The Role of Mutual Funds in the Real Economy

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Abstract

This thesis studies the roles of equity mutual funds in the real economy. I review the literature and identify two channels through which mutual funds can exert influences on the real economy: first as informed financiers in the new equity issues market and second as informed traders in the secondary market. I then focus on the first channel and present a simple model of mutual fund intermediation to show that when mutual funds have superior screening abilities relative to retail investors, the participation of mutual funds in new equity issues conveys information about the underlying productivity of the equity issuers and hence real economic output in the macroeconomy. Empirically I find that mutual fund participation in new equity issues predicts the sensitivity of output to new issues, at both the aggregate level and the industry level. In addition, smaller net fund flows are associated with a stronger sensitivity of output to fund participation, due to funds’ reduced information costs when they have less capital. At the firm level, I find that mutual fund participation positively predicts the productivity growth of the seasoned equity issuers, providing supporting evidence for the screening explanation. The results in this thesis offer a novel perspective by showing a relation between mutual fund screening and the real economy.
Declaration

This declaration is to certify that:

1. the thesis comprises only my original work towards the Doctor of Philosophy,

2. due acknowledgement has been made in the text to all other material used,

3. the thesis is fewer than the maximum word limit of 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.
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Chapter 1

Introduction

1.1 Background

This thesis studies the roles of equity mutual funds in the real economy. The mutual fund industry has grown immensely over the past few decades. In the United States, the industry has $134 billion total assets under management in 1980, and has since grown to $12 trillion assets under management as at the end of 2007. This amounts to approximately one-third of the total value of the United States stock market, making mutual funds the largest group of institutional investors. Figure 1 plots the growth in stock holdings by mutual funds and all institutional investors over time. Similar growth trends have also been observed in many other markets around the world (Khorana et al., 2005). Given the size of the industry, mutual funds have received much attention both in academic research as well as among practitioners.

The vast majority of academic studies on mutual funds focus on identifying funds’ ability to deliver excess returns above benchmarks, and the results remain inconclusive (Elton and Gruber, 2013). Identifying fund managers’ stock selection and market timing abilities and distinguishing between managers’ luck versus skill are important
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for the fund investors. However, they provide little understanding of the more general role of mutual funds in our society – namely, whether the existence and growth of the money management industry can bring real economic benefit to the society as a whole.

As pointed out by Sharpe (1991) and French (2008), the social benefit provided by mutual funds is not clear – since the average fund has to hold the market portfolio, the average fund investor would not beat the market. In addition, active funds incur substantial transaction costs from trading which further reduces the net returns to investors. However, simply focusing on the returns to investors does not fully justify the potential real impact of mutual funds. In order to answer this question, one needs to examine whether the pursuit of excess returns has implications for productivity growth and study the channels through which such activities can have an impact on the real activities of firms (Greenwood and Scharfstein, 2013).

1.2 Motivation and contribution

Despite its importance, the real effect of mutual funds has received little attention in the academic literature. In this thesis, I provide some evidence on the roles of mutual funds in the real economy as financial intermediaries. I review the existing literature on mutual funds and the real economy and identify two potential channels through which mutual funds could affect capital allocation efficiency and thereby firm productivity: firstly as financiers in the new equity issues market, and secondly as informed investors in the secondary equity market. I then focus closely on the informed financier channel and examine the mechanism through which mutual funds affect productivity and real economic output. I present a simple model of mutual fund intermediation where equity mutual funds have information advantages over house-
hold investors regarding the productivity of equity issuers, and examine the empirical implications of mutual fund intermediation on the real economy. I then test the model predictions using data from the United States, and provide empirical evidence for the model implications at the aggregate, industry and firm levels.

This thesis offers a new perspective on mutual funds and contributes to the literature by demonstrating the positive real effects of mutual funds, particularly at the macroeconomic level. As noted above, the extensive debate regarding fund managers’ secondary market stock-selection or market-timing skills provides little understanding of the funds’ role in the real economy, since any excess returns earned by funds in the secondary market represent only a transfer of wealth between different groups of investors. Recently, Brav et al. (2015) provide evidence on the real effect of hedge fund activism on productivity. I contribute by examining the screening function of mutual funds, and more importantly, provide evidence at the aggregate level in addition to the micro-level evidence.

The thesis also makes a contribution to the literature on financial intermediation and the real economy. The notion that mutual funds perform a screening function on equity issuers is largely consistent with the theories of financial intermediation. A body of theoretical literature argues that intermediaries help to reduce informational frictions, by screening, monitoring and certifying firm investments (Leland and Pyle, 1977; Diamond, 1984; Holmstrom and Tirole, 1997). These functions allow more productive investment projects to be funded, thereby enhancing economic growth (Greenwood and Jovanovic, 1990; Levine, 2005). However, the empirical literature testing these theories has largely focused on the banking sector, with little attention to intermediaries in equity markets.\footnote{See, among others, Chava and Purnanandam (2011), Ivashina and Scharfstein (2010), and Duchin et al. (2010).} The thesis complements this line of literature by
providing evidence of equity intermediaries’ role in the real economy, and motivates further research on these institutions regarding their intermediation activities.

In the following sections, I outline the chapters of this thesis, and provide an overview of each chapter. The thesis is organized into seven chapters. Chapter 2 reviews the literature on mutual funds and the real economy, outlining the potential roles of mutual funds in both the primary market and the secondary market. Chapter 3 develops a model of mutual fund intermediation in the new equity issues market, and provides the empirical hypotheses of funds’ information advantages. Chapter 4 provides the data description and describes the empirical specifications used to test the model implications. Chapter 5 documents the empirical results on mutual fund intermediation, at both the aggregate level and industry level in the United States. In Chapter 5, I also explore some alternative explanations and conduct further robustness checks in addition to the main tests. Chapter 6 documents the firm-level evidence on productivity growth, and confirms the previous findings on long-run stock returns. Chapter 7 concludes by discussing the limitations of the thesis and providing some suggestions for future research.

1.3 Outline of the thesis

Chapter 2: Literature review

In this chapter, I review the literature on the interactions between mutual funds and the real economy, and outline the potential channels in which mutual funds can exert influence on the real economy in terms of productivity and output growth.

Prior literature has suggested two main channels in which mutual funds could influence the real economy. First, the literature has established that as informed
financiers, mutual funds act as superior information producers relative to retail investors, and therefore can invest more in the equity-issuing firms with higher subsequent stock returns. Following these findings, I propose that given their superior information, mutual funds could enhance the efficiency of capital allocation in the real economy by financing the most productive firms and improving output and economic growth. This view of mutual funds is consistent with theories of financial intermediation, where intermediaries have advantages in alleviating information problems (Diamond, 1984; Holmstrom and Tirole, 1997).

However, empirical tests of the intermediation theories have mostly focused on the banking sector, with limited attention to non-banking intermediaries. I argue that given the scale of the asset management industry and the similarities between mutual funds and banks as information providers, it is worthwhile to examine the real effect of mutual fund investment in firms.

The second channel in which funds could have an effect on the real economy is through their investment and trading activities in the secondary market. A large effect that mutual funds can have on secondary market prices is through fund flows. Prior literature has established the relation between aggregate fund flows and stock returns (Warther, 1995) and between flows and real variables (Jank, 2012). Flow-induced trading can also have a significant price impact on individual stocks (Coval and Stafford, 2007), as well as on equilibrium returns and cross-sectional patterns (Basak and Pavlova, 2013; Vayanos and Woolley, 2013). However, in these papers, there is no active role of mutual funds in the economy, and fund flows merely serve as a signal of investors’ willingness to invest in the stock market.

Another strand of literature examines the effect of price efficiency on firms’ investment activities, and suggests that active investment by mutual funds in the secondary
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market may also have an indirect impact on the real economy. As active investors, fund managers are constantly seeking new information and acting on it, in order to beat their benchmarks. Through this process, new information is quickly impounded into stock prices, thereby improving price efficiency (Grossman and Stiglitz, 1980). Recent papers suggest that there may be important feedback effects from efficient prices to efficient real investment (Bond et al., 2012). To this extent, active investment by mutual funds may provide cleaner signals in stock prices, which further influences firms’ real decisions when there is managerial learning.

Chapter 3: A model of mutual fund intermediation

In this chapter, I present a simple model to study the real effects of mutual fund investment on productivity and output through their screening role as informed financiers in the new equity issues market. I show that due to their information advantages, mutual funds are able to identify and invest more in issuers with high productivity growth. More importantly, this screening effect translates into the macroeconomy, in that the extent of mutual fund participation in new equity issues predicts subsequent productivity and hence real output.

In the model, firms with different productivities raise equity to finance their investment projects and generate output. Mutual funds can acquire costly information about firm productivities, while individual investors cannot do so and can only invest randomly. With their information advantages, mutual funds finance more of the productive firms than individual investors do. The key result is that for a given amount of total equity issues in the economy, the fraction of issue proceeds invested by mutual funds (which I refer to as mutual fund participation) predicts the average productivity of the issuers and hence aggregate output. This is a novel prediction and provides
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a testable link between mutual funds’ screening skills in the primary market and the macroeconomy.

The model also predicts that fund flows create variability in the relation between fund participation and output. As individuals choose to allocate their wealth between mutual funds and direct investment in firms, more fund flows to mutual funds would entail better investment returns gross of costs, but individuals would also bear the funds’ higher information cost. The model shows that when individuals are pessimistic about investment opportunities, mutual funds receive less fund flows and become capital constrained. Given funds’ convex cost structure (following Berk and Green 2004; Pástor et al. 2015; Pástor and Stambaugh 2012), this leads to higher output net of information costs for funds’ investment. Thus, the model predicts that lower fund flows leads to an increasing sensitivity of output to fund participation.

Chapter 4: Data description

In this chapter, I provide a description of the data sources used in the empirical tests of the model. I use data from the United States, spanning from quarter 1, 1984 through quarter 4, 2011. There are five types of data used in the study – macroeconomic data, mutual fund flows data, equity issuance data, mutual fund investment data, and control variables. I separately describe the variable constructions for each type of data, at the aggregate, industry and firm levels. I also present the summary statistics for the dataset.

In addition, in this chapter I discuss the empirical specifications of the model and specify the testing equations.
Chapter 5: Empirical tests of mutual fund intermediation

In this chapter, I test the model predictions at both the aggregate and industry levels. Using data on mutual fund holdings, I construct proxies for mutual fund participation in new equity issues. I find that fund participation positively predicts the productivity of new issues, where productivity is measured as the sensitivity of subsequent aggregate output to current new issues. In periods of high fund participation (defined as above the sample median), new issues predict higher subsequent aggregate output than in periods of low fund participation (below the sample median). Economically, the difference in productivities between high and low fund participation periods is associated with an increase of 0.75 standard deviations of output. This result is also observed at the industry level, where industries with high mutual fund participation (above the cross-sectional median) exhibit higher sensitivity of output to new issues than industries with low fund participation (below the cross-sectional median).

I also find support for the model’s prediction on fund flows, participation and output. After controlling for the amount of new issues and fund participation, I find that the sensitivity of output to fund participation is negatively affected by net fund flows, suggesting that lower net fund flows would increase the sensitivity of output to participation. In addition, I find evidence in support of the convex cost structure, particularly in the industry level tests.

In the last section of the chapter, I conduct further analyses to address the potential reverse causality explanations. In particular, one may argue that mutual funds simply invest more when they receive more fund flows, and that more fund flows occur when anticipated productivity is high. This anticipation effect could induce a positive correlation between fund participation and future productivity, even in absence of funds’

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2I use two measures of aggregate output: GDP growth and the cyclical component of GDP. The results mostly affect the cyclical component of GDP. I describe the data in more detail in section (4).
screening skills. To address this concern, I separate mutual fund participation into two groups – participation by active funds versus participation by passive funds. If the positive relation between mutual fund participation and productivity is indeed driven by funds’ screening ability, one would expect the effect to predominantly come from active funds rather than passive funds. Indeed, the results show that almost of the effect is driven by active funds’ participation, and passive funds’ participation have no predictive power of future productivity. This analysis lends further support to the model’s hypotheses and suggests that the results are unlikely to be driven by reverse causality explanations.

Chapter 6: Firm-level evidence

In this chapter, I provide firm-level evidence of mutual funds’ screening ability. Due to data limitations, I focus on seasoned equity issuers only for the firm-level tests.

I find evidence consistent with mutual fund screening at the firm-level. Seasoned equity issuers that receive more mutual fund financing exhibit higher productivity growth\(^3\) compared to the issuers that receive less mutual fund financing, with mutual fund financing being measured by fund participation at the firm level. In addition, firms that receive more mutual fund financing also exhibit higher revenue growth and stock returns for five years post equity issue, consistent with previous findings in the literature. These results suggest that mutual funds are indeed able to identify productive equity issuers, and provide micro-level evidence for the aggregate effects of mutual fund investment.

\(^3\)Productivity growth is measured by firm-level total factor productivity (TFP), following King and Levine (1993a) and Olley and Pakes (1996).
Chapter 7: Concluding remarks

This chapter concludes the thesis with a summary of the findings and contributions. I also discuss some limitations of this study and recommendations for potential future research.
In this chapter, I review the literature on mutual funds and the real economy, and investigate the channels in which mutual funds can exert influence on the real economy in terms of productivity and output growth.

I provide an overview of mutual funds’ real economic roles in their capacity as institutional investors and financial intermediaries, in order to explore the potential mechanisms in which mutual funds can influence firms’ real investment decisions. Based on prior literature, I identify two channels in which mutual funds can influence the real economy: primary market participation as financiers and secondary market participation as informed investors and traders. Prior studies in both areas of research suggest that mutual funds could have an impact on the real economy through their activities as informed agents.

2.1 Mutual funds as informed financiers

The main activity of mutual funds is to pool savings and make investments on behalf of investors, either in the primary market or secondary market. This makes mutual funds
an important type of financial intermediary. In the primary market where firms issue new equities for external financing, mutual funds are largely regarded as informed financiers. Hence, their participation in the primary market has potentially important consequences in the real economy, as they allocate capital to finance real investments.

In this section, I first review the studies regarding mutual funds’ investment performance in the primary market, and then link them with the theoretical framework of financial intermediation.

2.1.1 Mutual fund returns in the primary equity market

If mutual funds are indeed informed institutions, one should expect them to have superior information to screen the profitable equity issues, or to exert monitoring efforts. Either function would entail better performance for the mutual funds’ primary market investments, in the forms of stock returns or better operating performance by the firm.

Mutual funds as screeners

In contrast to the mixed results in the ability for mutual funds to generate alphas on their total asset under management (see, for example, Elton and Gruber (2013); Fama and French (2010)), there is strong evidence for mutual funds and other financial institutions to outperform on their investment in the primary equity market. Several papers have shown, using different datasets, that institutions (including mutual funds) are able to identify above-average seasoned equity offering (SEO) firms with superior long-run returns. Gibson et al. (2004) find that seasoned equity issuers with the greatest institutional ownership increase around the offer date experience greater outperformance relative to their benchmarks, in the year following the issuance. Using transaction-level data, Chemmanur et al. (2009) find that institutions are able to identify and profit
from seasoned equity offerings with better long-run stock returns. Demiralp et al. (2011) confirm the above results, and also find that operating performance improvements are related to institutional ownership changes during the three years after the SEO. Regarding initial public offerings (IPOs), Chemmanur et al. (2010) find that institutions are able to obtain advantageous pricing on the IPOs and trade on the information post-IPO to profit, suggesting that they possess significant private information about the IPO firms.

Taken together, the evidence suggests that institutions including mutual funds have superior information to identify profitable and productive equity issues in the primary market. This ability for mutual funds to allocate capital to the most productive firms may have positive effects on the real economy.

**Mutual funds as institutional monitors**

In addition to their screening ability, mutual funds could also potentially influence managerial actions through their role as active monitors. Theoretical models predict that as block shareholders, institutional investors are likely to have an advantage in exerting monitoring efforts and reduce agency costs, since concentrated ownership helps to alleviate the public good problem in acquiring information and monitoring (Grossman and Hart, 1980; Shleifer and Vishny, 1986). The monitoring role could have positive impact on the real economy, as it improves operational efficiency and productivity.

Unlike the evidence on institutions screening ability, the empirical evidence on institutional investors’ ability to monitor is more mixed. Several papers have examined the effect of institutional monitoring roles on stock returns and operating performance around shareholder activism events. Gillan and Starks (2000) find that public pen-
sion fund activism announcements have a small but positive short-term effect on stock returns, whereas activism actions undertaken by individual investors receive little support from the market, suggesting that the stock market perceives institutions as having monitoring advantages. Further, activism events initiated by institutions receive more votes. However, Smith (1996) and Del-Guercio and Hawkins (1999), among others, find little evidence of long-term improvement in stock returns or operating performance from activism. In contrast, Cornett et al. (2007) find that firms’ operating cash-flow returns are positively related to both the percentage of institutional ownership as well as the number of institutional owners. Overall, the effect of institutional activism on stock returns and operating performance remains inconclusive.

In a different context, Chen et al. (2007b) examine firms’ acquisition decisions for signals of shareholder monitoring. They find that only concentrated holdings by independent institutions with long-term investments facilitate better post-merger performance. Firms with these types of institutional investors are more likely to withdraw bad bids, suggesting that heterogeneity among institutional investors is important. Brav et al. (2008) specifically study activism activities by hedge funds, and find an average abnormal return of 7% around the announcement of these activities. The authors attribute the stark contrast of results between hedge funds and other types of institutions to the differences in the governance and incentive structure of hedge funds.

More recently, Brav et al. (2015) examine the real effects of hedge fund activism using plant-level data. They find significant increases in the total factor productivity of target plants within two years after the activism event. In addition, the systematic risks of target firms decrease within three years post-activism event. These results complement the previous results on returns to hedge fund activism, and suggest that in addition to generating stock returns, institutional activism could have real effects in
the economy. This is one of the first papers to examine the real effects of institutional activism, and evidence on other types of institutions is still lacking.

Overall, the evidence supports mutual funds’ superior screening ability, and remains inconclusive regarding their monitoring effects as financiers. The notion that mutual funds act as informed agents in the real economy to screen and monitor firm investments are perfectly consistent with the theory of financial intermediation. Although largely overlooked in the literature, there are many similarities between mutual funds and other types of intermediaries within the theoretical framework of intermediation, and these linkages provide some interesting implications.

2.1.2 Mutual fund as financial intermediaries

Financial intermediation theory

In a frictionless economy with no information problems and no transaction costs, there would be little room for financial intermediaries. Thus financial intermediation theory has primarily focused on the roles and services they perform when frictions are prevalent.

As stated by Bhattacharya and Thakor (1993), some of the most important services provided by financial intermediaries is to monitor, screen, and certify investments, in order to overcome information problems created by differently informed agents. Leland and Pyle (1977) argue that by having firms that specialize in information acquisition and allowing the firms to capture a return on the information (by holding the valuable assets), one can mitigate the public good problem of information acquisition. Such an institutional arrangement would give rise to a financial intermediary. Diamond (1984) formalizes this argument and show that a financial intermediary has advantages in monitoring costs that stem from its delegated monitor role. As a re-
sult, financial intermediation enables the funding of some positive net present value projects which would otherwise be unfunded due to moral hazard problems. Since the model uses a costly-state-verification framework, it gives rise to a bank-like intermediary that uses debt contracts, both between depositors and the intermediary and between the intermediary and the entrepreneurs. Nevertheless, the general intuition that concentrated ownership reduces monitoring costs carries over to other types of intermediaries, including mutual funds and other investment vehicles.

