Seru, A. 2007. Fund Manager Use of Public Information. *Journal of Finance,* 62, 485-528.

Kacperczyk, M. T., Sialm, C. & Zheng, L. 2005. On Industry Concentration of Actively Managed Equity Mutual Funds. *Journal of Finance,* 60, 1983-2011.

Keim, D. & Madhavan, A. 1996. The Upstairs Market for Large Block Transactions: Analysis and Measurement of Price Effects. *Review of Financial Studies,* 9, 1-36.

Kosowski, R., Timmermann, A., Wermers, R. & White, H. 2006. Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis. *Journal of Finance,* 61, 2551-2595.

Kothari, S. P. & Warner, J. B. 2001. Evaluating Mutual Fund Performance. *Journal of Finance,* 56, 1985-2010.

Kyle, A. S. & Obizhaeva, A. A. 2011. Market Microstructure Invariants. *Working Paper*, 1-67

L

Lakonishok, J. & Smidt, S. 1986. Volume for WInners and Losers: Taxation and Other Motives for Stock Trading. *Journal of Finance,* 41, 951-974.

Lhabitant, F. S. & Learned, M. 2002. Hedge Fund Diversification: How Much is Enough? *SSRN Electronic Journal*, 1-44.

M

Malkiel, B. G. 1995. Returns from Investing in Equity Mutual Funds 1971 to 1991. *Journal of Finance,* 50, 549-572.

Mamaysky, H., Spiegel, M. & Zhang, H. 2007. Improved Forecasting of Mutual Fund Alphas and Betas. *Review of Finance,* 11, 359-400.

N

Nadarajah, S. 2008. Explicit Expressions for Moments of Log Normal Order Statistics. *Economic Quality Control,* 23, 267-279.

O

Odean, T. 1998. Are Investors Reluctant to Realize Their Losses? *Journal of Finance,* 53, 1775-1798.

P

Parwada, J. T. 2003. Trends and Determinants of Australian Managed Fund Transaction Costs. *Accounting & Finance,* 43, 345-363.

Pinnuck, M. 2003. An Examination of the Performance of the Trades and Stock Holdings of Fund Managers. *Journal of Financial and Quantitative Analysis,* 38, 811-828.

Puckett, A. & Yan, X. S. 2011. The Interim Trading Skills of Institutional Investors. *Journal of Finance,* 66, 601-633.

R

Rogers, R. K. & Grant, J. 1997. Content Analysis of Information Cited in Reports of Sell-Side Financial Analysts. *Journal of Financial Statement Analysis,* 3, 17-31.

Rosenberg, B. 1977. Institutional Investment with Multiple Portfolio Managers. *Proceedings of the Seminar on the Analysis of Security Prices*, 55-160.

Roulstone, D. T. 2003. Analyst Following and Market Liquidity. *Contemporary Accounting Research,* 20, 551-578.

S

Sharpe, W. F. 1981. Decentralized Investment Management. *Journal of Finance,* 36, 217-234.

Shefrin, H. & Statman, M. 1985. The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *Journal of Finance,* 40, 777-790.

Sias, R. 2004. Institutional Herding. *Review of Financial Studies,* 17, 165-206.

W

Wagner, W. H. & Zipkin, C. A. 1978. Can Inventory Index Funds Improve Active Equity Performance? *Financial Analysts Journal,* 34, 34-76.

Walther, B. 1997. Investor Sophistication and Market Earnings Expectations. *Journal of Accounting Research,* 35, 157-179.

Wermers, R. 1999. Mutual Fund Herding and the Impact on Stock Prices. *Journal of Finance,* 55, 581-622.

Wermers, R. 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs, and Expenses. *Journal of Finance,* 55, 1655-1694.

Wermers, R., Yao, T. & Zhao, J. 2012. Forecasting Stock Returns Through an Efficient Aggregation of Mutual Fund Holdings. *Review of Financial Studies,* 25, 3490-3529.