Word-of-Mouth Effects in the Holdings and Trading Activities among Canadian Mutual Fund Managers

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Abstract

The study tests the word-of-mouth effects among mutual fund managers in Canada with the methodology based on a previous study (Hong et al., 2005), yet with multiple modifications such as the method of locating mutual fund managers. The results confirm the original findings as well as finds some unexpected results. This study demonstrates smaller word-of-mouth effects compared to the original study and reverse word-of-mouth effects in the largest financial city of Canada. The possible interpretations are further discussed in detail, among which a dynamic model of word-of-mouths effects and product differentiation is introduced. The study also discusses the market structure's implications applied to the dynamic models.

JEL classification: G02; G15; G20; G21

Keywords: Word-of-Mouth; Product Differentiation; Herding Behavior

Table of Contents

I. Introduction

Economic agents, especially money investors, are trained professionals who make investment decisions in order to maximize economic benefits while maintaining risks. General households do not normally have the capacity or professional skills to process the overwhelming information generated from the financial market, and therefore money managers play a crucial role in investment decisions making process for the general public. Among the investment institutions, mutual funds are exceptionally important; they are responsible for $13,891 billion of equity assets globally, corresponding to nearly 40% of the global investable equity assets.[1] Hence, mutual fund managers are perceived as rational investing professionals who make countless investment decisions based on their complete market analysis on behalf of their clients. However, mutual fund managers do not always process information independently or even rationally. In contrast, there are large amounts of social influences that fund managers constantly experience when they make investing decisions without knowing the future returns and risks. It is well recognized that they may be much more likely to rely on other's behaviors via various forms of communications, especially when fund managers do not have enough information processing capacity or are not confident with their own evaluation. This study focuses on such social influence on mutual fund managers' holdings and trading behaviors.

Among all of the social influences that mutual fund managers experience, word-of-mouth effects are one of the least discussed topics. One main reason is that word-of-mouth effects almost perfectly blend into other kinds of herding behaviors, and thus cannot be easily detected or quantified. Specifically, word-of-mouth effects are defined as the herding behaviors among people who spread information and opinions through word-of-mouth communication (Trusov et al., 2009). The very first study focusing on word-of-mouth effects among mutual fund managers was conducted in 2005 and successfully detected the existence of such herding behaviors (Hong et al., 2005). However, the relationships between the degree of word-of-mouth effects and other "opposite forces" such as product differentiation, have received little attention. In addition, the word-of-mouth effects among mutual fund managers have not been studied in countries other than the United States. Therefore, this current study is designed to address such issues and specifically focus on the word-of-mouth effects among mutual fund managers in Canada - an

[1] http://www.ici.org/research/stats/worldwide/ww_12_14

economy shares many similarities with the United States but also differs dramatically respect to the market concentration structure.

In their original study, Hong and his colleagues have proved that with the behaviors of the rest of the mutual funds controlled, a manager's holdings in his or her portfolio are more likely to be affected by the fund managers who also work in the same city, compared to those who work in other cities (Hong et ., 2005). The current study performs a similar method when studying the Canadian financial market, with a few significant modifications with respect to the methodology, such as the way to identify the location of the fund managers. In addition, the current study combines the word-of-mouth effects with the tendency for fund managers to differentiate from each other's portfolios, and promotes a dynamic model of the two forces. Lastly, the study addresses the potential factors that determine the overall balance of the two opposite forces of word-of-mouth effects and product differentiation, such as the market structure respect to the distribution of the funds.

The rest of this thesis is divided into the following several parts. Section II offers a brief literature review, where I summarize a few trends of studies regarding word-of-mouth effects among mutual fund managers and product differentiation among different fund managers' portfolios. Section III focuses on the data I use in the current study, including the source of the raw data as well as a presentation of the basic data characteristics. Section IV discusses the methodology adopted in this study, with highlights on the modifications based on the 2005 original study. Section V presents the results of the data analysis, while highlighting the key findings and unexpected outcomes. Section VI serves as a discussion about the results as well as the implications of the findings. Section VII concludes. The detailed information about the fund locations and the STATA codes processing the data are presented in the Appendix section.

II. Literature Review

Unlike word-of-mouth effects, there has been a large body of studies exploring the social influence on mutual fund managers in general, among which “herding behavior” is intensively discussed. Herding, in financial markets specifically, has been defined as a behavioral tendency to follow the actions of others, especially among different individual economic agents (Hachicha 2010; DeCoster & Strange, 2012; Welch, 2000). There is also a considerable amount of studies focusing on the reputational herding phenomenon (Scharfestein & Stein, 1990). Some researchers have divided the previous empirical literature on social influence among mutual fund managers into two main strands, herding behaviors and word-of-mouth effects. They think that herding behaviors differ from word-of-mouth effects due to the methods fund managers learn about other fund managers’ investment decisions (Konig 2014). However, I believe the word-of-mouth effect is just one type of herding behavior among fund managers with an additional emphasis on fund managers’ direct interpersonal word-of-mouth communication, since the sources of the information that managers adopt are still the behaviors observed or opinions exchanged of other individuals. This opinion is supported by multiple studies focusing on empirical evidences of the existence of the word-of-mouth effects among mutual fund managers (Hong et al. 2005; Shiller and Pound 1989). In addition, there are studies exploring word-of-mouth effects in different financial market settings. For example, one study conducted in 2000 looked at the word-of-mouth communication throughout the neighborhoods during the banking downturns (Kelly & Granda, 2000). Another example would be the study focusing on how the individual’s retirement plans are influenced by their colleagues and coworkers (Duflo & Saez, 2002).

On the other hand, product differentiation has been a concept people are very familiar with (e.g., Waterson, 1989). However, there are not many studies treating mutual funds’ portfolios as one of the product in the mutual fund competitive market. Instead, many of the studies have focused on the product differentiation among mutual funds by highlighting search costs or other types of fund expenses (Hortacsu & Syverson, 2004; Nanigian, 2012). There are also some studies that address the portfolio construction process for the mutual funds from a marketing perspective (Ballestero & Pla-Santamaria, 2004; Chen et al., 2013). However, there have not been many studies designed to focus on the portfolio differences among mutual funds from a product differentiation perspective.

As for word-of-mouth effects among financial investors specifically, one study conducted in 1989 took a first touch on this topic through self-report empirical analysis by asking investors what drew their attention to the stock they had purchased, and many of those investors identified one specific friend or even relative (Shiller & Pound, 1989). One landmark study strictly looking at the word-of-mouth effects among mutual fund managers was conducted in 2005. The study is motivated by the idea of direct interpersonal communication among fund managers, and discovers that a manager is more likely to be affected by the portfolio of other fund managers who are in the same city, compared to those who are not. This study also performs robust checks under various scenarios such as the time delayed for information process (Hong et al, 2005). One of the concerns from the Hong et al.'s study is the way they located the fund managers. Specifically, they locate the fund managers by identifying the investment companies or fund families and then finding the locations of companies' headquarters. This could lead to bias because funds under the same fund family could be regulated in different locations, and therefore the fund managers could work at a city different from where the headquarters are located. Also the study has focused on the United States stock market, which is much more spread out respect to the distribution of different funds compared to other countries which have one or two absolute financial centers.

As a result, the lack of studies conducted in this specific area and the potential flaws in the design of one original study make me interested in exploring the word-of-mouth effects in another economy (Canada for the current study) and adopting different methods when locating the fund managers. In addition, this current study combines the previous separated areas together and explore the relationship between the two opposite forces of product differentiation, which encourage fund managers to have different portfolios, and word-of-mouth effects, which tend to increase the similarities among fund managers' portfolios.

III. Data

Since the primary purpose of this current study is to test an established theory in different markets and compare word-of-mouth effects under different market structures, the basic methodology is similar to the original study that firstly focused on word-of-mouth effects among mutual fund money managers (Hong et al., 2005).

