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A Closer Look at Firm--Group "Closeness"

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A CLOSER LOOK AT FIRM–GROUP "CLOSENESS"

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics at the University of Kentucky

By

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ABSTRACT OF DISSERTATION

A CLOSER LOOK AT FIRM–GROUP "CLOSENESS"

This study offers a more formal examination of firm–group closeness than offered previously in the literature. Studies usually implicitly assume a vague and arbitrary definition that close firms are firms which share similar characteristics. This study specifies those "similar" characteristics that "close" firms share. Accordingly, the contributions of this study are six–fold. First, a more explicit definition of firm–group closeness in an accounting information sense is given and a discussion of the challenges in forming a universal definition is made. Second, two new measures of firm–group closeness are rigorously developed, simulated and discussed. Through simulation I show that both measures capture firm–group closeness as conceptualized in the paper since groups of firms one would expect ex ante to not be as close rank lower on the closeness measures than those firms one would expect ex ante to be closer. Third, I evaluate the two most widely used industrial classification schemes (SIC & GIC) in regards to their ability to group "comparable" firms. I find that both schemes group firms into industries exhibiting smaller accounting closeness than most users realize. Fourth, I devise a trading strategy using information provided by the two measures which generates statistically significantly positive abnormal returns. Fifth, I contribute to the contagion literature, most notably Gleason et al. 2008, by showing that a contagion effect does not just exist as a result of negative news but also persists in the presence of positive news. Finally, I find evidence that contagion effects don't exist in all industries. Specifically, I find that the magnitude of the industry–specific contagion effect is a function of the closeness of that particular industry. That is, when an industry exhibits reasonably high closeness a contagion effect is present but when an industry exhibits closeness not statistically different from zero, no contagion effect is observed.

KEYWORDS: Firm–group Accounting Closeness, Financial Statement Comparability, Industrial Classification, Contagion Effects, Information Transfer

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1.1 Introduction

Determining which groups of firms are similar and which ones aren’t has interested researchers for a long time. Industrial classification schemes have been devised to help partition firms into groups that are similar on some dimension (usually primary revenue generating business activity, or market perception). Researchers then have examined the degree to which these schemes group similar firms. The benefits of developing ways to group similar firms seem to fall into two categories. The first category I would classify as methodological and the second theoretical.

From a methodological point of view, researchers often are looking for an effect of variable X on variable Y across companies holding other (often unobservable) variables constant. One way to do this is to group firms who are similar (hypothetically on many of these unobservable characteristics) so that the researcher can add a group similarity variable as a control in order that the explanatory power of X on Y is not confounded with the explanatory power of other variables across these firms on Y. Current industrial classification systems seek to group similar firms and researchers take advantage of these grouping schemes to control for any potential group–similar variables that may also have an affect on Y. The implicit assumption of course being that the firms in a given industry are similar in regards to these unobservable characteristics.

From a quasi–theoretical point of view, with fundamental analysis, analysts and investors seek to predict fundamental accounting measures of performance (i.e. earnings and cash flows) and it is helpful to have similar firms to look to as guidance in predicting other firms’ variables. From a pure theoretical point of view, it would seem interesting to me that we define what it means for a group of firms to be similar (i.e. which dimensions and from which users’ perspective we care about) and then develop a method to determine, if given a group of firms, the extent of similarity that exists within that group. Current industrial classification schemes seek to do this to some extent but the classifications mostly ignore fundamentals. For example, two firms could have the same revenue–generating business activity and therefore be included in the same GICS or SIC industry but, because of firm–level characteristics, have vastly different fundamental earnings processes (i.e. one firm outsources its' business but the other doesn't) and hence uncorrelated fundamentals over time. I am not aware of a study to–date which has examined the degree to which industrial classification schemes group firms whose fundamentals move together over time.

Another dimension used to group firms is market perception. A few studies have evaluated the industrial classification schemes in regards to their ability to group firms whose share prices move similarly. I would argue that this also potentially could group firms which do not have correlated underlying fundamentals. For this to be true one must relax the assumption that share price is exactly equal to the sum of discounted expected future earnings. In fact, a firm's share price is not only a function of fundamentals but also of market noise or bias[1]. Consider the following example. Suppose we have two firms, A and B which have the same revenue generating business activity. Firm A is an industry leader (i.e. Apple) while firm B is a follower. Suppose firm B has a good year greatly exceeding analysts' forecasts while firm A has a mediocre year but announces that they will come out with a highly anticipated product in two years (i.e. Apple announcing the launch of the iphone). Suppose the market increases its' price for firm A similarly to firm B (percentage–wise). The reason the market does this for firm B is because fundamentals were higher than expected. The reason the market does this for firm A is because the firm has been touted as an historically high performer and the market won't let one bad year affect its' favorable bias towards firm A. The market revises future expected earnings upward although current earnings just meets expectations due to the expected future potential related to the new product. The market may care more about the "coolness" of the new product than the underlying fundamentals of the firm and price the firm accordingly. Thus in this year underlying fundamentals are uncorrelated (B's high earnings are not associated with mediocre earnings for A) but share prices

[1] Lee 2001 provides an intuitive argument for why this is true.

move similarly for firms A and B.

The firm is the economic entity about which accountants, investors, analysts, and the rest of the market cares. In other fields the unit or entity of interest varies but the relationships among these units have been exhaustively studied . For example, in Psychology the unit of study is the individual and ample research regarding the degree of similarity among individuals has been conducted. Similar scores on psychometric tests and personality classification schemes (i.e. Myers–Briggs and the Five Factor personality test) have been devised in order to group personality–similar individuals.

In Genetics the unit of study is the gene and extensive research has been done regarding genetic distance (see for example, Nei (1972), Nei (1978), Reynolds et al. (1983)) . Genetic distance is a measure of genetic similarity and can be a function of many factors. In its' simplest form genetic distance between two populations is the differences in the frequencies of a trait. That is, if 80% of the U.S. population is right handed while 85% of the Chinese population is right–handed then the genetic distance between the U.S. and China with respect to the trait of right–handedness is 5%. A weighted average of the genetic distance of several individual traits could then be computed and be a measure of overall genetic similarity.

Furthermore, in Mathematics the units of study are numbers and a major branch of study —Number Theory — within mathematics is concerned with the relationship among these units. For example, many different metrics have been devised to measure the degree of similarity (distance) between two points in space. The Euclidean distance metric is the most intuitive measure of distance between two points and is what one would obtain if they measured the distance between the points with a ruler. Other measures of distance have been devised however such as the Minkowski or "taxicab" metric, the Chebyshev metric and the Mahalanobis distance.

Finally, in Computer Science, and more specifically the subfield of Computer Forensics, "datum" (or pieces of data) are the unit of consideration. While computers are great at identifying identical datum, they often perform poorly when required to identify similar datum. Accordingly, research has been conducted to help computers recognize and report that strings of datum are similar even when these strings are not identical. Specifically, cryptographic hash functions have been devised which transform a string of datum into a fixed-size bit string. Given hash function $\mathcal{H}$ and two strings of datum (A & B) which are not identical, if $\mathcal{H}(A) == \mathcal{H}(B)^*$, then A and B are similar to each other with a high–degree of certainty ($*$) (Paar et al. 2010).

In Accounting however, there does not exist much research regarding the similarity of firms. This is a deficiency being that the conceptual framework, put forth by the FASB, identifies "comparability" as one of the four enhancing characteristics of accounting information[2]. Industrial classification schemes have been devised by non–academics with the exception of the Fama–French classification. Even their classification however starts with the SIC classification and further refines it based on firms' differential exposure to risk (i.e. high cap vs. low cap and high book/market vs. low book/market firms). Only a handful of studies have examined how well the current industrial classification schemes classify similar firms. Most of these studies examine the degree to which the classifications can predict share prices. The underlying assumption being that if share prices move similarly so too must the underlying fundamentals.

To my knowledge only one recent study (De Franco et al. [2011]) has attempted to define what it means for two or more firms to be close in an accounting information sense. The reason for this logically seems to be due to a couple of factors. First, the set of accounting information is not well-defined. That is, some people would consider element x (i.e. MD&A disclosures) to be in the set of accounting information while others would consider it a part of another set of information. Second, even if one assumes that the set is well-defined universally then there are many elements in this set and these elements are available to many different users at different times. For example, suppose we all agree on what constitutes the set of accounting information for any firm. That is, suppose we agree that the set of accounting information is defined as $I = \{c, d, e\}$. Next, suppose we have two firms A and B, each with this set of accounting information. Further, suppose that information source c is available to management only (e.g. a budget) before the

[2] A discussion of this is provided later when I define "closeness".

firm engages in its business for the period while information sources d and e are output information sources available to all interested users ex post (e.g. income statement and statement of cash flows). In this example the question of whether firms A and B are close in an accounting information sense is a tough one since I haven't specified which elements in the set of accounting information that closeness should be judged in light of and which users' perspective should be considered (i.e. internal or external information users). For example, suppose I decide that closeness is based on the degree of similarity of element c between firms. Also, suppose firms A and B have very similar elements d and e (i.e. very similar income statements and statements of cash flows) but vastly different elements c (i.e. different budgets). The dissimilarity in element c between firms A and B is not known by external investors since they do not observe the budget for either firm. Therefore, given the elements they can observe (d and e), they would classify the two firms as more similar than a manager — who can observe all three elements — would.

From this simple example one should see that there cannot be one overall definition of closeness. Any proposed definition must first begin with the assumption that the set of accounting information is well–defined and then must specify on which elements in this set closeness is based and which users' perspective is being considered.

In addition, a major challenge in defining closeness for a group of firms in an accounting information sense is the specification of the time frame considered. That is, firms could have similar accounting information sources available to them before engaging in their business for the period (e.g., similar budgets) but have uncorrelated outputs ex post (e.g., uncorrelated earnings or cash flows) due to uncorrelated transactions. Or alternatively, firms could have correlated earnings and cash flows with other firms over some time periods but not over others.

Prior studies usually implicitly assume a vague and arbitrary definition that close firms are firms which share similar characteristics. Stock returns have been the characteristic that studies tend to focus on. Specifically, stock return comovement (e.g., Lee et al. 2003, Chan et al. 2007) has been proposed as one measure of firm–group closeness. Prior research has analyzed stock return comovement under the different industry classification schemes to see if the classification schemes group stocks which are reasonably close. The prior studies also assess the relative explanatory power of each scheme regarding covariation in returns. In an economic information sense, stock return comovement does seem to be a reasonable measure of closeness. However, I would argue that stock return comovement may be a rather poor operationalization of closeness in an accounting information sense as returns are not only a function of accounting variables but also of investors expectations and "biases".

A more formal discussion is provided in this study than what has been offered previously regarding firm "closeness" which offers insight into the theory of the firm as an economic entity and how it relates to other economic entities (firms). Furthermore, in light of this discussion, current industrial classification schemes can be evaluated qualitatively as to how they group firms and quantitatively with the two measures developed in this study. Finally, a trading strategy can be developed which utilizes information contained in the measures to generate returns higher than expected.

The first measure of closeness introduced in this study measures the correlation in abnormal[3] earnings and abnormal cash flows[4] among a group of firms over time. Correlation in earnings and other ex post accounting variables was examined in Ball and Brown (1967) and stock return comovements have also been examined in prior literature but abnormal earnings or abnormal cash flow correlation has never been measured in the literature. One benefit of using abnormal earnings and cash flows over stock returns to capture accounting closeness is that these variables are more a function of fundamentals than are stock returns. Stock prices are functions of investor response to supply and demand in the marketplace. The supply and demand for shares is, of course, a function of the underlying accounting fundamentals but also is a function of investor noise and/or bias. Prices (and thus returns) can change sometimes when the expected underlying

[3]Abnormal simply implies actual less expected with expected earnings and cash flows derived from a simple random walk model as discussed later.

[4]Since the measures in this study only include "profitability" variables, one could also include variables from other dimensions describing the firm. For example, variables from the liquidity, activity and leverage dimensions of the firm could be included thereby forming a multidimensional measure.

fundamentals do not (see Lee et al. 2001 for an intuitive argument for why this is true). Unexpected earnings however cannot change unless either actual earnings change and/or expected earnings change.

The second measure of closeness is the average determinant of the abnormal earnings and abnormal cash flow correlation matrices between each pair of firms in a group of firms. The determinant is a mathematical measure of the volume of a figure represented by the row vectors of a square matrix. The closer the determinant is to zero, the closer the rows are correlated with each other and thus the smaller the angle between each of the row vectors. A zero determinant implies perfect correlation between each of the rows and thus each of the row vectors lie on top of each other giving zero–volume. The determinant is thus an intuitive measure of closeness of the row vectors[5].

When developing a measure for closeness it is essential to ensure that the measure adequately captures the desired construct. Specifically, in this study, the Feltham, Ohlson (1996) earnings model is simulated. I simulate the model for 10 groups of 100 firms. Model parameters, shock distributions and mean and variance of shocks are equal within–groups[6] while parameters and shock variances vary across groups. This should ensure within–group correlation in abnormal earnings and cash flows ex post and between–group differences in correlation of abnormal earnings and cash flows. Thus, the closeness measures can be judged against this backdrop. Differences between groups in the closeness measures should be observed since each group has a different threshhold of randomness in its' earnings process (i.e., different second moment for each groups' shock distribution). Specifically, a trend of decreasing within–group closeness should be observed as variances of shocks increase since the firms within each group are the same ex ante in every other respect and the less deterministic the model is made (i.e., increasing the variance of the shocks), the lower the within–group closeness should be.

The contributions of this study are six–fold. The first (Chapter 1) is a more explicit definition of firm closeness from a more fundamental accounting information perspective

[5] See Appendix B

[6] Within–group, the firms' accounting functions are identical.

and a discussion of the challenges in forming a universal definition. The second (Chapter 1) is a rigorous development, discussion and simulation of two new measures of firm–group closeness. Through simulation, I ensure that the measures adequately capture the "closeness" construct as defined in the paper. Third (Chapter 2), I evaluate the two most widely used industrial classification schemes (SIC & GIC) in regards to their ability to group "comparable" firms. I find that both schemes group firms into industries exhibiting smaller accounting closeness than most users realize. Fourth (Chapter 3), I devise a simple trading strategy using information provided by the two measures which generates statistically significantly positive abnormal returns. Thus, there is value–relevant information contained in the measures that the market (at least historically) does not seem to fully appreciate. Fifth (Chapter 3), I contribute to the contagion literature, most notably Gleason et al. 2008, by showing that a contagion effect does not just exist as a result of negative news but also persists in the presence of positive news. Finally (Chapter 3), I find evidence that contagion effects don't exist in all industries. This suggests that the magnitude of the industry–specific contagion effect is a function of the closeness of that particular industry. That is, when an industry exhibits reasonably high closeness a contagion effect is present but when an industry exhibits closeness not statistically different from zero, no contagion effect is observed.