Holmstrom and Tirole (1997) examine the role of financial intermediaries in the real economy. In their model, intermediaries perform a monitoring role to reduce moral hazard problems similar to Diamond (1984). Due to intermediaries’ superior monitoring technology, there is reduction in information costs in the economy such that some valuable projects are able to be funded with the presence of intermediaries. The key difference between Diamond (1984) and Holmstrom and Tirole (1997) is that in the former, investment projects are uncorrelated, thus the intermediary is able to perfectly diversify across projects. On the other hand, Holmstrom and Tirole (1997) assume that projects are perfectly correlated, which means that it is possible for intermediaries to default, hence the need to commit capital to avoid ex-post moral hazard problems. This difference highlights the importance of intermediary capital. In order to maintain monitoring incentives, the intermediaries need to have sufficient stake in the firms. Capital shocks to intermediaries will reduce monitoring incentives, thereby reducing the amount of projects funded (known as a “credit crunch”), and this creates a flight-to-quality effect where intermediary capital is rationed to higher quality firms. As a result, capital shocks to intermediaries could result in sub-optimal real investment and have an adverse impact on the real economy.

Empirical tests of intermediation theories have mostly focused on the banking sec-
tor. Chava and Purnanandam (2011) use the Russian crisis in 1998 as an exogenous shock to the U.S. banking sector, and find that bank-dependent firms experience larger valuation losses and reductions in real investment. Lemmon and Roberts (2010) examine regulatory changes in the banking sector that adversely affect below-investment-grade firms’ borrowing ability, and find that reductions in firms’ bank borrowing lead to an almost one-to-one reduction in net investment. Ivashina and Scharfstein (2010) and Duchin et al. (2010) provide evidence of reduced bank lending and real investment after the financial crisis in 2008, suggesting that capital supply constraints have real effects. These evidence is largely supportive of Holmstrom and Tirole (1997).

In addition to the banking sector, Bhattacharya and Thakor (1993) suggest that ratings agencies also act as intermediaries in providing screening and certification services. In this spirit, Faulkender and Petersen (2006) find that firms that have bond ratings have significantly higher leverage. Similarly, Sufi (2009) finds that the introduction of syndicate loan ratings leads to an increase in firms’ subsequent asset growth, cash acquisitions, and investment. These results suggest that ratings agencies provide valuable certification in the bond market to reduce information problems.

Despite the strong support for the importance of the credit market to real investments and economic growth, the literature has provided little evidence on the roles of non-banking intermediaries in equity markets. As noted above, equity intermediaries such as mutual funds are similar to banks in their capacity in reducing information costs, therefore one would expect their activities in the primary market to result in efficient capital allocation, hence promoting investment efficiency and productivity. Moreover, if intermediation helps to reduce information problems, one should expect them to be most useful in equity markets, where information problems are arguably more severe than debt markets.¹

¹See, for example, Myers and Majluf (1984).
Intermediaries in the macroeconomy

Numerous papers have also examined the role of financial intermediaries in the macroeconomy. Seminal papers by Bernanke and Gertler (1989), Bernanke et al. (1999) and Kiyotaki and Moore (1997) show that in the presence of agency frictions, shocks to borrowers’ balance sheet could amplify and prolong productivity shocks through the collateral channel. Reductions in the asset value of borrowers reduce the value of collaterals, and amplify the information asymmetry problem, thereby generating cyclical behavior in investment and output. More recently, Brunnermeier and Sannikov (2014) explore the dynamics of the system away from the steady-state, and analyze the effect of shocks during crisis states. In their model, the economy’s reaction to extreme shocks is highly nonlinear, and the amplification effect of negative shocks is much greater in crisis states than in normal states. Intermediaries also play a role in amplifying these shocks, since they are also exposed to macro shocks due to their monitoring relationship with the borrowers. Chen (2001) and Meh and Moran (2010) apply the set up of Holmstrom and Tirole (1997) to dynamic settings to show that the intermediary capital channel also amplifies and propagates the real effects of technology shocks, and that intermediary capital shocks create quantitatively sizable declines in real investment and output. Kurlat (2013) analyzes a macroeconomic model with asymmetric information about asset quality, and show that the friction distorts real investment, and amplifies productivity shocks. In addition, the model is able to generate the procyclical behavior of external financing, as observed in Erel et al. (2012) and Covas and Den Haan (2011).

In addition to the effect on business cycles, financial intermediaries are also important in affecting the long-run growth. Schumpeterian models of finance and growth argue that financial intermediaries and markets help to reduce monitoring costs (King
and Levine, 1993b), or produce information that improves the allocation of resources (Greenwood and Jovanovic, 1990). Levine (2005) defines five functions through which financial systems may exert influences to savings and investment decisions in the economy, hence influencing long-run growth. These are: 1) producing information about possible investments and allocate capital; 2) monitor investments and exert corporate governance; 3) facilitate trading, diversification and management of risk; 4) mobilize and pool savings; and 5) ease the exchange of goods and services. Well-functioning financial intermediaries that perform the screening and monitoring roles would help with the first two functions, and intermediaries in equity markets would also greatly improve the third function.

Empirically, studies have found strong support for the causal relation between financial development and economic growth. King and Levine (1993a) show that bank development helps to explain cross-country economic growth. Beck et al. (2000) find that financial development exerts a large and positive impact on total factor productivity growth, which in turn leads to GDP growth. They identify productivity as the main channel for financial development to drive economic development, rather than through physical accumulation or saving rates. Beck and Levine (2004) find that stock market development – as measured by the turnover ratio, a measure of liquidity – also explains economic growth, after controlling for bank development. Rousseau and Wachtel (2000) use a panel vector-autoregression to show that both stock market depth and liquidity promotes economic growth.

While the stock market itself is important in determining economic growth, it is also worthwhile to study the roles of equity intermediaries in the stock market. As argued by Levine (2005), in order for financial development to influence growth, insti-
tutions need to influence resource allocation decisions that foster productivity growth, rather than simply promoting physical capital accumulation. If one expects equity markets to have positive roles on resource allocation, then intermediaries in equity markets seem to be natural candidates for such roles.

2.2 Mutual funds in the secondary market

In addition to their activities in the primary market as financiers, mutual funds also play a big role in the secondary market as traders and investors. There has been a long-standing literature regarding mutual fund performance and their ability to outperform their benchmarks, either through stock-selection or market-timing, which I do not review here (see Elton and Gruber (2013) for an extensive survey). Instead, I focus on the implications of mutual funds’ return-chasing activities on the secondary market, and whether these activities have further implications in the real economy in the way they affect firms’ financing and investment decisions. Note that unlike the primary equity market, activities in the secondary market do not directly lead to additional financing or investment for firms. Therefore, any effect mutual funds can have on firms must be through the information role of market prices.

2.2.1 Mutual funds and stock returns

As a major group of investors, mutual funds’ activities have significant impact on stock returns. Fund flows in and out of mutual funds can influence fund managers’ investment decisions and lead to price pressure effects. Furthermore, due to institutional constraints and benchmarking concerns, mutual fund investment also has implications on equilibrium returns. I review each of these aspects below.
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Mutual fund flows and stock returns

There are several competing theories for the relation between aggregate fund flows and stock returns. The feedback-trader hypothesis suggests that market returns cause flows, and investors respond to rising prices by investing more in mutual funds. The price-pressure hypothesis argues that causality could run the opposite way, and that uninformed fund flows could temporarily lead to price-pressure on the market, driving stock prices away from fundamentals. In this sense, it is the fund flows that cause share price movements. An alternative explanation is the information-response hypothesis, which argues that both the market return and fund flows react to fundamental news, causing the co-movement.

Using quarterly data, Warther (1995) finds that stock market returns and aggregate fund flows are contemporaneously correlated, but returns are unrelated to subsequent fund flows. This result is against the feedback-trader hypothesis, but does not differentiate between the information-response hypothesis and the price-pressure hypothesis. Using daily flow information, Goetzmann and Massa (2003) find that investors systematically withdraw funds after market drops, but do not buy after previous day’s rise. They also find that short-horizon returns related to flows do not reverse themselves. Unlike Warther’s low-frequency results, these results from higher frequency data lend support to the price-pressure hypothesis.

Jank (2012) tests for the information hypothesis, and find that stock market returns and mutual fund flows simultaneously react to macroeconomic news. He finds that fund flows co-move with predictor variables of real economic activities, such as the default spread or the consumption-wealth ratio ($c_{ay}$). The correlation between fund flows and market returns is largely explained by these predictive variables. Furthermore, fund flows predict future economic activities, as measured by real GDP.
growth, industrial production, consumption and labor income. These results suggest that investors respond to future prospects in the real economy through fund flows.

At a more micro-level, studies have shown that mutual fund trades may have price impacts at the individual stock level. Coval and Stafford (2007) find that mutual funds that experience large outflows tend to fire-sell existing positions, which creates long-lasting price pressure (as long as 18 quarters before full reversal) in securities that are also held by other distressed funds. An opposite pattern holds for funds that experience large inflows, and the upward price pressure can also be long-lasting. Hau and Lai (2013) find that firms whose stocks that are fire-sold by distressed mutual funds exhibit considerably lower investment and employment than industry peers that are not subject to fire sales. Lou and Wang (2013) find that in addition to the effect on investment, fire-sale driven mispricing also affects new equity issues. Firms that are temporarily overpriced issue more equity, but do not change their investment behavior significantly. On the other hand, firms that are fire-sold by mutual funds issue less equity and also invest less.

These papers on fund flows, stock returns and related real effects do not provide any mechanism for the real economic roles of mutual funds. In these papers, mutual funds are simply a medium for retail investors to invest in (or withdraw money from) the stock market. However, as mentioned in the previous section, an alternative interpretation that follows from intermediation theory is that funds can actively influence real activities or returns, over and above the retail investors’ actions. This is an area worth investigating.
Asset pricing with financial intermediaries

More recently, another strand of literature studies the effect of institutional investors’ trading activities on equilibrium stock returns, from an asset pricing perspective. Standard theories of asset pricing often stipulate that prices are determined by households (or the “representative” consumer). However, in reality a large part of trading is attributed to institutional investors such as mutual funds. Therefore, the different incentive structures of institutions versus households may have implications on the prices of assets they hold.

Brennan (1993) shows that in a static mean-variance framework where constant absolute risk aversion (CARA) agents care about their performance relative to a benchmark index, the equilibrium expected returns are given by a two-factor model, where the factors are market returns and the benchmark index returns. Basak and Pavlova (2013) study a dynamic equilibrium model with both institutions and log-utility households, and show that institutions optimally tilt their portfolios towards the benchmark index stocks, lowering equilibrium returns for the these stocks, and makes the these stocks more correlated with other stocks in the same index. Since institutions in the model have higher demand for risky assets, they also exacerbate leverage as well as return volatility in the economy. Cuoco and Kaniel (2011) examine a similar problem with constant relative risk aversion (CRRA) agents, and find similar results numerically in a two-stock economy. Vayanos and Woolley (2013) show that flow-driven trades could enhance shocks to stock prices and lead to short-term price momentum and long-run price reversal. Dasgupta et al. (2011) show that career-concerned fund managers are likely to imitate past trades, which leads to herding behavior that pushes up prices in the short-run and later reverses.

Another strand of literature considers the constraints faced by financial interme-
diaries and institutions. He and Krishnamurthy (2012, 2013) develop a framework where the marginal investor is a financial intermediary facing leverage constraints. The constraint is motivated by the presence of moral hazard problems between the intermediary and its investors, similar to Holmstrom and Tirole (1997). When intermediary capital falls, the leverage constraint binds, and risk premium spikes up to reflect the capital scarcity. The model is able to generate non-linear risk premia during financial crises. Empirical studies of Adrian et al. (2010) and Adrian et al. (2014) lend support to the model, by showing that intermediary balance sheet aggregates and leverage can explain the cross-section of a broad set of asset portfolio returns. Brunnermeier and Pedersen (2009) show that margin constraints can also amplify fundamental shocks and drive up risk premia.

However, the constraints in these models apply to the entire financial sector (as a representative intermediary), and do not differentiate between the heterogenous leverage taken by different types of intermediaries. In this sense, the models may not apply to institutions that do not take on much leverage or margins (for example mutual funds).

2.2.2 Implications for the real economy

As seen in the above section, secondary market activities by mutual funds have important effect on asset prices. Apart from equilibrium return effects, one additional implication of mutual fund trading is that information is quickly impounded into stock prices, thereby improving price efficiency. As Fama (1970) states, security prices that fully reflect all available information can provide accurate signals that can be used for resource allocation. Therefore, if mutual fund trading in the secondary market enhances price efficiency, this may create positive externalities in the real economy.
In this spirit, Piacentino (2013) presents a market microstructure model where career-concerned delegated portfolio managers induce more efficient capital allocation than pure profit-maximizing individual investors, by embedding information more efficiently into prices. This is consistent with the insight from Grossman and Stiglitz (1980), in that informed agents can help to improve the informativeness of the price system through trading (and receiving compensation for the information). Boehmer and Kelley (2009) find support for this hypothesis by showing that stocks with higher institutional trading activities are priced more efficiently, where efficiency is measured a deviations from a random walk.

The channel through which secondary financial markets can affect real economic activities has recently received more attention. Bond et al. (2012) provide an extensive survey of this literature. As opposed to the traditional view that prices merely reflect expectations about future cash flows but do not affect them, this strand of literature shows that there can be important feedback effects from security prices back to firms, influencing their real decisions. As prices aggregate diverse pieces of information, real decision makers (such as managers, capital providers and customers) can learn from this information to guide their decisions.

Several theoretical papers have modeled various aspects of this idea. Edmans et al. (2011) explore the idea that the value of a firm is endogenous to the exploitation of arbitrage. In their model, prices reveal information to managers, who in turn use the information to make real decisions. With this setup, speculators are reluctant to trade on negative information, since managerial learning from secondary market prices will lead them to cancel bad investment projects, reducing the speculators’ profits from short-selling the stock in the first place. This feedback effect causes asymmetry between trading on positive and negative information, and presents a natural limits to
Chapter 2. Literature Review

arbitrage. Dow et al. (2011) show that in a feedback economy, incentives to produce costly information lead to strategic complementarities, where investment projects would not be undertaken if traders do not produce information about investment opportunities. Subrahmanyam and Titman (2013) study how stock price movements caused by uninformed participation shocks can influence real investment of private firms and thus real economic activities. The model is able to generate positive correlations between stock returns and real economic activities, and between stock returns and investment, as well as low or negative correlation between stock returns and dividends, all of which are observed in the data.

Empirical studies on the feedback effects of financial markets have found support for the theoretical models. Luo (2005) find that acquisitions are more likely to be canceled if the market reaction implies it to be non-synergistic. Edmans et al. (2012) find a strong effect of market prices on takeover activity, and find that lower valuations lead to substantial increase in the likelihood of being acquired. Chen et al. (2007a) find that measures of private information in stock prices have strong and positive effects on the sensitivity of corporate investment to stock price. This suggests that managers learn from the private information in stock prices, and use this information in their real investment decisions. If mutual funds help to incorporate value-relevant information into prices, then their actions could potentially have important consequences on real activities through this channel.

2.3 Summary

Although there exists an extensive body of literature on mutual funds, little attention has been paid to the real effects of these financial intermediaries. The literature review above has identified two channels in which mutual funds could play important roles in
affecting the real economy. Through the primary market, mutual funds act as informed financiers and can help channel capital through to the most productive firms with their superior screening ability. Further, with effective ex-post monitoring, mutual funds may also improve productivity and reduce moral hazard costs. Consistent with intermediation theory, these activities in the primary market should yield more efficient real investments, hence enhancing output and economic growth. In the remainder of this study, I investigate this channel in more depth, providing both theoretical arguments and empirical evidence.

In addition to the primary market channel, mutual funds’ activities in the secondary market may help to improve price efficiency by impounding value-relevant information into prices. The recent literature on the feedback effect shows that market prices provide important signals for managers to aid their real investment decisions. Incorporating institutional investors into this framework is a promising research area to investigate, and I leave this as a future research agenda beyond the scope of this study.
Chapter 3

A model of mutual fund intermediation

In this section, I present a model of mutual fund intermediation. The model describes an economy in which mutual funds act as informed financiers by allocating equity capital efficiently to productive firms, and generates some testable empirical predictions. I first present the model set-up and the related assumptions, and then solve the model and discuss the empirical implications.

3.1 Model set-up

In this section I provide an overview of the model set-up. The model economy has one period, and consists of two production sectors, a representative mutual fund, and a representative household. Each sector is described in detail below.
3.1.1 Production technology

There are two production sectors of equal mass, denoted as sector $H$ and sector $L$. There is a continuum of identical firms in each sector. Firms in both sectors raise equity capital to fund their investment projects to produce the same final good,\(^1\) and the investment projects pay off at the end of the period. Firms in the two sectors differ in their productivities. Specifically, firms in the $L$ sector have productivity $A_L$, while firms in the $H$ sector have productivity $A_L + \theta$, with $\theta > 0$. In this model, $\theta$ is one of the key parameters. It controls the difference in productivities between the two sectors, as well as the average productivity in the economy (the average productivity is given by $A_L + \theta / 2$).

Firms in both sectors have constant-returns-to-scale production technologies that take capital (which I denote as $I$) as the only input:

\[
Y_L = A_L I, \quad Y_H = (A_L + \theta)I \tag{3.1}
\]

Since firms in the two sectors raise new equity to make investments, I refer to the market for newly issued equity in these firms as the “primary market”.\(^2\) In addition to the primary market, there is also a secondary market that trades shares in existing investment projects in the economy. One could think of the secondary market as a stock market index. These existing projects will deliver some fixed level of output at the end of the period, regardless of who is owning the shares. I assume that at the

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\(^1\)In this model, the decision for firms to issue equity is taken to be exogenous, and I assume that issuing equity is optimal for the firms. This is a simplifying assumption. In reality, firms can and do issue other securities to finance their investment projects. One may think of this model as a case where firms have used up their debt capacity, and can only issue equity as a form of external financing.

\(^2\)In the model, I assume that all the new equity raised will be invested in new projects. In reality, there are many equity issues involving senior management or board members selling their shares to outsiders for liquidity reasons. These equity issues do not represent an increase in capital to the firm and therefore should not be related to output. The inclusion of these issues in the empirical tests is not a concern, because one should expect these uninformative issues to weaken the results.
beginning of the period, the shares in the secondary market are held by liquidity traders and are available for trading. I denote the amount of capital stock in the secondary market as \( S \), and assume that these existing capital stock produces output that is equal to the average of the two primary sectors, i.e. the secondary market returns \( R_m \) where \( R_m = A_L + \frac{\theta}{2} \), and thus the existing projects will produce \( R_mS \) of output at period end. Further, I assume that the average investment project is profitable, i.e. \( A_L + \frac{\theta}{2} > 1 \), therefore all investors are willing to invest either directly in the primary market or in the secondary market in the absence of a mutual fund.

### 3.1.2 Mutual fund sector

There is one representative mutual fund in the economy that can invest on behalf of the representative household. The mutual fund is run by a risk-neutral fund manager. The fund starts with no capital and cannot issue debt, thus it can only invest up to the amount of fund inflows it receives at the beginning of the period, which I denote as \( F \). The assumption that the mutual fund start with no capital and can only invest its fund inflows is made for simplicity. In reality, the fund manager may be able to liquidate some of the existing holdings in order to invest in profitable new issues, but this ability is limited by the liquidation costs (such as bid-ask spreads and commissions) and the tax paid on realizing capital gains. These costs could potentially be substantial and could outweigh any profits the manager is able to make in the primary market. In this case, the fund manager would strictly prefer investing with the new fund inflows to investing by selling existing shares.