The original study stays in the United States market (Hong et al, 2005), while this current study shifts the focus to the Canadian financial market. The current study picks Canada over other global markets for the following reasons: Firstly, the Canadian financial market is very similar to the financial market of the United States with respect to the government regulation characteristics. As a well-developed financial market, the Canadian financial market is well regulated with significant amount of detailed information required to be disclosed on a quarter basis for mutual funds. The similarities in government regulation, especially on disclosure of mutual funds' holdings and trading activities, allow me to directly compare the data results to the original study without making too many modifications and hence rule out many potential confounding factors that could potentially undermine the validity of the comparison. Secondly, similar to mutual funds in the United States, Canadian mutual funds mainly invest in the equity market (Fitzpatrick et al, 2010). Therefore as I specify the funds that are classified as stock funds (i.e., funds in my database with investment objective codes of 2, 3, 4, and 7, similar to the original study[2]), I will be able minimize the selection bias since the funds I choose still cover the majority of the mutual funds market. Thirdly, the database I choose to obtain data from is an updated version of the database used in the original study in 2005, and therefore the data specifications are generally consistent. The database (which will be discussed below) incorporates the reported securities including not only NYSE, AMEX, and NASDAQ, but also the Toronto Montreal common stocks. Therefore it is very convenient to study Canadian

[2] The investment objective codes of 2, 3, 4, and 7 specified in WRDS database are corresponded to aggressive-growth, growth, growth-and-income, and balanced funds, respectively. The main reason to specify in this way is to be consistent with the original study.

financial market based on the information extracted from the similar database compared to any other country, which requires customization in order to merge the datasets together.

My main data on mutual fund holdings are obtained from Thomson Reuters Mutual Funds Holding – S12 Master File, provided by the Wharton Research Data Services (WRDS) database. The database summarizes security holding information for all registered mutual funds that report their holdings with the SEC, plus thousands of global funds, especially those in Canada. WRDS database provides information about mutual fund characteristics, stock characteristics, stock holdings, and the change in holdings in market value. It also allows the researchers to specify not only the time frame of the data, but also the specific portfolio details such as shares held at the end of the quarter, price of the stock, stock class description and CUSIP number, in addition to the basic fund characteristics.

I further augment the data in the following ways: Firstly, I document the fund names and then individually identify the specific fund managers, who are actually in charge of the portfolio construction. This is very different from the previous studies. Different from the current study, the previous studies all determin the mutual funds by locating the city where the headquarters of mutual funds' management companies are located (Coval & Moskowitz, 1990 & Hong et al, 2005). I, instead, hand collect the individual data points for over 162 mutual funds and identify the managers as well as the locations of their offices, regardless of the headquarter locations. For example, Dynamic Value Fund of Canada has a management company of Dynamic Funds which is headquartered in Montreal, Quebec, while the fund itself is monitored and regulated by Cecelia Mo, who works in Toronto, Ontario, compared to the other two Dynamic Funds' fund products operated in Montreal. This kind of situation is not unique. Among 162 funds included in the study, 10.5% of fund managers (17 funds) work and manage funds in different locations from the headquarters of their management companies. This makes a huge difference when preforming the estimation based on the location of the funds. Because word-of-mouth effects differ from other types of herding behaviors that word-of-mouth mainly happens at a local level, working in the same city or not serves as the independent variable in my data analysis. In other words, if the funds' locations are determined solely based on the cities of the headquarters of the management companies of the funds, the word-of-mouth effects could be mistakenly magnified and blended into other herding behaviors.

Table I

Summary of Fund and Fund Assets Distributions

City	Number of Funds	% of All Fund Assets
Toronto	91	61%
Montreal	41	14%
Vancouver	16	12%
Winnipeg	6	11%
Calgary	5	1%
Ottawa	3	1%

After locating the managers of each fund, I summarize the funds distribution across the six cities in Canada as well as the funds' assets managed in each city. Table I reports the specific number of funds located in each of the six cities along with the portion of overall fund assets that funds in each city manage. In addition, Figure I reports a summary statistics in percentage on the distribution of 162 Canadian mutual funds across six Canadian cities of Toronto, Montreal, Vancouver, Calgary, Winnipeg, and Ottawa. And Figure II presents the distribution of fund assets managed across cities. As shown, Toronto is the dominant player of Canadian financial market, with 91 of 162 Canadian funds located in Toronto managing over 60% of the overall fund assets. Montreal has 25% of the total funds in town, but manages only about 14% of Canadian fund assets. In contrast, there are only 4% of Canadian mutual funds located in Winnipeg but covering over 10% of the overall Canadian fund assets. This is due to the fact that funds in Montreal tend to be smaller in assets size compared to only a few yet very large mutual funds in Winnipeg.

FIGURE I
DISTRIBUTION OF CANADIAN MUTUAL FUNDS ACROSS SIX CITIES

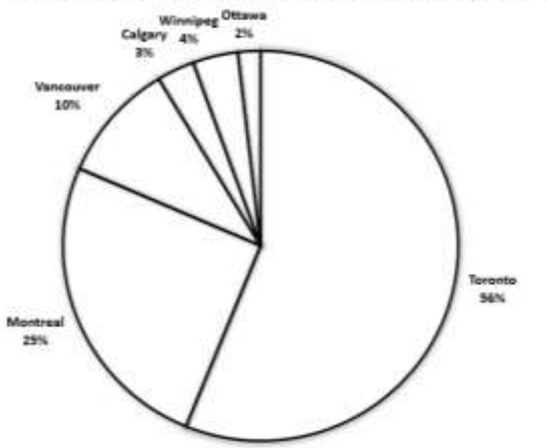
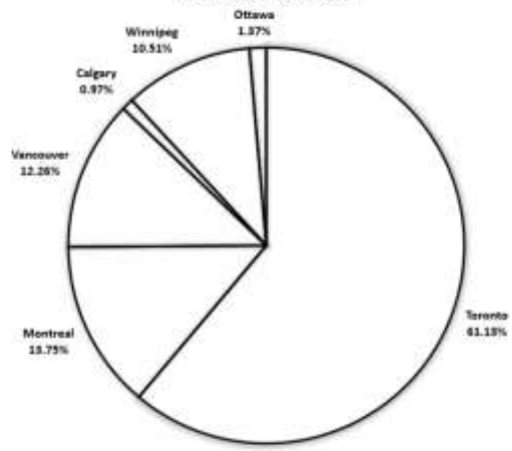


FIGURE II
% OF ALL FUND ASSETS



Secondly, I perform a few screening practices on the raw data I have obtained from WRDS database. First, I retain those funds whose locations are in Canada only. There are a few small funds invested in the Canadian market but are located in the United States, and therefore they are dropped from this study. Second, I drop all the index funds from the dataset. It is a replicate practice of the original study in 2005 since the funds' performance is purely mechanically determined ahead and cannot be influenced by word-of-mouth communications (Hong et al, 2005). Third, since the current research is studying the fund managers' behavior through analyzing quarterly reports, I have to drop funds reporting their holdings only semi-annually or sometimes even on a random basis. As for the possible estimation of the trading activities based on the previous and latter report, I cannot perform such estimation since it will greatly undermine the validity of my analysis. For example, even if a fund has the same holdings in a stock in the first quarter and the third quarter, with the second quarter report data missing, I cannot conclude that the holdings in the second quarter does not change throughout the six months period, since the fund could double the holdings in the second quarter and half it immediately in the third quarter. After the previous three steps of screening, I have 162 funds left in my dataset and 1079 stocks being held and traded during my time frame. All of the previous screening practices are necessary in order to ensure the robustness and validity of the estimation in the next section.

Thirdly, I specify the time interval as from January 2005 to December 2006. Because the data of stock holdings are reported quarterly, the modified dataset is consisted of 8 quarterly holdings reports from March 31st 2005 to December 31st 2006. In other words, for each stock held in the portfolio of each fund, 8 snapshots of holdings are reported along with other information such as the price and net change in market value from last quarter. The reason I set the time frame to the years of 2005 and 2006 is because of the overall stock market performance during those 8

Chart I

North America Major Stock Market Index, January 2005 to December 2006

quarters. As shown in Chart I, from 2005 to 2006, the performance of stocking markets in North America in general was bullish yet stable[3]. This could help rule out the confounding impacts of major markets movement such as the financial crisis in 2008.

IV. Methodology

[3] The charts reports the performance of four major indexes in North America from January 2005 to December 2006, including TSX Composite Index (Canada), Dow Jones Industrial Average, S&P 500, and NASDAQ Composite Index.