1.2 Related Research

A recent study by De Franco et. al. (2011) is the first towards grasping the concept of "closeness" in an accounting information sense. This study was refreshing to read as it provides a clever way to analyze a fundamental concept of accounting information. In their study they first define the accounting system of a firm as a mapping from economic events to financial statements. The mapping they have in mind takes the form below...

$$FinancialStatements_i = f_i(EconomicEvents) \tag{1}$$

That is, the information summarized in firm i's financial statements is a function of the economic events which give rise to that information. Next they let firm specific returns proxy for the effect of economic events on the firm and earnings proxy for financial statement information and they assume the following f_i...

$$Earnings_{it} = \alpha_i + \beta_i Returns_{it} + \epsilon_{it} \tag{2}$$

They thus assume that $\hat{\alpha_i}$ and $\hat{\beta_i}$ proxy for the accounting function $f(\cdot)$ for firm i. Similarly the accounting function for firm j is proxied by $\hat{\alpha_j}$ and $\hat{\beta_j}$. They reason that the "closeness" of the functions f_i and f_j represents the comparability between firms i and j. To proxy for this comparability they first estimate earnings for firms i and j using firm i's function. That is, they estimate the following regression...

$$E(Earnings)_{iit} = \hat{\alpha}_i + \hat{\beta}_i Return_{it} \tag{3}$$

$$E(Earnings)_{ijt} = \hat{\alpha}_j + \hat{\beta}_j Return_{it} \tag{4}$$

where $E(Earnings)_{iit}$ is the estimated earnings for firm i using firm i's function and firm i's return in period t and $E(Earnings)_{ijt}$ is the estimated earnings for firm j using firm j's function and firm i's return in period t. Thus they are holding the economic events constant and asking the question of how close the expected fundamental accounting performance summary measure is for both firms ceteris paribus. Closeness of these expected fundamentals implies closeness of the accounting functions f_i and f_j since the economic events (i.e. returns) are held constant. They measure these expectations for each of the previous 16 quarters leading up to each time period and take the average of the sum of the absolute value differences between expectations in each of these 16 quarters. This gives them a measure of comparability between firm i and firm j using the economic events of firm i.

There are several points I would like to make regarding the above study. First, there seem to be some construct validity issues with the equation (2) operationalization of the equation (1) theoretical setup. Returns can capture some economic events but not all of them. Those events that are held in confidence by the firm would flow through to the financial statements in period t but would not affect returns until those statement were released to the market. Thus, in some sense, returns are a function of the financial statement information rather than the converse. Along the same theme, returns capture things other than economic events. Returns are also a function of investor bias however we would not surmise that any part of the financial statements is a function of this bias. In summary, I am arguing that the equation (2) estimate of the accounting system in equation (1) is somewhat noisy. While equation (1) is an attractive and intuitive theoretical setup of the accounting system, its' simplicity undermines attempts to estimate it. For example, what is an economic event? Is it simply a transaction that the firm records with a journal entry or is it anything that affects the firm even if no accounting entry is made? What exactly is the function that is to be modeled? Is the function double–entry accounting? Is it more than just the journal entries. Without answers to these questions, approximations of equation (1) will be somewhat noisy. With this being said however, the equation (2) ,(3) and (4) approximations are a clever way to model equation (1) and a good first step towards understanding closeness between firms.

Second, knowing that prices lead earnings in time, they assume that similar mapping functions from returns to earnings for two firms indicates the two are comparable. I would argue however that returns are a function of fundamentals and investor bias. Lee (2001) provides an intuitive argument for why this is true. Share prices (and therefore returns) are a result of buying and selling in the marketplace with supply/demand economics fueling the equilibrium prices that obtain. Demand for and the supply of shares is a function of fundamentals and investor bias. Thus I would argue, as before, that two firms (i and j) could have correlated returns but have uncorrelated (or weakly correlated) underlying fundamentals[7]. In this situation, as long as the mapping functions were similar ($f_i(\cdot) \simeq f_j(\cdot)$), De Franco et. al. (2011) would imply that the two firms are comparable or "close" whereas it seems that fundamentally they are not[8].

Third, it is possible that two firms could have been exposed to identical economic events, accounted for them with different mapping functions and still have identical

[7] See Chan et al. 2007 for example who find that mean GIC 2–digit industry pair–wise correlation in stock returns is 0.39 while mean pair–wise correlation in sales is only 0.19.

[8] See the example given earlier (page 3) for this situation.

financial statements. I discuss this possibility in more detail in the next section.

Finally, De Franco et. al. (2011) do allow for the possibility that fundamental accounting information (i.e. earnings) could fulfill a comparability role to investors even when the accounting functions per se are different (i.e. possibly because the economic events each firm is exposed to are different). They agree that information regarding the covariance of earnings between two firms could be helpful in forecasting earnings of one of the firms. An advantage of this idea is one does not have to specify and estimate the accounting system. They provide an alternative measure of comparability which takes advantage of this. Specifically, they estimate the following regression...

$$Earnings_{it} = \Phi_{0ij} + \Phi_{1ij} Earnings_{jt} + \epsilon_{ijt} \tag{5}$$

They estimate this regression for all possible pairs of firms (i, j) in each two–digit SIC industry and the 16 previous quarters of data. They then calculate the adjusted R^2 [9] [10] and this is their measure of closeness. It is important to note that this measure only captures the strength of correlation rather than the sign since it is bounded below by zero and above by one. Therefore the measure cannot distinguish those firms whose earnings are positively correlated from those whose earnings are negatively correlated. Knowing that two firms have negatively correlated earnings is just as beneficial as knowing that they have positively correlated earnings since both forms of knowledge yield equal predictive power. Also, their main measure uses estimated earnings where this alternative measure uses actual earnings. For those firms whose returns do a poor job of predicting earnings their main measure could conceivably classify a pair of firms as close when in fact their actual earnings are uncorrelated or vice versa. It would be helpful to know the degree to which this "alternative" measure and their main measure coincide with each other. Specifically, it would be interesting to know for a given firm–pair (i, j) in a two–digit SIC industry how often the two measures both agree that the two firms are comparable (or "close"). In order to do this sort of analysis one must first define

[9] The adjusted R^2 is the same as the normal R^2 in this case since there is only one explanatory variable.

[10] The R^2 of a regression with only one explanatory variable is equivalent to the square of the Pearson Product Moment correlation between the two variables.

the threshold at which each measure would rank two firms as comparable versus non–comparable. It is interesting to note that their main measure is statistically significantly associated with analyst forecast accuracy and dispersion while this measure is not. However why does this result hold? Is it because the alternative measure fails to adequately capture "closeness" or does this result depend on how "closeness" is defined?

Prior to the most recent study regarding this topic discussed above, a few studies have offered measures of closeness and tested these measures for firms grouped according to the major classification schemes (SIC, GICS^{SM}, NAICS and FF)[11]. These classification schemes usually group firms based on primary revenue generating business activity with diversified firms usually put in separate industry groups or industries. Industrial classification schemes are rather important in archival financial research. Weiner (2005) finds that on average 30% of papers published in the top three finance and top two accounting journals use industrial classification systems. He finds that the main purposes for using them are sample restriction (34%), comparable company selection (31%), and detection of industry effects (12%). Thus there is a demand for a measure of economic relatedness among firms in financial research and current industrial classification systems have been developed to meet this demand. Several studies have examined how each of these systems capture "economic relatedness" among firms. A few of these studies further examine the degree of homogeneity among firms in regards to accounting variables (sales, earnings etc.) as a result of being grouped according to these classification systems.

An important early study by Ball and Brown (1967) estimates the degree of association between the earnings of a firm and the average earnings of the other firms in the same industry and in the economy. They don't define closeness however as the degree of association in earnings, rather they assume that industry classifications group together firms which are similar in significant ways (earnings association being one of these ways). They find that $35-40\%$ of the variances in firm's annual earnings are associated with the market (earnings averaged over all firms) and $10-15\%$ can be explained by the

[11] Standard Industrial Classification, Global Industry Classification System, North American Industrial Classification System and Fama & French's (1997) classification

variance in the industry (earnings averaged over firms grouped by two–digit Standard and Poor's industry classification). This is consistent with King (1966) who finds similar results with returns the variable of interest instead of earnings. Furthermore, they find that correlations between firm earnings and average industry earnings over time are mostly positively significantly greater than zero and thus they conclude that firms are reasonably well classified by industry. Throughout their analysis they reason that any operational definition of an industry is arbitrary. Theoretically, they agree that an industry is a group of firms who share similar characteristics. However, operationalizing this conceptual definition depends on which characteristics one wants to ensure are similar for a group of firms. They offer one potential redefining of an "industry" in terms of the covariability of earnings of firms but they do not elaborate and leave the idea for potential future research. This is exactly the idea that this study hopes to exploit, although unintentionally. A definition along these lines would capture closeness in an accounting information sense since most would agree that earnings are a key element in the set of accounting information.

Ball and Brown (1967) also discuss an alternative definition of an industry put forth in the finance literature by Miller and Modigliani (1958). There, an industry has been defined as the set of all firms whose individual ex ante probability distribution of returns differ at most by a scale factor and whose ex ante returns for every anticipated state of the world are perfectly positively correlated with those of every other firm in the same set. They point out however that this confirms the idea that an operational definition of an industry may be entirely arbitrary since the ex ante distributions of returns of firms are not generally observable. Also, the definition is in an economic information sense in that the market – along with accounting information – helps to determine share prices. One could argue that any sort of economic definition of an industry is not in one–to–one correspondence with an accounting definition since there is not a one–to–one mapping between elements in the set of accounting information (e.g. earnings) and those in the set of economic information (e.g. returns). Finally, they argue that studies should be concerned with ex post distributions and that an industry might be better defined in terms of the proximity of association between the ex post earnings of various firms.

A 1989 study by Clarke seeks to answer the question of whether industries based on SIC codes are able to separate firms into homogeneous economic groups. Using Compustat North America and a sample period of $1975 - 1983$, he uses a regression approach and concludes that profit ratios, sales changes and stock price changes of companies cannot be well explained by the SIC industry structure.

Another more recent study by Bhojraj and Lee (2001) uses a valuation approach to group firms. They argue that the choice of comparable firms should be a function of the variables that drive cross–sectional variation in a given valuation multiple. They develop a "warranted multiple" for each firm based on annual cross–sectional regressions of two fundamental accounting ratios (price to book and price to sales) on variables which drive cross–sectional variation in these ratios (e.g. profitability, growth and proxies for risk characteristics). They then use the estimated coefficients to predict future ratios for each firm. These future predictions are each firms' "warranted multiples". They find that when regressing the two ratios on the explanatory variables for firms grouped by industry the R^2 is around 14%. When grouping by size the R^2 marginally increases to 15% and when grouping by warranted multiples the R^2 triples for the current year and more than doubles for the other years (they are running regressions predicting current, one–year ahead and two–year ahead EV\S and P\B ratios). They conclude that using "warranted multiples" as a procedure for identifying comparable firms offers sharp improvements over choosing comparable firms by industry or size.

An additional study by Bhojraj, Lee and Oler (2003) compares industry classification schemes on their ability to explain comovements in stock returns as well as cross–sectional variations in valuation multiples, research and development expenditures, key financial ratios and forecasted and realized growth rates. They find that the GICS is superior to the NAICS, SIC and FF classifications at accomplishing this goal. Again, they do not attempt to define closeness in an accounting information sense, rather they offer that one measure of economic relatedness of firms is the extent to which their stock returns are contemporaneously correlated. I would argue that groups of firms could rank high on this measure but low in regards to correlation in their earnings. In theory when expected earnings equal realized earnings the two measures would agree with each other since price is a function of investors, expectations. However the degree to which the measures diverge should be increasing with the magnitude and sign of the correlation in unexpected earnings. For example consider two firms A and B which have high positive correlation in returns over a period of time. Also assume that firm A has low positive abnormal earnings (relative to the mean) each period over the time frame considered while firm B has high positive abnormal earnings (thus abnormal earnings for the two firms are negatively correlated). Also suppose that the earnings expectation function for both firms is identical. One explanation for this scenario is if firms A and B have low correlation in earnings over the time frame such that firm A experiences earnings just beating expectations each period while firm B experiences earnings greatly exceeding expectations each period.

Finally, Chan, Lakonishok and Swaminathan (2007) also find that both the GICS and FF do a relatively good job at grouping companies based on return co–movement. Specifically, they find that stocks belonging to the same industry share a higher correlation in returns than those belonging to different industries. Furthermore, this difference in correlation is increasing with the size of the companies considered and the fineness of the partition. They find for example, with a sample of large–cap stocks, correlations in returns between industry members differ from correlations in returns between non–member companies by, on average, 0.13 at the two–digit level, 0.14 at the four–digit level, 0.17 at the six digit level, and 0.18 at the eight digit level. They also find that companies in an industry, on average, share much weaker comovements in sales growth rates than in their returns. This is consistent with the idea that high correlation in returns does not necessarily imply high correlation in earnings.

Ball and Brown (1967) highlight the challenges with developing a non–arbitrary definition of an "industry". In short, they speak to the idea of defining closeness for a group of firms. Later, researchers arbitrarily analyze measures of closeness empirically without first attempting to define closeness or offering much reasoning[12] for why they choose the measure they do. Thus a gap in the literature exists in which a theoretically defended definition and measure of closeness would fill. Also, prior literature offers one statistical measure of closeness; simple correlation in the characteristics of interest. A second mathematically intuitive measure of closeness would help with construct validity. If two measures of the same construct converge, one can be more confident that each measure captures the desired construct. Related to this is the idea that all prior studies assume that a correlation measure will accurately capture closeness. A simulation can help to bolster confidence in this assumption. In a simulation, the researcher can ensure that two firms have highly correlated earnings processes ex ante which under certain assumptions would lead to high correlation in earnings ex post. Thus high closeness measures calculated for the two firms ex post would help to ease concerns that the measures fail to adequately capture closeness. This study employs such a procedure.

1.3 A Definition of Closeness

A definition is proposed based on the idea that firms engage in economic transactions . These transactions are then accounted for by the firm during its' accounting cycle and, upon completion of the reporting process, the financial statements are produced. In theory, the function that maps the transactions to the financial statements should be the firm–specific application of the pervading accounting principles/standards (i.e. GAAP in the U.S.). These applications are of course expressed in the form of journal entries. However, since any organized system of accounting principles/standards allows subjective discretion at times, each firm will have its' own specific mapping. Thus, analogous to De Franco et al. 2011, I am qualitatively describing the following idea ...

$$(Financial\ \ Statements)_i = f_i(Economic\ \ Transactions) \tag{6}$$

The financial statements I am referring to are the statements themselves absent the footnotes. The economic transactions are defined as economic events that the firm

[12] With the exception of De Franco et. al. 2011.

captures with a journal entry. Now the financial statements alone are functions of more than just economic transactions. For example, accruing bad debts expense does not directly follow as a result of an economic transaction but is accounted for and thus embedded in the financial statements. Since I only consider the financial statements themselves, the function f_i in equation (6) is the double–entry accounting system (i.e. the journal entries) which is a linear mapping of the transactions to the financials. Of course this setup is overly simplistic since f_i itself is a function of firm i's particular interpretation of GAAP. However, I abstract away from these conceptual difficulties with the goal being a definition of closeness free from construct validity issues in regards to the equation (6) theoretical setup.