I assume that the mutual fund has access to a technology that can identify the more productive sector \( H \), and therefore allows them to only invest in that sector and avoid sector \( L \). The technology also allows the mutual fund to observe the value of \( \theta \). To
obtain the information, the mutual fund has to incur a cost, and I assume that the cost is convex in the amount of investment. Specifically, for an investment of $f$ into the $H$ sector, the mutual fund incurs $\frac{1}{2} \phi f^2$ of information cost, where $\phi$ is a cost parameter. Ultimately this cost is borne by the household investor. Note that in this model setup, since the mutual fund starts with no assets, the variable $f$ is equivalent to the amount of active funds under management. Hence the information cost is assumed to be convex in the amount of active funds under management, since the mutual fund is only expected to incur the information cost when it invests in the primary market.

The convex information cost structure is one of the key assumptions of the model, as it gives the fund investor decreasing returns to scale in their mutual fund investment. The assumption of diseconomies of scale in asset management firms is commonly adopted in the literature to rationalize the low excess returns of mutual funds, even when fund managers possess superior skills (see, for example, Perold and Salomon Jr, 1991; Berk and Green, 2004). More recently, Pástor and Stambaugh (2012) extend the idea of diseconomies of scale to the industry level, and argue that as the asset management industry grows in size, competition among fund managers and investors would erode the profits from active management and could produce diminishing returns to investors.

A number of papers have examined empirically the relation between fund sizes and returns. Chen et al. (2004) document a negative relation between fund returns and lagged fund size, consistent with decreasing returns to scale. Moreover, they find that this relation is only significantly negative among the small-cap funds, providing a liquidity-based explanation. Yan (2008) uses a more direct measure of liquidity, namely the bid-ask spread, and finds further support for the liquidity-based explanation. The evidence of decreasing returns to scale at the fund level is not universal
across all fund types. In particular, the effect is the strongest among the small-cap funds (Chen et al., 2004), funds that hold the less liquid stocks (Yan, 2008), and funds that receive the largest fund inflows (Bris et al., 2007). Further, Ferreira et al. (2012) show that the negative relation between individual fund sizes and returns is mostly a phenomenon among the U.S. funds, with some funds in other countries even exhibiting increasing returns to scale. In contrast to the mixed evidence at the fund-level, Pástor et al. (2015) provide empirical evidence for the industry level decreasing returns to scale in the mutual fund industry. Using a fixed-effect estimator that accounts for the potential endogenous relation between fund size and returns, they find that at the fund level, there is some, albeit weak, evidence of decreasing returns to scale. On the other hand, at the industry level, they find consistent and strong evidence of decreasing returns to scale.

Taken together, the evidence on decreasing returns to scale in mutual funds is supportive of a convex information cost structure in my model. In the current set-up, there is a representative mutual fund, hence one can either interpret the convex information cost as a cost faced by an individual fund within the entire industry, or alternatively as the information cost faced by the entire fund industry (since the industry consists of a continuum of identical funds). Therefore, given the empirical evidence on decreasing returns to scale at the industry level, it is reasonable to assume a convex cost function faced by the mutual fund.

It is also worth noting here that when the mutual fund invests in the primary market, I assume that it will always incur the information cost and invest in the more productive $H$ sector. It is not a choice for the mutual fund to not incur the information cost and simply randomize between the two sectors, or to invest in both sectors. This assumption can be justified from the following argument: mutual funds are able to
employ skilled analysts to evaluate firms to make an informed investment decision. However, it would not be appropriate for mutual funds to employ unskilled analysts to simply make uninformed investments by randomizing between firms and not incur a cost for doing so, since mutual funds are in the business of professional money management. On the other hand, it would be reasonable for an uninformed household to make such investments by themselves and save on costs.

In addition to investing in the primary market, the mutual fund can also invest in the secondary market. I denote the primary market investment by mutual funds as $f$, and thus the secondary market investment is given by $F - f$. I assume that there is no screening in the secondary market, therefore no information cost is incurred. One can think of this as a situation where any mispricings in the secondary market have already been traded away, and the secondary market prices reflect the fair value of the existing projects. However, in order to invest in the secondary market, the mutual fund has to incur a brokerage fee that is proportional to the amount of the investment. This fee represents transaction costs that the fund faces when trading in the secondary market, and includes both direct transaction costs such as brokerage commissions as well as indirect costs such as bid-ask spreads. This fee is ultimately also borne by the household investor. I denote the per-dollar brokerage fee as $\eta$, so the after-fee secondary market investment return is given by $R_m - \eta$. The only assumption I place on $\eta$ is that it satisfies:

$$\eta < A_L + \frac{\theta^h}{2}$$

(3.2)

which states that the brokerage fee is strictly less than the gross return on the average real investment project in the economy. This is a reasonable assumption given the

---

I do not explicitly model the supply of the secondary market shares, and assume that there are liquidity traders who supply shares to the mutual fund. The liquidity traders do not participate in the primary market, and hence do not affect real output.
relatively low cost observed in the data (French, 2008). I assume that there is no agency conflict between the mutual fund and the household. A large body of literature has investigated the potential agency conflicts between fund managers and fund investors. In particular, much focus has been devoted to the optimal compensation contracts of fund managers and the implications of such contracts on market prices (see Stracca, 2006 for a review). In my model, I take the compensation contracts as given, and assume that any agency conflicts between the fund manager and fund investors are already taken care of by the manager’s contract. Hence the fund will seek to maximize the return to households.

Given their fund flows $F$, the mutual fund solves the following problem:

$$
\max_{0 \leq f \leq F} \left( (A_L + \theta)f - \frac{1}{2} \phi f^2 + (F - f)(R_m - \eta) \right)
$$

(3.3)

where $R_m = \left( A_L + \frac{\theta}{2} \right)$

In the above problem, the mutual fund chooses an optimal amount of investment in the primary market $f$, given their information about the underlying productivity in the economy $\theta$. Their primary market investment is constrained by the fund inflows they receive $F$, which itself is determined endogenously by the household. I describe the household’s setup and decisions in more detail in the next subsection.

Note that under this model setup, there are no asset pricing implication since all firms raise the same amount of equity to make real investments (normalized to one dollar), and the mutual fund only chooses the amount of investment to make in each sector without explicitly pricing the shares. Therefore, in this model, maximizing the expected returns from investment is equivalent to maximizing the productivity of the firms invested in, since the price paid for each firm is the same. This type of setup is
commonly adopted in the financial intermediation literature, where firms issue a fixed amount of proceeds to engage in real activities (see, for example, Diamond, 1984; Holmstrom and Tirole, 1997).

One may argue that in reality, funds can choose to bid up the share prices of the more productive firms, thereby reducing the expected returns on these firms. In equilibrium, investors may be indifferent between investing in the two sectors, even though some firms are more productive in the real economy than others. This view of the primary market is not inconsistent with my setup here. Indeed, in models of equity issuances (for example, Rock, 1986), there exists an equilibrium such that the informed investors can profit from their private information about firm qualities, while the uninformed investors break even on average from investing in new issues, even when the investors are bidding for the share prices. The setup in my model can be viewed as a reduced-form way of describing the equilibrium in Rock (1986), where informed investors can profit from their private information and uninformed investors are willing to participate in the primary market.

Another key feature in the primary equity market that is missing from the model setup is the underwriter. A number of studies argue that the underwriters possess valuable information regarding the issuing firms’ qualities, and they are willing to allocate more of the good issues to their most valuable clients. Aggarwal et al. (2002) document a positive relation between institutional investors’ allocations in initial public offerings and day one IPO returns. In addition, their results suggest that the allocation of underpriced issues to institutions cannot be fully explained by bookbuilding theories such as Benveniste and Spindt (1989). Ljungqvist and Wilhelm (2002) study institutional allocations at the international level, and find that allocation policies tend to favor institutional investors not only in the U.S., but also in a large number of
markets around the world. Using a detailed dataset on brokerage commissions by mutual funds, Reuter (2006) documents a positive relation between commissions paid to lead underwriters by mutual funds and the reported mutual fund holdings of the IPOs. Moreover, this positive relation is only present in IPOs with non-negative first day returns. The author interprets the results as investor favoritism, where the IPO underwriters use their private information about issuer qualities to reward institutional investors for brokerage businesses, by allocating the best issues to these institutions.

The evidence in these studies suggest that underwriters possess superior information about the quality of the issuers. Given the empirical evidence, one may argue that any superior performance obtained by the mutual funds in the primary market is not due to the fund’s superior ability to identify productive firms, but instead is simply due to the funds’ close relationship with the underwriters. In my model, I do not rule out this explanation. In fact, I do not explicitly distinguish between the two explanations. The mutual fund simply incurs a cost to obtain some private information about the productivity of the issuers, and the cost is convex in the amount of investment made by the mutual fund. The information cost can be interpreted as a cost incurred by the mutual fund to hire professional analysts to gather and produce information about the firm’s fundamentals. Alternatively, it can also be interpreted as a cost incurred by the mutual fund through brokerage commissions for information provided by the underwriter in return. Either way, the cost is incurred by the mutual fund to obtain some private information that is unavailable to the household investors, and as I will show in the next subsections, this superior information possessed by mutual funds has implications for the real economy, in addition to their superior returns.
3.1.3 Representative household

In this subsection, I describe the set-up of the household investors.

I assume that there is one representative household that maximizes its period-end consumption. The household is risk-neutral, and is endowed with initial wealth $W$, which it can invest in the primary market or the secondary market. I assume that capital is in short supply, i.e. the household’s wealth $W$ is less than the amount of investment opportunities in the economy, which is given by the mass of $H$ and $L$ firms combined.\(^4\)

The household is uninformed in two ways. First, it cannot differentiate between the two production sectors. Second, the household does not observe the true value of $\theta$. Instead, the household has its own information about $\theta$, which I denote as $\theta^h$, and it bases all of its investment decisions on $\theta^h$. I do not explicitly model how the household arrives at $\theta^h$, and instead takes it as given. After solving the model, I examine the implications of the difference between the household’s perceived productivity $\theta^h$ and the true productivity $\theta$ on fund flows, mutual fund investment and real economic activities.

The household believes that the mutual fund also observes $\theta^h$ as the true productivity, and allocates their fund flows accordingly. At the time the household makes its investment decision, it cannot observe the mutual funds’ actions. Therefore in the model, there is no channel for the households to learn about funds’ information. In reality, households can try to infer funds’ information from public sources. In this case, $\theta^h$ would represent the household’s conjecture of the funds’ information, and the difference between $\theta^h$ and $\theta$ would represent the difference between households’ inferred information and the actual information that funds have.

\(^4\)This assumption ensures that not all available projects are being invested in, thus creating a need for differentiating between good and bad projects.
Chapter 3. A model of mutual fund intermediation

The household can choose to invest through the mutual fund sector by giving $F$ to the mutual fund, or invest directly. When investing directly in the primary market, the household has an expected return of $A_L + \theta^h/2$, as it would allocate half of the capital to each sector. On the other hand, if the household invests directly in the secondary market, it would earn a return of $R_m$, but would also incur a brokerage cost $\eta$.\(^5\) Given that the household’s expected secondary market return $E(R_m) = A_L + \theta^h/2$, it is never optimal for the household to invest in the secondary market, due to the brokerage cost. Therefore the household would either invest in the mutual fund, or invest directly in the primary market to earn the uninformed return.

Given their initial wealth $W$, the household solves the following problem:

$$\max_{0 \leq F \leq W} \ E(R_{MF}(F)) + D \times E(R_D)$$

s.t. \hspace{1em} W = F + D

where $E(R_{MF}(F))$ represents the expected return from mutual fund investment, given the fund flows, and $E(R_D)$ is the household’s expected return from direct investment in the primary market, which is equal to $A_L + \theta^h/2$. Since the household believes that the mutual fund has information $\theta^h$, the household’s expected return from the mutual

\(^5\)I assume that the brokerage cost is the same for the household and the mutual fund. This assumption is not crucial, and allowing for different brokerage costs would not affect the results.
fund is also based on $\theta^h$. Hence the above problem can be re-written as:

$$
\max_{0 \leq F \leq W} \left( A_L + \theta^h \hat{f} - \frac{1}{2} \phi \hat{f}^2 + (F - \hat{f}) \left( A_L + \frac{\theta^h}{2} - \eta \right) \right) + D \left( A_L + \frac{\theta^h}{2} \right)
$$

(3.5)

s.t. $\hat{f} = \arg\max_{0 \leq f \leq F} \left( A_L + \theta^h f - \frac{1}{2} \phi f^2 + (F - f) \left( A_L + \frac{\theta^h}{2} - \eta \right) \right)$

(3.6)

$$
W = F + D
$$

where $F$ denotes the household’s fund flows, and $\hat{f}$ denotes the household’s expectation of the mutual fund’s investment in the $H$ sector in the primary market.

The first three terms in equation (3.5) are the household’s expected return from the mutual fund, while the last term is the household’s expected return from direct investment in the primary market. The household’s expected return from the mutual fund is determined by the household’s perception of the mutual fund’s information, $\theta^h$. The constraint in equation (3.6) simply states that the household believes that the mutual fund will act in its best interest and maximize the household’s return, by investing $\hat{f}$ in the primary market and $F - \hat{f}$ in the secondary market. Note that equation (3.6) is almost identical to the mutual fund’s problem in equation (3.3), the only difference being that in (3.6) the decisions are based on the household’s information $\theta^h$ rather than the mutual fund’s information $\theta$.

In this setup, the assumption of a risk-neutral household is made for tractability. In many other models of delegated portfolio management, both the fund investors and the fund managers are modeled as risk-averse agents (see, for example, He and Krishnamurthy, 2013; Vayanos and Woolley, 2013). These papers focus on the asset pricing implications of delegated portfolio management, and hence model the problem in a traditional asset pricing setup with risk-averse agents and risky assets. In my
model, having risk-averse agents would not change the model intuition, but would make the model less tractable.

### 3.2 Equilibrium analysis

I now solve for the mutual fund and the household’s optimization problems, and discuss the implications on the aggregate economy.

#### 3.2.1 Mutual fund’s problem

First, I solve for the mutual fund’s problem. The optimization problem in equation (3.3) implies the first order condition:

\[(A_L + \theta) - \phi f - (A_L + \theta/2 - \eta) = 0\]

Hence, the optimal primary market investment is given by:

\[f_{unconstr} = \frac{\theta + 2\eta}{2\phi}\]

if the fund manager is unconstrained.

However, since the mutual fund cannot issue debt, its investment in the primary market is constrained to its fund inflows, \(F\), which is endogenously determined by the household. Hence the feasible optimal primary market investment by the mutual fund is given by:

\[f^* = \min \left( \frac{\theta + 2\eta}{2\phi}, F \right)\]  \hspace{1cm} (3.7)

In order to explicitly write down the optimal mutual fund investment, I now proceed to solve the household’s problem.
3.2.2 Household’s problem

To solve the household’s problem one needs to solve for the optimal fund flows $F$. Given the household’s problem in (3.5), I show that the optimal fund flows and optimal direct investment are given by:

\[ F^* = \frac{\theta^h + 2\eta}{2\phi} \]  
\[ D^* = W - \frac{\theta^h + 2\eta}{2\phi} \]  

Proof: I proceed in two steps. First start by solving for $\hat{f}$ in equation (3.6). The first order condition is given by:

\[(A_L + \theta) - \phi \hat{f} - (A_L + \theta/2 - \eta) = 0\]

Since the household’s perceived amount of mutual fund investment in the primary market $\hat{f}$ is constrained to their fund flows, this implies that for any given $F$:

\[ \hat{f} = \min\left(\frac{\theta^h + 2\eta}{2\phi}, F\right) \]  

Equation (3.10) shows that any fund flows above $\frac{\theta^h + 2\eta}{2\phi}$ will not be invested in sector $H$ by the mutual funds, and will instead be invested in the secondary market. Since the secondary market incurs a brokerage cost, it is strictly dominated by the uninformed primary investment by the household. This can be seen by comparing the third and last term in equation (3.5), where the return on $D$ is strictly better than the return on $F - \hat{f}$. Hence, the household would never provide any fund flows that exceeds $\frac{\theta^h + 2\eta}{2\phi}$, i.e. fund flows $F \leq \frac{\theta^h + 2\eta}{2\phi}$.

Next, I show that the equilibrium fund flows $F$ is equal to $\frac{\theta^h + 2\eta}{2\phi}$. Suppose that
Given the assumption on the brokerage fee $\eta < A_L + \frac{\theta^h}{\bar{F}}$ (see (3.2)), and that $F < \frac{\theta^h + 2\eta}{2\bar{F}}$, the value function is increasing in $F$. To see this, note that $\frac{\partial V}{\partial F} = A_L + \theta^h - \phi F$. Further, $F < \frac{\theta^h + 2\eta}{2\bar{F}}$ implies $\phi F < \eta + \theta^h/2$. Substitute this into $\frac{\partial V}{\partial F}$ and we get:

$$\frac{\partial V}{\partial F} = A_L + \theta^h - (\eta + \frac{\theta^h}{2}) = A_L + \frac{\theta^h}{2} - \eta > 0$$

where the last inequality follows from the assumption that $\eta < A_L + \frac{\theta^h}{\bar{F}}$.

Since the value function is strictly increasing in $F$ when $F < \frac{\theta^h + 2\eta}{2\bar{F}}$, $F = \frac{\theta^h + 2\eta}{2\bar{F}}$.

Substituting the optimal fund flows in (3.8) into the optimal primary market investment in (3.7) gives the actual primary market investment for the fund manager:

$$f^* = \min\left(\frac{\theta + 2\eta}{2\bar{F}}, \frac{\theta^h + 2\eta}{2\bar{F}}\right)$$

A simple comparison between (3.11) and (3.8) shows that if the household has perfect information about investment opportunities, that is, if $\theta^h = \theta$, then the household will provide the fund flows that match with the optimal investment strategy of the mutual fund, i.e. $f^* = F^*$. However, if the household has different (and incorrect) information about investment opportunities, then the supply of funds to the mutual fund sector may not coincide with the fund manager’s desired investment strategy. Specifically, if the household is pessimistic and perceives productivity to be too low relative
to the true value, and allocates too little capital to the mutual fund relative to what the
fund desires, this may carry negative consequences for the aggregate economy, since
some of the capital would be unnecessarily invested in the unproductive sector.

Overall, the model equilibrium shows that the extent to which the fund manager
invests in the primary market will provide some information about investment oppor-
tunities, as long as the mutual fund has superior information relative to households.

3.2.3 The aggregate economy

To examine the aggregate effect of mutual funds’ intermediation activities, I define
aggregate output in the economy by:

\[
Y = (A_L + \theta)f - \frac{1}{2} \phi f^2 + (W - F) \left( A_L + \frac{\theta}{2} \right) - (F - f) \eta + R_m S
\]

(3.12)

where the first two terms represent output attributed to mutual fund investment less
information costs, the third term represents output produced by direct investment by
the household, the fourth term is the brokerage cost, and the last term represents output
from the existing projects (the secondary market). Note that the trading cost in the
secondary market represents an actual loss to society, since resources are consumed in
the process but there is no additional output being produced.

As noted in the previous subsection, mutual fund investment \( f \) contains informa-
tion about investment opportunities \( \theta \). However, the extent to which this is true may
depend on the size of \( \theta^h \) versus \( \theta \). In particular, (3.11) shows that if \( \theta^f \leq \theta \), mutual
fund investment \( f \) would reflect the household’s perceived productivity, but if \( \theta^f > \theta \),
\( f \) would reflect the true productivity. This suggests that aggregate output can take two
possible forms in terms of the observables, which I analyze separately.