The basic assumption of this study is that fund managers who work in the same Canadian cities are more likely to contact each other when compared to those who work in different cities. Such contacts could be from networking events, local conferences, or any other city-level group activity that fund managers can have direct interactions and hence exchange their investment opinions with each other. Therefore, if I examine the word-of-mouth effects by observing the change of the holdings and trading activities of mutual fund money managers, I should be expecting to see that a change in a fund's portfolio should be affected more by other fund managers trading activities who are in the same city, compared to those who are not in the same Canadian cities. For example, a Toronto fund manager's investment decision should be more heavily influenced by the decisions of fund managers who also work in Toronto, than by the decisions of fund managers who work in Montreal.

Here I define a few key variables that I am interested in as an effort towards my regression estimation later. Firstly, I define $h^{i}_{j,l,t}$ as the fraction share (in market value) of stock i in fund j's portfolio in quarter t, and l is the city where the fund i's manager(s) works in. One important step is to set up a "universal portfolio" for all of the 162 funds. This is very important when performing the regression analysis later because funds are holding very different portfolios. Specifically, I collect all of the stocks that at least one of the 162 funds hold some shares at some point during the two years. As a result I document 1079 stocks in total as my "universal portfolio". Of course each fund will only buy a relatively small fraction of the 1079 stocks as their individual portfolio, so I assign a value of zero to the stocks that the funds do not invest in. Therefore, for each quarter, I will have a unique observation of the number of shares and price of each share for every stock-fund pair in my dataset. In particular, the dataset that is ready to be further processed has 162 funds with a portfolio of 1079 stocks for each fund, for a period of 8 quarters. Therefore, there are in total 1,398,384 observations on $h^{i}_{j,l,t}$ in my dataset. Secondly I define $H^{i}_{c,t}$ as the equally weighted average of coefficients across all funds in city c of the investment in stock i in quarter t. This variable is the same as the original study in 2005 by Hong et al. It measures how heavily funds in city c invest in stock i. Variable $H^{i}_{c,t}$ will serve as an important independent variable to reveal the different-city effects on a fund manager's portfolio by other managers from other cities. Thirdly, I define $H^{i}_{c,xj,t}$ as the equally weighted average of coefficients across all funds c of the investment in stock i in quarter t, except fund j

itself. This should make intuitive sense since we want to measure how heavily a fund manager is affected by other managers who work in the same city. Therefore, the average to estimate the same-city effects have to exclude the very fund I am focusing on.

Finally in order to discriminate the specific city a fund is located in, I create a dozen of dummy variables. Since I have 6 Canadian cities in total, I need to create one same-city effects indicator variable and one different-city effects indicator variable for each of the six cities separately. In other words, the regression equation will have six dummy variables for same-city effects and another six dummy variables for the different-city effects. Specifically, I donate $I(l = c)$ as 1 if city l and city c are the same and 0 otherwise. In other words, $I(l = c)$ takes a value of 1 when fund managers' office locations match that city's dummy variable and 0 when they do not match. Therefore when measuring the same city effects, each observation will have one dummy variable with value of one and five dummy variables with value of zero. Complementarily, I define $I(l \neq c)$ as 1 if city l and city c are different and 0 if they are the same. These six different-city effects dummy variables will, on the contrary, have one variable with value of 0 and the rest with value of 1. This is exactly the same design as the original study by Hong et al. in order to discriminate the same-city effects and different-city effects in one estimation (Hong et al., 2005).

After pooling my data covering fund managers' portfolios from January 2005 to December 2006 in Canadian financial market, I firstly perform the following two ordinary least squares (OLS) regressions as an effort to separately explore the same-city effects and different-city effects in order to detect the existence of herding behavior:

$$\Delta h^i_{j,l,t} = \sum_c \alpha_c \left\{ \Delta H^i_{c,xj,t} \cdot I(l = c) \right\} + \epsilon^i_{j,l,t} \qquad (1)$$

$$\Delta h^i_{j,l,t} = \sum_c \beta_c \left\{ \Delta H^i_{c,t} \cdot I(l \neq c) \right\} + \epsilon^i_{j,l,t} \qquad (2)$$

The reason I run those two estimations first is to prove the existence of herding behavior among the fund managers when they are managing funds' portfolios. This is very important because if there is no sign of general herding behaviors, combining the same-city effects variables and different-city effects variables will be meaningless regardless of the results. Only can I detect the positive correlations among fund managers regardless of managers working in the same city or not, I will then be able to further explore the word-of-mouth effects by focusing on the different magnitude of such positive relationships. Specifically, I am interested to see if the coefficients of two regressions (6 αs for the first estimation and 6 βs for the second one) are positive. This assumption is reasonable because there have been large amount of literatures proving the herding behavior under various social settings (see literature review sections).

Next I combine the two effects together to explore the word-of-mouth effects among money managers in Canada and run the following regression:

$$\Delta h^{i}_{j,l,t} = \sum_c \alpha_c \left\{ \Delta H^{i}_{c,xj,t} \cdot I(l = c) \right\} + \sum_c \beta_c \left\{ \Delta H^{i}_{c,t} \cdot I(l \neq c) \right\} + \epsilon^{i}_{j,l,t} \tag{3}$$

The main estimation is performed under the following logic. After testing the existence of herding behavior among fund managers, I can comfortably explore the word-of-mouth effects by comparing the differences in magnitude between same-city effects and different-city effects. My main assumption is that because of word-of-mouth effects, same-city effects should be stronger than other-city effects when keeping everything else constant. Therefore, for any c (any of the six Canadian cities), I should be able to observe $\alpha_c > \beta_c$, unless there are other effects working on the interactions among fund managers such as the incentives for product differentiation. For example, if $l = 1$ for the fund located in Toronto, I should expect that when studying the word-of-mouth effects in Toronto ($c = 1$), the estimation will indicate $\alpha_1 > \beta_1$. In other words, the fund managers in Toronto should be more responsive to other managers in Toronto, compared to those who work in Montreal, Vancouver, Calgary, Winnipeg, and Ottawa. This effect should hold for the other five cities as well if there are word-of-mouths effects existing. If the results for all cities are consistent, I can further quantify the magnitude of word-of-mouth effects by comparing the weighted average of α_c and β_c, according to the number of funds in each city or fund assets managed in each city.

V. Results

Table II
Summary of Results (standard error in parentheses)

	Same City Estimation	Different City Estimation	Word-of-Mouth Effects	
			Same-City (α)	Different-City (β)
Toronto	**0.8113** (0.0047)	**0.5607** (0.0061)	**0.3047** (0.0079)	**0.4006** (0.0085)
Montreal	**0.8030** (0.0050)	**0.2019** (0.0039)	**0.3580** (0.0073)	**0.1714** (0.0050)
Vancouver	**0.7258** (0.0076)	**0.1842** (0.0037)	**0.2859** (0.0091)	**0.1234** (0.0042)
Calgary	**0.3825** (0.0132)	**0.0522** (0.0027)	**0.1699** (0.0134)	**0.0347** (0.0028)
Winnipeg	**0.2792** (0.0124)	**0.1190** (0.0032)	**-0.0758** (0.0128)	**0.0693** (0.0033)
Ottawa	**0.5880** (0.0090)	**0.0940** (0.0018)	**0.3493** (0.0092)	**0.0586** (0.0019)
Weighted Average Difference			**0.0136** (0.0075)	

Table II presents the results of the three estimations I have performed. As specified in the previous sections, the estimation includes 162 funds' holdings in 6 Canadian cities with over 1079 stocks in a period of eight quarters from 2005 to 2006, that is, 1,398,384 snapshot data points in total. Firstly, the first column "Same City Estimation" corresponds to the herding behavior test in estimation (1), and the second column of "Different City Estimation" corresponds to the herding behavior test in estimation (2). The positive coefficients in both estimations firmly support the assumption of herding behavior among mutual fund money managers. Secondly, the word-of-mouth effects are tested in the third estimation via regression equation (3). All of the coefficients of the independent variables in the regression are positive except the same-city effect estimation for city Winnipeg, and the negative value is very close to zero. More importantly, my key test statistic – the weighted average difference value – is positive and significant. Though the value is small, the significant difference supports the assumption that same-City effects are larger than different-City effects, further indicating the existence (though small) of word-of-mouth effects among the managers in Canada.