Now I propose that, for a given set of economic transactions, two firms could have vastly different mappings (i.e. different f_i's) but produce similar financial statements. If we abstract away from an accounting context, equation (6) is of the form $y = f(x)$ and there are many functions which can map a given x to a given y. For example, consider three functions defined as follows and graphed in the x–y plane on the following page.

$$f_i(x) = sin(x) + \frac{3}{2}$$

$$f_j(x) = \frac{1}{\sqrt{2}} cos\left(x - \frac{\pi}{4}\right) + \frac{3}{2}$$

$$f_k(x) = \begin{cases} \frac{-2}{\pi\sqrt{2}}x \text{ for } x \in \left[\frac{(4n-3)\pi}{4}, \frac{(4n+1)\pi}{4}\right] & n \text{ odd} \\ \frac{2}{\pi\sqrt{2}}x \text{ for } x \in \left[\frac{(4n-3)\pi}{4}, \frac{(4n+1)\pi}{4}\right] & n \text{ even} \end{cases}$$

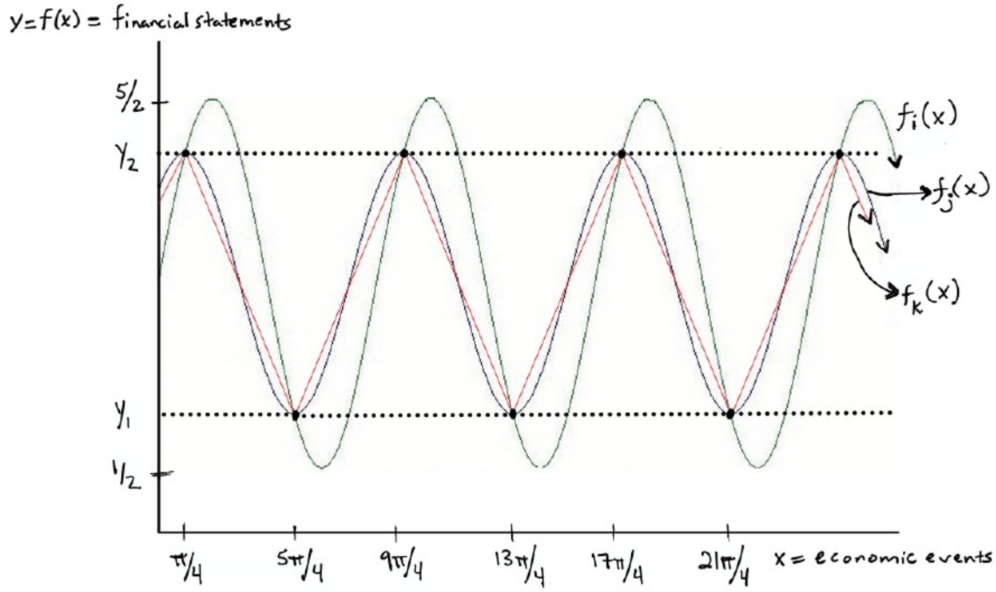

Figure 1.1: Different Functions Mapping Same Inputs to the Same Output

One realizes that $f_i \not\approx f_j \not\approx f_k$[13] when in fact there is an infinite set of points $\mathcal{X}_1 = \{x_1, x_2, x_3, \ldots\}$ such that $f_i(x_i) = f_j(x_i) = f_k(x_i) = y_1$ and another infinite set of points $\mathcal{X}_2 = \{b_1, b_2, b_3, \ldots\}$ such that $f_i(b_i) = f_j(b_i) = f_k(b_i) = y_2$. These points occur at the intersection of the functions and are shaded dark in Figure 1.1.

In this sense it seems that firms i, j & k are comparable or close since we have infinitely many cases where the economic transactions are the same, the functions are different but the financial statements are identical and also infinitely many points where the economic transactions are different, the functions are different but the financial statements are still identical.

Viewing equation (6) in an accounting context, it is known[14] that, given a set of financial statements and a set of transactions, there can be different sets of non–negative journal entries that can generate those financial statements. The journal entries are the func-

[13] That is, graphing how they each respond to changes in their inputs (i.e. their derivatives) shows that sometimes f_i is increasing whenever f_j and f_k are decreasing etc. Also, their ranges are different and f_k is linear whereas f_i and f_j are curvilinear.

[14] For example, see Fellingham et. al. (CAR 2000). They show that, given a linear representation of the accounting system $Ay = x$ and a quadratic loss function for the reader, a vector representation of the set of journal entries which produces the financial statements given and minimizes the readers' loss exists and is in fact the sum of the null space and row space component of A. Incidentally this solution is the readers' Bayesian posterior mean and best guess. Furthermore, this solution is not necessarily unique.

tion that maps the transactions to the financial statements and for a given firm i we thus know that there are many possible f_i's which could generate $(Financial\ Statements)_i$ holding the economic transactions constant. Therefore two firms could have different mappings (i.e. $f_i \not\approx f_j$) over time simply due to different interpretations/applications of GAAP but have similar financial statements. In this scenario it would seem that from a fundamental ex post accounting information sense the two firms are similar even though each firm processed the same set of economic transactions differently.

So it appears that we have a tradeoff when attempting to define closeness. If we define closeness as the closeness in functions then we have to address the possibility that two firms could have different functions but identical financial statements. From an investors' or analysts' standpoint, should these firms be viewed as similar or not?

Also, the similarity in functions (and thus financial statements) will be driven by the fact that each firm is constrained by GAAP. I would argue that the vast majority of journal entries made by firms are identical due to application of the objective parts of GAAP. It is only in those areas where GAAP allows subjective interpretation or multiple methods that the journal entries would differ between a pair of firms. Observing that a pair of firms has similar functions (i.e. similar set of journal entries) doesn't tell us how much of that similarity is due to both firms being subject to the same set of objective accounting principles and standards versus how much is due to those firms processing/interpreting those subjective parts of these standards in a similar way.

The benefit however of defining closeness as the similarity in functions allows us to explicitly control for the economic transactions. Defining similarity as the closeness in financial statements however and observing that two firms are close does not tell us how much of this closeness is due to both firms being exposed to similar economic transactions versus how much of this closeness is unrelated to the closeness of the underlying economic transactions.

Also, it should be pointed out that if two firms have dissimilar financial statements, it is possible for them to have similar functions given the same economic transactions. That is, the same issue illustrated in Figure 1 can arise if closeness is defined as similarity in financial statements. For example suppose $f_i(x) = x + 3$ and $f_j(x) = x + 15$. The functions are similar (i.e. same shape with same slope) but each takes economic transactions of $x = 5$ to dissimilar financials (i.e. $f_i(5) = 8 \not\approx f_j(5) = 20$).

The financial statements however give an overall picture of the financial health of a company and provide key indicators which help market participants judge the future performance of the company. Since I will define closeness considering that investors are the users, I would argue that they would care less about knowing whether the underlying functions for two companies are similar given two vastly different sets of financial statements than they would about knowing whether the financial statements were similar given the companies processed the same set of economic transactions differently (i.e. different functions). That is, investors care more about similarity in financial statements when comparing two companies than in similarity in the way each company processed the economic transactions they were exposed to. Since most investors realize that all firms face the same set of accounting principles and standards[15], it seems reasonable to assume that these investors care more about ex post financial statement similarity than whether firms interpret the standards similarly.

It should be pointed out at this point how the previous discussion relates to the FASBs' conceptual framework definition of comparability.

> "*Comparability* is the quality of information that enables users to identify similarities and differences between two sets of economic phenomena. *Consistency* refers to the use of the same accounting policies and procedures, either from period to period within an entity or in a single period across entities. Comparability is the goal; consistency is a means to an end that helps in achieving that goal." (¶111–122, emphasis mine)

The above definition of comparability does not map directly into equation (6). I interpret the definition given to mean that two companies are comparable if the quality of the ex post information contained in each of their sets of financial statements is high enough to enable a user to identify the similarities and differences in the ex ante economic transactions each company was exposed to. This is much different than saying that two

[15]Some industries (e.g. Oil & Gas) have specific standards applicable only to them. However, for the most part, the principles and standards that govern firms' reporting are common to all firms.

firms are comparable if their financial statements themselves are similar. In fact, the above definition leaves open the possibility that firms i and j could have "non–similar" financials but be comparable firms as long as the quality of the information contained in their respective sets of financial statements is high enough. Comparability defined in such a way though is rather vague and non–intuitive. The word "comparability" implies similarity and vice versa, not the quality of information that helps one determine similarity. Therefore, to comprehend the definition, one has to divorce themselves from the notion that comparability implies similarity or that similarity implies comparability. That is, two firms could be subject to vastly **different** sets of economic transactions but still be comparable (according to the definition) so long as the quality of the information contained in their respective sets of financial statements is high enough to enable ex post users to identify these ex ante differences.

Based on the preceding discussion I will define "closeness" as **the degree of similarity in the outputs of the accounting system** rather than the degree of similarity in what I will loosely refer to as the "structure" of the accounting system (i.e. the degree of similarity between f_i and f_j). The outputs of the accounting system should reflect the underlying transactions from which they are derived and thus if two firms have fundamental outputs which move predictably (i.e. positively or negatively correlated), then I view those firms as "close" or similar whether or not they process their respective transactions similarly.

In defining closeness as the degree of similarity in ex post accounting information I am implicitly allowing this "similarity" to proxy for the "quality" that the conceptual framework definition refers to. I interpret the FASB definition as implying that comparability is viewed as similarity in ex post financial statements (I call this "closeness") while consistency (which is a necessary means to comparability) is similarity in accounting functions across periods within an entity or across entities within a single period.

1.4 Measuring Closeness

Given the conceptual definition above, a second–level conceptualization is proposed. I assume the users (i.e. those interested in determining closeness) are potential investors. I also assume that the financial statements of a firm do a good job of faithfully representing the underlying transactions from which they are derived[16]. There are many pieces of accounting information displayed in the financial statements and related disclosures of a firm. The degree of correlation between the **level** of each of the pieces of financial statement information across firms and time is how closeness will be operationalized[17]. That is, given a group of N firms, one can say that the higher the correlation between each of these firms' financial statement information levels (i.e. earnings and cash flow dollar values) across time, the closer is the group of firms. Notice the definition is ex post in the sense that I don't consider accounting information available for firms before they engage in their specific business activity; I only look at the between–firm relatedness of the level of the financial accounting information after the firms have completed their periodic financial reporting process. Therefore, two firms could be close ex ante in the sense that they have the same principal business activity (and thus be classified in the same industry) and same potential consumer base etc. but not be close ex post due to the by–products of their accounting information systems being uncorrelated.

1.4.1 Measure One

As conceptualized, closeness is hard to measure since each piece of information in the financial statements and related disclosures should be considered. Incorporating the information in disclosures into an overall measure of firm closeness is difficult so I will focus on just the information in the basic financial statements[18]. Still, incorporat-

[16] Li (2010) provides evidence that this assumption should be tempered by the readability and tone of the annual report. Decreased readability and increased negativeness in the tone of the annual report (from a textual analysis perspective) may indicate that key financial statement summary measures of performance do not faithfully represent the underlying transactions from which they are derived.

[17] Thus I am not capturing other dimensions of "similarity" in the conceptual definition such as similarity in information quality (i.e. earnings quality) for example.

[18] i.e. income statement, balance sheet, statement of cash flows.

ing each piece of financial statement information into an overall closeness measure is cumbersome unless a key assumption is made. Assume that the summary performance measures (e.g. earnings and cash flows) of a firm do a good job of capturing all of the information available in the financial statements and thus all available information in the underlying transactions. Then looking at the correlation between these measures across time, between firms will capture closeness as defined above. After all, earnings and cash flows are both functions of the other information contained in the financial statements. More specifically, we know that both earnings and cash flows capture changes in assets, liabilities and equity across periods. In this sense, the assumption that earnings and cash flows capture all available information in the financial statements is warranted[19].

However, rather than develop a measure based on realized earnings and cash flows, it seems more appropriate to consider unexpected earnings and cash flows. Ohlson, (1995) demonstrates that assuming linear information dynamics, the value of the firm is a linear function of the firms' abnormal earnings, book value and "other" information available to market participants. In theory, if market participants know that earnings and cash flows will always be as expected then the price they are willing to pay for the firm will remain constant. It is only when market participants revise their estimates of future expected earnings and cash flows based on unexpected earnings and cash flows that their valuation changes. Abnormal earnings and abnormal cash flows capture not only realized earnings and cash flows but also the expectations of investors and thus a measure of closeness based on unexpected earnings and unexpected cash flows seems appropriate. Recall, closeness was defined with investors assumed as the users of the accounting information. With this being said, the same argument made earlier regarding why correlation in returns may not capture closeness of the underlying fundamentals applies here. Abnormal earnings and cash flows for two firms could be correlated over time with underlying earnings and cash flows for these same firms being uncorrelated due

[19] In reality however, there are often items on the balance sheet that do not flow through the income statement (i.e. dirty surplus items) and thus closeness in these items across firms through time would not be captured by a measure that was simply a function of earnings and cash flows. A balance sheet summary item such as book value of equity could be added to both measures introduced in this study to address this concern.

to the former capturing "noise" and investor bias[20]. However, since potential investors are considered as the information users rather than a theoretically–minded hypothetical person(s) which cares only about similarity in the underlying fundamental outputs of the accounting information system, unexpected earnings and cash flows take precedence. From an individual investors' standpoint, abnormal earnings and cash flows capture not only what is going on at the firm level but also capture other investors thoughts and beliefs. With that being said, the measures introduced in this study can easily incorporate actual earnings, cash flows, R&D and any other fundamental output of the accounting system as well as any linear combination of these outputs.

Given the definition of closeness proposed and the preceding discussion regarding precedence of the abnormal earnings and cash flow summary performance measures, the first measure introduced is rather straightforward. Suppose there is a group of N firms for which summary performance measure data is available for p periods. Let one measure of closeness be defined as the weighted average of the average correlation in abnormal earnings and abnormal cash flows[21] for firm i with each of the other $N-1$ firms in the group with an equal weight of $\frac{1}{2}$ given to both variables. More specifically let r_{ij} be the sample Pearson Product Moment Correlation between firm i and j's abnormal earnings over p periods with $i = \{1, 2, \ldots, N\}$ and $j = \{1, 2, \ldots, i-1, i+1, \ldots, N\}$. Then the following statistic measures the closeness of the N firms.

$$C^1_{AE}(r) = \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} r_{ij} \tag{7}$$

where

$$r_{ij} = \frac{\displaystyle\sum_{p=1}^{T}(AE_{ip} - \overline{AE}_{ip})(AE_{jp} - \overline{AE}_{jp})}{\sqrt{\displaystyle\sum_{p=1}^{T}(AE_{ip} - \overline{AE}_{ip})^2}\sqrt{\displaystyle\sum_{p=1}^{T}(AE_{jp} - \overline{AE}_{jp})^2}} \tag{8}$$

[20] The same example given earlier applies here.