Case 1: \( \theta^h \leq \theta \) and \( F = f \). In this case, one can substitute \( F = f \) into equation
(3.12) and obtain

\[ Y = (A_L + \theta) f - \frac{1}{2} \phi f^2 + W \left( A_L + \frac{\theta}{2} \right) - f \left( A_L + \frac{\theta}{2} \right) + R_m S \]

\[ = \frac{\theta}{2} f - \frac{1}{2} \phi f^2 + W \left( A_L + \frac{\theta}{2} \right) + R_m S \quad (3.13) \]

Aggregate output is increasing in the linear term of mutual fund investment \( f \), and is decreasing in the square term of fund investment \( f^2 \), due to the convex information cost. Further, since output is determined by the actual productivity \( \theta \) and not the household’s perceived \( \theta^h \), fund flows do not play a part in determining output here.

**Case 2:** \( \theta^h > \theta \) and \( F > f \). In this case, mutual fund investment \( f \) is determined by the fund’s information about true productivity \( \theta \). Therefore, one can rewrite the aggregate output in equation (3.12) in terms of the observable \( f \), given that \( \theta = 2\phi f - 2\eta \) from equation (3.11):

\[ Y = (A_L + 2\phi f - 2\eta) f - \frac{1}{2} \phi f^2 + (W - F) \left( A_L + \frac{2\phi f - 2\eta}{2} \right) - (F - f)\eta + R_m S \]

\[ = (A_L + W\phi - \eta) f + \frac{3}{2} \phi f^2 + (A_L - \eta)W - A_L F - \phi F f + R_m S \quad (3.14) \]

Consistent with the first case, equation (3.14) shows that mutual fund investment in primary issues conveys information about the true productivity \( \theta \). In particular, aggregate output is positively related to the linear term of \( f \). This is due to the fund’s information advantage and its ability to invest in the more productive sector, so that its investment decision reveals future productivity and hence output. This is the key prediction of the model. As shown above, this result does not depend on the relative size of \( \theta^h \) and \( \theta \), i.e. the extent to which the household overestimates or underestimates productivity. Another interesting prediction is in the interaction term between fund
flows $F$ and fund primary investment $f$. This interaction term has a negative effect on aggregate output. As fund flow $F$ decreases, the sensitivity of aggregate output to mutual fund investment $f$ becomes stronger.

## 3.3 Empirical implications and hypotheses

Building on the insights from the model equilibrium above, I develop the empirical hypotheses in this section.

Equations (3.14) and (3.13) provide similar predictions about the empirical relation between mutual fund investment and output, albeit different in magnitude. In addition, equation (3.14) provides additional predictions on the interaction effect between fund flows and mutual fund investment. Hence, in the empirical tests I adopt (3.14) as the testing equation. Note that the interaction term is only negatively related to output when $\theta^h > \theta$, and is expected to be zero when $\theta^h \leq \theta$. Empirically one cannot observe the relative size of $\theta^h$ and $\theta$, but as long as $\theta^h > \theta$ holds for some parts of the sample, the interaction term is expected to be negatively related to output in the empirical tests.

Although the variables $f$, $R_m$, and $F$ in equation (3.14) are all empirically observable, one problem with estimating the equation directly is that the variables are in levels. Therefore I scale equation (3.14) by initial wealth $W$ to obtain a relation with stationary variables:

$$
\frac{Y}{W} = A_L - \eta + (A_L + W\phi - \eta) \frac{f}{W} + 3\frac{\phi f^2}{W} - \frac{F f}{W} A_L + \frac{S}{W} R_m \tag{3.15}
$$

One may argue that the two equations do not give the same predictions, because the coefficient on the square term of $f$ is positive in (3.13), while it is negative in (3.14). This difference is due to the functional form adopted for the convex information cost, and is a caveat of the model. Intuitively, the square term of $f$ should load negatively on aggregate output due to the assumption of convex costs.
Equation (3.15) can then be tested using empirical counterparts of $f/W, F/W,$ and $R_m$. The relation should hold at both the aggregate and industry level, since in the model, the sectors $H$ and $L$ could either be within an industry, or be different industries within the whole economy. I summarize these predictions in the hypotheses below:

**Hypothesis 1:** At the aggregate level, mutual fund investment in the primary market ($f$) is positively related to subsequent output growth. Furthermore, the interaction between fund flows and mutual fund investment negatively predicts future growth.

**Hypothesis 2:** At the industry level, mutual fund investment in the primary market positively predicts subsequent industry output. The interaction between fund flows and mutual fund investment negatively predicts industry output.

An important assumption of the model is that mutual funds have superior screening skills. If this is indeed the case, the equity issuing firms that receive more mutual fund investment should have higher productivity growth in subsequent periods. This is a testable assumption which will also be explored.
Data description

In this chapter, I describe the data sources and the construction of the variables used to empirically test the model. I use data from the U.S. in this study, with the sample period spanning from quarter 1, 1984 to quarter 4, 2011. I first describe the data sources used and how the variables are constructed. I then present the summary statistics of the variables. Lastly, I discuss the empirical specifications to test the model.

4.1 Data sources

The data used in this study come from several sources, and can largely be categorized into five types: (1) macroeconomic data, (2) mutual fund flows data, (3) equity issues data, (4) mutual fund investment data, and (5) control variables. I describe each category in detail below.

4.1.1 Macroeconomic data

I use Gross Domestic Product (GDP) and industry value-added to measure aggregate and industry output, respectively. GDP is measured at the quarterly frequency, while
industry value-added is measured at the annual frequency. I obtain both measures (seasonally adjusted) from the U.S. Bureau of Economic Analysis (BEA). Real GDP is provided by BEA directly and is measured in chained 2009 dollars. Real industry value-added is calculated using the nominal values provided by BEA deflated by the BEA industry price indices, with the base being measured in chained 2005 dollars. I calculate the growth rates of output as:

\[ Grth_t = \ln GDP_t - \ln GDP_{t-1} \]

\[ Grth_{i,t} = \ln IndVA_{i,t} - \ln IndVA_{i,t-1} \]

where \( Grth_t \) denotes the growth rate of real GDP from quarter \( t - 1 \) to quarter \( t \), \( GDP_t \) denotes real GDP in quarter \( t \), \( Grth_{i,t} \) denotes the growth rate of real industry value-added in industry \( i \) from quarter \( t - 1 \) to quarter \( t \), and \( IndVA_{i,t} \) denotes real industry value-added in industry \( i \) in quarter \( t \).

In addition to the overall growth in output, I also use the cyclical component of output as an alternative measure. The cyclical component of output is defined as the residual component of output after extracting a long-run trend from the overall output, and represent transitory fluctuations from the long-run trend growth. Prior studies in the macroeconomics literature that examine firms’ financing decisions over the business cycle have used both the overall growth in output (Erel et al., 2012) as well as the cyclical component of output (Covas and Den Haan, 2011) as measures of macroeconomic conditions. Covas and Den Haan (2011) show that firms’ debt and equity financing covary strongly with the cyclical component of GDP, with the exception of the largest firms. In addition, Peress (2014) shows that information aggregation in the stock market can have an impact on the transitory component of output growth. Al-
though the model in this thesis does not differentiate between the long-run trend and the cyclical component, the macroeconomics literature provides some motivation for examining the two components of growth separately.

I follow Covas and Den Haan (2011) and use the HP filter (Hodrick and Prescott, 1997) to extract the cyclical component of output. Specifically, the HP filter assumes that the time-series of output $y_t$ is consisted of a trend component $g_t$ and a cyclical component (deviations from trend) $c_t$, such that $y_t = g_t + c_t$. Given the parameter $\lambda$, the filter solves the problem:

$$\min_{g_t} \left( \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=1}^{T} [(g_{t+1} - g_t) - (g_t - g_{t-1})]^2 \right)$$

The parameter $\lambda$ penalizes the variability in the trend component series. Following Ravn and Uhlig (2002), I use a value of 1600 for quarterly data and 6.25 for annual data for this parameter. The cyclical component of output is given by the difference between the level of output and the trend component from the filter.¹

### 4.1.2 Mutual fund flows data

To measure fund flows to mutual funds, I focus on domestic equity funds in the U.S. I obtain data on aggregate fund flows from the *Investment Company Institute* (ICI).² ICI collects and aggregates data on fund sales, redemptions, and exchanges, as well as total net asset values (TNA) at a monthly frequency.

According to ICI, the database covers about 98% of assets in the mutual fund

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¹The filter used here is a two-sided filter, meaning that it uses the full sample period to extract the cyclical component. However, this is not an issue for the empirical results. Although the filter used here contains forward looking data, the regressions are also predictive in nature – the explanatory variables are predicting cyclical GDP one step ahead rather than the other way round. Therefore even though the measured cyclical GDP may be correlated with future realizations through the filter, this would not contaminate my empirical results.

²I am grateful for Erin Short’s help on providing the dataset.
industry in the U.S. The advantage of using ICI data for aggregate flows over other mutual fund databases such as the CRSP Survivorship-bias-free database is that ICI reports actual flows, whereas other fund-level databases do not have such information, and thus fund flows would have to be estimated (see, for example, Sirri and Tufano, 1998; Kumar et al., 2015).

I follow Warther (1995) and Jank (2012), and calculate net fund flows as new sales minus redemptions plus exchanges-in minus exchanges-out. I aggregate monthly flows to the quarterly and annual levels in order to match up with the frequency of macroeconomic variables. Exchanges-in represent transfers from other fund groups such as bond funds into equity funds, while exchanges-out represent transfers from equity funds to other fund groups. Exchanges-in and exchanges-out differ from sales and redemptions in that there is no cashflow between the funds and the investor. Nevertheless, they represent funds’ reduced ability to invest in equity. Since the fund flows are in nominal levels, I deflate the series by the GDP deflator (base year 2009), obtained from BEA.

### 4.1.3 Equity issuance data

To measure new equity issues in the economy, I focus on seasoned equity offerings and initial public offerings. Although firms may issue new equity through other channels such as private placements, SEOs and IPOs represent the ways of equity financing where both institutional investors and retail investors can participate. On the other hand, in equity issues such as private placements, only institutional investors tend to participate. Since mutual fund participation in equity issues is endogenous in the model, it is more accurate to test the model using equity issues in which mutual fund participation can vary over time and across firms.
I obtain data on new equity issues from the *Securities Data Corporation’s (SDC) Global New Issues* database. SDC provides information on issuer profile, issuer SIC code, issue price, issue size, issue date, filing date, among other details, of all seasoned equity offerings and initial public offerings issued on the NYSE, AMEX, and NASDAQ. Following prior work (Demiralp et al., 2011; Gibson et al., 2004; Chen et al., 2007b) I exclude units, ADRs, and closed-end funds issues, and exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4949) from the sample. I match the firms’ issue information to their accounting information, obtained from COMPUSTAT, and their stock market information, obtained from CRSP.

The industry value-added data from BEA uses the NAICS (North American Industry Classification System) codes for classifying industries. For the equity issuers, I use the firms’ NAICS codes from COMPUSTAT to match with the industry value-added data. For firms with missing NAICS codes but available SIC codes in COMPUSTAT or CRSP, I use the NAICS-SIC matching table provided by the U.S. Census to extract the NAICS codes. The final sample yields a total of 15,038 firm-issue observations.

Lastly, I deflate the total issue proceeds at the aggregate level by the GDP deflator (base year 2009), and deflate the industry level total issue proceeds by the industry value-added price index (base year 2005), both obtained from the BEA.

### 4.1.4 Mutual fund investment

It is very difficult to obtain information on allocations to institutions in new equity issues (Chemmanur et al., 2009), since this information is considered sensitive business information by the underwriters. Therefore I follow the approach commonly used in the literature (Gibson et al., 2004; Reuter, 2006; Demiralp et al., 2011), and use the

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change in mutual fund holdings as a proxy to gauge the extent of fund investment in these issues.

I calculate a measure of mutual fund participation for each new issue (SEO or IPO). I obtain information on mutual fund holdings at the quarter-end prior to and the quarter-end immediately after each issue, from the Thomson Reuters Mutual Fund Holdings (s12) database. The database reports mutual fund holdings of NYSE, AMEX and NASDAQ listed securities for all U.S. registered mutual funds. The original source of the holdings data is from the mutual funds’ filings with the U.S. Securities and Exchange Commission.

I define mutual fund participation for issue $i$ at time $t$ to be the increase in the number of shares held by all mutual funds that report their holdings over the issuing quarter, scaled by the number of shares in the issue. Total mutual fund participation in the economy is then defined as the average participation rate over all issues during the quarter/year, and represents the proportion of all new issues that is contributed by mutual funds. In addition to the economy-wide participation rate, I also calculate a participation rate for each industry each year, in order to test the model at the industry level.

Since this measure of participation is based on holdings, it can be quite noisy. In particular, the change in holdings can either be due to the funds buying shares in the primary market as part of the new issue, or alternatively can also be due to funds buying shares in the secondary market. Any change in holdings resulting from the latter would introduce noise into the measure of participation, and this problem is particularly severe when the issue date is far away from the quarter-end reporting date, allowing the mutual funds more time to trade in the secondary market. In addition, there are cases where the seasoned equity issuer issues relatively small amounts of
new shares, but the existing shares are very liquid and heavily traded by mutual funds on a regular basis. This could result in large changes in the number of shares held over the issuing quarter being scaled by a small number of shares newly issues, resulting in extreme values in the participation measure.

To reduce the noise in the measurement of fund participation, I create a dummy variable $PART_t$ that equals to one for quarters where the average participation is higher than the sample median, and zero otherwise. For the industry tests, the dummy equals one when the average participation is higher than the cross-sectional median across all industries for each year. I use the dummy variables instead of the actual participation rates in the regressions.

To obtain the amount of mutual fund participation $f$, I multiply the dummy variable of high mutual fund participation $PART_t$ with the total proceeds in equity issues $Issue_t$ (total issues multiplied by the proportion coming from mutual funds).

4.1.5 Control variables

In addition to equity issues and fund flows, many other variables have been shown to predict real economic output. I employ several control variables to isolate the effect of equity issues, fund flows and mutual fund participation on economic output.

I control for the stock market returns $R_m$ following Fama (1981) and Jank (2012), who show that stock returns can predict real economic output due to their forward-looking nature. Including the stock market returns in the tests can also control for the level of pricing in the equity-issuing firm, since prior papers have shown that firms may engage in market-timing strategies when issuing new equity (Baker and Wurgler, 2002). For the aggregate level tests, I use construct a value-weighted market return of the CRSP universe and use it as a proxy for the aggregate stock market return.
For industry level tests, I construct industry level value-weighted returns based on the NAICS codes in CRSP, in order to align with the industry value-added data.

To proxy for the wealth available for investment $W$ at the aggregate level, I use the total assets of non-financial business sectors $Bus Assets$, obtained from the Federal Reserve, deflated by the GDP deflator (base year 2009). For the industry level tests, I use the market value of equity in each industry ($IndMV$) to proxy for industry wealth, deflated by the corresponding industry value-added price index (base year 2005). I use equity instead of assets as the scaling variable for industry tests, because industries vary in their use of leverage. Since some industries rely more on equity financing than others, scaling new equity issues by the value of existing equity in each industry is more appropriate than scaling equity issues by assets.\footnote{For robustness I also use the book value of industry assets and market value of industry assets as alternative proxies, and results are qualitatively similar.}

Another important control variable is the total credit issuance in the economy, $Credit$. I obtain annual and quarterly data on total credit borrowings in non-financial business sectors from the Federal Reserve deflated by the GDP deflator and use them as proxies for credit issuance. The amount of credit issues influences firms’ ability to invest, in the same way as equity issues. As Baker and Wurgler (2000) show, the total amount of debt issues is significantly larger than the total amount of equity issues in the economy, and constitutes a large proportion of external financing for firms. Further, the variation in debt issues over time does not perfectly correspond with the variation in equity issues (the share of equity issues to equity plus debt issues varies significantly over time), suggesting that it is important to control for total debt issues to isolate the effect of equity capital on output.

I also control for the consensus GDP growth forecasts. The macroeconomics literature shows that the consensus forecasts by professional forecasters have strong pre-
dictive power of future economic activities (Konchitchki and Patatoukas, 2014; Ang et al., 2007). Further, these forecasts often incorporate information that themselves contain predictive power of future economic activities, such as aggregate accounting earnings growth (Konchitchki and Patatoukas, 2014). Including the professional forecasts as a control variable would capture some of these additional information that predicts real output.

I use the consensus forecasts of GDP growth from the Survey of Professional Forecasters, compiled by the Federal Reserve of Philadelphia. The Survey is conducted on a quarterly basis, and takes forecasts of economic variables including output and inflation from private sector economists, including economists from Wall Street firms, banks, consulting firms, research centers and large private-sector companies (Croushore, 1993). The forecasters are asked to submit their forecasts of the economic variables as well as their estimated probability of an increase/decline in the variables. In my empirical tests, I use the one-period ahead mean forecasts of real GDP growth from the Survey.

In addition, for the firm-level tests I control for firm characteristics. Specifically, I control for firm size using the market value of assets as a proxy. The market value of assets is calculated as the book value of total assets (COMPUSTAT item AT) minus the book value of equity plus the market value of equity (share price times the number of shares outstanding). The book value of equity is calculated following Cohen et al. (2003). Specifically, book equity is defined as the stockholders equity plus balance sheet deferred taxes (COMPUSTAT item TXDB) and investment tax credit (item ITCB), plus postretirement benefit liabilities (item PRBA), minus the book value of preferred stock. For the book value of preferred stock, I use the redemption value (item PSTKRV), liquidation value (item PSTKL), or par value (item PSTK), depend-
ing on the availability. Stockholders equity used is calculated as follows. I use the COMPUSTAT stockholders’ equity number when available (item SEQ). If not available, I compute stockholders equity as the book value of common equity (item CEQ) plus the par value of preferred stock. If common equity is not available, I compute stockholders equity as the book value of assets (item AT) minus total liabilities (item LT).

I also control for the book-to-market ratio, calculated as the book value of equity (calculated as above) divided by the market value of common equity (share price times the number of shares outstanding). In addition, I control for the cumulative stock returns from months \( t - 12 \) to \( t - 1 \) prior to the equity issue for SEO firms.

### 4.2 Summary statistics

In this section I present the summary statistics for the variables used. I present the aggregate level, industry level, and firm level variables separately.

Table 1 shows the summary statistics for the variables at the aggregate level, industry level and firm levels. Panel A shows the aggregate level variable statistics. Average quarterly GDP growth rates are about 0.68%, while market returns are about 2.8% per quarter. The consensus GDP forecast is on average fairly accurate at 0.65%, and with a smaller standard deviation compared to the actual GDP growth rates. Total proceeds from primary issues are similar to net fund flows as a ratio of total assets of non-financial business sectors, however fund flows display larger variation than equity issues. The average participation rate in primary issues by mutual funds is about 24%, which is slightly higher than the average holdings of the stock market by mutual funds (Elton and Gruber, 2013). This participation rate also exhibits a fair amount of variation, suggesting that mutual funds actively move in and out of primary issues,
rather than passively investing in the issues. However, this average participation rate is very noisy since the measure is constructed from change in holdings (which contains trading activities in the secondary market), therefore I use the dummy variable PART for high/low participation in the regressions.\footnote{Using the actual participation rate yields similar estimates.}

Panel B in table 1 shows the summary statistics for the industry level variables. Note that the industry variables are reported at an annual frequency, while the aggregate variables are reported at a quarterly frequency. The industry output growth rates is on average higher than the aggregate growth rate, but also exhibits a larger standard deviation. This suggests that output cycles across industries do not co-move perfectly with each other, and there is substantial variation in the cross-section of industry output growth. The average industry level mutual fund participation rate is similar to the aggregate level participation rate (22.7\% at the industry level versus 23.7\% at the aggregate level). However the industry level participation also exhibits higher standard deviation, suggesting that there is some variation in the extent of mutual fund participation across industries.