There are several similarities in my results when comparing to the original study. Firstly, the current study supports the herding behaviors theory among mutual fund money managers that many previous studies have argued (Shiller& Pound, 1988, Chen et al., 2004, Hong et al., 2005). All of the positive values of the coefficients are consistent with the original study. Secondly, the positive relationship between the size of the mutual fund market and the degree of herding behavior effects is observed in both of the original and the current studies. Just like New York and Boston as the financial investment center in Hong and his colleagues' study, Toronto and Montreal in the current study stand out from the rest of the cities with relatively larger coefficients in both same-city effects estimations and different-city effects estimations. The third similarity with the original study conducted in 2005 lies in the word-of-mouth effects' existence. Similar to the original study in 2005, the current study has same-city effects larger than different-city effects. This is the key indicator for the existence of the word-of-mouth effects, and the degree of the effects will be further discussed in the next section.

There are also differences between the current study and the original study, which focuses on the United States financial market. Firstly, both of the same-city effects and different-city effects are generally stronger in all of the Canadian cities from the current study, compared to the 15

American cities. The largest “own-city” effect in the original study emerged in the city of Atlanta, with a degree of 0.3047 (Hong et al., 2005). This means for a fund in Atlanta, if other fund in Atlanta increase their holdings in one stock by 1%, the fund is likely to increase its holding in the same stock by about 0.3%. In contrast, in the current study, the weighted average of the same-city effects across six Canadian cities weighting by the number of the funds, is 0.2989, indicating that the average same-city effects in Canadian market is about the same degree as the largest “own-city” effects in the United States. This is an indicator of stronger herding behavior among the fund managers, and the interpretations will be further discussed in details in the next section. Secondly, the key test statistic of both studies, the weighted average difference between same-city effects and different-city effects, though both positive, are very different in magnitude. Specifically, the weighted average difference in the current study is only 0.0136, indicating that if all the other funds in the city increase their purchases of a particular stock by 1%, the target fund is expected to increase its holding of the same stock by only 0.0136%, compared to 0.131% in the original study (Hong et al., 2005). In other words, the degree of word-of-mouth effects in the Canadian financial market, though existing, is only about one tenth of the degree in the United States financial market. This difference in results will be interpreted with the help of other data in the next section. Eventually, the leading cities of each country determined by the number of funds located in the cities have the opposite word-of-mouth effects. Specifically, in the original study, 444 of the total 1327 American funds are located in New York City, and the Big Apple has an “own-city” effects of 0.2842, compared to other-city effects of 0.1441(Hong et al., 2005). This means that for a given fund in New York, if all the other funds in New York increase their holdings of a stock by 1% of their total assets managed, this very fund is likely to increase the holdings in its own portfolio by 0.144% more than a fund located in cities other than New York. This key value of difference in the leader city of the current study is, however, not only smaller, but also negative. The same-city effects in Toronto is 0.3047 while the different-city effects is 0.4006. Therefore the word-of-mouth indicator has a value of -0.0959. This indicates that the fund managers are affected less by those who work in the same city than those who work far away. This very surprising finding will also be discussed in details in the discussion section.

VI. Discussion

Overall, the current study supports the herding behaviors theory among mutual fund managers suggested in the previous studies, but the results for word-of-mouth effects, though seen in the same direction, are very different in magnitude. Furthermore, the results discover a "reverse word-of-mouth effects" for the Canadian financial market leading city Toronto. In other words, Toronto's same-city effects (0.3047) is significantly smaller than its different-city effects (0.4006). Such reverse word-of-mouth effects are unexpected for the leading city of the country (Toronto). The potential interpretations for the results discussed in the previous section are discussed in detail below by sub-sections.

VI. a. Herding Behavior focusing on word-of-mouth effects

All of the positive and significant estimation coefficients suggest positive relationships between the holdings of various stocks among Canadian fund managers. This serves as a very strong indication of herding behaviors as the previous studies suggested. In other words, part of the investment decisions mutual fund money managers make are not based on their professional analysis. Instead, they choose which stocks to buy by observing other managers as an "analysis shortcut". Though the entire finance industry is a professional industry where the majority of the participants are trained professionals such as fund managers or investment bankers, it does not necessarily mean that the fund managers process their information solely with their professional knowledge and skills. This current study serves as a very strong proof of the fact that fund managers could be affected solely by the holdings of other managers around them regardless of the nature of the stocks they are buying. Word-of-mouth effects and more generally herding behaviors have been proved true under different social situations among the economic agents (Ellison & Fudenberg, 1995), and mutual fund market is just one of those situations. This is very different from mutual fund managers' public images, especially in the eyes of investors and the funds' clients.

In this current study, the degree of herding behavior effects are stronger than the original study. This could be due to the data selection with respect to the time frame. Specifically, the original study conducted by Hong et al. in 2005 chose to collect data during a two year period from 1997 to 1998 (Hong et al., 2005). The current study however, obtained data from 2005 to 2006, nearly a decade later than the original study. During those eight years from 1997 to 2005, internet technology has developed dramatically. Fund managers now have much easier access to instant market information via their computer or mobile phones. More importantly, it became much easier for fund managers to have direct contact with each other while not physically being together. With the improvement of technology, mutual fund managers individually contacted each other more frequently than years ago even they were not actually meeting with each other in 2005 compared to 1997. Though based on the definition of word-of-mouth effects, fund managers in 2005 did not actually spread the information via private face-to-face communication more than 1997 (could be even less), fund managers could actually increase the inter-personal contacts and exchange their opinions toward stock market due to the more popular mobile technology. While this current study cannot discriminate the specific types of inter-personal communication, I argue that it is ultimately close to the nature of word-of-mouth communication. In other words, the mutual fund managers still follow somebody who is physically proximate, either by communicating in person or exchanging opinions through the internet.

VI. b. Different information generation mechanisms

When trying to interpret the different magnitudes of word-of-mouth effects between the current and the original studies, I focused on the market consensus generation process in different two markets. In other words, I attribute at least part of the difference in degrees of word-or-mouth effects between the United States and Canada to the "industry leader and follower" relationship in financial investment industry.

Specifically, as the global economy leader, the United States does not have other economy to observe and follow after. When building a consensus from blank, the economic agents in the United States are more likely to communicate with each other and come to a common conclusion about the market. Canadian agents, on the other hand, do not have to start from zero when studying a market movement. Instead, as the economic agent in the follower market, Canadian economic agents could directly observe the reactions from the United States market and then perform their analysis based on the already established consensus. Another reason Canadian fund managers have less demand for word-of-mouth communications is the closeness between the two markets. Compared to other international markets, for example, The United Kingdom, Canada economy has much more interactions with the United States. In fact, the United States and Canada have the largest trade relationship in the world with the help of North American Free Trade Agreement (NAFTA). Many Canadian fund managers have directly held American stocks in their portfolios in the database. Therefore, the stock market atmosphere in the United States has a direct impact on Canadian market. Canadian fund managers do not need to communicate each other in order to obtain a "base line analysis" for the market. As a result, they tend to have a smaller degree of word-of-mouth effects compared to American fund managers.