[21] Actual earnings & cash flows as well as the difference between actual earnings & cash flows and abnormal earnings & cash flows (i.e. "true" earnings & cash flows) were also used in the measures.

with AE_{ip} representing abnormal earnings for firm i in period p and $\overline{AE}$ is the mean. Also, $\binom{N}{2} = \frac{N!}{2!(N-2)!}$ is the number of ways to choose a pair of items from N items. Analogously let C^1_{ACF} measure closeness of the N firms with respect to their abnormal cash flows as defined above with ACF substituted for AE. Then the first measure of closeness is $C^1 = \frac{1}{2}\left(C^1_{AE} + C^1_{ACF}\right)$[22]. Note that since the sample Pearson Product Moment correlation r is bounded between negative and positive one, so is C^1_{AE}. High positive values of C^1_{AE} indicate that on average relatively (relative to each firm's mean) high abnormal earnings for firm i are associated with relatively high abnormal earnings for the other $N-1$ firms in the group. In contrast, high negative values of C^1_{AE} indicate that on average relatively high abnormal earnings for firm i are associated with relatively low abnormal earnings for the other $N-1$ firms in the group. Another way to think of C^1_{AE} is that high absolute values of C^1_{AE} imply closer firms in the sense that the ability to predict the other $N-1$ firm's abnormal earnings from knowing firm i's abnormal earnings is increasing in C^1_{AE}. In contrast, low absolute values of C^1_{AE} for a group of firms implies that knowledge of any one of the firm's abnormal earnings gives little to no information aiding in the prediction of the other $N-1$ firm's abnormal earnings.

Furthermore, Pearson's correlation is a measure of linear correlation between variables. That is, it is a quantification of how well the association is represented by a straight line. Two variables may be highly related to one another with $r = 0$ simply because a non–linear relationship exists. For example if both high and low abnormal earnings for firm i are paired with low abnormal earnings for firm j but medium abnormal earnings for firm i are paired with high abnormal earnings for firm j then there is a curvilinear association between the abnormal earnings of firm i and j. A U-shaped figure would describe this association rather than a straight line.

The interpretation of the correlation coefficient in (7) is subjective. Several authors have offered guidelines for the interpretation of a correlation coefficient. Cohen (1988) however points out that all such criteria are arbitrary and should not be observed too

[22]Intuitively, the first measure is the average of all pair–wise abnormal earnings correlations among a group of firms.

strictly. He argues that the interpretation of a correlation coefficient depends on the context. For example, a correlation of 0.9 may be very low if one is verifying a physical law using precise instruments but may be regarded as very high in the social sciences where many other complicating factors are present. Fortunately there are statistical tests developed to test the significance of correlation[23]. These tests don't have to be used however since the measures are means of correlations. With a large sample ($N > 30$) a regular Z-test can be used since, according to the Centra Limit Theorem, the sampling distribution of C^1 and C^2 (introduced later) will be approximately normal.

Example 1

An example is in order to illustrate the application of the first measure. Suppose, without loss of generality, I have the following abnormal earnings and cash flow matrices ...

$$AE = \begin{bmatrix} 17 & 3 & 4 & 10 \\ 2 & 19 & 1 & 12 \\ 5 & 23 & 3 & 13 \\ 8 & 7 & 6 & 18 \end{bmatrix} \qquad ACF = \begin{bmatrix} 9 & 3 & 4 & 7 \\ 5 & 14 & 10 & 6 \\ 13 & 8 & 9 & 2 \\ 1 & 7 & 15 & 11 \end{bmatrix}$$

which represent abnormal earnings and cash flows for four firms (columns) over four periods (rows). Now calculate the matrix P of correlations where entry r_{ij} corresponds to the correlation in abnormal earnings between firm i and j over the four periods and is calculated using (8). That is I find the Pearson Product Moment Correlations between each pair of columns of the abnormal earnings matrix ...

[23]See Fishers (1915) test. Also, a standard t–test can be applied since the sampling distribution of the Pearson Product Moment Correlation coefficient approximately follows a Student's t distribution with $N-2$ degrees of freedom and test statistic $t = r/\sqrt{(1-r^2)/(N-2)}$.

$$P = \begin{pmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{21} & r_{22} & r_{23} & r_{24} \\ r_{31} & r_{32} & r_{33} & r_{34} \\ r_{41} & r_{42} & r_{43} & r_{44} \end{pmatrix}$$

$$= \begin{pmatrix} 1 & -0.8427 & 0.5189 & -0.3174 \\ -0.8427 & 1 & -0.6727 & -0.0617 \\ 0.5189 & -0.6727 & 1 & 0.6352 \\ -0.3174 & -0.0617 & 0.6352 & 1 \end{pmatrix}$$

Each row of P is the correlation of firm i's abnormal earnings with itself and the other firms in the group. Now calculate C^1_{AE} by taking the average of the upper triangular part of P according to (1) as follows ...

$$\begin{aligned} C^1_{AE} &= \frac{1}{\binom{4}{2}} \sum_{i=1}^{3} \sum_{j=i+1}^{4} r_{ij} \\ &= \frac{1}{6}(-0.8427 + 0.5189 - 0.3174 - 0.6727 - 0.0617 + 0.6352) \\ &\approx -0.1234 \end{aligned}$$

Next, I calculate C^1_{ACF} using the same procedure as above and get $C^1_{ACF} = -0.1890$. Finally, I find C^1 as the equally–weighted average of C^1_{AE} and C^1_{ACF} ...

$$\begin{aligned} C^1 &= \frac{1}{2}C^1_{AE} + \frac{1}{2}C^1_{ACF} \\ &= \frac{1}{2}(-0.1234 - 0.1890) = -0.1562 \end{aligned}$$

Comparing the z-stat to the critical value in this example gives ...

$$\textit{z-stat} = -0.5594 > -1.645$$

The null hypothesis that there is not a statistically significant association between the four firm's abnormal earnings and cash flows (i.e. H_0: $C^1 = 0$) is not rejected at the 5%

level since the z-score is not less than the critical value[24].

1.4.2 Measure Two

The determinant of a matrix is a measure of the closeness of the individual column vectors of the matrix. More specifically, the determinant of a square matrix represents the volume of the figure that the columns of the matrix form[25]. The closer the determinant is to zero the smaller the volume and thus the more correlated the column vectors. When the determinant is zero the column vectors are superimposed on each other and thus perfectly correlated. This property of the determinant implies that I can form a matrix whose columns are abnormal earnings for firm i and whose rows are the number of time periods considered. The determinant of this matrix is an overall measure of closeness of the individual columns which represent different firm's abnormal earnings[26].

The determinant of this matrix however is unbounded and therefore hard to interpret. Therefore, a better idea is to form a variance–covariance matrix of abnormal earnings between a pair of firms and calculate the determinant for this matrix. The determinant of a variance–covariance matrix for a pair of random variables is known as the *generalized variance* and is a measure of the overall co–variability of the two variables. Another way to describe it is the determinant of the variance–covariance matrix measures the overall information in the matrix which is the combined variance of the variables less any correlation/co–variance in the variables. Thus the closer the determinant is to zero, the more the variables co–vary and are correlated with each other. Similarly, taking the determinant of a correlation matrix gives a measure of closeness of the variables. The correlation matrix is simply a standardized variance–covariance matrix where each (i, j) entry is standardized by the product of variable i and j's standard deviation. The determinant of the correlation matrix enjoys the added benefit of being bounded below by zero and above by one, thereby making interpretation and comparison to closeness

[24]Note that it is hard to reject the null if the sample size is small—as it is in this example.
[25]See Appendix C for a proof of the two by two correlation matrix case.
[26]See Appendix B for a visual depiction of measure two.

measure one much easier.

Specifically, suppose I have a group of N firms and suppose abnormal earnings for each firm is a random variable with a specified mean and variance. Next, suppose I first calculate the correlation matrix for each pair of firms in the group...

$$CORR_{AE}(i,j) = \begin{bmatrix} r_{ii} & r_{ij} \\ r_{ji} & r_{jj} \end{bmatrix} = \begin{bmatrix} 1 & r_{ij} \\ r_{ji} & 1 \end{bmatrix} \tag{10}$$

with r_{ij} the Pearson Product Moment Correlation between abnormal earnings for firm i and j over a specific time period.

Next, suppose I form a matrix whose (i,j)'th entry is the determinant of the correlation matrix of abnormal earnings for firms i and j as follows (the vertical bars represent the determinant)...

$$DET_{AE} = \begin{bmatrix} |CORR_{AE}(1,1)| & |CORR_{AE}(1,2)| & \cdots & |CORR_{AE}(1,N)| \\ |CORR_{AE}(2,1)| & |CORR_{AE}(2,2)| & \cdots & |CORR_{AE}(2,N)| \\ \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ |CORR_{AE}(N,1)| & |CORR_{AE}(N,2)| & \cdots & |CORR_{AE}(N,N)| \end{bmatrix} \tag{11}$$

Next, take the average of the upper triangular part of DET_{AE}. This gives the average determinant of each of the abnormal earnings correlation matrices for each distinct pair of firms in the group. This is the second measure of overall firm group closeness in regards to abnormal earnings...

$$C^2_{AE} = \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |CORR_{AE}(i,j)| \tag{12}$$

Repeating the above procedure with abnormal cash flows gives C^2_{ACF} and thus the second overall measure of firm group closeness is $C^2 = \frac{1}{2}\left(C^2_{AE} + C^2_{ACF}\right)$.

In general, a couple of things to note about the determinant are the following. First, if the columns of the matrix are linearly dependent — that is one or more of the columns in the matrix can be obtained by a linear combination of the other columns — then the determinant will always be zero. This implies that if two firms in a group of N firms have abnormal earnings which are perfectly positively correlated then the determinant of the matrix of abnormal earnings for these two firms will always be zero. More specifically, if I examine the determinant of $CORR_{AE}(i,j)$[27] I see that it is bounded below by zero and above by one.

$$det(CORR_{AE}(i,j)) = |CORR_{AE}(i,j)| = \begin{vmatrix} 1 & r_{ij} \\ r_{ji} & 1 \end{vmatrix}$$
$$= 0 \leq 1 - r_{ij}^2 \leq 1 \quad \text{since } 0 \leq r_{ij}^2 \leq 1$$

The only way for the determinant of $CORR_{AE}(i,j)$ to equal zero is if the abnormal earnings for the two firms are perfectly correlated ($r_{ij} = 1$). Therefore all of the entries in DET_{AE} are constrained between zero and one immediately implying that $0 \leq C_{AE}^2 \leq 1$ since C_{AE}^2 is the average of all the upper triangular entries in DET_{AE}. Thus, values close to one for C_{AE}^2 indicate low group closeness while values close to zero indicate high group closeness. This is in contrast to C_{AE}^1 where values close to one indicate high group closeness while values close to zero indicate low group closeness.

Second, determinants have ordinal, interval and ratio properties. To illustrate order suppose I calculate $C_{AE}^2 = 0.8$ for a group of firms and $C_{AE}^2 = 0.4$ for another distinct group of firms. I can say that the abnormal earnings of the first group of firms co–vary less with each other than those of the second group. That is, the second group of firms with $C_{AE}^2 = 0.4$ are closer as defined earlier than the first group of firms with $C_{AE}^2 = 0.8$. To illustrate the interval property assume the same example as above. I can also say that the abnormal earnings of the second group of firms co–vary twice as much with each other than those of the first group. Thus the second group of firms are twice as close as the first group.

[27] The following discussion applies to C_{ACF}^2 as well.

Example 2

An example illustrating C^2 will be informative. Assume the same information in Example 1. That is, suppose I have the following matrix of abnormal earnings over four periods (rows) for a group of four firms (columns)...

$$AE = \begin{bmatrix} 17 & 3 & 4 & 10 \\ 2 & 19 & 1 & 12 \\ 5 & 23 & 3 & 13 \\ 8 & 7 & 6 & 18 \end{bmatrix} \qquad ACF = \begin{bmatrix} 9 & 3 & 4 & 7 \\ 5 & 14 & 10 & 6 \\ 13 & 8 & 9 & 2 \\ 1 & 7 & 15 & 11 \end{bmatrix}$$

First, I calculate $CORR_{AE}(i,j)$ for each pair of firms to form DET_{AE} and keep only the upper triangular part as follows...

$$DET_{AE} = \begin{bmatrix} \begin{vmatrix} 1 & -0.8427 \\ -0.8427 & 1 \end{vmatrix} & \begin{vmatrix} 1 & 0.5189 \\ 0.5189 & 1 \end{vmatrix} & \begin{vmatrix} 1 & -0.3174 \\ -0.3174 & 1 \end{vmatrix} \\ - & \begin{vmatrix} 1 & -0.6727 \\ -0.6727 & 1 \end{vmatrix} & \begin{vmatrix} 1 & -0.0617 \\ -0.0617 & 1 \end{vmatrix} \\ - & - & \begin{vmatrix} 1 & 0.6352 \\ 0.6352 & 1 \end{vmatrix} \\ - & - & - \end{bmatrix}$$

$$= \begin{bmatrix} 0 & .2899 & .7307 & .8993 \\ - & 0 & .5475 & .9962 \\ - & - & 0 & .5965 \\ - & - & - & 0 \end{bmatrix}$$

I have filled in the lower triangular part with "$-$" since it is the same as the upper triangular part. Also the omitted diagonal contains zeros since $|CORR_{AE}(i,i)| = 0$ for all i. Finally, calculating the average of the upper triangular portion of DET_{AE} gives C^2_{AE} ...

$$\begin{aligned} C^2_{AE} &= \frac{1}{\binom{4}{2}} \sum_{i=1}^{3} \sum_{j=i+1}^{4} |CORR_{AE}(i,j)| \\ &= \frac{1}{6}(0.2899 + 0.7307 + 0.8993 + 0.5475 + 0.9962 + 0.5965) \\ &\approx 0.6767 \end{aligned}$$

Next, I repeat the above procedure and find $C^2_{ACF} = 0.7028$. Thus the second overall measure of firm group closeness in this example is ...

$$\begin{aligned} C^2 &= \frac{1}{2}(C^2_{AE} + C^2_{ACF}) \\ &= \frac{1}{2}(0.6767 + 0.7028) = 0.6897 \end{aligned}$$

Now applying a standard Z-test as in Example 1 gives ...

$$z\text{-}stat = -2.3204 < -1.645$$

Thus, the null hypothesis that there is a not a statistically significant association between the four firm's abnormal earnings and cash flows (i.e. H_0: $C^2 = 1$) is rejected at the 5% level since the *z-stat* is less than the critical value. Thus we see that C^1 and C^2 do not yield consistent results in this example.