Firm level variables are reported in Panel C of table 1. Due to data limitations prior to IPO, I focus only on the SEO firms in the firm level tests. For the productivity variables $KLTFP$, $OPTFP$, $RevGrth$ and $AvgROA$, I report the statistics for these variables during the five years after the equity issue. For the firm characteristics $Issue/MVAT$, $BM$, $LnSize$ and $Priorret$, I report the statistics of these variables at the time of equity issue. On average, SEO firms tend to exhibit high revenue growth post equity issue. They also have relatively low book-to-market ratios and high cumulative stock returns prior to the SEO. This is consistent with prior evidence that firms tend to
issue equity after a stock price run-up (see, for example, Baker and Wurgler, 2002).

In Figure 2, I plot the time-series of aggregate fund flows against quarterly GDP growth over the sample. The figure shows a strong positive correlation between aggregate fund flows and GDP growth, particularly towards the second half of the sample when mutual funds are more predominant in the market. This indicates that as mutual funds become increasingly important in the market, the relation between fund flows and the real economy is also stronger, suggesting that there may be active effect of fund flows on real economic activities coming from mutual funds’ investment.

Table 2 reports the correlation matrix for the aggregate level regression variables. The specification of the regressions will be described in detail in the next section. A few points are worth noting from the correlation table. First, equity issues appear to lead GDP growth, though they are not significantly correlated with the subsequent cyclical component of growth (without controlling for other factors). Second, although mutual fund participation is positively correlated with equity issues, the coefficient is only 0.24, suggesting that the mutual fund participation is not only driven by equity issues. Third, fund flows are positively correlated with subsequent GDP growth, confirming the previous findings of Jank (2012). Notably, fund flows are positively correlated with equity issues contemporaneously and the coefficient is fairly high at 0.76. To address potential concerns of multicollinearity in the regression, I also conduct industry level tests and firm level tests, as well as control for time fixed-effects (in which the fund flow variable drops out) and demonstrate that the empirical results are not driven by this correlation.
4.3 Empirical specifications

In this section, I discuss the empirical specifications of the model. Recall that the model can be tested by directly testing the following relation:

\[
\frac{Y}{W} = A_L - \eta + (A_L + W\phi - \eta) \frac{f}{W} + \frac{3}{2} \phi \frac{f^2}{W} - \phi \frac{ff}{W} - \frac{F}{W} A_L + \frac{S}{W} R_m
\]

I use the total assets of non-financial business sectors as a proxy for \(W\), and scale all aggregate variables by it.\(^6\) For industry tests, I scale the variables by the lagged industry market value of equity (for all firms in that industry in CRSP). For firm-level tests, I scale by the lagged market value of assets (the market value of equity plus the book value of total liabilities).

The full specification for the growth rate regression and cyclical component regression is as follows:

\[
Grth_t = \alpha + \frac{1}{BusAssets_{t-2}} \left( \beta_1 \times f_{t-1} + \beta_2 \times f_{t-1}^2 + \beta_3 \times Flow_{t-1} + \beta_4 \times (Flow_{t-1}f_{t-1}) \right) + \frac{1}{BusAssets_{t-2}} \left( \gamma_1 \times Issue_{t-1} + \gamma_2 \times (Flow_{t-1}PART_{t-1}) + \gamma_3 \times (Flow_{t-1}Issue_{t-1}) \right) + \gamma_4 \times PART_{t-1} + \gamma_5 \times R_{m,t} + \gamma_6 \times R_{m,t-1} + \delta \times Controls_{t-1} + \epsilon_t
\]  

\((4.1)\)

\(^6\)For robustness I also use total market capitalization (of CRSP stocks) as an alternative proxy, and all the results are similar.
\[
\frac{Ln(Cycl)_t}{BusAssets_{t-2}} = \alpha + \frac{1}{BusAssets_{t-2}} \left( \beta_1 \times f_{t-1} + \beta_2 \times f_{t-1}^2 + \beta_3 \times Flow_{t-1} \right.
\]
\[
+ \beta_4 \times (Flow_{t-1} f_{t-1}) \left) + \frac{1}{BusAsset_{t-2}} \left( \gamma_1 \times Issue_{t-1} + \gamma_2 \times (Flow_{t-1} PART_{t-1}) \right.
\]
\[
+ \gamma_3 \times (Flow_{t-1} Issue_{t-1}) \left) + \gamma_4 \times PART_{t-1} + \gamma_5 \times R_{m,t} + \gamma_6 \times R_{m,t-1} \right.\]
\[
+ \delta \times Controls_{t-1} + \epsilon_t \tag{4.2}
\]

where

\[
f_{t-1} \equiv Issue_{t-1} \times PART_{t-1}
\]

The control variables include credit issuance \(\frac{Credit_{t-1}}{BusAssets_{t-2}}\), consensus forecast of GDP growth \(Forecast_{t-1}\), total assets of non-financial business sectors \(BusAssets_{t-2}\) (to control for the scale effect), and four lags of the dependent variable to account for autocorrelation in output growth or the cyclical component of output.

The first four variables along with \(R_{m,t}\) in equation (4.1) correspond to those in equation (3.15) implied by the model. The main coefficients of interest are \(\beta_1\) (positive) and \(\beta_4\) (negative). The second set of variables with coefficients \(\gamma_1\) through \(\gamma_3\) are included in the regression to control for the base effects arising from the interaction terms in the main variables. In the case of \(Flow \times f\), I include both \(Flow \times PART\) and \(Flow \times Issue\) to control for the base effects.

The empirical specification above corresponds to the model in specifying a lead-lag relation between equity issues, mutual fund investment and subsequent output. The only period \(t\) independent variable is the stock market return \(R_m\), and this is because in the model, the output from new issues \(Y\) and existing projects \(R_m\) are realized at the same time. I scale the model by \(BusAssets_{t-2}\), because this corresponds to the beginning-of-period assets when agents make their issue/investment decisions, which
is consistent with the model. Empirically, this choice does not affect the results, and all the results remain consistent when the model is scaled by $BusAssets_{t-1}$. 
Chapter 5

Empirical tests of mutual fund intermediation

In this chapter, I present the empirical results on testing the model of mutual fund intermediation. I first present results on the aggregate level tests, and then present results on the industry level tests.

In addition to the main tests, I also conduct further robustness tests. Specifically, for both the aggregate and industry level tests, I split the mutual fund sample into active and passive funds, and examine the effect of their investment in new issues on real economic output separately. The model predicts a relation between mutual fund investment in new issues and real economic output through the funds’ ability to actively pursue productive firms. Therefore, one would only expect the results to be driven by the active funds’ investment and not the passive funds. In the industry level tests, I examine some of the alternative estimators that address the potential endogeneity problem in dynamic panel regressions, and find that the conclusions are not affected by the estimator used.
5.1 Aggregate level tests of mutual fund intermediation

To test the model at the aggregate level, I perform ordinary least squares (OLS) regressions on equations (4.1) and (4.2) using various specifications. The model predicts a positive relation between mutual fund investment and subsequent productivity in the real economy. To account for the autocorrelation structure of real output, I include four lags of the dependent variable in all regression specifications, and I use Newey-West standard errors with four lags to calculate the t-statistics.\(^1\)

5.1.1 Mutual fund intermediation and output growth

Table 3 reports the predictive regression results where quarterly GDP growth is the dependent variable.

Panel 1 shows that fund flows are positively correlated with subsequent economic growth, with the coefficient being 0.9811 and statistically significant at the 1% level. This rejects the null hypothesis that fund flows contain no information about future real economic activities. In addition, the consensus forecast by professional forecasters is a strong predictor of future growth. However, mutual fund flows remain significant even after controlling for the consensus forecast, suggesting that fund flows contain additional information about real economic activities that is not captured by the forecasters. The result also suggests that although individual investors may not know the true productivity, they do have some noisy signals and are able to contribute more capital to mutual funds when future economic growth is high.

\(^1\)For brevity I do not report the coefficients on the lagged dependent variables.
In panel 2, I add in the lagged stock market return as an additional independent variable. Prior studies have shown that the stock market return is a good predictor of future real economic activities (Fama, 1981). However, the results in panel 2 show that the predictive power of fund flows subsumes the predictive power of stock market returns in forecasting real economic growth. This is consistent with the findings in Jank (2012). Note that although equation (3.15) shows that fund flows should negatively predict output, the empirical findings of a positive prediction does not invalidate the model. In the model, the household’s information $\theta^h$ is not correlated with the true productivity $\theta$. In reality, when households have some information about the true productivity, their fund flows would positively predict output. This is the story in Jank (2012). The negative prediction in the model is due to the budget constraint $D = W - F$. Less fund flows would increase direct investment, and as long as $f$ is held constant, more direct investment would increase output, hence the negative sign on $F$.

In panel 3, the regression shows that the stock market return is weakly and positively related to contemporaneous output, with a t-statistic of 1.77. In panel 4, I include the amount of total equity issues in the regression. The result shows that total equity issues by itself does not have predictive power for growth. Indeed, models of finance and growth (Levine, 2005) suggest that the accumulation of physical capital does not contribute strongly to growth, but rather it is the advances in productivity that drive growth.

Panels 5 and 6 show the results for two specifications of the main model, with panel 6 being the full regression in equation (4.1). The main variable of interest is $f$ here. Although not statistically significant in either regression, the coefficients on $f$ are all positive, and have opposite signs than Issue with similar magnitudes. This provides some suggestive evidence in support of the model, albeit weak. The empirical
specification of $f$ as $\text{Issue} \times \text{PART}$ gives an additional interpretation. Since $\text{PART}$ is a dummy variable, the coefficient on $\text{Issue}$ itself measures the impact of new equity issues on subsequent growth when mutual funds have low participation in these issues (i.e. when $\text{PART} = 0$), and the coefficient on $f$ is the effect of new issues on subsequent growth when mutual funds participate more in the issues (when $\text{PART} = 1$). The opposite signs on these coefficients suggest that when mutual funds do not participate in the issues, the issues do not generate growth (or are even associated with lower subsequent growth)\(^2\), but when mutual funds participate more the issues are more productive. This is consistent with the model and the notion that mutual funds are informed. However, given the weak statistical significance (and lack of significance on the other variables), the results on aggregate growth is not conclusive.

### 5.1.2 Mutual fund intermediation and cyclical growth

Next I examine whether mutual fund intermediation affects the cyclical component of growth. Erel et al. (2012) and Covas and Den Haan (2011) have shown that equity issues vary greatly over the business cycle. Further, macroeconomic models of financial intermediation and financial frictions often make predictions about the business cycle effects of such frictions (Bernanke and Gertler, 1989; Jermann and Quadrini, 2012; Kurlat, 2013). In this sense, mutual fund intermediation may also affect the cyclical component of output.

To test the effect of mutual fund intermediation on the cyclical component of output, I perform regressions using the same specifications as table 3, but using the cyclical component of output as the dependent variable. Table 4 shows the regression

\(^2\)It may seem strange that increasing equity issues lowers subsequent growth. However this may be consistent with market-timing by firms to issue new securities when prices are high. If high prices are followed by slowing growth, one may observe high issues followed by lower growth.
results. The variables are as defined in table 3.

[INSERT TABLE 4 HERE]

Panel 1 and 2 of table 4 show that in contrast to the aggregate growth results, fund flows do not predict cyclical growth unconditionally. Panel 3 shows that the stock market return is not a good predictor of cyclical growth either. In panel 4, total equity issues itself has little predictive power of cyclical growth unconditionally, and this result is similar to the aggregate growth results.

In the main regressions in panels 5 and 6, the key variable $f$ is significantly positive. Consistent with the model, more equity issues invested by mutual funds predict higher output. The empirical specification of $Issue \times PART$ can also be interpreted in a similar fashion. When mutual funds participate less in equity issues ($PART = 0$), new issues are associated with lower subsequent growth than when mutual funds participate more in those issues ($PART = 1$), controlling for the level of total issues. Put differently, the same amount of equity issues can generate more subsequent cyclical growth in the real economy when mutual funds are heavily participating in those issues, relative to times when mutual funds are not participating. Economically the difference in productivities between high and low fund participation periods is associated with roughly 0.75 standard deviations of increase in output, for the average size of total new issues ($0.000821 \times 0.5377 / 0.000589 = 0.75$). The result are consistent with the hypothesis that mutual funds are able to identify the productive issues and invest when their private signals are good. This gives them a positive role in the economy. Note that while mutual fund participation $PART$ negatively predicts growth unconditionally, the magnitude is small compared to the interaction term with $Issue$ (-0.0004 versus 0.5377).

In addition, the interaction variable $Flow \times PART$ negatively predicts subsequent
cyclical growth. This variable is included as a base for Flow × f. Although the variable Flow × f is insignificant in the regression, the negative coefficient on Flow × PART suggests that when fund flows are low, higher mutual fund participation can generate higher subsequent output, over and above the unconditional high fund participation effect from PART. Although the model does not predict an interaction effect between Flow and PART, the regression result suggests that mutual funds may be particularly effective when they are capital constrained, such that the benefit of intermediation is larger when mutual funds have less capital to invest. This is also consistent with the convex information cost structure in the model, where less capital held by mutual funds entails less information cost incurred, thus the higher return to investment. Other significant predictors of cyclical growth include the consensus professional forecast and fund flows after controlling for other variables. These results are similar to those in the overall growth regressions.

In terms of model fit, all of the regression specifications have relatively high adjusted $R^2$. This is due to the lagged dependent variables in the regressions explaining much of the variation in the current-period cyclical component growth, since the cyclical component of growth is highly persistent.

Overall the aggregate-level evidence is largely consistent with the model predictions, where mutual funds’ participation in new issues predicts the productivity of these issues in generating output. However, the aggregate results have weak statistical power due to the small sample and the point estimates are noisier than they would be if a larger sample was employed. This problem can be partially alleviated by extending the tests to the industry level, and exploiting both the time-series and cross-sectional variations.
5.2 Industry level tests of mutual fund intermediation

In this section, I present the results of the model tests at the industry level. Specifically, I test whether the relations in equation (4.1) and (4.2) are able to explain cross-industry variations in value-added growth and the cyclical component of value-added. If mutual funds are skilled in selecting the productive firms, one should observe higher productivity growth in industries with high mutual fund participation in new issues, relative to industries with low mutual fund participation, given the aggregate fund flows received by the mutual fund sector. Similar to the aggregate level tests, I separately examine the effect of mutual fund intermediation on the overall growth rate of industry value-added and the cyclical component of industry value-added.

5.2.1 Mutual fund intermediation and industry output growth

I run OLS panel regressions using annual industry value-added growth as the dependent variable. For the independent variables, only the variables Flow, Credit and Forecast are aggregate-level variables, and all other variables are defined at the industry level. Issue$_{i,t}$ is the new equity issues in industry $i$ in year $t$, and PART$_{i,t}$ is the mutual fund participation dummy for industry $i$ in year $t$, and equals to one if industry $i$ has higher mutual fund participation in new issues relative to the cross-sectional median in year $t$, zero otherwise. As in the aggregate tests, $f_{i,t}$ is defined as Issue$_{i,t} \times$ PART$_{i,t}$. The market return $R_{i,t}$ is defined as the industry’s value-weighted return. To scale the regression, I replace BusAssets$_{i,-2}$ in equation (4.1) with the industry market value of equity IndMV$_{i,-2}$.

Table 5 reports the pooled panel regression results. As with the aggregate level regressions, all of the specifications here include four lags of the dependent variable. I cluster the standard errors at the industry level to account for correlations of produc-
Ch. 5. Empirical tests of mutual fund intermediation

I also include industry fixed-effects to capture unobservable sources of value-added specific to each industry. For exposition purposes, I only present the results for the full model here.

Panel 1 in table 5 reports the predictive regression results for value-added growth. The control variables credit issuance, consensus forecast, lagged industry market capitalization and lagged market return are significant predictors of value-added growth. The main variables of interest, $f$, is positive and weakly significant (t-stat 1.74), while the industry level equity issues is not a significant predictor of industry output growth. These results are similar to the aggregate evidence in suggesting that mutual fund intermediation has some impact on the overall growth of industry value-added, albeit weak.

5.2.2 Mutual fund intermediation and industry cyclical growth

I also examine the effect of mutual fund intermediation on the industry level cyclical component of value-added. Panel 2 in table 5 presents the predictive regression results, where the dependent variable is the log of the cyclical component of industry value-added.

In line with the aggregate evidence, the main variable of interest $f$ has a strong effect on the cyclical component of output at the industry level. When mutual fund participation in the new equity issues in an industry is low relative to the industry cross-sectional median ($\text{PART} = 0$), the new issues in that industry are associated with lower subsequent cyclical output (coefficient -1.1039). On the other hand, when mutual fund participation in new issues in an industry is higher than the cross-sectional median ($\text{PART} = 1$), the new issues in that industry predict higher subsequent cyclical
output (coefficient 1.7154 and statistically significant at the 1% level). Moreover, the estimated coefficient on \( f \) has a larger magnitude than the coefficient on Issue, so that the net effect is positive when there is more mutual fund intermediation (1.7154 – 1.1039 – 0.0014 = 0.6101).

Panel 2 also shows that the coefficient on the interaction term \( Flow \times PART \) is significantly negative. This result is also consistent with the aggregate evidence. In times of low net fund flows, higher mutual fund participation predicts even higher cyclical output above the baseline effect, which suggests that funds are particularly effective at identifying productive industries and projects in low fund inflow times (which are often associated with bad economic conditions). In addition, the coefficient on the squared term of mutual fund investment \( f^2 \) is significantly negative. This is consistent with the convex information cost structure in the model, where more mutual fund investment is associated with higher real output but at a decreasing rate.

### 5.2.3 Industry level tests with time fixed-effects

In this subsection, I report the regression results for industry level tests with time fixed-effects in addition to the industry fixed-effects. Including time fixed-effects in the regressions accounts for the potential cross-sectional correlations among industry growth rates due to common macroeconomic shocks, which cannot be captured by within-industry clustered standard errors alone. However, due to collinearity with the time dummies, the aggregate independent variables \( Flow_t, Credit_t \) and \( Forecast_t \) need to be dropped from the regressions.

Panels 3 and 4 in table 5 report the results for the overall growth in industry value-added and the cyclical growth for industry value-added, respectively. Overall, the results are still very similar to those reported in panels 1 and 2, both in coefficient
estimates and significance levels. Panel 3 shows that neither the new equity issues by itself nor new issues interacted with fund participation has significant predictive power for industry value-added growth. However, both variables are statistically significant in the cyclical growth regression. When fund participation is below the cross-sectional median, new equity issues negatively predicts subsequent cyclical growth, and the magnitude is very similar to the results in panel 2 even when controlling for time fixed-effects (-1.1028 with time fixed-effects versus -1.1039 without time fixed-effects). On the other hand, when fund participation is high, new equity issues positively predicts subsequent cyclical growth (coefficient of 1.7351), and the positive effect subsumes the negative effect from the equity issues itself. Again, the magnitude of the coefficient on $f$ is similar in both regressions (2) and (4). This suggests that the industry level results are not driven by time fixed-effects, but are instead driven by cross-sectional differences in mutual fund intermediation that is unrelated to common macroeconomic shocks.