VI. c. Comparison of mutual fund market structures

FIGURE III
DISTRIBUTION OF AMERICAN MUTUAL FUNDS ACROSS CITIES

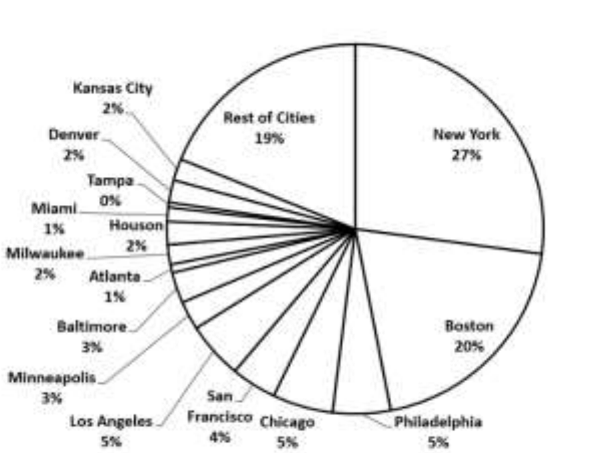
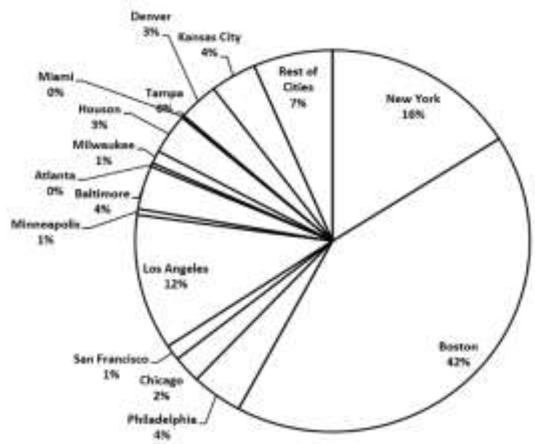


FIGURE IV
% OF ALL FUND ASSETS



There is another alternate interpretation of the close-to-zero word-of-mouth effects in Canadian mutual fund market when I introduce the market concentration structure into the conversation. According to the data obtained from the original study and as shown in Figure III and Figure IV, though New York and Boston are the two distinguishable large cities in terms of the number of funds and the fund assets managed, the overall distribution of the funds are more spread out compared to the current study (See Figure I and II).[4] Specifically, as the largest two cities in this regard, New York and Boston combined together have taken only 47% of the total funds in the United States. On the other hand, Toronto, as the largest financial center of the country, has 56% of the total mutual funds alone and over 61% of the total investment assets managed in town. Such a concentrated market could dramatically undermine the degree of word-of-mouth effects

[4] The original data is obtained from the original study and further edited for the purpose of comparing with the outcomes of the current thesis (Hong et al., 2005).

due to the lack of sub-markets diversity. In other words, since the majority of the funds are concentrated in Toronto, fund managers will, at some level, perceive Toronto market as Canada's national market. Therefore within one market, fund managers would tend to differentiate their portfolios from each other, just like product differentiation in goods markets. This product differentiation force goes against the same-city effects and in Toronto's case could dramatically reduce the perceived same-city effects value, which further lead to the negative value in word-of-mouth effects.

This concentrated market theory is also supported by the large value of different-city effects in Toronto. As I have stated above, Toronto is the dominating sub-market in Canada, and could have much larger impacts on the decisions of fund managers in other Canadian cities than vice versa. Specifically, the different-city effects in Toronto is 0.4006, a value even larger than the rest cities' different-city effects coefficients combined. This indicates the dominating role Toronto plays in the Canadian financial market. If my concentrate market theory is correct, I should expect to see the same reverse word-of-mouth effects in the dominating cities in other countries as well where the financial market is not spread out enough and has leading financial centers (e.g., London in United Kingdom). This could be one of the future study directions.

VII. Conclusion

In conclusion, the primary purpose of this study is to test the word-of-mouth effects in Canadian market based on the previous study, with modifications such as the new way to locate the mutual fund managers. As for the results, the study firstly confirmed the existence of herding behaviors among Canadian mutual fund managers. However, the close-to-zero key test value indicates a very small word-of-mouth effects when compared to the original study. In addition, the reverse word-of-mouth effects in Toronto appears as an unexpected result. The results could be explained by bringing the factor of market concentration into the consideration, and one possible explanation is the concentrated nature of the Canadian financial market.

If the theory regarding the role market structure plays in product differentiation and word-of-mouth effects holds true, we should expect to see similar results in the countries where financial markets are also highly concentrated (e.g., London as the financial center of the United Kingdom). In addition, another interesting future research direction is to combine the United States and Canada together as one economy, and see the dynamics of word-of-mouth effects as well as product differentiation degrees among different North American cities.

VIII. Appendix A

Detailed Fund Locations

BMO DIV FUND	Toronto, Ontario	Fund Profile	Lutz Zeitler & Philip Harrington
BMO EQUITY FUND	Toronto, Ontario	Fund Profile & LinkedIn	Jeffrey Bradacs & Jordan Luckock
BMO SPECIAL EQUITY FUND	Toronto, Ontario	Fund Profile & LinkedIn	Tyler Hewlett & David Taylor
BMO RESOURCE FUND	Toronto, Ontario	Fund Profile & LinkedIn	Mark Serdan & Kyle Hunter
BMO NORTH AMERICAN DIV F	Toronto, Ontario	Fund Profile & LinkedIn	
BMO NAFTA ADVANTAGE FUND	Toronto, Ontario	Fund Profile & LinkedIn	Fund name was changed from BMO BAFTA Advantage Fund to BMO North American Dividend Fund
TALVEST SML CAPITAL CNDN	Toronto, Ontario	Fund Profile & News	
ALTAMIRA DIV FUND	Montreal, Quebec	Fund Profile & LinkedIn	Now named National Bank Dividend Income Fund Inc. (Jean-Guy Desjardins)
CLARICA CNDN DIVERSIFIED	Toronto, Ontario	Fund Website	Michael J. Killeen
LEITH WHEELER CANADIAN E	Vancouver, British Columbia	Financial Reporting & Linkedin	Jim Gilliland
LEITH WHEELER U.S. EQUIT	Vancouver, British Columbia	Financial Reporting & Linkedin	Jim Gilliland
LEITH WHEELER BALANCED F	Vancouver, British Columbia	Financial Reporting & Linkedin	Jim Gilliland (Individual Manager not identified but highly likely located in Vancouver)
CI EXPLORER FUND	Waterloo, Ontario	Financial Post, Linkedin & News	Moved to Synergy which is acqired by CI Investment
TD DIV INCOME FUND	Toronto, Ontario	Fund Profile & LinkedIn	Geoff Wilson
DESJARDINS DIV FUND	Montreal, Quebec	Fund Financial Data Page	

DESJARDINS CNDN SML CAP	Montreal, Quebec	Fund Financial Data Page	
NATIONAL BK BALANCED DIV	Montreal, Quebec	Sedar, Fund Profile & Linkedin	Marie Brault
NATIONAL BK SMALL CAPTN	Montreal, Quebec	Fund Profile & LinkedIn	Marc Lecavalier
ELLIOTT & PAGE CANADIAN	Toronto, Ontario	Sedar	Clive Anderson
MIDDLEFIELD GROWTH FUND	Toronto, Ontario	Company Website & Businessweek	Andy Nasr & Matt Watson
QUEBEC PROFESSIONALS CND	Montreal, Quebec	Sedar	Jean-François Levasseur
QUEBEC PROFESSIONALS CND	Toronto	Fund fact sheet	Lisa Myers, Norman Boersma, James Harper
MAWER CDN BAL RET SAVING	Calgary, Alberta	Fund Profile & personal profile	Greg Peterson
MAWER CNDN EQUITY FUND	Calgary, Alberta	Fund Profile & personal profile	Jim Hall & Vijay Viswanathan
MAWER NEW CANADA FUND	Calgary, Alberta	Fund Profile & personal profile	Martin Ferguson & Jeff Mo
MAWER CNDN DIVERSIFIED I	Calgary, Alberta	Fund Profile & personal profile	Craig Senyk
MAWER U.S. EQUITY FUND	Calgary, Alberta	Fund Profile & personal profile	Grayson Witcher
NORTHWEST SPECIALTY EQUI	Toronto, Ontario	Businessweek profile	Christian Godin & Wayne Deans
AIM GBL HEALTH SCIENCES	Toronto, Ontario	Fund subaccount	Michael Yallen, Sunaina Murphy, & Derek Taner
RENAISSANCE CNDN CORE VA	Toronto, Ontario	Fund Portfolio, manager bio & Linkedin	Colum Mckinley & David Winters
BEUTEL GOODMAN BALANCED	Toronto, Ontario	Morningstar & Linkedin	Rui Cardoso, etc.
BEUTEL GOODMAN	Toronto, Ontario	Morningstar & Linkedin	Steve Arpin