The example was constructed to be an extreme example. That is, one in which C^1 is negative while C^2 is positive and the sample size is extremely small. With larger sample sizes and C^1 agreeing in sign with C^2 the measures usually interpret consistently with each other. This will be demonstrated later in the simulation section and with real data.

1.4.3 Interpreting the Measures

While it is useful to have these tests, it is likely that empirically there will be some association between a group of firm's abnormal earnings. I wish to not only say that this association is statistically significant but also be able to interpret the magnitude.

Unfortunately with the determinant measure (C^2), there is no guidance on interpreting the magnitude. I will therefore employ the same interpretation scale that has been proposed for the correlation measure and only modify it for the determinant measure based on some insight obtained through the simulations that are discussed in section 1.7. Also, notice that C^1 is between negative and positive one while C^2 is between zero and one. Thus C^1 can tell us something about negative correlation while C^2 cannot. C^2 only measures the degree of correlation not the direction while C^1 measures both. The following table gives a possible interpretation of C^1 and C^2 which will be followed in the next section when interpreting the two measures for simulated abnormal earnings and cash flows[28].

Table 1.1: Interpreting C^1 and C^2

Firm-Group Association	$-1 \leq C^1 \leq 0$	$0 \leq C^1 \leq 1$	$0 \leq C^2 \leq 1$
High	[-1, -0.5)	(0.5, 1.0]	[0, 0.35)
Med	[-0.5, -0.3)	[0.3, 0.5)	[0.35, 0.6)
Low	[-0.3, -0.1)	[0.1, 0.3)	[0.60, 0.85)
None	[-0.1, 0]	[0, 0.1)	[0.85, 1.0]

Note that in Example 1 $C^1 = -0.1511$ and in Example 2 applying C^2 to the same matrix of abnormal earnings gives $C^2 = 0.6897$. From Table 1.1 one sees that C^1 classifies the group as having small association since $-0.3 \leq -0.1511 \leq -0.1$. Also, C^2 classifies the group as having small association since $0.6 \leq 0.6897 \leq 0.85$. Additionally, the first measure tells us the small association is negative while the second measure does not give us information regarding the direction of association. We could therefore infer from this evidence that the group of firms from Examples 1 & 2 has small negative association.

[28]The reason for the bigger range on the C^2 interpretation intervals above is due to the fact that C^2 is more sensitive to the randomness in a firms earnings process than C^1 as demonstrated in the simulations.

1.5 Theoretical Discussion of the Measures

1.5.1 Properties of the Measures

It turns out that the closeness measures C^1 and C^2 are not measures in a formal mathematical sense. Before understanding why, I will provide some background introduction to mathematical measure theory. First, a measure in mathematics is defined over a "set". A set is simply a collection of elements. For example, the set $X = \{a, b, c, d\}$ is a collection of the four elements a, b, c and d. The set that must exist before a measure can be defined over it is called a σ–algebra. Before defining a σ–algebra I will define a power set since it will be used in the definition of a σ–algebra. A power set $\mathcal{P}$ is the set of all subsets[29] of a set X. Now let X be some non–empty set and let $\mathcal{P}$ be the power set of X. Then a subset $\Sigma \subset \mathcal{P}$ is called a σ–algebra if it satisfies the following three properties ...

(1) Σ is non–empty: There is at least one $A \subset X$ in Σ.

(2) Σ is closed under complementation: If A is in Σ, then so is its complement, $X \backslash A$.

(3) Σ is closed under countable unions: If $A_1, A_2, A_3, \ldots$ are in Σ then so is $A = A_1 \cup A_2 \cup A_3 \cup \ldots$.

From these properties it also follows that X itself and the empty set $\emptyset$ are also in Σ. To see this note that by (1) since Σ is non–empty, you can pick some $A \subset X$ that is in Σ, and by (2) you know that $X \backslash A$ is also in Σ. Thus by (3) we know that $A \cup (X \backslash A) = X \subset \Sigma$. Finally, if $X \subset \Sigma$ then by (2) we know that the complement of X or the empty set is in Σ.

An example now will suffice to illustrate a σ–algebra. Suppose I have the set described above $X = \{a, b, c, d\}$. One possible σ–algebra on X is $\Sigma = \{\emptyset, \{a, b\}, \{c, d\}, \{a, b, c, d\}\}$. One can see that Σ is non–empty. Also one can see that Σ is closed under complementation since the complement of each set in Σ is also in Σ. Finally, Σ is closed

[29] A subset is a collection of elements from a set.

under unions since the union of any of the subsets of Σ is also in Σ.

Now that I have introduced the concept of a σ–algebra I will discuss what a measure is. Let Σ be a σ–algebra over a set X. A function μ from Σ to the extended real number line (i.e. including positive infinity) is called a measure if it satisfies the following properties ...

(i) Non–negativity: $\mu(E) \geq 0$ for all $E \subset \Sigma$.

(ii) Countable additivity: For all countable collections $\{E_i\}_{i \in I}$ of pairwise disjoint sets in Σ: $\mu\left(\bigcup_{i \in I} E_i\right) = \sum_{i \in I} \mu(E_i)$.

(iii) Null Empty Set: $\mu(\emptyset) = 0$.

If we let X be the set of all U.S. current publicly traded firms and Σ be the power set of X. We can quickly see that Σ is a σ–algebra as it is non–empty and closed under complementation and unions. However, we can also just as quickly see that neither C^1 nor C^2 are measures in a formal mathematical sense as both violate property (ii) above. That is the closeness of a particular set of firms is not necessarily equal to the sum of the closeness of a particular combination of pairwise disjoint subsets of that set. Using Example 1 again let $\Sigma = \{\emptyset, 1, 2, 3, 4, \{1,2\}, \{1,3\}, \{1,4\}, \{2,3\}, \{2,4\}, \{3,4\}, \{1,2,3\}, \{1,2,4\}, \{1,3,4\}, \{2,3,4\}, \{1,2,3,4\}\}$ with $E_1 = \emptyset$, $E_2 = 1$, $E_3 = 2$, ..., $E_{16} = \{1,2,3,4\}$. We saw that $C^1\left(\bigcup_{i \in I} E_i\right) = -0.1562$ but a calculation gives $\sum_{i \in I} C^1(E_i) = -1.7183$. Thus C^1 does not display countable additivity. A similar calculation shows that C^2 is not countably additive either. Also, C^1 violates property (i) above since $-1 \leq C^1 \leq 1$ however C^2 is non–negative as shown earlier.

In summary, neither C^1 nor C^2 are formal mathematical measures. C^1 violates properties (i) and (ii) that mathematical measures must possess (i.e. non–negativity and countable additivity) while C^2 violates property (ii). So I have shown that neither of the closeness measures introduced in this study are formal mathematical measures. Rather, C^1 and C^2 intend (and do) capture closeness and in this sense they are considered measures[30]. It turns out that C^1 and C^2 would satisfy the properties above and be considered formal mathematical measures if the formula for each was altered. For C^1 to be a measure it should be calculated as[31] ...

$$C^1_M = \left(1 + \frac{5}{\binom{N}{2}}\right) \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} r_{ij}$$

The expression above takes into consideration not only all possible pairwise correlations but also considers all possible correlations while treating 3 firms as a group or 4 firms as a group; up to $N-1$ firms as a group. That is, C^1 is calculated for each E_i in Σ above to form C^1_M. This measure however, while mathematically correct, is hard to interpret as it is not bounded above or below and considers the correlation between any possible pair of firms more than once.

The previous discussion regarding why C^1 and C^2 are not formal mathematical measures points to a potential drawback of the "measures". C^1 and C^2 are functions of pair–wise correlations and pair–wise correlation matrix determinants. Thus, given a group of firms, we can only judge closeness of the group in light of averages of pairs. Given a group of N firms it would be helpful to not only condition on firm j's information when considering firm i but also to condition on known information about the other $N-2$ firms in the group. Simply averaging pair–wise correlations and pair–wise correlation matrix determinants may be an inefficient use of available information about each firm in the group. Another measure, entropy, enjoys the advantage of being countably additive thus qualifying itself as a formal mathematical measure. Entropy is able to condition information about firm i on information about all of the other $N-1$ firms in the group and is not restricted to conditioning only on information about firm j. Unfortunately however, it would be beyond the scope of this study to examine measures of entropy.

[30] A potential "measure" need not satisfy the properties of a formal mathematical measure in order to "measure" something.

[31] C^2_M should be calculated similarly.

1.5.2 Other Properties of the Measures

Monotonicity

A measure μ is monotonic if, given two measurable sets E_1 and E_2 with $E_1 \subseteq E_2$, we have $\mu(E_1) \leq \mu(E_2)$. Neither C^1 nor C^2 are monotonic.[32] Take C^2 for example. Suppose we have Σ as defined earlier with $E_{10} = \{2, 4\}$ and $E_{13} = \{1, 2, 4\}$. You can see that $E_{10} \subseteq E_{13}$ and calculating gives $C^2(E_{10}) = 0.9962 > C^2(E_{13}) = 0.7285$.

Transitivity

A measure μ is transitive if, given three measurable disjoint sets A, B and C with $\mu(A \cup B) > 0$ and $\mu(B \cup C) > 0$, we have $\mu(A \cup C) > 0$. Again, neither C^1 nor C^2 are transitive.[33] To see this it will suffice to prove that the sample Pearson Product Moment Correlation r in (8) is not transitive. This is sufficient since C^1 and C^2 are simply functions of the Pearson correlation and thus any problems which cause the Pearson correlation to not exhibit transitivity will also prohibit C^1 and C^2 from exhibiting transitivity. Since I have reduced the transitivity question to showing that the Pearson correlation fails to exhibit transitivity I will define transitivity with the Pearson correlation in mind. The sample Pearson correlation r is transitive[34] if, given three random variables X, Y and Z with $r_{X,Y} > 0$ and $r_{Y,Z} > 0$, we have $r_{X,Z} > 0$.[35] Of course a simple counterexample which fails to satisfy the definition will suffice to prove the non–transitivity of the Pearson correlation. The following illustrative example is borrowed from Langford et al. (2001) published in the American Statistician. The authors collected baseball data from the New York Yankees in the following tabular form ...

[32] Of course they aren't by the fact that they are not formal mathematical measures since they violate one or more of the conditions given above (i–iii).
[33] See footnote above.
[34] Transitivity of the Pearson Correlation can be positive, negative or zero. Without loss of generality I only discuss the positive transitive case.
[35] Where $r_{X,Y}$ represents the Pearson correlation between random variables X and Y.

Table 1.2: Year 2000 Yankees Batters

Player	X(triples)	Y(base hits)	Z(home runs)
Jeter	4	201	15
Williams	6	165	30
Posada	1	145	28
Justice	1	150	41
O'Neill	0	160	18
Knoblauch	2	113	5
Polonia	5	140	7
Martinez	4	147	16
Canseco	0	83	15
Brosius	0	108	16

where X, Y and Z represent the number of triples, base hits and home runs for that particular player. Calculating gives $r_{X,Y} = 0.526$, $r_{Y,Z} = 0.293$ and $r_{X,Z} = -0.096$. The intuition here is relatively straightforward. One would expect that the more hits a player has the more triples and home runs they will have. However, it is also not surprising that the number of triples a player has is negatively correlated with the number of home runs they have since smaller, faster players (e.g., Polonia) tend to hit triples and not home runs, whereas larger, more powerful players (e.g., Canseco) tend to hit home runs and not triples.

The previous example is a specific counterexample illustrating the non–transitivity of the Pearson correlation where $r_{X,Y} > 0$ and $r_{Y,Z} > 0$ but $r_{X,Z} < 0$. A broader example is the following. If we let P, S and Q be any non–trivial, n–dimensional and independent vector random variables[36] and set $X = P + S$, $Y = S + Q$ and $Z = Q - P$ with $r_{X,Y}$ and $r_{Y,Z}$ positive. Then $r_{X,Z}$ will be negative. I omit the proof here in the interest of time and space.

One interesting thing to note however regarding transitivity of the Pearson correlation is that if we constrain $r_{X,Y}$ and $r_{Y,Z}$ such that $r^2_{X,Y} + r^2_{Y,Z} > 1$ then X and Z will be

[36] i.e. $P = \{p_1, p_2, \ldots, p_n\}$ etc.

positively correlated. See Appendix A for a geometric proof of this.

To relate this discussion regarding the non–transitivity of the Pearson correlation back to the measures introduced in the study. Non–transitivity implies that if we have a set of firms X and we choose three disjoint (i.e., mutually exclusive) subsets of firms A, B and C from X and calculate the closeness measures C^1 and C^2 then it is not necessarily the case that if firm–group $A \cup B$ are close[37] and firm–group $B \cup C$ are close that firm–group $A \cup C$ will be close. To illustrate, suppose that $A = \{i\}$, $B = \{j\}$ and $C = \{k\}$ (three groups each with one firm). Then, $A \cup B = \{i, j\}$, $B \cup C = \{j, k\}$ and $A \cup C = \{i, k\}$. Because of the non–transitivity of the Pearson correlation we could have, for example, cases where the earnings of firms i and j are positively correlated ($r_{ij} > 0$) and the earnings of firms j and k are positively correlated ($r_{jk} > 0$) but the earnings of firms i and k are negatively correlated ($r_{ik} < 0$).

1.5.3 Relationship Between the Measures

Since I know that the determinant of the correlation matrix for two variables is one less the square of the Pearson correlation between each of the variables, it becomes clear that the two measures introduced previously have a non–linear relationship. That is, I have the following ...

$$\begin{aligned} C^2_{AE}(r) &= \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |CORR_{AE}(i,j)| = \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (1 - r_{i,j}^2) \\ &= \frac{1}{\binom{N}{2}} - \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} r_{i,j}^2 \end{aligned}$$

Differentiating $C^2(r)$ with respect to r gives ...

$$\begin{aligned} \frac{\partial C^2}{\partial r} &= -\ 2 * \frac{1}{\binom{N}{2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} r_{i,j} \\ &= -\ 2 * C^1(r) \end{aligned}$$

Thus, interestingly, the derivative of closeness measure two is a linear decreasing function

[37] Again, there is positive, negative and zero–closeness but non–transitivity applies to every case.

of closeness measure one. The fact that the derivative of C^2 with respect to r is negative is intuitive. As r increases we know, from the equation on page thirty, that $|CORR_{AE}(i,j)|$ decreases for all (i,j) pairs. Therefore, C^2 decreases since it is an average of decreasing determinants.

1.6 Limitations of the Measures

Based on the previous theoretical discussion of C^1 and C^2 at least four limitations can be identified related to these measures. First, as stated earlier, the measures only capture a linear closeness relation between a group of firms. To the extent that a non–linear relation exists within a firm–group, the measures are not fit to capture this since C^1 and C^2 are functions of the Pearson Correlation (r) and r is a measure of the linear association between two variables. This limitation is eased somewhat in the next section where simulation is used to provide assurance that the measures capture closeness as defined in the paper.