5.3 Alternative explanations and robustness tests

Overall, the results above are in support of a positive role of mutual funds in the economy in their capacity as informed financiers to efficiently allocate capital and promote real economic output. However, one cannot fully reject alternative explanations of the findings. In this section, I examine one of the alternative explanations that poses the most challenge to my explanation, and perform further tests to differentiate between the two competing explanations. In addition, I perform further industry level tests based on an alternative estimator, namely the dynamic panel generalized method of moments (GMM) estimator, to test the effect of potential endogeneity problems in the industry level OLS regressions.
5.3.1 Tests on active versus passive mutual funds

One alternative explanation for the empirical relation between mutual fund investment and real economic growth documented above is that the effect is driven by mutual funds’ fund inflows instead of the funds’ ability to screen. Specifically, when investors perceive future productivity to be high (and rightly so), they would invest more into mutual funds. Given their mandates, fund managers are then forced to invest some of the additional fund flows into the primary market, driving up their participation and hence $f$. This would naturally create a positive relation between mutual fund investment in new issues and subsequent growth, even when fund managers do not possess superior information. In fact, in this reverse causality explanation, it is the individual investors that are doing the work, rather than mutual funds. This is the explanation offered by Jank (2012) in explaining the predictive power of fund flows on GDP growth.

In order to alleviate this reverse causality concern, I make two observations. First, if this alternative story is true, there should be high correlations between fund flows $F$ and mutual fund participation in equity issues $PART$, at both the aggregate and industry level, as fund managers would passively invest more into new equity issues upon receiving large fund inflows. However, the data shows that at the aggregate level, the contemporaneous correlation between fund flows and participation is only 0.16 and statistically significant only at the 10% level (p-value = 0.08). At the industry level, this correlation is even lower, at only 0.002 and is statistically insignificant with a p-value of 0.94. This suggests that on average, mutual funds do not passively invest upon receiving fund inflows, but instead make active decisions to move in and out of the new issues market over time. Furthermore, the passive effect of fund flows is already partially taken into account by including fund flows as an independent variable.
in the regressions.

Second, the reverse causality story implies that when fund flows are high, mutual funds would participate more in equity issues, and future output would increase (although not due to mutual fund investment). This implies a positive relation between the interaction term \( F \times PART \) and subsequent output, or at least no relation. Instead, the regression results at both the aggregate and industry level show a strong negative relation. This result cannot be explained by the reverse causality story, where individuals and mutual funds invest more at the same time.

To further examine this alternative explanation, I separate mutual fund investment into participation by active funds and passive (index) funds, and examine their effects on output. If the reverse causality explanation is true, there should be no distinction between active and passive funds, since all mutual funds are passive in their primary market investment. However, in the information story, the effect should be predominantly coming from active funds, while investment by passive funds should have little real effects.

I use the fund names in the Thomson Reuters s12 fund holdings database to identify passive funds. I follow Schwarz (2012), and classify funds with names containing “index”, “indx”, or “idx” as index or passive funds. All other funds are considered as active. I perform regressions at both the aggregate and industry level, and include participation by active (Act\( PART \)) and passive funds (Pass\( PART \)) separately in the regression. In addition, I interact \( \text{Issue} \) with both the active and passive participation, to obtain investment by active funds (\( f_{\text{act}} \)) and passive funds (\( f_{\text{pass}} \)). The other variables \( f^2 \) and \( \text{Flow} \times f \) are constructed using only the active funds’ participation. In the industry level tests, I include industry fixed-effects to account for time-invariant industry effects.
Table 6 presents the results. Since the previous results suggest that mutual funds mainly affect the cyclical component of output, I only present the cyclical results here. Panel 1 shows the aggregate regression results. When the overall mutual fund investment is separated into active and passive, neither has a significant relation with subsequent output. Nevertheless, the coefficients on $f_{act}$ and $f_{pass}$ have opposite signs, and $f_{act}$ is positively related to subsequent output, which is in line with the previous results in table 3. On the other hand, $f_{pass}$ has a negative sign. However since none of the coefficients are significant, one cannot infer much from this regression. The lack of significance may be due to the weakened statistical power from separating participation into two groups, since the aggregate regression only has 107 observations.

Panel 2 of table 6 presents the industry level results. New issues invested by active funds ($f_{act}$) positively predicts subsequent growth, while the coefficient on issues invested by passive funds ($f_{pass}$) is insignificant. This is consistent with the active screening explanation, where active funds have superior information and are able to invest more into the more productive equity issues, but is inconsistent with the passive investment explanation. In addition, $Flow \times f_{act}$ is significantly negative, and this is consistent with the model’s prediction. When fund flows are lower, more equity investment by active funds facilitates higher subsequent growth. In table 5, this coefficient is insignificant, and the results here suggest that this may be due to the weakened power when including passive funds in the sample.

These test results on active versus passive funds suggest that the main results are unlikely to be due to the reverse causality story, and are more in line with the active screening story. Although the tests here have weak statistical power due to the split sample, they do suggest that mutual funds have an active role in the real economy.
by improving real economic output through their capital allocation, and that these benefits are primarily driven by active mutual funds.

5.3.2 Robustness: industry dynamic panel regressions

In this subsection, I examine the effect of alternative estimators on the industry panel regressions. The industry results presented in section 5.2 support the model’s main hypotheses, but there is one econometric problem in the panel regressions due to the inclusion of industry fixed effects. The unobservable industry fixed effects in the panel regressions are captured by the error terms, and due to the lagged dependent variables in the specification, this creates a positive correlation between the dependent variables and the error term, leading to biased coefficients when performing OLS regressions.

One way to address this problem is to apply the dynamic panel regression technique proposed by Arellano and Bond (1991) as a Generalized Method of Moments (GMM) estimator. This estimator takes first-difference of the regression equation to eliminate the fixed-effect, and then uses lagged values of the dependent variable in levels as instruments for the first-differences. Asymptotically, this approach produces consistent and efficient estimates even when the industry fixed effect is correlated with the lagged dependent variable. In this section, I examine the robustness of the industry regression results to this alternative estimator.

As pointed out by Beck et al. (2000), there are several shortcomings with the first-difference estimator, the main one being that in finite samples, the difference estimator has a large bias and poor precision. To address this problem, Arellano and Bover (1995) propose a system GMM estimator that estimates the difference equation jointly with the regression equation in levels. In addition to having better precision in finite samples, the system estimator maintains the cross-industry variation by including the
regression in levels, and also improves the strength of the instruments (Blundell and Bond, 1998).

The consistency of the dynamic panel GMM estimators requires two critical assumptions, one being that the error term does not exhibit serial correlation, and second being that the instruments are valid. Arellano and Bond (1991) propose two tests for these assumptions. The serial correlation test examines the first- and second-order serial correlation in the error term, under the null hypothesis of no serial correlation (with a normal distribution). The Hansen’s $J$-test of overidentifying restrictions tests the overall validity of the instruments, and has a $\chi^2$ distribution with $J - K$ degrees of freedom, where $J$ is the number of instruments and $K$ is the number of regressors. Under the null hypothesis, the instruments are valid and exogenous, and failure to reject the null hypothesis lends support to the model.

At this point, it is important to note that although the GMM estimators produce consistent and efficient estimates asymptotically, one should be careful with their performances in finite samples, due to the potential over-fitting problem when instrument numbers are large. In particular, when the lagged dependent variable is persistent, lagged levels of these variables may be weak instruments for the difference equations (Blundell and Bond, 1998). Thus, the advantage of using the GMM estimators to achieve asymptotic consistency needs to be balanced with the potential biases in finite samples and the potential poor performance of using internal instruments. Therefore, as Beck and Levine (2004) point out, it is important to apply different estimators (GMM and OLS), and to use these results as complements to draw inferences. With this in mind, I now proceed to the regression results. I only report results for the cyclical component of industry value-added, as the previous results suggest that the effect of mutual fund intermediation is primarily on the cyclical component of growth.
Table 7 reports the GMM results for the main regression in equation (4.1), using lags six and further of the dependent variable $\ln(Cycl)/BusAssets_{t-2}$ as instruments for the four lags of dependent variable for the difference equation, and lags five and further as instruments in the levels equation. All other independent variables are treated as predetermined variables, and are instrumented with the original variable and all lags. Tests in panels 1 and 2 apply the one-step estimator with robust standard errors, while tests in panels 3 and 4 apply the two-step estimator. Results in panels 2 and 4 also include time fixed-effects to capture cross-sectional correlation across industries.

Overall, results are very similar across the four regressions, and are similar to those reported in table 5. In times of low fund participation, new equity issues are associated with lower subsequent cyclical output, with the coefficient being negative and statistically significant across all four specifications. The magnitude of the coefficients are also similar at around -0.3. When mutual fund participation is high relative to the cross-sectional median, the new equity issues in that industry becomes more productive with a coefficient of around 1.8 across the four specifications and statistically significant. In addition, $f^2$ is significantly negative in all specifications, suggesting that mutual fund intermediation may exhibit decreasing returns to scale, in support of the convex information cost structure specified in the model. The interaction term $Flow \times PART$ is negative at the 10% level in all specifications. Also note that all the coefficient estimates are similar in magnitude and significance across the four regressions, suggesting that the estimator used does not affect the results qualitatively.

The autocorrelation tests fail to reject the null hypothesis of no first and second order autocorrelation for the two-step estimators, and there is only weak evidence
of first-order autocorrelation for the one-step estimators. The Hansen test fails to reject the null hypothesis of valid instruments in all four specifications. However, it is important to note that in the case of large instrument count in finite samples, the Hansen test could be weakened to generate implausibly good \( p \)-values (Roodman, 2009), and should be interpreted with caution.

## 5.4 Summary of results

The results in this chapter provide support for the model of mutual fund intermediation. At the aggregate level, there is strong evidence of mutual fund investment in new issues predicting the cyclical component of growth and some weak evidence of mutual fund investment in new issues predicting the overall output growth. In particular, the sensitivity of cyclical output to new equity issues is substantially higher in times of high mutual fund participation compared to times of low mutual fund participation. The economic magnitude of this effect is also large, with the difference in productivities between high and low participation times is associated with approximately 0.75 standard deviation of increase in cyclical output. Moreover, the interaction of aggregate net fund flows and mutual fund participation has a negative predictive effect on subsequent cyclical output. This implies that in times of low net fund flows, mutual fund participation is particularly informative of future output, and is consistent with the model predictions.

At the industry level results are similar to those in the aggregate tests. When mutual fund participation is above the cross-sectional median of all industries, new equity issues in that industry predict higher subsequent cyclical value-added relative to industries with low mutual fund participation (below the cross-sectional median). In addition, a lower aggregate fund inflow is associated with a larger sensitivity of
industry cyclical output to fund participation in that industry, supporting the aggregate level results. Moreover, mutual fund investment at the industry level exhibits decreasing returns to scale, indicated by the negative coefficient on the square term of mutual fund investment. Further tests show that these results are robust to the inclusion of time fixed-effects to control for the cross-correlation among industries due to common macroeconomic shocks.

I conduct further robustness tests to evaluate potential alternative explanations to the results. In particular, I perform tests of the model at both the aggregate and the industry level, examining the effect of active mutual funds versus passive mutual funds separately. Results show that almost all of the effects in the main results are driven by active mutual funds' investment, rather than the passive mutual funds. The results are stronger in the industry level tests than the aggregate level tests, possibly due to the small sample and hence weak power in the aggregate level data. Overall the tests are in support of the active screening explanation of the mutual funds, rather than the passive investment explanation of mutual funds riding the wave of fund inflows when expected productivity is high, and lend further support to the model assumptions and implications.
Chapter 6

Firm-level evidence

In the previous chapter, empirical tests on the model of mutual fund intermediation have largely found support of the model’s empirical implications and predictions at the aggregate and industry levels. In this chapter, I test a key assumption of the model, which is that mutual funds have superior information relative to uninformed investors and invest more in the more productive firms. A direct test of this assumption is to examine the relation between mutual fund investment and the individual equity-issuing firms’ future productivity growth. If mutual funds indeed have superior information, their investment in firms should predict the firms’ future productivity. In these analyses, I restrict the sample to SEO-issuing firms only, due to data requirements for variables prior to the issue, which are unavailable for IPO firms.

In addition to the productivity tests, I also examine the relation between mutual fund investment and the equity issuing firms’ subsequent stock returns. Prior studies show that institutional investors tend to invest more in equity issuing firms that exhibit higher subsequent stock returns and interpret this result as institutions having better information (Chemmanur et al., 2009; Demiralp et al., 2011). I examine this relation in my sample and confirm the previous findings.
6.1 Firm level productivity tests

In this section, I test whether mutual fund investment is associated with productivity growth in the equity issuing firms subsequent to the equity issues. In order to measure productivity in line with the model, I employ several proxies. I explain each of the proxies in detail below.

First, I follow King and Levine (1993a) and estimate the firm-level total factor productivity (TFP) using a Solow-residual approach. I assume a Cobb-Douglas production function of the form:

\[ Y = AK^\alpha L^\beta, \]

where \( Y \) is output, \( K \) is capital, and \( L \) is labor. \( A \) denotes TFP, which is the component of output unrelated to the two production inputs – capital and labor. Taking logarithms and differencing over five years yields:

\[ \Delta Y = \alpha \Delta K + \beta \Delta L + \Delta A, \]

where \( \Delta Y \) is the growth rate of output, \( \Delta K \) is the growth rate of capital, \( \Delta L \) is the growth rate of labor, and \( \Delta A \) is the growth rate of TFP, which captures the growth rate of all other inputs than capital and labor that contributes to output growth. I denote this growth rate for firm \( j \) as \( KLT FP_{j,t+5} \) for firm \( j \) over the five years post-SEO. I follow King and Levine (1993a) and use \( \alpha = 0.3 \) and \( \beta = 0.7 \) in the calculation.

To obtain the proxies for the production function, I use revenue (COMPUSTAT item REV) as a proxy for output \( Y \). I use property, plant and equipment (net of depreciation, COMPUSTAT item PPENT) as a proxy for capital \( K \), and number of employees (COMPUSTAT item EMP) as a proxy for labor \( L \).

The shortcoming of \( KLT FP \) is that capital and labor shares are exogenously spec-
ified rather than estimated. One alternative is to estimate these shares using OLS regressions of the log-linearized production function. However, as Olley and Pakes (1996) demonstrate, such estimates obtained from log-linear production functions may suffer from simultaneity and selection biases. Simultaneity arises because productivity is known to the profit-maximizing firms at the time that they choose their input levels. Since productivity is observed by the firms but not the econometrician, failing to account for increases in inputs due to increased productivity will result in biased OLS estimates, due to a correlation between the production inputs and the residual term (measure of productivity), violating the OLS estimator assumptions. On the other hand, selection biases result from the correlation between productivity shocks and exit decisions. Firms with more capital stock are more likely to stay in the market when facing a negative productivity shock than firms with less capital stock, because more capital stock can be expected to produce greater future profits. Therefore, the exit decision and the amount of capital stock held by a firm for a given productivity shock need to be controlled for when estimating $\alpha$. To address these problems, Olley and Pakes (1996) propose a three-step semi-parametric estimator. They use firm level real investment as an instrument for unobserved time-varying productivity shocks, thus controlling for simultaneity problems. The selection biases are addressed by estimating survival probabilities using a probit model. The resulting estimator gives consistent estimates of $\alpha$ and $\beta$, from which estimates of time-varying firm-level productivity can be obtained.\footnote{For detailed algorithms on the estimation method, see Yasar et al. (2008) and Keller and Yeaple (2009) Appendix A.}

Applying the estimator to the production function $Y = AK^\alpha L^\beta$ and the sample of SEO firms, I obtain estimates of $\alpha = 0.1934$ and $\beta = 0.6397$. From these I calculate annual TFP in the same way as King and Levine (1993a), and calculate productivity
growth for five years post-SEO issue for each firm-issue. I denote this growth rate as $OPTFP_{j,t+5}$.

Complementary to the TFP measures above, I also employ two additional measures, revenue growth and five-year average return on assets (ROA). Revenue growth ($RevGrth_{j,t+5}$) is calculated as the five-year growth rate in revenue (COMPUSTAT item REV) for firm $j$ post-SEO issue. ROA is defined as operating income before depreciation (COMPUSTAT item OIBDP) divided by beginning-of-period book value of assets (COMPUSTAT item AT), and average ROA is obtained by taking a five-year average, starting from the year of the SEO issue. The advantage of these two measures is that they do not rely on structural assumptions about production functions. However, this is also a drawback at the same time, because it is unclear how these measures map to TFP in a theoretical framework.

Since the test here is on the effect of mutual fund investment on firm-level productivity growth, the full regression implied by the model does not apply here. Instead, I run OLS regressions of the various productivity measures on equity issue, fund participation and other control variables. If mutual funds indeed have superior information, their investment should lead to higher productivity growth. Therefore, I only include a subset of the variables in equation (4.1) that are consistent with this prediction. For control variables, I include firm size ($LnSize_{j,t}$, defined as log of market value of total assets in the year before the SEO issue), book-to-market ratio of equity ($BM_{j,t}$, where the book value of equity is measured as in Cohen et al. 2003), prior 12-month cumulative stock returns ($Priorret_{j,t}$), aggregate fund flows during the quarter of issue scaled by total assets of non-financial business sectors ($Flow_t$), and aggregate credit issuance during the quarter of the issue scaled by total assets of non-financial business sectors ($Credit_t$). I define firm-level equity issue $Issue_{j,t}$ as issue proceeds scaled by market
value of assets prior to the issue. The mutual fund participation dummy \( \text{PART}_{j,t} \) is equal to one if fund participation for issue \( j \) is above the median across all issues during the same year. In all regressions, I include industry and year fixed effects, and cluster the standard errors at the industry level.

Table 8 reports the regression results. Panels 1 and 2 report results on TFP measures, and panels 3 and 4 report results on operating performance measures.

\[ \text{[INSERT TABLE 8 HERE]} \]

For both TFP measures, equity issues have an insignificant predictive power on TFP growth when mutual fund participation in the equity issues is low. However, when mutual fund participation is high relative to the cross-sectional median across all equity issues during the year, the new issues lead to significantly higher subsequent TFP growth, given by the coefficient on \( \text{Issue} \times \text{PART} \).

For the accounting-based operating performance measures, results are more mixed. More equity issues lead to higher subsequent revenue growth, and the effect is even stronger during high fund participation times. However for ROA this is not the case. More equity issues lead to lower subsequent ROA (the coefficient is negative and marginally significant at the 10% level), and fund participation has an insignificant predictive power on productivity. However, high participation unconditionally leads to higher subsequent ROA. These results are in contrast with the results on productivity growth and revenue growth, and suggest that the accounting-based measures contain different information than the TFP measures.

One other result worth noting is that the coefficient on \( \text{Flow} \times \text{PART} \) is insignificant across all four measures of productivity. This is in contrary to both the aggregate and industry level results, and suggests that aggregate fund flows have little impact on the firm-level participation-growth relation, albeit being significant at the macro level.
Overall the results are in support of the model assumption, in showing that mutual fund participation in new issues is positively associated with subsequent productivity growth of the equity issuing firms. This result suggests that funds have superior information about equity issuers, and on average invest more in the more productive firms. The result offers a micro-foundation for the aggregate and industry level tests above.

### 6.2 Post-SEO return tests

In this subsection, I examine another proxy for firm performance, namely the issuing firms’ stock returns post-SEO. If mutual funds indeed have screening ability, the equity issuing firms that receive more mutual fund investment should outperform those that receive less mutual fund investment.

To test this assumption, I conduct similar analyses to those in Table 8. I regress the post-SEO firm stock returns on equity issues, the participation dummy, the interaction variable, as well as firm-level control variables. I include industry and year fixed-effects to capture firm-specific and industry-specific variations in returns, and cluster the standard errors at the industry level. I separately examine the firms’ return performance at the one-quarter, one-year, three-year and five-year horizons.