CANADIAN			
BEUTEL GOODMAN SML CAPIT	Toronto, Ontario	Morningstar & Linkedin	Steve Arpin
BEUTEL GOODMAN AMERICAN	Toronto, Ontario	Morningstar & Linkedin	Steve Arpin
ETHICAL SPECIAL EQUITY F	Toronto, Ontario	Google Finance	Joe Jugovic, Darren Dansereau, & Ian Cooke
INVESTORS TACT ASSET ALL	Winnipeg, Manitoba	Sedar	Douglas Jones
UNITED-CANADIAN EQ VALU	Winnipeg, Manitoba	Morningstar & Linkedin	Daniel Dubis, Alec McIsaac, & Aaron Clark
ASSANTE CANADIAN EQ VALU	Winnipeg, Manitoba	Morningstar & Linkedin	Same Fund
HSBC DIV INCOME FUND	Toronto, Ontario		Fund Family headquater
HSBC CNDN SML CAP EQ POO	Vancouver, British Columbia	Fund facts & fund list	
INTEGRA BALANCED FUND	Toronto, Ontario	bloomberg & Company website	Craig Honey
STANDARD LIFE CNDN DIV G	Montreal, Quebec	bloomberg & Linkedin	Peter Hill
STANDARD LIFE U.S. EQUIT	Toronto, Ontario	bloomberg & Company website	Stephen Clark, Brian Fox, & Glen Petraglia
STANDARD LIFE CNDN SML C	Montreal. Quebec	bloomberg & Company website	Mark Pugsley
SIGNATURE CANADIAN INCOM	Toronto, Ontario	Sedar	Chris Von Boetticher (CI - Terminated funds)
AGF AMERICAN GROWTH CLAS	Toronto, Ontario	Company Website	Tony Genua
AGF CANADIAN	Toronto,	Company Website &	Stephen Bonnyman

RESOURCES F	Ontario	Linkedin	
AGF SPECIAL U.S. CLASS F	Toronto, Ontario	Company Website	Merged into AGF American Growth Class in 2009 (Tony Genua)
AGF CANADIAN BALANCED FU	Toronto, Ontario	Company Website & Linkedin	Michael White
AIC ADVANTAGE FUND	Toronto, Ontario	Sedar & Company website	Currently Manulife Advantage Fund (Jennifer Mercanti)
TALVEST DIV FUND	Montreal. Quebec	Linkedin & Yahoo Finance	Domenic Monteferrante
TRIMARK DISCOVERY FUND	Toronto, Ontario	bloomberg	Heather Peirce & Jim Young
ALTAMIRA BALANCED FUND	Toronto, Ontario	bloomberg VS. Sedar	
ALTAMIRA CAPITAL GR FD L	Montreal, Quebec	bloomberg vs. Sedar	
ALTAMIRA EQUITY FUND	Montreal, Quebec	Company Website & Linkedin	Jean-Philippe Choquette, Jean-François Gagnon, &Daniel Lavoie
ALTAMIRA GROWTH & INCOME	Montreal, Quebec	Company website	
ALTAMIRA CANADIAN VALUE	Montreal, Quebec	Sedar	François Bourassa
ALTAMIRA RESOURCE FUND	Montreal, Quebec	Fund profile	Jean-Philippe Choquette, Frank Zwarts, & Jean-François Gagnon
ALTAMIRA U.S. LARGER CO	Montreal, Quebec	Fund profile	Merged with Select American Fund and renamed Altamira Equity Fund
AGF EMER MRKT VALUE FUND	Toronto, Ontario	Company Website & Linkedin	Stephen Way & Alpha Ba
COTE 100 U.S.	Montreal. Quebec	Sedar	1543, Montarville St-Bruno, Qc, J3V 3T8
COTE 100 PREMIER	Montreal, Quebec	Sedar	
COTE 100 EXP FUND	Montreal, Quebec	Sedar	

AGF CANADIAN SMALL CAP F	Vancouver, British Columbia	Company Website	Greg Bay & Michael Fricker
AGF GLOBAL EQUITY CLASS	Toronto, Ontario	Funds profile	Stephen Way
SIGNATURE DIV FUND	Toronto, Ontario	Funds profile & Linkedin	Jogn Hadwen, Eric Bushell, & John Shaw
TALVEST MILLENNIUM NEXT	Toronto, Ontario	morningstar & Sedar	Barry A. Morrison
NORTHWEST SPECIALTY QUEB	Montreal, Quebec	bloomberg	
NORTHWEST SPECIALTY GR F	Montreal, Quebec	bloomberg	
AIC ADVANTAGE FUND II	Toronto, Ontario	Sedar	Jennifer Mercanti (Terminated)
HSBC EMER MRKT FUND	Vancouver, British Columbia	bloomberg	Terence Mahoney
RENAISSANCE CNDN SML CAP	Toronto, Ontario	Company Website	Jennifer Law
TALVEST CANADIAN EQ GROW	Montreal, Quebec	Morning star & Company Website	Denis Ouellet
IG BEUTEL GOODMAN CNDN E	Winnipeg, Manitoba	Investors Group & Fund fact	Mark Thomson
INVESTORS CNDN NAT RESOU	Toronto, Ontario	Morning star, Company Website, & Linkedin	Benoit Gervais
INVESTORS CANADIAN SML C	Winnipeg, Manitoba	Zoominfo & Morning star	Mark Rarog
INVESTORS U.S. OPPS FD	Montreal. Quebec	Fund Profile & Linkedin	Valerie Cecchini
IG AGF CANADIAN GROWTH F	Toronto, Ontario	Businessweek & company website	Peter Frost

DYNAMIC FOCUS PLUS SML B	Toronto, Ontario	Company website	Fund Family headquater
CLARINGTON CNDN EQUITY F	Toronto, Ontario	Linkedin & company website	Douglas Kee & Ryan Bushell
CLARINGTON CNDN SMALL CA	Toronto, Ontario	Morningstar	Leigh Pullen, Joe Jugovic, & Ian Cooke
CLARINGTON U.S. GROWTH F	Toronto, Ontario	Fund profile & Sedar	Pierre Trottier
SIGNATURE CANADIAN RESOU	Toronto, Ontario	Fund Profile & Linkedin	Scott Vali
CI ALPINE GROWTH EQUITY	Toronto, Ontario	Linkedin & bloomberg	Ted Whitehead
CLARICA ALPINE GROWTH EQ	Toronto, Ontario	Linkedin & bloomberg	Ted Whitehead
CLARICA SUMMIT CANADIAN	Toronto, Ontario	Sedar & Linkedin	Michael Killeen
CLARICA SUMMIT DIV GROWT	Toronto, Ontario	Sedar & Linkedin	Michael Killeen
SCOTIA AMERICAN STOCK IN	Toronto, Ontario	Fund profile & linkedin	
SCOTIA CANADIAN STOCK IN	Toronto, Ontario	Fund profile & linkedin	
MAVRIX CNDN STRATEGIC EQ	Toronto, Ontario	Businessweek & Funds profiles	
MAVRIX CANADA FUND	Toronto, Ontario	Sedar	
MAVRIX GROWTH FUND	Toronto, Ontario	Businessweek & Funds profiles	
CI CNDN INVESTMENT FUND	Winnipeg, Manitoba	Company website	Daniel Dubis, Alec McIsaac, & Aaron Clark

CI CNDN ASSET ALLOCATION	Toronto, Ontario	Google Finance & company website	Robert Swanson (Bob)
CANADIAN GEN INVTS LIMIT	Toronto, Ontario	Company website & Google finance	The company is the fund (Morgan Meighen)
CIBC BALANCED FUND	Toronto, Ontario	Bloomberg	Based on office phone (cannot locate manager)
CIBC CAPITAL APPRECIATIO	Toronto, Ontario	Company profile	
CIBC DIV FUND	Montreal, Quebec	CFA & Global and Mail	CIBC DIVIDEND GROWTH / INCOME FUND?
MACKENZIE CUNDILL CDN SE	Vancouver, British Columbia	Company website & linkedin	Larence Chin & Ratul Kapur
DYNAMIC DIV FUND	Montreal, Quebec	Company website	Domenic Monteferrante
DYNAMIC DIV VALUE FUND	Montreal, Quebec	Company website	Bruce Ebnother & Jonathan Mondillo
DYNAMIC VALUE FUND OF CA	Toronto, Ontario	Fund Portfolio	Cecilia Mo
ETHICAL BALANCED FUND	Toronto, Ontario	Company website & Global & Mail	OtterWood capital management in
ETHICAL GROWTH FUND	Toronto, Ontario	Sedar & Morningstar	Jogn Mountain
TD BALANCED FUND	Toronto, Ontario	Company website & linkedin	Damian Fernandes
TD NORTH AMERICAN DIV FU	Toronto, Ontario	Linkedin & Bloomberg	Rhonda Dalley & David Sykes
TD U.S. EQUITY FUND	Toronto, Ontario	Linkedin & Bloomberg	Rhonda Dalley & David Sykes
FERIQUE EQUITY FUND	Montreal. Quebec	Bloomberg, Phone area number	Jacques Chartrand & Rajiv Rai Silgardo
FERIQUE BALANCED FUND	Montreal, Quebec	Bloomberg, Phone area number & Linkedin	Karl Gauvin & Benoit Durocher
RENAISSANCE CNDN BALANCE	Montreal, Quebec	Company Website & Linkedin	Luc De La Durantaye
RENAISSANCE	Toronto,	Compnay website &	Gary Chapman, Gary Baker, & David Picton