Second, the measures do not display countable additivity. That is, for a given group of firms, the closeness of the group is not equal to the sum of the closeness of any combination of pair–wise disjoint subsets of that group. This is an inconvenience since if we lose a firm from a group, we have to re–calculate closeness of the new group as a whole rather than re–calculating only the closeness of the particular subset that contained the omitted firm (a much easier empirical task).

Third, the measures, since they measure the closeness in ex post financial statement information, do not control for differences in firm–specific exposure to economic events. Therefore, one must attempt to control for these differences by putting firms into groups which have exposure to similar economic events first before calculating the closeness of the group. The measures are thus not designed to take a population of firms and optimally parcel them into respectively "close" groups; rather they are designed to, once given a group of firms, determine how close those firms are based on historical accounting fundamental co–movement.

Finally, the measures do not speak to the closeness in accounting functions. That is, for a given set of economic events (x) that firm i and firm j are both exposed to, the closeness of these two firms treated as a group could be high when the accounting functions that each firm employs are vastly different $f_i \neq f_j$. This, of course, is only a limitation however if "closeness" is defined in terms of the closeness in accounting functions. No "closeness" measure can measure the closeness in accounting functions **and** ex post fundamentals simultaneously while controlling for the economic events. This is mathematically impossible.

1.7 Simulating Closeness

As discussed previously, simulating an earnings process and then applying the closeness measures introduced helps to add to the construct validity of the measures. In simulation space I have an experiment where I can ensure that groups of firms have similar earnings processes ex ante (i.e., before the simulation based on the parameter values set up in the model) and should have correlated abnormal earnings and cash flows ex post. I can then simulate and apply the measures to those ex post performance summary variables. Relatively high values of the measures (i.e., relative to what I would expect ex ante) bolsters confidence that the measures are effective operationalizations of the closeness construct I wish to capture.

I begin with the framework proposed by Feltham and Ohlson (1996). They consider a firm with stochastic operating cash flows at a sequence of dates $t \in \{0, 1, 2, \ldots\}$. At date t the firm receives cash revenue CR_t and invests cash CI_t, where cash receipts are a function of prior cash investments. They initially assume that current cash receipts and investments constitute the only relevant information for predicting future cash flows. Thus the model is specified below.

$$CR_{t+1} = \gamma CR_t + \kappa CI_t + \epsilon_{CR_{t+1}} \tag{14}$$

$$CI_{t+1} = \omega CI_t + \epsilon_{CI_{t+1}} \tag{15}$$

where $\epsilon_{CR_{t+1}}$ and $\epsilon_{CI_{t+1}}$ are zero–mean stochastic terms (i.e. $E_t[\epsilon] = 0$ for all $t \geq 0$). The model above is fully determined by three parameters γ, κ and ω. $\kappa > 0$ represents the impact of date t cash investments on date $t+1$ cash receipts. $\gamma \in (0, 1)$ is the persistence in cash receipts. $\omega \in [0, R)$ represents the expected growth in cash investments and R represents one plus the risk–free interest rate. Note that from Feltham, Ohlson [1996] (p. 214, Corollary 1 and also see proof of Proposition 1) if we have zero net–present value (NPV) investments then $\gamma + \kappa = R$. The rest of the model is as follows [38].

$$CF_{t+1} = CR_{t+1} - CI_{t+1} \tag{16}$$

$$OA_{t+1} = \delta OA_t + CI_{t+1} \tag{17}$$

$$INC_{t+1} = CR_{t+1} - (1 - \delta)OA_t \tag{18}$$

where CF represents cash flows. OA represents non–cash operating assets with $\delta \in (0, 1)$ the accrual accounting choice parameter which can be thought of as 1 minus a (declining balance) depreciation rate. INC represents accrual accounting income or earnings.

Matlab was used to simulate the time series equations (14) – (18) for ten groups of firms — each with one hundred firms — for one hundred periods [39]. The groups represent industries in the sense that each group has equal parameter values, and normally distributed shock terms with equal variance. Kappa is set to satisfy the zero–NPV condition and $R = 1.05$ throughout. Finally, I arbitrarily assign $CI_0 = 100$ and initial values of the other variables equal to their steady state without shocks [40]. The following table summarizes the portion of the parameter space in which the simulations are run.

[38]FO (1996) have time series equations in their model for firm value and economic income but for simplicity's sake I omit these.

[39]Results were very similar when each group only consisted of ten firms and the number of periods was ten.

[40]That is CR_0, INC_0, CF_0 and OA_0 are set equal to the value that these variables would approach if given no shock terms. Mathematical derivation of the steady states is a relatively straightforward algebra exercise.

Table 1.3: Simulation Parameters and Shocks

Group	N	# of Periods	R	$\omega = \gamma = \delta$	$\kappa = R - \gamma$	$\sigma^2(\epsilon)$
1	100	100	1.05	0.99	0.96	0.05
2	100	100	1.05	0.89	0.86	0.10
3	100	100	1.05	0.79	0.76	0.15
4	100	100	1.05	0.69	0.66	0.20
5	100	100	1.05	0.59	0.56	0.25
6	100	100	1.05	0.49	0.46	0.30
7	100	100	1.05	0.39	0.36	0.35
7	100	100	1.05	0.29	0.26	0.40
9	100	100	1.05	0.19	0.16	0.45
10	100	100	1.05	0.09	0.06	0.50

Since I am only concerned with the ability of the measures to capture closeness, I only need to ensure that groups of firms have similar earnings processes within–group and that there are between group differences in this initial similarity. Ensuring this will imply that, post simulation, closeness in abnormal earnings should follow a decreasing trend between groups since the variance of the shocks is increasing. The reason is that increasing variance of shocks introduces increasing randomness to each groups' earnings process and thus less probability that their abnormal earnings will move together. In fact if there are no shocks to cash receipts or investments within–group then each group will have perfectly close abnormal earnings over the one hundred periods since each firm within a particular group has the same parameter values. Similarly, if each group has shocks too large then no group will have statistically significantly close abnormal earnings. The variance of the shocks was arbitrarily assigned so that each groups' variance only differed by a very small amount (i.e., 0.05) to see if the measures really can capture differences in closeness ex post. Furthermore, I would expect ex ante that abnormal cash flows will have high closeness across the groups and likely will not follow a decreasing trend in closeness as variance of shocks increases. This is due to cash flows simply being cash receipts less cash investment for the period (see equation 16) and since both cash receipts and investment are given equal variance shocks within–groups, cash flows will still be very close (i.e. I expect $C^1_{ACF} \approx 1$ and $C^2_{ACF} \approx 0$) within–group due to the small variance of the shock terms.

Next, I employed a simple lagged time–series earnings and cash flow expectations model to calculate abnormal earnings and cash flows respectively[41]. Specifically, I ran the following cross–sectional linear regressions with $\theta_{i,t}$ and $\lambda_{i,t}$ assumed to be zero–mean, random variables.

$$INC_{i,t+1} = \alpha_i + \beta_i * INC_{i,t} + \theta_{i,t} \tag{19}$$

$$CF_{i,t+1} = \delta_i + \gamma_i * CF_{i,t} + \lambda_{i,t} \tag{20}$$

Then abnormal earnings and cash flows for each firm in each period (i.e., $AE_{i,t}$, $ACF_{i,t}$) were set equal to their respective fitted residuals from (19) and (20) as follows

$$AE_{i,t} = \hat{\theta}_{i,t} = INC_{i,t+1} - \hat{\alpha}_i - \hat{\beta}_i * INC_{i,t} \tag{21}$$

$$ACF_{i,t} = \hat{\lambda}_{i,t} = CF_{i,t+1} - \hat{\delta}_i - \hat{\gamma}_i * CF_{i,t} \tag{22}$$

Once abnormal earnings and abnormal cash flows were calculated for each firm for each period, matrices were formed where the columns represented the firms abnormal earnings or abnormal cash flows and the rows represented the periods. Then the same procedure as in Examples 1 and 2 was used to calculate the two measures. Upon simulating the above model the following results were obtained.

[41]Other variations of earnings and cash flow expectations models (e.g., different ARIMA models) were used to calculate abnormal earnings and cash flows but the results were robust.

Table 1.4: Closeness Measures from Simulation

Group	$\sigma^2(\epsilon_{CR}) = \sigma^2(\epsilon_{CI})$	C^1_{AE}	C^1_{ACF}	C^2_{AE}	C^2_{ACF}	C^1	C^2
1	0.05	0.9633	0.9777	0.0720	0.0441	0.9705	0.0580
2	0.10	0.9286	0.9943	0.1377	0.0114	0.9614	0.0745
3	0.15	0.7876	0.9934	0.3788	0.0132	0.8905	0.1960
4	0.20	0.6283	0.9922	0.6027	0.0155	0.8103	0.3091
5	0.25	0.5019	0.9915	0.7433	0.0169	0.7467	0.3801
6	0.30	0.4094	0.9914	0.8262	0.0171	0.7004	0.4217
7	0.35	0.3453	0.9912	0.8727	0.0174	0.6683	0.4451
8	0.40	0.3088	0.9914	0.8965	0.0172	0.6501	0.4568
9	0.45	0.3009	0.9913	0.9010	0.0173	0.6461	0.4592
10	0.50	0.2907	0.9917	0.9066	0.0166	0.6412	0.4616

Several interesting things are evident from the simulation results. First, one can see that abnormal cash flows don't change much regarding their closeness across the groups as I expected ex ante for the reason given. If the variance of the shocks were made larger I would expect abnormal cash flows to exhibit less closeness across periods. Second, I see overall that the equally weighted measures C^1 and C^2 both follow a strictly decreasing trend of closeness as variances of shocks increase which is what I would expect of a measure that adequately captures closeness. What is interesting is that the measures do not follow a linearly decreasing trend of closeness even as the variance of shocks follows a linearly increasing trend (increasing by 0.05 for each group). I however had no ex ante expectation regarding how the closeness measures would decrease as variance of shocks increased, only that the measures would show a strictly decreasing trend. Furthermore I see that the abnormal earnings component measures capture closeness across the range of large closeness to small closeness. One can see this by using the above Table 1.4 and the guidelines from Table 1.1. Finally, using Table 1.1 and Table 1.4 one can see that the measures are always consistent. That is, when C^1 ranked a group in a closeness category according to Table 1.1 then C^2 also ranked the same group in that closeness category[42]. The following graph displays how the closeness measures change with regard to increasing the variance of the shocks to cash revenue and investment.

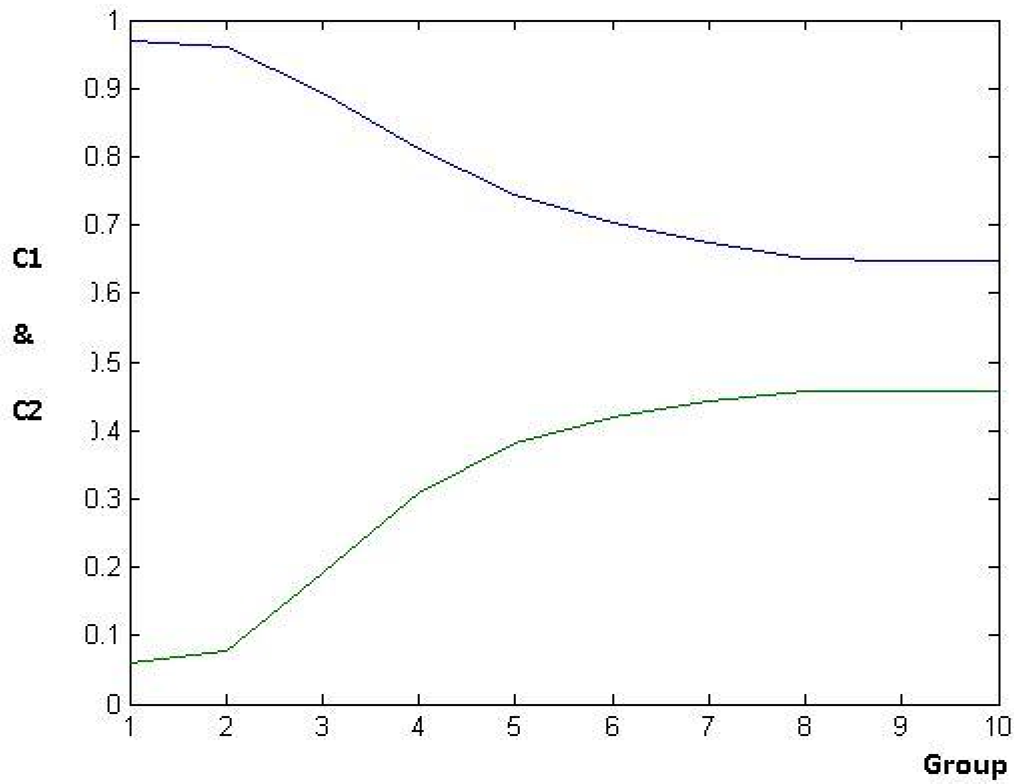

Figure 1.2: Closeness Measures

From above, one can see that closeness is a concave decreasing function of the variance of the shocks to cash receipts and investment for both measures. Furthermore, one should notice that C^2 is decreasing at a faster rate and is slightly more concave than C^1 suggesting that C^2 is more sensitive to changes in the randomness of the earnings process (i.e., variance of the shocks). Additional simulations with both larger initial variances and/or bigger step sizes shows that the concavity diminishes for both measures but faster for C^1. The measures approach a linear decreasing function of the variance on the shocks as the variances and/or step sizes are increased. The important point though is

[42]Every group exhibited large closeness with this simulation due to the low relative variance on the shock terms. Additional simulations with higher shock variances showed that the measures also identify firms with medium, low and small closeness as one would expect.

that closeness decreases (as one would expect ex ante) with randomness in the earnings process across groups of firms. In summary, the simulations provide evidence that the measures introduced in this study adequately capture the closeness construct as defined.

I will next apply the measures to firms which have been grouped mostly based on similarity in primary revenue generating activities (i.e. firms grouped according to the SIC and GIC schemes). This exercise helps to assess whether similarity in primary revenue generating activity implies similarity in financial statements and thus "closeness" of firm–groups. Researchers often use the SIC and GIC industrial classification schemes to control for similarity among firms. At best, this seems a rough proxy for the transactions x (see equation (6)) that each firm in the group is exposed to as there are many firm–specific transactions that are independent of the firms' primary revenue generating activity. These existing schemes cannot capture similarity in the way firm–groups process their individual sets of economic transactions (f_i) and thus cannot capture similarity in the fundamental outputs of this processing ($FinancialStatements_i$). The measures introduced herein can capture similarity in the fundamental outputs and thus researchers could use them as a second–stage grouping exercise after first forming firm–groups using the SIC and GIC schemes.

Analysts could also use the measures to help them in forecasting future firm performance. Firms grouped according to correlation of financial statement information over time (as proxied for by correlation in earnings and cash flows) should be easier to analyze and develop forecasts of future performance. Specifically, knowing that firms i and j are close would make it easier to forecast firm j's earnings given firm i's earnings and vice versa. The forecast errors for firm–groups exhibiting higher closeness should be lower than those groups exhibiting lower closeness.