[INSERT TABLE 9 HERE]

Table 9 reports the results. The key variable of interest here is $\text{PART}_{,,}$. As the results show, higher mutual fund participation in equity issues predicts higher subsequent stock returns at the one-quarter, three-year and five-year horizons. The one-year prediction is also positive albeit statistically insignificant. In addition, more equity issues predict lower subsequent stock returns following the issue at the one-year, three-year and five-year horizons. This is consistent with the equity-issuance anomaly doc-
Chapter 6. Firm-level evidence

umented by Pontiff and Woodgate (2008). However, in my sample, at the one-quarter horizon, more equity issues predict higher subsequent returns, which is in contrast to the findings of Pontiff and Woodgate (2008), where equity issues predict negative returns at all horizons. This difference in the results may be due to the different samples used. Pontiff and Woodgate (2008) use the data on shares outstanding from CRSP to identify share issuances in all CRSP firms, whereas I limit my sample to the SDC SEO firms only.

Overall, the evidence on firm-level returns is consistent with those results on productivity, and also consistent with prior findings by Chemmanur et al. (2009) and Gibson et al. (2004) to show that mutual funds invest more in equity issuing firms with better subsequent stock returns and productivity growth. These results also lend further support to the key assumption of my model, which states that funds have superior information relative to households and can identify the more productive equity issuers.

It is important to note that although the results on productivity and returns are consistent with each other here, they do not necessarily need to be. In particular, realized stock returns reflect both the firms’ realized cashflows as well as the firms’ expected returns, while productivity in the model is mostly related to the cashflows produced by the investment project. A firm might exhibit lower stock returns post-issue due to the change in its exposure to systematic risk (Eckbo et al., 2000), while its productivity growth could still be high relative to its peers. Hence, it is important to empirically examine the effect on both productivity and stock returns.
Chapter 7

Concluding remarks

This thesis studies the roles of equity mutual funds in the real economy in terms of the effects on productivity and output growth, at the aggregate, industry and firm levels. Prior literature on mutual funds has largely focused on identifying fund managers’ skills and identifying their stock-picking or market-timing abilities, and little attention has been paid to mutual funds’ roles in influencing firms in the real economy and exerting real economic impact. In this thesis, I shed some light on this question, and provide evidence of mutual funds’ positive roles in the real economy as informed financial intermediaries.

In this chapter, I firstly provide a summary of the thesis. I then discuss some limitations of the thesis, and offer some possible directions for future research.

7.1 Summary of thesis

In Chapter 2, I review the extensive literature on mutual funds and the real economy. I identify two potential channels in which mutual funds could exert influence on firms and the real economy. The first channel is through mutual funds’ investment in the
new equity issues market. When possessing superior information relative to retail investors, mutual funds can act as financial intermediaries and can invest more in the equity-issuing firms with higher subsequent stock returns. With this ability, mutual funds can enhance the efficiency of capital allocation by financing the most productive investment projects, thereby improving productivity and economic output. This view of mutual funds is consistent with theories of financial intermediation, where intermediaries have advantages in alleviating information problems (Diamond, 1984; Holmstrom and Tirole, 1997).

The second channel through which mutual funds could influence the real economy lies in their secondary market activities. As active investors, mutual funds constantly produce and seek new information and impound such information in stock prices. If firm managers do not possess perfect information about their real investment projects, they may resort to market prices to learn about the value of their investment. As such, new information that is quickly impounded into stock prices (thereby improving price efficiency in the sense of Grossman and Stiglitz, 1980) could be valuable to firm managers, and this may create important feedback effects from efficient prices to efficient real investments. To this extent, active investment by mutual funds may provide cleaner signals in stock prices, which further influences firms’ real decisions.

In Chapter 3, I focus closely on the first channel, namely the mutual fund intermediation channel. I present a simple model of mutual fund intermediation in the new equity issues market to study the economic mechanism of mutual funds’ effect on productivity and output. My model shows that when mutual funds have informational advantages over household investors, their decisions to participate in the new equity issues convey information about the underlying productivity of the equity-issuing firms and hence real economic output. Specifically, holding all else constant, more mutual
fund participation implies higher productivity in the economy and hence higher subsequent real output. Furthermore, the model establishes a relation between mutual fund flows, fund participation and output. In particular, when mutual funds face convex information costs as in Berk and Green (2004) and Pástor et al. (2015), lower fund flows predict higher sensitivity of output to mutual fund investment. This is because when mutual funds have less fund flows, they become capital constrained and receive high net investment returns due to the convex information costs. These are two key empirical predictions of the model which I then test in the data.

In Chapter 4, I describe the data used to empirically test the model. I obtain data on mutual fund holdings, equity issues, firm-level accounting and stock return data, as well as macroeconomic data from several sources, all for the United States for the time period from quarter 1, 1984 through quarter 4, 2011. I construct proxies for mutual fund participation in new equity issues at the aggregate, industry and firm levels separately, using changes in the number of shares held by all mutual funds. The summary statistics show that although mutual fund participation is similar to fund flows in levels, there is substantial variation at both the aggregate and industry levels.

In Chapter 5, I present empirical test results at the aggregate and industry levels for the model’s predictions. Consistent with the model, I find that mutual fund participation positively predicts the sensitivity of output to new equity issues. In time of high fund participation, new equity issues predicts higher subsequent real output (as measured by the cyclical component of GDP) than in times of low fund participation. The difference in productivities between high and low fund participation periods is associated with an increase of 0.75 standard deviations of output at the aggregate level. This result is also observed at the industry level, where industries with high mutual fund participation have higher sensitivities of output to new issues than industries with
low fund participation. In addition, I find that net fund flows are negatively associated with the sensitivity of output to fund participation, supporting the model’s prediction in that lower fund flows work as a capital constraint on mutual funds and result in higher returns to mutual funds when they face convex information costs.

In addition, in Chapter 5 I test some alternative explanations for the empirical results. Specifically I test the reverse causality explanation, which states that the positive relation between mutual fund investment and real output is not driven by funds’ information advantage, but is instead due to the passive investments that mutual funds make when they receive more fund inflows. To test this hypothesis, I split the mutual fund sample into active and passive funds, and separately examine the effects of their participation on real output. I find that all of the results are driven by the participation by active funds, and investments by passive funds have no real economic effects over and above the control variables. These results support the information story, and suggest that the main findings are not driven by reverse causality explanations. I also examine the effect of alternative panel regression estimators in the industry level tests, and find that the main findings are not affected by the choice of estimators used.

In Chapter 6, I test the model’s key assumption, which states that mutual funds possess superior information and invest more in the more productive firms. I focus on the SEO sample of firms, and find that firms that receive more mutual fund investment around their equity issues exhibit higher productivity growth as measured by five-year TFP growth after their equity issue, following the methodology in King and Levine (1993a) and Olley and Pakes (1996). In addition, the firms that receive more mutual fund investment also have higher subsequent revenue growth and stock returns, suggesting that mutual funds are able to identify and invest more in the more productive firms.
Overall the results in this thesis provide some support for the positive role of mutual funds in the real economy in their capacity as informed financiers. The evidence shows that the ability of mutual funds to actively screen in the new equity issues market can enhance the productivity in the economy, thereby improving real economic output.

7.2 Limitations of the thesis and potential future research

No research is without limitations, and in this section I discuss some of the limitations of this thesis as well as potential future research.

First, in the current model, equity issues are taken as exogenous. However, as the literature has well documented, equity issues are often strategic decisions by firms and therefore can be modeled as endogenous decisions (Myers and Majluf, 1984). A natural extension of the model would be to consider strategic decisions by firms to issue new equity and how mutual fund intermediation affects the real economy in those situations.

Second, on the empirical side, future research could examine exogenous shocks to mutual fund participation and the effect on subsequent output, in order to further test the model. The current tests can only identify the association between mutual fund participation and real output, which is consistent with the model. However a stronger test would be to identify shocks to mutual funds’ capital levels and hence participation.

The findings in this thesis have additional implications for future research on the relation between financial development and economic growth. Levine (2005) suggests
that financial intermediaries and financial development can foster growth, and a large body of empirical literature has found support for the role of both the banking sector development and stock market development in promoting economic growth (Beck and Levine, 2004). In measuring stock market development, the literature has often used measures such as the size and liquidity of the stock market as proxies. The findings in this thesis suggest that these may not be complete measures of stock market development. In addition to the size and liquidity of the stock market, the level of stock market intermediation may also be an important measure of market development, and can be proxied by the relative size of financial institutions to retail investors in the stock market. Further research could examine the cross-country growth implications of such measures.
Figures and tables
Figure 1: Institutional ownership and mutual fund ownership as a percentage of total U.S. stock market capitalization.

This figure shows the time series of institutional ownership and mutual fund ownership as a percentage of the total market capitalization in the U.S., from 1980Q1 through 2011Q4. Institutional ownership and mutual fund ownership data is obtained from Thomson Reuters 13f/s12 filings, respectively. The total market capitalization is calculated as price times shares outstanding for all stocks in CRSP.
Figure 2: Time series of quarterly real GDP growth and aggregate equity fund flows

This figure shows the time series of aggregate quarterly fund flows, as a ratio of beginning total assets of non-financial business sectors, plotted against quarterly real GDP growth. The left vertical axis is quarterly real GDP growth rates, and the right vertical axis is the aggregate fund flows ratio. The horizontal axis is the year.
Table 1: Summary Statistics

Reported are summary statistics of variables. Panel A reports the aggregate level variables, Panel B reports the industry level variables, and Panel C reports the firm level variables. Subscript $i$ denotes industry $i$, while subscript $j$ denotes firm $j$. $Grth_t$ is the quarterly growth rate of real GDP levels. $Grth_{i,t}$ is the annual growth rate in real industry value-added for industry $i$. $Ln(Cycl)_{i,t}$ is the log of the cyclical component of real GDP from the HP-filter. $Ln(Cycl)_{i,t}$ is the log of the cyclical component of real value-added. $BusAssets_{t-2}$ is the total assets of the non-financial business sectors. $IndMV_{i,t}$ is the market value of total assets for all firms in industry $i$. $FLOW_t$ is the net cash flow into domestic equity funds during the quarter. $Credit_t$ is the total borrowing in non-financial business sectors during the quarter. $Rm_t$ is the quarterly value-weighted return of the CRSP universe. $Issue_t$ is the sum of proceeds from all SEOs and IPOs during the quarter. $AvgPart_t$ is the change of holdings of firms that issued equity by all mutual funds over the quarter scaled by issue proceeds. $Forecast_t$ is the one-quarter ahead real GDP growth rate consensus forecast. $IndRet_{i,t}$ is the value-weighted stock return for all firms in industry $i$. $KLTFP_{j,t+5}$ is the five-year King-Levine TFP growth for firm $j$. $OPTFP_{j,t+5}$ is the Olley-Pakes TFP growth. $RevGrth_{j,t+5}$ is the five-year revenue growth rate for firm $j$ post-SEO. $AvgROA_{j,t+5}$ is the five-year average return on assets for firm $j$ post-SEO. $BM_{j,t}$ is the book-to-market ratio of equity. $LnSize_{j,t}$ is the log of market value of assets. $Priorret_{j,t}$ is the cumulative stock return from month t-12 to t-2, prior to the SEO.

<table>
<thead>
<tr>
<th>Panel A: Aggregate level variables</th>
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<tbody>
<tr>
<td>Variable</td>
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<tr>
<td>-----------------------------------</td>
</tr>
<tr>
<td>$Grth_t$</td>
</tr>
<tr>
<td>$Ln(Cycl)<em>{t}/BusAssets</em>{t-2}$</td>
</tr>
<tr>
<td>$Flow_t/BusAssets_{t-1}$</td>
</tr>
<tr>
<td>$Credit_t/BusAssets_{t-1}$</td>
</tr>
<tr>
<td>$Rm_t$</td>
</tr>
<tr>
<td>$Issue_t/IndMV_{i,t-1}$</td>
</tr>
<tr>
<td>$AvgPart_t$</td>
</tr>
<tr>
<td>$Forecast_t$</td>
</tr>
</tbody>
</table>

<table>
<thead>
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<th>Panel B: Industry level variables</th>
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</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
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<td>-----------------------------------</td>
</tr>
<tr>
<td>$Grth_{i,t}$</td>
</tr>
<tr>
<td>$Ln(Cycl)<em>{i,t}/IndMV</em>{i,t-2}$</td>
</tr>
<tr>
<td>$Issue_{i,t}/IndMV_{i,t-1}$</td>
</tr>
<tr>
<td>$AvgPart_{i,t}$</td>
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<tr>
<td>$IndRet_{i,t}$</td>
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<table>
<thead>
<tr>
<th>Panel C: Firm level variables (SEO firms only)</th>
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<tbody>
<tr>
<td>Variable</td>
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<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>$KLTFP_{j,t}$</td>
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<tr>
<td>$OPTFP_{j,t}$</td>
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<tr>
<td>$RevGrth_{j,t}$</td>
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<tr>
<td>$LnSize_{j,t}$</td>
</tr>
<tr>
<td>$Priorret_{j,t}$</td>
</tr>
</tbody>
</table>

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Table 2: Correlation matrix

Reported is the pairwise Pearson correlation matrix for the aggregate level regression variables. $\text{Grth}_t$ is the quarterly growth rate of real GDP levels. $\text{Ln(Cycl)}_t$ is the log of the cyclical component of real GDP from the HP-filter. $\text{Flow}_t$ is the net cash flow into domestic equity funds during the quarter. $\text{Credit}_t$ is the total borrowing in non-financial business sectors during the quarter. $\text{R}_{m,t-1}$ is the quarterly value-weighted return of the CRSP universe. $\text{Issue}_t$ is the sum of proceeds from all SEOs and IPOs during the quarter. $\text{AvgPart}_t$ is the change of holdings of firms that issued equity by all mutual funds over the quarter scaled by issue proceeds. $\text{PART}_t$ is a dummy variable that equals one if the quarter has higher average mutual fund participation in new issues than the median over the sample period, zero otherwise. $\text{Forecast}_t$ is the one-quarter ahead real GDP growth rate consensus forecast. Correlations in bold indicate statistical significance at or below the 5% level.

<table>
<thead>
<tr>
<th></th>
<th>Grth_t</th>
<th>Ln(Cycl)/BusAssets_t-2</th>
<th>Flow_t-1/BusAssets_t-2</th>
<th>Credit_t-1/BusAssets_t-2</th>
<th>R_m,t-1</th>
<th>Issue_t-1/BusAssets_t-2</th>
<th>PART_t-1</th>
<th>Forecast_t-1</th>
<th>AvgPart_t-1</th>
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</thead>
<tbody>
<tr>
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<tr>
<td>Credit_t-1/BusAssets_t-2</td>
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<tr>
<td>R_m,t-1</td>
<td><strong>0.29</strong></td>
<td>0.02</td>
<td><strong>0.36</strong></td>
<td>0.04</td>
<td>1.00</td>
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</tr>
<tr>
<td>Issue_t-1/BusAssets_t-2</td>
<td><strong>0.25</strong></td>
<td>-0.08</td>
<td><strong>0.76</strong></td>
<td><strong>-0.27</strong></td>
<td><strong>0.20</strong></td>
<td>1.00</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>PART_t-1</td>
<td><strong>-0.19</strong></td>
<td>-0.16</td>
<td>0.14</td>
<td><strong>-0.23</strong></td>
<td>0.12</td>
<td><strong>0.29</strong></td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecast_t-1</td>
<td><strong>0.44</strong></td>
<td><strong>0.34</strong></td>
<td><strong>0.21</strong></td>
<td><strong>0.28</strong></td>
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<td>AvgPart_t-1</td>
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<td><strong>0.24</strong></td>
<td><strong>0.73</strong></td>
<td>-0.01</td>
<td>1.00</td>
</tr>
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</table>
Table 3: GDP growth rates regressions

Reported are predictive OLS regression results for GDP growth rates. The dependent variable is log-differences of real GDP. \( R_{mt} \) is the value-weighted market return of the CRSP universe of stocks. \( \text{Credit}_t \) is the total borrowing in non-financial business sectors during the quarter, scaled by beginning total assets of the non-financial business sectors. \( \text{Flow}_t \) is the net cash flow into domestic equity funds, scaled by beginning total assets of the non-financial business sectors. \( \text{Issue}_t \) is the sum of proceeds from all SEOs and IPOs during the quarter, scaled by beginning total assets of the non-financial business sectors. \( \text{PART}_t \) is a dummy variable that equals one if the quarter has higher average mutual fund participation in new issues than the median over the sample period, zero otherwise. \( f_t \) is defined as \( \text{Issue}_t \times \text{PART}_t \). \( \text{Forecast}_t \) is the one-quarter ahead real GDP growth rate forecast by the Survey of Professional Forecasters. \( \text{BusAssets}_t \) is the total assets of the non-financial business sectors. All regression specifications include four lags of the dependent variable (unreported for brevity). t-statistics are reported in parentheses and are calculated using Newey-West standard errors with four lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable: ( \text{Grth}_t )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
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<tbody>
<tr>
<td>( \text{Flow}_{t-1} )</td>
<td>0.9811***</td>
<td>0.7850**</td>
<td>0.9227***</td>
<td>0.9471**</td>
<td>1.1157**</td>
<td>2.8991</td>
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<td></td>
<td>(3.09)</td>
<td>(2.38)</td>
<td>(2.67)</td>
<td>(2.05)</td>
<td>(2.27)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>( \text{Credit}_{t-1} )</td>
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<td>0.0155</td>
<td>0.0119</td>
<td>0.0119</td>
<td>0.0108</td>
<td>0.0090</td>
</tr>
<tr>
<td></td>
<td>(0.90)</td>
<td>(0.70)</td>
<td>(0.52)</td>
<td>(0.52)</td>
<td>(0.47)</td>
<td>(0.39)</td>
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<tr>
<td>( \text{Forecast}_{t-1} )</td>
<td>0.1716**</td>
<td>0.1779**</td>
<td>0.2057**</td>
<td>0.2057**</td>
<td>0.2044**</td>
<td>0.2121**</td>
</tr>
<tr>
<td></td>
<td>(2.19)</td>
<td>(2.36)</td>
<td>(2.53)</td>
<td>(2.52)</td>
<td>(2.48)</td>
<td>(2.59)</td>
</tr>
<tr>
<td>( \text{BusAssets}_{t-2} )</td>
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<td>-0.0000**</td>
<td>-0.0000*</td>
<td>-0.0000*</td>
<td>-0.0000</td>
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<td>(-2.10)</td>
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<td>(-1.93)</td>
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<tr>
<td>( R_{mt} )</td>
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<td>-0.0042*</td>
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<td>-0.0042*</td>
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<td>(-1.73)</td>
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<td>(1.63)</td>
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<tr>
<td>( N )</td>
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<td>107</td>
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<td>107</td>
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<tr>
<td>( \text{Adj. } R^2 )</td>
<td>32.29%</td>
<td>33.16%</td>
<td>38.59%</td>
<td>37.94%</td>
<td>38.44%</td>
<td>38.23%</td>
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</table>
Table 4: Cyclical component of GDP regressions