CANADIAN GRO	Ontario	Fund profile	
BMO ASSET ALLOCATION FUN	Toronto, Ontario	Company website & linkedin	Paul Taylor, Jeffrey Bradacs, & Jordan Luckock
DESJARDINS CNDN BALANCED	Montreal, Quebec	Company website & Fund profile	Now named Desjardins Tactical Balanced Fund
DESJARDINS CANADIAN EQUI	Montreal, Quebec	Company website & Fund profile	Canadian Equity Funds
DESJARDINS ENVIRONNMENT	Montreal, Quebec	Company website & Fund profile	Desjardins Environment Fund
GBC CANADIAN GROWTH FUND	Montreal, Quebec	Sedar & Fund Profile	Michael P. McLaughlin
GBC NORTH AMERICAN GROWT	Montreal, Quebec	Yelp	
AGF CANADIAN VALUE FUND	Toronto, Ontario	Fundlibrary & Morningstar	Terry Chong
TD BALANCED INCOME FUND	Toronto, Ontario	Morningstar & Linkedin	Geoff Wilson
TD CANADIAN EQUITY FUND	Toronto, Ontario	Company website, Fund profile, & Linkedin	Justin Flowerday
TD CANADIAN VALUE FUND	Toronto, Ontario	CFA directory & Morningstar	Jennifer Nowski
TD CANADIAN BLUE CHIP EQ	Toronto, Ontario	Morningstar	Justin Flowerday
TD BALANCED GROWTH FUND	Toronto, Ontario	Company website & Fund profile	Geoff Wilson
TD DIV GROWTH FUND	Toronto, Ontario	CFA directory & Morningstar	Michael Lough
TD RESOURCE FUND	Toronto, Ontario	CFA directory & Fund Profile	Thomas George
GGOF ENTERPRISE FUND	Calgary, Alberta	CFA directory & Fund Profile	Martin Ferguson (Now named BMO Guardian Enterprise Fund)
GGOF CANADIAN BALANCED F	Toronto, Ontario	CFA directory & Morningstar	Stephen Kearns

HSBC CANADIAN BALANCED F	Vancouver, British Columbia	CFA Directory & Bloomberg	Stephen Machinnes
HSBC EQUITY FUND	Vancouver, British Columbia	Compnay website, Fund profile, &Linkedin	Neelotpal Saha
INVESTORS CANADIAN EQUIT	Montreal, Quebec	CFA directory, company website, & linkedin	Keith Johansson
INVESTORS MUTUAL OF CANA	Toronto, Ontario	Company website, Fund profile, & Linkedin	Martin Downie & Rounak Langhe
INVESTORS NORTH AMERICAN	Montreal, Quebec	Company website & linkedin	Keith Johansson
INVESTORS CNDN LG CAP VA	Toronto, Ontario	Fund profile & CFA Directory	Martin Downie
INVESTORS U.S. LARGE CAP	Montreal, Quebec	Fund profile & CFA Directory	Mark Chaput
INVESTORS SUMMA FUND	Winnipeg, Manitoba	Fund profile & CFA Directory	Paul Hancock
INVESTORS U.S. LG CAP VA	Montreal, Quebec	Fund profile & CFA Directory	Mark Chaput
MACKENZIE MAXXUM DIV GRO	Toronto, Ontario	bloomberg & Linkedin	Darren Mckiernan & Hovig Moushian
MACKENZIE SENTINEL INCOM	Toronto, Ontario	globeandmail & CFA Directory	Steve Locke
NATIONAL BK RETIRE BALAN	Montreal, Quebec	Sedar & Bloomberg	
NATIONAL BK CANADIAN EQU	Montreal, Quebec	CFA directory, company website, & linkedin	Patrick Potvin, Patrice Filliatrault, & Michael Brown
INVESTORS DIV FUND	Toronto, Ontario	Fund profile	Dom Grestoni & Downie
DYNAMIC CNDN DIV FUND LT	Toronto, Ontario	CFA directory & Fund Profile	David Fingold & Don Simpson

MD DIV FUND	Ottawa, Ontario	Fund Website	
MD BALANCED FUND	Ottawa, Ontario	Fund Website	
MD SELECT FUND	Ottawa, Ontario	Fund Website	
MACKENZIE IVY ENTERPRISE	Toronto, Ontario	Bloomburg & Morningstar	
MCLEAN BUDDEN AMERICAN E	Toronto, Ontario	Fund Profile	Now under Sun Life Global Investment
MCLEAN BUDDEN BALANCED G	Toronto, Ontario	Fund Profile	Now under Sun Life Global Investment
MCLEAN BUDDEN CNDN EQ GR	Toronto, Ontario	Fund Profile	Now under Sun Life Global Investment
SCOTIA TOTAL RETURN FUND	Vancouver, British Columbia	Company website & CFA	Now named Socita Canadian Tactical Allocation Fund
SCOTIA CANADIAN DIV FUND	Toronto, Ontario	Fund Profile & Linkedin	Jason Gibbs
SCOTIA CANADIAN GROWTH F	Toronto, Ontario	Fund profile & CFA Directory	Alexander Lane
CLARICA CANADIAN BLUE CH	Toronto, Ontario	Morning star & CFA	Eric Bushell
CLARICA CNDN SML/MID CAP	Toronto, Ontario	Morning star & Linkedin	Dariusz Niececki
CI CNDN SMALL/MID CAP FU	Toronto, Ontario	Morning star & Linkedin	Dariusz Niececki
PHILLIPS HAGER & NORTH B	Vancouver, British Columbia	Company website	Joined RBC
PHILLIPS HAGER	Vancouver,	Company website	Joined RBC

& NORTH D	British Columbia		
PHILLIPS HAGER&NORTH CDN	Vancouver, British Columbia	Company website	Joined RBC
PHILLIPS HAGER&NORTH U.S	Vancouver, British Columbia	Company website	Joined RBC
MACKENZIE MAXXUM DIV FUN	Toronto, Ontario	Company website & CFA	Darren Mckiernan & Hovig Moushian
RBC BALANCED FUND	Toronto, Ontario	Fund Bio & CFA	Daniel E. Chornous
RBC NORTH AMERICAN GROWT	Toronto, Ontario	Fund Bio & CFA	Ray Mawhinney, Warner Sulz, & Marcello Montanari
RBC CANADIAN GROWTH FUND	Toronto, Ontario	Fund Bio & CFA	Ray Mawhinney, Warner Sulz, & Marcello Montanari
RBC ENERGY FUND	Toronto, Ontario	Fund Bio & CFA	Chris Beer & Brahm Spilfogel
RBC GBL ENERGY FUND	Toronto, Ontario	Fund Bio & CFA	Chris Beer & Brahm Spilfogel
SAXON BALANCED FUND	Toronto, Ontario	Fund Library	Steve Locke & Suzann Pennington
SAXON STOCK FUND	Toronto, Ontario	Fund Library & Linkedin	Suzann Pennington
SAXON SMALL CAPITAL FUND	Toronto, Ontario	Company website & CFA	Scott Carscallen & Dongwei Ye
SAXON WORLD GROWTH FUND	Toronto, Ontario	Fund report & CFA	renamed Mackenzie Cundill World Fund (Robert Tattersall)
SCEPTRE BALANCED GROWTH	Montreal, Quebec	Fund profile & CFA Directory	renamed Fiera Capital Balanced Fund (François Bourdon)
SCEPTRE EQUITY GROWTH FU	Toronto, Ontario	Fund website & CFA	Michael Chan
STANDARD LIFE	Montreal,	Fund profile	Contact info