Finally, investors could possibly employ the measures in choosing among investment portfolio alternatives. More specifically, suppose there are two groups of firms — portfolio A and portfolio B — that one wishes to invest in. Further, suppose that firm–group A ranks high on closeness measure one and two (i.e. $C^1 > 0.5$, $C^2 < 0.35$) while firm–group B ranks low (i.e. $C^1 < 0.3$, $C^2 > 0.6$) using the Table 1.1 interpretations. Assuming that all firms in group A do not announce earnings at the same time, an investor could use this knowledge to earn an abnormal return. When firm i from portfolio A announces earnings the investor could observe how the announced earnings relate to firm i's mean earnings over a historical time period. High earnings (relative to this mean) coupled with the knowledge that the firms in portfolio A have historically highly correlated fundamentals should increase the expected return from a "buy" decision for shares in portfolio A firms. This of course is assuming that the market fails to take into account the historical closeness information of portfolio B firms and therefore undervalues these firms at $t = 0$. Similarly, if firm i's earnings announcement is low (relative to mean) an investor could sell shares in portfolio A firms and incur a smaller loss. The strategy described above is examined formally in Chapter 3.

Accordingly, an examination of how historical returns relate to firm–group closeness could speak to the feasibility of the strategy described above. Specifically, if firm–group cumulative abnormal returns are increasing in firm–group closeness (as measured by C^1 and C^2 introduced in this study) then the strategy described above would be validated, at least historically. This idea is examined in Chapter 3.

Chapter 2: Closeness and Industrial Classification

2.1 Current Industrial Classification Schemes

The four most recognized industrial classification systems are the SIC (Standard Industrial Classification System), GICS (Global Industrial Classification Standard), NAICS (North American Industrial Classification System) and the FF classification (Fama & French). It turns out that the NAICS and the FF are just refinements of the SIC. Weiner (2005) does a good job of describing each of these systems[43] so I refer the interested reader to his paper. The main finding in his paper is that on average 30% of papers published in the top 3 finance and top 2 accounting journals use industrial classification systems. He finds that the main purposes for using them are sample restriction (34%), comparable company selection (31%), and detection of industry effects (12%). Thus there is a demand for a measure of economic relatedness among firms in financial research and current industrial classification systems have been developed to meet this demand. Since the SIC is the oldest and most widely used classification system I will talk a little about the history and methodology of this system as well as the replacement of this system with the NAICS. Also, the GICS was created with the finance community in mind and was shown by Bhojraj et al. (2003) to be superior to the SIC, FF and NAICS at explaining co–movements in stock returns as well as cross–sectional variations in valuation multiples, research and development expenditures, key financial ratios and forecasted and realized growth rates. Therefore, I will also discuss the history and methodology of this system. Analysis in later sections will evaluate the measures in light of these two classification systems. Therefore, this section seeks to provide the reader with an introduction to the two systems.

[43] He gives a short historical background on each system and talks a little about the methodology of each system.

2.1.1 Standard Industrial Classification

In the 1930's the agencies of the U.S. government had classification schemes to group establishments[44] into homogeneous groups for the purpose of data collection and analysis. Recommendation was made in 1934 at an Interdepartmental Conference on Industrial Classification to establish a continuing committee to explore the problems of industrial classification of statistical data. This recommendation was transmitted to the Central Statistical Board and in 1937 they established an Interdepartmental Committee on Industrial Classification. The committees' charge was "to develop a plan of classification of various types of statistical data by industries and to promote the general adoption of such classification as the standard classification of the Federal Government."(Pearce, 1957) Standardization was an important objective since agencies collecting industrial data used their own classification, and sometimes would thus classify a given establishment into two different industries. The project was designed to classify "industry" in the broad sense of all economic activity; i.e., agriculture, forestry and fisheries, mining, construction, manufacturing, wholesale and retail trade, finance, insurance, real estate, transportation, communication, electric, gas, sanitary services, and services. Soon after the committee was formed the first SIC was published in 1939. In 1941 the Central Statistical Board was transferred to the Bureau of the Budget and it was decided that the SIC should be evaluated in light of recent changes and revised. New editions of the SIC were made in 1945, 49, 57, 80 and 1987. In 1997 the Office of Management and Budget (formerly the Bureau of Budget) developed the North American Industrial Classification system to replace the SIC and jointly developed the U.S. Economic Classification Policy Committee (ECPC), Statistics Canada and Mexico's Instituto Nacional de Estadistica y Geografia to allow for a high level of comparability in business statistics among North American countries. Despite the new name, most former SIC industries were still employed but the ECPC eliminated certain industries that were no longer well–represented in the current technological environment and also added new industries. The ECPC set

[44] This was the term used to refer to various entities from small businesses to larger companies.

a 5–year mandatory revision cycle ensure that the classification continues to reflect the rapidly changing structure of the economies of North American countries New revisions to the NAICS thus came out in 2002 and 2007.

The overall methodology of the SIC/NAICS is relatively simple in theory. Entities are grouped based on similarity of processes and products involved in production. For example, the first sector in the former SIC and now NAICS system is 11–Agriculture, Forestry, Fishing and Hunting. This sector is comprised of five subsectors and each subsector is comprised of industries. The first subsector in the 11 industry is 111–Crop Production. This subsector is comprised of industries which grow crops for food and fiber. One such industry in this subsector is Oilseed and Grain Farming which is comprised of entities which are primarily engaged in growing oilseed and/or grain crops and/or producing oilseed and grain seeds. The NAICS thus uses a six–digit hierarchical coding system to classify all economic activity into twenty industry sectors[45]. Five sectors are mainly goods–producing sectors and fifteen are entirely services–producing sectors. This six–digit hierarchical structure allows greater coding flexibility than the four–digit structure of the SIC. This leads to the NAICS identifying 1,170 industries compared to the 1,004 found in the SIC system.

2.1.2 Global Industrial Classification Standard

In 1999 Standard & Poors (S&P) joined with Morgan Stanley Capital International (MSCI) to form the GICS with the purpose of developing a global standard for grouping companies into sectors and industries. Being a global company classification standard, the GICS covers approximately 98% of the world's equity market capitalization representing more than 34,000 active companies and 38,000 active securities. According to a document published by the S&P ...

> *The GICS was developed in response to the global financial community's need for one complete, consistent set of global sector and industry definitions,*

[45] The first two digits represent the sector, the 3rd digit represents the subsector, the 4th represents the industry group, the 5th digit represents the industry and the 6th digit represents the country (either U.S., Canada or Mexico).

thereby enabling asset owners, asset managers and investment research specialists to make seamless company, sector and industry comparisons across countries, regions and globally.

The GICS was thus created with the financial community in mind and is popular among practitioners. Academics also have begun to rely on the GICS to help with grouping comparable firms. The GICS currently consists of 10 sectors, 24 industry groups, 67 industries and 147 sub–industries. Under the GICS firms are grouped based on similarity of primary business activity. Revenues are used as a key measure of primary business activity but earnings and market perception of a companies' primary business activity are also taken into consideration when assigning a company to a sub–industry. The exact algorithm that S&P uses when assigning a company to a sub–industry is not known as S&P and MSCI make a strong effort to keep the specifics of their methodology confidential. However we do know that a company is re–assigned to a different industry only if there is a major corporate action which redefines a company's main line of business. Annual reviews are done to assess this possibility for each company.

2.2 Industrial Classification Schemes and Closeness

Current industrial classification schemes have been designed with the goal of grouping comparable firms. The dimension of comparability commonly chosen to group firms is primary revenue generating business activity (GICS), or product and process production similarity (SIC/NAICS). There is probably a higher likelihood that accounting fundamentals for a group of firms with the same primary revenue generating business activity move similarly than the same fundamentals for a group of firms with different primary revenue generating business activities. However, one can only assume this is true. The measures introduced in Chapter 1 provide a way to group firms based on financial statement accounting information, and not only to group them, but to rank these groups in terms of closeness. Industrial classification systems simply inform us that a group of firms is comparable in the sense that they have the same primary revenue generating business activity, product or production process. However the magnitude of comparability is not specified nor the comparability of the groups' financial statement information. The implicit assumption with the schemes is that within–industry closeness is constant across industries. This, as I find, is not necessarily true.

Although the GICS was designed with the financial community in mind, SIC codes were originally designed for the traditional manufacturing–based economy. For example, major sectors in the two–digit designation still include mining and agriculture which play a decreasingly important role in today's information and service–based economy. It would thus seem a useful exercise to evaluate the GICS and SIC/NAICS in regards to their ability to group firms who are close in the accounting information sense described in Chapter 1. After all if two firms have the same primary revenue generating business activity but due to firm–specific characteristics have uncorrelated financial statement information levels over time then does knowing that they are classified in the same industry really help us? Are these firms really comparable in an accounting information sense?

The rest of Chapter 2 is devoted to evaluating the SIC/NAICS and GICS classification schemes in regards to their ability to group firms who are close in an accounting information sense as captured in the two measures introduced in Chapter 1. It should be pointed out that the two measures are useful for the purpose of evaluating the closeness of a proposed grouping of firms. The development of a new classification scheme based on the application of the two measures with no constraints would be infeasible since the correlation between all possible pairs of firms, all possible triplets of firms, and so on would have to be calculated to determine the optimal grouping of a given number of firms (i.e. how many groups, how many firms per group and which firms belong in each group?). One would have to constrain the problem to the extent that the number of "comparable" firms in a group be set at say 100 for example. Then you could calculate the two measures for all possible combinations of 100 firms out of the total number of firms and rank each 100 firm group in terms of closeness. Because of these theoretical difficulties the measures introduced in this study are best suited to giving the researcher a way to — once given a group of firms — evaluate the extent to which that group of firms is comparable in an ex post fundamental accounting information sense.

2.2.1 Methodology

A search of COMPUSTAT over the time period 1999–2010 produced a sample of 98,922 firm–year observations representing 9,229 firms, each with net income and operating net cash flow data (COMPUSTAT variables NI and OANCF respectively) for at least one year of the 12–year time period. This particular sample period was chosen because the GIC was introduced in 1999 and for comparison I didn't want to examine industry closeness using different time periods for the SIC and GIC. The sample size was reduced to 79,934 firm–year observations after deleting firm–years with missing observations on either net income or operating cash flow. An additional 34,430 firm–year observations were lost after requiring each firm to have 12 years of net income and operating cash flow observations (e.g. for 1999–2010)[46]. Finally, 48 firm–year observations were lost after requiring that each industry (using both the GIC and SIC schemes) have at least two representing firms. This loss of observations was due to the fact that SIC two–digit industries 8, 41,81 and 89 only had one representing firm. The final sample consisted of 45,456 firm–year observations representing 3,788 unique firms.

The final sample was then organized into two–digit SIC industry sectors[47] and the closeness measures were calculated[48] for each industry using net income and operating net cash flow as well as using abnormal net income and operating net cash flow[49]. This analysis was repeated after organizing the final sample into 6–digit GIC industries. Tables 5 and 6 show the two–digit SIC and 6–digit GIC industries represented in the final sample[50]. Of the 83 two–digit SIC industries, 66 were represented and all 68 of the GIC six–digit industries were represented with at least two firms over the sample period.

[46]In order to calculate the closeness measures, each firm must have the same number of observations.

[47]I could have also grouped by four–digit to do industry analysis. However, grouping by four–digit would have led to analyzing many industry samples with 5 firms or less.

[48]MATLAB was used throughout for analysis.

[49]Abnormal earnings and operating net cash flow are estimated as the fitted residuals from the lagged model in equations (19) and (20) used in the simulations in Chapter 1.

[50]The two–digit SIC scheme aligns with the six–digit GIC scheme in that both levels of granularity respectively refer to one level of detail finer than the industry sector.

Table 2.1: SIC two–digit Industries Represented (66/83)

01 - - AGRICULTURE PRODUCTION–CROPS
02 - - AGRICULTURAL PRODUCTION–LIVESTOCK
07 - - AGRICULTURAL SERVICES
10 - - METAL MINING
12 - - COAL MINING
13 - - OIL AND GAS EXTRACTION
14 - - NONMETALLIC MINERALS EXCEPT FUELS
15 - - GENERAL BUILDING CONTRACTORS
16 - - HEAVY CONSTRUCTION EXCEPT BUILDING
17 - - SPECIAL TRADE CONTRACTORS
20 - - FOOD AND KINDRED PRODUCTS
21 - - TOBACCO PRODUCTS
22 - - TEXTILE MILL PRODUCTS
23 - - APPAREL AND OTHER TEXTILE PRODUCTS
24 - - LUMBER AND WOOD PRODUCTS
25 - - FURNITURE AND FIXTURES
26 - - PAPER AND ALLIED PRODUCTS
27 - - PRINTING AND PUBLISHING
28 - - CHEMICALS AND ALLIED PRODUCTS
29 - - PETROLEUM AND COAL PRODUCTS
30 - - RUBBER AND MISC. PLASTICS PRODUCTS
31 - - LEATHER AND LEATHER PRODUCTS
32 - - STONE, CLAY, AND GLASS PRODUCTS
33 - - PRIMARY METAL INDUSTRIES
34 - - FABRICATED METAL PRODUCTS
35 - - INDUSTRIAL MACHINERY AND EQUIPMENT
36 - - ELECTRONIC & OTHER ELECTRIC EQUIPMENT
37 - - TRANSPORTATION EQUIPMENT
38 - - INSTRUMENTS AND RELATED PRODUCTS
39 - - MISC. MANUFACTURING INDUSTRIES
40 - - RAILROAD TRANSPORTATION
42 - - TRUCKING AND WAREHOUSING
44 - - WATER TRANSPORTATION
45 - - TRANSPORTATION BY AIR
46 - - PIPELINES, EXCEPT NATURAL GAS
47 - - TRANSPORTATION SERVICES
48 - - COMMUNICATION
49 - - ELECTRIC, GAS, AND SANITARY SERVICES
50 - - WHOLESALE TRADE - DURABLE GOODS
51 - - WHOLESALE TRADE - NONDURABLE GOODS
52 - - BUILDING MATERIALS, HARDWR, GARDEN SUPPLY
53 - - GENERAL MERCHANDISE STORES

Table 2.1: Continued

54 - - FOOD STORES
55 - - AUTOMOTIVE DEALERS & SERVICE STATIONS
56 - - APPAREL AND ACCESSORY STORES
57 - - FURNITURE AND HOMEFURNISHINGS STORES
58 - - EATING AND DRINKING PLACES
59 - - MISCELLANEOUS RETAIL
60 - - DEPOSITORY INSTITUTIONS
61 - - NONDEPOSITORY INSTITUTIONS
62 - - SECURITY AND COMMODITY BROKERS
63 - - INSURANCE CARRIERS
64 - - INSURANCE AGENTS, BROKERS, & SERVICE
65 - - REAL ESTATE
67 - - HOLDING AND OTHER INVESTMENT OFFICES
70 - - HOTELS AND OTHER LODGING PLACES
72 - - PERSONAL SERVICES
73 - - BUSINESS SERVICES
75 - - AUTO REPAIR, SERVICES, AND PARKING
78 - - MOTION PICTURES
79 - - AMUSEMENT & RECREATION SERVICES
80 - - HEALTH SERVICES
82 - - EDUCATIONAL SERVICES
83 - - SOCIAL SERVICES
87 - - ENGINEERING & MANAGEMENT SERVICES
99 - - NONCLASSIFIABLE ESTABLISHMENTS