Reported are predictive OLS regression results for the cyclical component of GDP. The dependent variable is the log of the cyclical component of real GDP, extracted using the HP-filter, scaled by two-quarter lagged total assets of the non-financial business sectors. \( R_{mt} \) is the value-weighted market return of the CRSP universe of stocks. \( Credit_t \) is the total borrowing in non-financial business sectors during the quarter, scaled by beginning total assets of the non-financial business sectors. \( Flow_t \) is the net cash flow into domestic equity funds, scaled by beginning total assets of the non-financial business sectors. \( Issue_t \) is the sum of proceeds from all SEOs and IPOs during the quarter, scaled by beginning total assets of the non-financial business sectors. \( PART_t \) is a dummy variable that equals one if the quarter has higher average mutual fund participation in new issues than the median over the sample period, zero otherwise. \( f_t \) is defined as \( Issue_t \times PART_t \). \( Forecast_t \) is the one-quarter ahead real GDP growth rate forecast by the Survey of Professional Forecasters. \( BusAssets_t \) is the total assets of the non-financial business sectors. All regression specifications include four lags of the dependent variable (unreported for brevity). t-statistics are reported in parentheses and are calculated using Newey-West standard errors with four lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
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<th>Dependent Variable: ( \ln(Cycl_t)/BusAssets_{t-2} )</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>0.0379*</td>
<td>0.2999**</td>
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<td>(1.08)</td>
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<td>(1.31)</td>
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<td>(1.85)</td>
</tr>
<tr>
<td>Forecast_{t-1}</td>
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<td>0.0061*</td>
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<td>0.0061*</td>
<td>0.0068**</td>
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<td>(1.89)</td>
<td>(1.85)</td>
<td>(1.89)</td>
<td>(1.87)</td>
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<td>0.0005</td>
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<td>(1.36)</td>
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<tr>
<td>( R_{mt} )</td>
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<td>0.0001</td>
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<tr>
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<td>(0.14)</td>
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<tr>
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<td>-0.8798***</td>
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<td>PART_{t-1}</td>
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<td>-0.0004***</td>
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<td>( f_t )</td>
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<td>0.5377**</td>
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<tr>
<td>Flow_{t-1} \times PART_{t-1}</td>
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<td>Adj. ( R^2 )</td>
<td>82.27%</td>
<td>82.41%</td>
<td>82.27%</td>
<td>82.13%</td>
<td>82.88%</td>
<td>83.71%</td>
</tr>
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</table>
Table 5: Industry Panel Regressions

Reported are predictive OLS regressions for annual industry value-added growth and the cyclical component. \( \text{Grth}_{i,t+1} \) is the log-differences in real industry value-added for industry \( i \) in year \( t \). \( \frac{\text{Ln} \left( \text{Cycl}_{i,t} \right)}{\text{IndMV}_{i,t-2}} \) is the log cyclical component of industry value-added, scaled by two-period lagged industry market value of equity in CRSP. \( \text{R}_{i,t} \) is the value-weighted industry return of all CRSP stocks within industry \( i \) in year \( t \). \( \text{Credit}_{t} \), \( \text{Flow}_{t} \), and \( \text{Forecast}_{t} \) are as defined in Table 2 and 3. \( \text{Issue}_{i,t} \) is the sum of proceeds from all SEOs and IPOs during the quarter in industry \( i \), scaled by beginning industry market value of equity. \( \text{PART}_{i,t} \) is a dummy variable that equals one if the industry has higher average mutual fund participation in new issues than the median industry in year \( t \), zero otherwise. \( f_{i,t} \) is defined as \( \text{Issue}_{i,t} \times \text{PART}_{i,t} \). \( \text{IndMV}_{i,t} \) is the industry market value of equity in CRSP. All regressions include four lags of the dependent variable (unreported for brevity). t-statistics are reported in parentheses, and standard errors are clustered at the industry level. The first two panels include industry fixed effects, and the last two panels include both industry and year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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<td>-</td>
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<td>( \text{IndMV}_{i,t-2} )</td>
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<td>(1.83)</td>
<td>(1.83)</td>
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<tr>
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<td>0.0060*</td>
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<tr>
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<td>( \text{Flow}<em>{t-1} \times \text{PART}</em>{i,t-1} )</td>
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<td>( \text{Adj.} \text{R}^2 )</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>( \text{Time FE} )</td>
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<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
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</table>
Table 6: Robustness: Active versus passive funds

Reported are OLS regression results for active versus passive funds. Panel (1) shows the aggregate results, the dependent variable being the log of the cyclical component of real GDP, extracted using the HP-filter, scaled by two-quarter lagged total assets of the non-financial business sectors. $\text{ActPART}_t$ ($\text{PassPART}_t$) is a dummy variable that equals one if the average participation in new equity issues by all active (passive) funds are above the sample median, zero otherwise. $f_{\text{act},t}$ is defined as $\text{Issue}_t \times \text{ActPART}_t$. $f_{\text{pass},t}$ is defined as $\text{Issue}_t \times \text{PassPART}_t$. The other variables are defined as in Table 3. Panel (2) shows the industry level results, with the dependent variable being the log cyclical component of industry value-added, scaled by two-period lagged industry market value of equity in CRSP. Industry fixed effects are included (not reported for brevity). $\text{ActPART}_{i,t}$ ($\text{PassPART}_{i,t}$) is a dummy variable that equals one if the average participation in new equity issues in industry $i$ by all active (passive) funds are above the cross-sectional sample median, zero otherwise. $f_{\text{act},i,t}$ is defined as $\text{Issue}_{i,t} \times \text{ActPART}_{i,t}$, and $f_{\text{pass},i,t}$ is defined as $\text{Issue}_{i,t} \times \text{PassPART}_{i,t}$. The other variables are defined as in Table 4. All regressions include four lags of the dependent variable. t-statistics are reported in parentheses, and standard errors are clustered by industry in Panel (2). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Panel (1): Aggregate

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<th>t-statistic</th>
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<tr>
<td>$\text{Forecast}_{t-1}$</td>
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<td>(2.40)</td>
</tr>
<tr>
<td>$\text{BusAssets}_{t-2}$</td>
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<td>(-0.14)</td>
</tr>
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<td>$\text{R}_{m,t-1}$</td>
<td>0.0004</td>
<td>(1.35)</td>
</tr>
<tr>
<td>$\text{R}_{m,t}$</td>
<td>-0.0001</td>
<td>(-0.23)</td>
</tr>
<tr>
<td>$\text{Issue}_{t-1}$</td>
<td>-0.1159</td>
<td>(-0.38)</td>
</tr>
<tr>
<td>$\text{ActPART}_{t-1}$</td>
<td>-0.0000</td>
<td>(-0.01)</td>
</tr>
<tr>
<td>$\text{PassPART}_{t-1}$</td>
<td>0.0001</td>
<td>(0.62)</td>
</tr>
<tr>
<td>$f_{\text{act},t-1}$</td>
<td>0.0504</td>
<td>(0.17)</td>
</tr>
<tr>
<td>$f_{\text{pass},t-1}$</td>
<td>-0.0736</td>
<td>(-0.74)</td>
</tr>
<tr>
<td>$f^2_{\text{act},t-1}$</td>
<td>-0.0002</td>
<td>(-0.32)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times f</em>{\text{act},t-1}$</td>
<td>0.0046</td>
<td>(0.71)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times \text{ActPART}</em>{t-1}$</td>
<td>-0.1351</td>
<td>(-1.45)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times \text{Issue}</em>{t-1}$</td>
<td>-0.0000</td>
<td>(-0.20)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.0002</td>
<td>(-1.11)</td>
</tr>
</tbody>
</table>

Panel (2): Industry

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Flow}_{t-1}$</td>
<td>-0.1794</td>
<td>(-1.38)</td>
</tr>
<tr>
<td>$\text{Credit}_{t-1}$</td>
<td>0.0001</td>
<td>(0.15)</td>
</tr>
<tr>
<td>$\text{Forecast}_{t-1}$</td>
<td>0.0135</td>
<td>(0.42)</td>
</tr>
<tr>
<td>$\text{IndMV}_{i,t-2}$</td>
<td>0.0000*</td>
<td>(1.75)</td>
</tr>
<tr>
<td>$\text{R}_{i,t-1}$</td>
<td>0.0054*</td>
<td>(1.88)</td>
</tr>
<tr>
<td>$\text{R}_{i,t}$</td>
<td>0.0010*</td>
<td>(1.97)</td>
</tr>
<tr>
<td>$\text{Issue}_{i,t-1}$</td>
<td>-1.9571***</td>
<td>(-3.66)</td>
</tr>
<tr>
<td>$\text{ActPART}_{i,t-1}$</td>
<td>-0.0026**</td>
<td>(-2.52)</td>
</tr>
<tr>
<td>$\text{PassPART}_{i,t-1}$</td>
<td>-0.0006*</td>
<td>(-1.80)</td>
</tr>
<tr>
<td>$f_{\text{act},i,t-1}$</td>
<td>2.6880***</td>
<td>(2.76)</td>
</tr>
<tr>
<td>$f_{\text{pass},i,t-1}$</td>
<td>0.2299</td>
<td>(0.42)</td>
</tr>
<tr>
<td>$f^2_{\text{act},i,t-1}$</td>
<td>-1.5779</td>
<td>(-1.35)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times f</em>{\text{act},i,t-1}$</td>
<td>-0.0114*</td>
<td>(-2.00)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times \text{ActPART}</em>{i,t-1}$</td>
<td>0.0642</td>
<td>(0.54)</td>
</tr>
<tr>
<td>$\text{Flow}<em>{t-1} \times \text{Issue}</em>{i,t-1}$</td>
<td>0.0000**</td>
<td>(2.33)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0003</td>
<td>(0.48)</td>
</tr>
</tbody>
</table>

Adj. $R^2$ 82.64% Adj. $R^2$ 83.06%
Table 7: Industry Dynamic Panel Regressions

Reported are dynamic panel GMM regressions for cyclical component of annual industry value-added, using the Arellano and Bover (1995) system GMM estimator. \( \ln(\text{Cycl}_{it})/\text{IndMV}_{t-2} \) is the log cyclical component of industry value-added, scaled by two-period lagged industry market value of equity in CRSP. Independent variables are defined as in Table 4. All regressions include four lags of the dependent variable (unreported for brevity), instrumented with lags 6 and further. t-statistics are reported in parentheses, and standard errors are robust for both the one-step and two-step estimators. Panels 1 and 3 include industry fixed effects, and Panels 2 and 4 include both industry and year fixed effects. The Wald test is for joint significance of all independent variables. The autocorrelation test tests for first and second order autocorrelation in the residuals according to Arellano and Bond (1991). The Hansen’s J-test tests for validity of instruments. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable: ( \ln(\text{Cycl}<em>{it})/\text{IndMV}</em>{t-2} )</th>
<th>One-step</th>
<th>Two-step</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Flow_{t-1}</td>
<td>0.0597</td>
<td>0.0614</td>
</tr>
<tr>
<td></td>
<td>(1.37)</td>
<td>(1.35)</td>
</tr>
<tr>
<td>Credit_{t-1}</td>
<td>0.0073**</td>
<td>0.0064</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(1.51)</td>
</tr>
<tr>
<td>Forecast_{t-1}</td>
<td>0.0015</td>
<td>0.0064</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>IndMV_{t-2}</td>
<td>0.0000**</td>
<td>0.0000***</td>
</tr>
<tr>
<td></td>
<td>(2.53)</td>
<td>(2.65)</td>
</tr>
<tr>
<td>R_{it-1}</td>
<td>0.0046*</td>
<td>0.0049</td>
</tr>
<tr>
<td></td>
<td>(1.74)</td>
<td>(1.60)</td>
</tr>
<tr>
<td>R_{it}</td>
<td>0.0009*</td>
<td>0.0007</td>
</tr>
<tr>
<td></td>
<td>(1.70)</td>
<td>(1.02)</td>
</tr>
<tr>
<td>Issue_{it-1}</td>
<td>-0.3784**</td>
<td>-0.3428**</td>
</tr>
<tr>
<td></td>
<td>(-2.11)</td>
<td>(-2.00)</td>
</tr>
<tr>
<td>PART_{it-1}</td>
<td>-0.0018***</td>
<td>-0.0020***</td>
</tr>
<tr>
<td></td>
<td>(-2.83)</td>
<td>(-2.87)</td>
</tr>
<tr>
<td>f_{it-1}</td>
<td>1.8439***</td>
<td>1.8452***</td>
</tr>
<tr>
<td></td>
<td>(3.41)</td>
<td>(3.46)</td>
</tr>
<tr>
<td>f^2_{it-1}</td>
<td>-3.3307***</td>
<td>-3.4829***</td>
</tr>
<tr>
<td></td>
<td>(-3.34)</td>
<td>(-3.25)</td>
</tr>
<tr>
<td>Flow_{t-1} × f_{it-1}</td>
<td>0.0300</td>
<td>0.0266</td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td>(1.44)</td>
</tr>
<tr>
<td>Flow_{t-1} × PART_{it-1}</td>
<td>-0.1487*</td>
<td>-0.1439*</td>
</tr>
<tr>
<td></td>
<td>(-1.94)</td>
<td>(-1.71)</td>
</tr>
<tr>
<td>Flow_{t-1} × Issue_{it-1}</td>
<td>-0.0000</td>
<td>-0.0000</td>
</tr>
<tr>
<td></td>
<td>(-0.82)</td>
<td>(-1.06)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.0032***</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(-3.03)</td>
<td>(-0.13)</td>
</tr>
<tr>
<td>N</td>
<td>1043</td>
<td>1043</td>
</tr>
<tr>
<td>Time FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Wald test (p-value)</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Autocorrelation test</td>
<td>1st order</td>
<td>0.075</td>
</tr>
<tr>
<td>(p-value)</td>
<td>2nd order</td>
<td>0.768</td>
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<tr>
<td>Hansen test</td>
<td>Chi-sq</td>
<td>42.02</td>
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<tr>
<td>p-value</td>
<td>1.000</td>
<td>1.000</td>
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</table>

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Reported are OLS regression results for firm-level productivity measures on equity issues and mutual fund participation, for SEO issuing firms. \( KLTFP_{jt+5} \) is the five-year growth rate in productivity, with the productivity measured using the method in King and Levine (1993a). \( OPTFP_{jt+5} \) is the five-year growth rate in total factor productivity post-SEO, with the productivity measured using the method in Olley and Pakes (1996). \( RevGrth_{jt+5} \) is the five-year revenue growth rate post-SEO. \( AvgROA_{jt+5} \) is the average return on assets over the five years post SEO issuance. \( Issue_{jt} \) is issue proceeds scaled by market value of assets prior to the issue. \( PART_{jt} \) is a dummy equal to 1 if fund participation is above the median across all stocks during the issuing year. \( LnSize_{jt} \) is the natural log of market value of assets ending the year before the issue. \( BM_{jt} \) is the book-to-market ratio of equity, where the book-value of equity is measured as in Cohen et al. (2003). \( Priorret_{jt} \) is the cumulative stock returns from month t-12 to t-1. Other variables are defined as in Table 3. All regressions include industry and year fixed effects. t-statistics are reported in parentheses, and standard errors are clustered by industry. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Issue_{jt} )</td>
<td>0.0482</td>
<td>0.1311</td>
<td>0.3843**</td>
<td>-0.0702*</td>
</tr>
<tr>
<td>( PART_{jt} )</td>
<td>-0.0836**</td>
<td>-0.0968***</td>
<td>-0.0385</td>
<td>0.0368**</td>
</tr>
<tr>
<td>( Issue_{jt} \times PART_{jt} )</td>
<td>0.1955*</td>
<td>0.2445**</td>
<td>0.2548*</td>
<td>-0.0316</td>
</tr>
<tr>
<td>( LnSize_{jt} )</td>
<td>-0.0003</td>
<td>-0.0007</td>
<td>-0.0024</td>
<td>0.0004</td>
</tr>
<tr>
<td>( BM_{jt} )</td>
<td>0.0005</td>
<td>-0.0000**</td>
<td>-0.0077</td>
<td>0.0012</td>
</tr>
<tr>
<td>( Priorret_{jt} )</td>
<td>-0.0128</td>
<td>-0.0048</td>
<td>0.0157</td>
<td>0.0001</td>
</tr>
<tr>
<td>( Flow_t )</td>
<td>-1.8037</td>
<td>-21.3768*</td>
<td>-36.7770**</td>
<td>-7.4262***</td>
</tr>
<tr>
<td>( Credit_t )</td>
<td>0.9982</td>
<td>-0.8199</td>
<td>-3.6856**</td>
<td>0.1960</td>
</tr>
<tr>
<td>( Flow_t \times PART_{jt} )</td>
<td>7.6387</td>
<td>10.0282</td>
<td>7.3307</td>
<td>0.0048</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.5813</td>
<td>0.9278***</td>
<td>1.4824***</td>
<td>0.1450***</td>
</tr>
<tr>
<td>Industry &amp; Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>3201</td>
<td>3240</td>
<td>3354</td>
<td>3294</td>
</tr>
<tr>
<td>Adj. ( R^2 )</td>
<td>5.62%</td>
<td>8.05%</td>
<td>7.46%</td>
<td>30.49%</td>
</tr>
</tbody>
</table>
Table 9: Firm-level Return Regressions: SEO firms

Reported are OLS regression results for post-SEO firm-level stock returns on equity issues and mutual fund participation, for SEO issuing firms. The dependent variables in panels (1) through (4) are the one-quarter, one-year, three-year and five-year stock returns for firms post-SEO, respectively. Issue\(_{jt}\) is issue proceeds scaled by market value of assets prior to the issue. PART\(_{jt}\) is a dummy equal to 1 if fund participation is above the median across all stocks during the issuing year. LnSize\(_{jt}\) is the natural log of market value of assets ending the year before the issue. BM\(_{jt}\) is the book-to-market ratio of equity, where the book-value of equity is measured as in Cohen et al. (2003). Priorret\(_{jt}\) is the cumulative stock returns from month t-12 to t-1. All regressions include industry and year fixed effects. t-statistics are reported in parentheses, and standard errors are clustered by industry. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) One-quarter returns</th>
<th>(2) One-year returns</th>
<th>(3) Three-year returns</th>
<th>(4) Five-year returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Issue(_{jt})</td>
<td>0.0432***</td>
<td>-0.0818***</td>
<td>-0.1876***</td>
<td>-0.3165***</td>
</tr>
<tr>
<td></td>
<td>(3.43)</td>
<td>(-2.81)</td>
<td>(-2.77)</td>
<td>(-3.26)</td>
</tr>
<tr>
<td>PART(_{jt})</td>
<td>0.0215***</td>
<td>0.0135</td>
<td>0.0694**</td>
<td>0.1170**</td>
</tr>
<tr>
<td></td>
<td>(3.48)</td>
<td>(0.48)</td>
<td>(2.31)</td>
<td>(2.04)</td>
</tr>
<tr>
<td>Issue(<em>{jt}) × PART(</em>{jt})</td>
<td>-0.0143</td>
<td>0.0099</td>
<td>-0.2343**</td>
<td>-0.1232</td>
</tr>
<tr>
<td></td>
<td>(-0.30)</td>
<td>(0.12)</td>
<td>(-2.56)</td>
<td>(-0.75)</td>
</tr>
<tr>
<td>LnSize(_{jt})</td>
<td>-0.0000</td>
<td>0.0004*</td>
<td>0.0005</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(-0.37)</td>
<td>(1.74)</td>
<td>(0.97)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>BM(_{jt})</td>
<td>0.0041*</td>
<td>0.0094**</td>
<td>0.0333**</td>
<td>0.0495**</td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
<td>(2.39)</td>
<td>(2.60)</td>
<td>(2.10)</td>
</tr>
<tr>
<td>Priorret(_{jt})</td>
<td>-0.0028</td>
<td>-0.0027</td>
<td>-0.0142**</td>
<td>0.0051</td>
</tr>
<tr>
<td></td>
<td>(-1.40)</td>
<td>(-0.40)</td>
<td>(-2.19)</td>
<td>(0.42)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0581***</td>
<td>0.2288***</td>
<td>0.9674***</td>
<td>1.1364***</td>
</tr>
<tr>
<td></td>
<td>(3.37)</td>
<td>(4.66)</td>
<td>(8.35)</td>
<td>(4.18)</td>
</tr>
</tbody>
</table>

Industry & Year FE | Y | Y | Y | Y |
N                   | 5938 | 5938 | 5938 | 5938 |
Adj. R\(^2\)        | 7.32% | 7.97% | 6.18% | 3.32% |
Bibliography


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The role of mutual funds in the real economy

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2016

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