BALANCED F	Quebec		
STANDARD LIFE CANADIAN E	Montreal, Quebec	Fund profile	
TALVEST CNDN ASSET ALLOC	Toronto, Ontario	Fund website	
TALVEST CANADIAN EQ VALU	Toronto, Ontario	Morningstar & CFA	Gaelen Morphet
TALVEST GBL SCIENCE & TE	Montreal, Quebec	Company website & CFA	Named Renaissance Global Science & Technology Fund (Mark Lin)
TEMPLETON BALANCED FUND	Toronto, Ontario	Company website & CFA	Norm J. Boersma, James Harper
TEMPLETON GBL SMALLER CO	Toronto, Ontario	Company website & CFA	David Tuttle & Heather Waddell
THIRD CNDN GEN INVT TRUS	Toronto, Ontario	company website	Vanessa Morgan & Frank Fuernkranz
TRADEX EQUITY FUND LIMIT	Vancouver, British Columbia	Company website & Fund profile	
TRIMARK CANADIAN FUND	Toronto, Ontario	Company website	Ian Hardacre, Alan Mannik, Eric Mencke, & Jason Whiting
TRIMARK INCOME GROWTH FU	Toronto, Ontario	Company website	Jennifer Hartviksen, Alan Mannik, Albert Ngo, & Mark Uptigrove
TRIMARK CANADIAN ENDEAVO	Toronto, Ontario	Company website	Mark Uptigrove & Clayton Zacharias
TRIMARK SEL BALANCED FUN	Toronto, Ontario	Company website	Ian Hardacre, Jennifer Hartviksen, Alan Mannik, & Eric Mencke
AGF CNDN TACT ASSET ALLO	Toronto, Ontario	Company website & CFA	Brian Madden & Michael White
AGF CANADIAN STOCK FUND	Toronto, Ontario	Company website & CFA	Caterina Prato & Peter Frost
AGF CANADIAN LARGE CAP D	Vancouver, British Columbia	Company website & CFA	Phillip Cotterill & Gary Baker
CI CNDN SMALL	Toronto,	Company website &	Keith Lam, Timothy Lazaris, & Dariusz Nieciecki

CAP FUND	Ontario	CFA	

Appendix B

STATA Codes

```
*generate marketvalue of stock
gen marketvalue= SharesHeldatEndofQtr* SharePriceasofFDATE
*replace missing value
replace marketvalue=0 if marketvalue >= .
*compute total marketvalue
sort Time Fund StockNumber
by Time Fund: egen totalmarketvalue=total (marketvalue)
*compuate fraction
gen h= marketvalue/ totalmarketvalue
*compute delta fraction
```

```
sort Fund StockNumber Time
gen delta_h=h[_n]-h[_n-1] if Time!=1
*Hdiff_1
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_1=mean(h) if Location==1
*Hdiff_2
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_2=mean(h) if Location==2
*Hdiff_3
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_3=mean(h) if Location==3
*Hdiff_4
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_4=mean(h) if Location==4
*Hdiff_5
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_5=mean(h) if Location==5
*Hdiff_6
sort Time StockNumber Fund
by Time StockNumber: egen Hdiff_6=mean(h) if Location==6
*Hsame_1
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_1=(Hdiff_1*91-h)/90 if Location==1
*Hsame_2
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_2=(Hdiff_2*41-h)/40 if Location==2
*Hsame_3
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_3=(Hdiff_3*16-h)/15 if Location==3
*Hsame_4
```

```
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_4=(Hdiff_4*5-h)/4 if Location==4
*Hsame_5
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_5=(Hdiff_5*6-h)/5 if Location==5
*Hsame_6
sort Time StockNumber Fund
by Time StockNumber: gen Hsame_6=(Hdiff_6*3-h)/2 if Location==6
*replacing missing values of Hdiff_c
*e.g., c=1
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_1= Hdiff_1[_n-1] if Hdiff_1 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hdiff_1= Hdiff_1[_n-1] if Hdiff_1 >= .
*for the rest
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_2= Hdiff_2[_n-1] if Hdiff_2 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hdiff_2= Hdiff_2[_n-1] if Hdiff_2 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_3= Hdiff_3[_n-1] if Hdiff_3 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hdiff_3= Hdiff_3[_n-1] if Hdiff_3 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_4= Hdiff_4[_n-1] if Hdiff_4 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hdiff_4= Hdiff_4[_n-1] if Hdiff_4 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_5= Hdiff_5[_n-1] if Hdiff_5 >= .
gsort Time StockNumber -Fund
```

```
quietly by Time StockNumber: replace Hdiff_5= Hdiff_5[_n-1] if Hdiff_5 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hdiff_6= Hdiff_6[_n-1] if Hdiff_6 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hdiff_6= Hdiff_6[_n-1] if Hdiff_6 >= .
*replacing missing values of Hsame_c
*e.g., c=1
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_1= Hsame_1[_n-1] if Hsame_1 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_1= Hsame_1[_n-1] if Hsame_1 >= .
*for the rest
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_2= Hsame_2[_n-1] if Hsame_2 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_2= Hsame_2[_n-1] if Hsame_2 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_3= Hsame_3[_n-1] if Hsame_3 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_3= Hsame_3[_n-1] if Hsame_3 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_4= Hsame_4[_n-1] if Hsame_4 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_4= Hsame_4[_n-1] if Hsame_4 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_5= Hsame_5[_n-1] if Hsame_5 >= .
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_5= Hsame_5[_n-1] if Hsame_5 >= .
gsort Time StockNumber Fund
quietly by Time StockNumber: replace Hsame_6= Hsame_6[_n-1] if Hsame_6 >= .
```

```
gsort Time StockNumber -Fund
quietly by Time StockNumber: replace Hsame_6= Hsame_6[_n-1] if Hsame_6 >= .
*compute delta Hdiff_c
sort Fund StockNumber Time
gen deltaHdiff_1=Hdiff_1[_n]-Hdiff_1[_n-1] if Time!=1
gen deltaHdiff_2=Hdiff_2[_n]-Hdiff_2[_n-1] if Time!=1
gen deltaHdiff_3=Hdiff_3[_n]-Hdiff_3[_n-1] if Time!=1
gen deltaHdiff_4=Hdiff_4[_n]-Hdiff_4[_n-1] if Time!=1
gen deltaHdiff_5=Hdiff_5[_n]-Hdiff_5[_n-1] if Time!=1
gen deltaHdiff_6=Hdiff_6[_n]-Hdiff_6[_n-1] if Time!=1
*compute delta Hsame_c
sort Fund StockNumber Time
gen deltaHsame_1=Hsame_1[_n]-Hsame_1[_n-1] if Time!=1
gen deltaHsame_2=Hsame_2[_n]-Hsame_2[_n-1] if Time!=1
gen deltaHsame_3=Hsame_3[_n]-Hsame_3[_n-1] if Time!=1
gen deltaHsame_4=Hsame_4[_n]-Hsame_4[_n-1] if Time!=1
gen deltaHsame_5=Hsame_5[_n]-Hsame_5[_n-1] if Time!=1
gen deltaHsame_6=Hsame_6[_n]-Hsame_6[_n-1] if Time!=1
*generate regressors for same city effect
gen A=deltaHsame_1*Toronto
gen B=deltaHsame_2*Montreal
gen C=deltaHsame_3*Vancouver
gen D=deltaHsame_4*Calgary
gen E=deltaHsame_5*Winnipeg
gen F=deltaHsame_6*Ottawa
*generate regressors for diff city effect
gen Ax=deltaHdiff_1*Torontox
gen Bx=deltaHdiff_2*Montrealx
gen Cx=deltaHdiff_3*Vancouverx
gen Dx=deltaHdiff_4*Calgaryx
```

```
gen Ex=deltaHdiff_5*Winnipegx
gen Fx=deltaHdiff_6*Calgaryx
*final regress
regress delta_h A B C D E F Ax Bx Cx Dx Ex Fx
*difference key test
lincom 91/162*A+41/162*B+16/162*C+5/162*D+6/162*E+3/162*F-91/162*Ax-41/162*Bx-16/162*Cx-5/162*Dx-6/162*Ex-3/162*Fx
```

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