Table 2.2: GIC six–digit Industries Represented (68/68)

101010 – ENERGY EQUIPMENT & SERVICES
101020 – OIL, GAS & CONSUMABLE FUELS
151010 – CHEMICALS
151020 – CONSTRUCTION MATERIALS
151030 – CONTAINERS & PACKAGING
151040 – METALS & MINING
151050 – PAPER & FOREST PRODUCTS
201010 – AEROSPACE & DEFENSE
201020 – BUILDING PRODUCTS
201030 – CONSTRUCTION & ENGINEERING
201040 – ELECTRICAL EQUIPMENT
201050 – INDUSTRIAL CONGLOMERATES
201060 – MACHINERY
201070 – TRADING COMPANIES & DISTRIBUTORS
202010 – COMMERCIAL SERVICES & SUPPLIES
202020 – PROFESSIONAL SERVICES
203010 – AIR FREIGHT & LOGISTICS
203020 – AIRLINES
203030 – MARINE
203040 – ROAD & RAIL
203050 – TRANSPORTATION INFRASTRUCTURE
251010 – AUTO COMPONENTS
251020 – AUTOMOBILES
252010 – HOUSEHOLD DURABLES
252020 – LEISURE EQUIPMENT & PRODUCTS
252030 – TEXTILES, APPAREL & LUXURY GOODS
253010 – HOTELS, RESTAURANTS & LEISURE
253020 – DIVERSIFIED CONSUMER SERVICES
254010 – MEDIA
255010 – DISTRIBUTORS
255020 – INTERNET & CATALOG RETAIL
255030 – MULTILINE RETAIL
255040 – SPECIALTY RETAIL
301010 – FOOD & STAPLES RETAILING
302010 – BEVERAGES
302020 – FOOD PRODUCTS
302030 – TOBACCO
303010 – HOUSEHOLD PRODUCTS
303020 – PERSONAL PRODUCTS
351010 – HEALTH CARE EQUIPMENT & SUPPLIES
351020 – HEALTH CARE PROVIDERS & SERVICES
351030 – HEALTH CARE TECHNOLOGY

Table 2.2: Continued

352010 – BIOTECHNOLOGY
352020 – PHARMACEUTICALS
352030 – LIFE SCIENCES TOOLS & SERVICES
401010 – COMMERCIAL BANKS
401020 – THRIFTS & MORTGAGE FINANCE
402010 – DIVERSIFIED FINANCIAL SERVICES
402020 – CONSUMER FINANCE
402030 – CAPITAL MARKETS
403010 – INSURANCE
404020 – REAL ESTATE INVESTMENT TRUSTS
404030 – REAL ESTATE MANAGEMENT & DEVELOPMENT
451010 – INTERNET SOFTWARE & SERVICES
451020 – IT SERVICES
451030 – SOFTWARE
452010 – COMMUNICATIONS EQUIPMENT
452020 – COMPUTERS & PERISPHERALS
452030 – ELECTRONIC EQUIPMENT & INSTRUMENTS
452040 – OFFICE ELECTRONICS
453010 – SEMICONDUCTORS & SEMICONDUCTOR EQUIPMENT
501010 – DIVERSIFIED TELECOMMUNICATION SERVICES
501020 – WIRELESS TELECOMMUNICATION SERVICES
551010 – ELECTRIC UTILITIES
551020 – GAS UTILITIES
551030 – MULTI-UTILITIES
551040 – WATER UTILITIES
551050 – INDEPENDENT POWER PRODUCERS & ENERGY TRADERS

Firms with extreme observations on either net income or net operating cash flow in any of the 12 years could bias against closeness depending on the direction and magnitude of these observations. To control for this bias I repeated the method described earlier after deleting firms with net income and/or net operating cash flow observations greater than two standard deviations from their respective 12 year means. This trimming procedure reduced the sample to 11,916 firm–year observations representing 993 unique firms. In addition several SIC and GIC industries were lost due to the requirement that at least two firms be present to represent an industry. Accordingly, the trimmed sample represented 56 of the 83 SIC industries and 63 of the 68 GIC industries.

Finally, I took 10 random samples[51] of 250 firms each and calculated the closeness measures both before deleting outliers and after. I believe the sample size chosen for the random samples is large enough to ensure that firms from vastly different SIC and GIC industries are included. The idea behind this procedure was to establish the baseline closeness of a group of firms with regards to their net income and net operating cash flows (both realized and unexpected). Ex ante, I would expect the average random 250–firm sample closeness to be close to zero[52]. Average SIC/GIC industry closeness could then be judged in light of this. If the average SIC/GIC industry closeness is not much different than the closeness of a random group of 250 firms then, either the industrial classification schemes do little in terms of grouping firms whose fundamentals move similarly, or they do and my measures fail to adequately capture this similarity[53]. I expected ex ante that the closeness of most SIC/GIC industries would be statistically different than zero because I believe that firms engaging in the same primary revenue generating activity (and hence in the same industry according to both schemes) likely face somewhat similar demand and supply–side markets and this would lead to their fundamentals moving at least somewhat similarly. I didn't have an expectation though regarding the magnitude

[51] I collected all the company identifying GVKEYS in a vector and then had MATLAB's random number generator generate a pseudorandom number ranging from one to the size of the vector drawn from a uniform probability distribution. Therefore, in theory, each GVKEY had an equal chance of being selected

[52] Close to one for measure two.

[53] I highly doubt this is the case though as the simulation exercise from Chapter 1 provides strong evidence that the measures capture closeness as defined.

of average industry closeness. I do believe though that each schemes' methodology (i.e. basically grouping firms with similar primary revenue generating activities) is neither necessary nor sufficient for grouping firms whose fundamentals are correlated over time.

2.2.2 SIC Results

Some interesting results emerge upon analysis[54]. First, average SIC industry closeness using measure one with unexpected earnings and net operating cash flows is 0.0918[55]. Using Table 1.1 I interpret this result to mean that on average, there is no relationship between a group of firms' unexpected earnings and unexpected net operating cash flows formed according to the SIC scheme. Measure two yields the same inference in that the average SIC industry closeness with unexpected earnings and net operating cash flows is 0.8684. I am using Table 1.1 to interpret the results as it is simpler to use and somewhat intuitive. The drawback to Table 1.1 however is that it is a somewhat arbitrary classification of the cutoffs for C^1 and C^2. Accordingly, hypothesis tests were done for each industry where the null hypothesis was that the closeness of the industry was not statistically significantly different from zero (from one if measure two was used). P–values were then calculated and results from this analysis were that 37/66 industries exhibited statistically significant closeness at the 10% level or better while the other 29/66 did not.

[54]See Appendix D for a more concise summary of the results for the SIC, GIC and random sampling procedure.

[55]See Table 1.1 for interpretation cutoffs for measure one and measure two.

Below is a table summarizing the results for the SIC classification using closeness measure one with unexpected earnings and net operating cash flows[56].

Table 2.3: C^1_A Measure Results for SIC

SIC Code	**Sample Size**	C^1_{AE}	C^1_{ACF}	C^1_A	**p-value**
1	9	0.1236	0.0097	0.0666	0.2470
2	2	-0.1149	-0.0018	-0.0583	0.6055
7	2	0.3056	0.2430	0.2743	0.0985 *
10	98	0.0383	0.0002	0.0192	0.2551
12	9	-0.0116	0.0048	-0.0034	0.5140
13	146	0.1510	0.1789	0.1650	0.0000 ***
14	12	0.0270	-0.0147	0.0062	0.4707
15	17	0.3775	0.2981	0.3378	0.0000 ***
16	14	0.0465	0.1265	0.0865	0.1327
17	8	0.2686	0.1176	0.1931	0.0296 **
20	90	0.0755	0.0961	0.0858	0.0024 ***
21	7	0.2055	0.0011	0.1033	0.1754
22	10	0.2001	0.1031	0.1516	0.0493 **
23	28	0.0718	0.0775	0.0747	0.0861 *
24	23	0.1441	0.1661	0.1551	0.0049 ***
25	21	0.0857	0.0193	0.0525	0.2036
26	35	0.0928	0.1500	0.1214	0.0064 ***
27	32	0.1546	0.0072	0.0809	0.0568 *
28	328	0.0175	0.0222	0.0198	0.1066
29	31	0.3551	0.2161	0.2856	0.0000 ***
30	25	0.0136	0.0990	0.0563	0.1658
31	15	0.1221	0.0857	0.1039	0.0827 *
32	22	0.1209	0.0281	0.0745	0.1140
33	47	0.2738	0.0865	0.1801	0.0000 ***
34	50	0.0905	0.0638	0.0772	0.0294 **
35	199	0.1398	0.0445	0.0921	0.0000 ***
36	319	0.1164	0.0267	0.0716	0.0000 ***
37	84	0.1319	0.0161	0.0740	0.0094 ***
38	229	0.0426	0.0370	0.0398	0.0184 **
39	26	0.0115	-0.0018	0.0049	0.4658
40	10	0.2424	0.1488	0.1956	0.0160 **
42	27	0.2307	0.0948	0.1627	0.0016 ***

[56] Note that C^1_A is simply the equally–weighted average of C^1_{AE} and C^1_{ACF}.

Table 2.3: Continued

SIC Code	Sample Size	C^1_{AE}	C^1_{ACF}	C^1_{A}	p-value
44	23	0.2211	0.0894	0.1552	0.0049 ***
45	23	0.2984	0.1645	0.2315	0.0000 ***
46	5	0.2695	0.5280	0.3988	0.0007 ***
47	11	0.3239	0.0274	0.1757	0.0219 **
48	132	0.0867	0.0723	0.0795	0.0008 ***
49	257	0.0571	0.1169	0.0870	0.0000 ***
50	80	0.1270	0.0823	0.1047	0.0006 ***
51	43	0.0503	0.0803	0.0653	0.0693 *
52	5	0.2117	-0.0029	0.1044	0.2145
53	24	0.0848	0.0787	0.0817	0.0834 *
54	25	0.0008	0.0930	0.0469	0.2091
55	18	0.2104	0.0050	0.1077	0.0573 *
56	38	0.0761	0.0784	0.0773	0.0497 **
57	14	-0.0031	0.0414	0.0192	0.4027
58	39	0.0793	0.0314	0.0553	0.1162
59	47	0.1101	0.0400	0.0750	0.0375 **
60	13	0.1880	0.0043	0.0962	0.1164
61	48	0.1731	0.0190	0.0961	0.0105 **
62	51	0.1214	0.0331	0.0772	0.0281 **
63	114	0.3362	0.0814	0.2088	0.0000 ***
64	14	0.0481	-0.0471	0.0005	0.4975
65	39	0.0138	0.0055	0.0097	0.4174
67	165	0.0617	0.0548	0.0583	0.0048 ***
70	11	0.0988	-0.0606	0.0191	0.4142
72	12	-0.0331	0.0112	-0.0109	0.5517
73	345	0.0906	0.0495	0.0701	0.0000 ***
75	9	0.0755	0.0650	0.0703	0.2354
78	11	-0.0215	-0.0569	-0.0392	0.6721
79	40	0.0654	0.0084	0.0369	0.2098
80	50	0.0067	0.0704	0.0386	0.1728
82	13	-0.0184	0.0032	-0.0076	0.5375
83	6	-0.0791	0.1604	0.0406	0.3677
87	66	0.0464	0.0428	0.0446	0.1049
99	22	0.0322	0.0336	0.0329	0.2973
MEAN:	**57**	**0.1146**	**0.0690**	**0.0918**	
MEDIAN:	**25**	**0.0906**	**0.0470**	**0.0761**	
MAX:	**345**	**0.3775**	**0.5280**	**0.3988**	
MIN:	**2**	**-0.1149**	**-0.0606**	**-0.0583**	
VAR:	**6447**	**0.0117**	**0.0080**	**0.0072**	

Several interesting results emerge from Table 2.3 above. First, we see that average closeness of the industries using abnormal earnings (C^1_{AE}) is higher (0.1146) than using abnormal net operating cash flows (0.0690). This makes intuitive sense as one would surmise that since earnings smooth cash flows, unexpected earnings should also be more highly correlated than unexpected cash flows across time within–industry. Second, the industry with the highest closeness was SIC code 46 or Pipelines, Except Natural Gas (see Table 2.5 for reference) at 0.3988. This of course is statistically significantly different than zero at the 1% level (p–value 0.0007) and ranks as "medium" closeness according to Table 1.1. This industry however was only represented by 5 firms which had the required data available over the twelve–year time frame 1999-2010. Third, several industries exhibited negative closeness but none of these were statistically less than zero. Fourth, there were two industries represented by only two firms (SIC codes 02 and 07), so closeness inferences for these industries are limited. Fifth, several industries (e.g. SIC codes 55, 60, 61 and 63) have much higher closeness in unexpected earnings than unexpected net operating cash flows which likely implies that these industries are smoothing earnings to a greater extent than other industries. Sixth, the difference in industry closeness across industries is sometimes very large; counterintuitive to the notion that the SIC's grouping scheme ensures that within–industry similarity is mostly constant across industries. Finally, with almost half of the industries having closeness not statistically different from zero ($\frac{29}{66}$ at the 10% level or greater), and average closeness over the SIC industries of 0.0918, it appears that the SIC does a poor job of grouping firms whose unexpected earnings and net operating cash flows move similarly over time.

The table below gives the results for the SIC scheme using measure two with unexpected earnings and net operating cash flow. In interpreting the results, the reader should remember that measure two is bounded between 0 and 1 with closeness decreasing over this range.

Table 2.4: C_A^2 Measure Results for SIC

SIC Code	Sample Size	C_{AE}^2	C_{ACF}^2	C_A^2	p-value
1	9	0.9071	0.9076	0.9074	0.1706
2	2	0.9868	1.0000	0.9934	0.4879
7	2	0.9066	0.9409	0.9238	0.3632
10	98	0.8658	0.8616	0.8637	0.0000 ***
12	9	0.8407	0.8402	0.8404	0.0496 **
13	146	0.8032	0.8053	0.8042	0.0000 ***
14	12	0.9068	0.8912	0.8990	0.1145
15	17	0.5298	0.7992	0.6645	0.0000 ***
16	14	0.8580	0.8932	0.8756	0.0542 *
17	8	0.7593	0.9228	0.8410	0.0610 *
20	90	0.8765	0.8701	0.8733	0.0000 ***
21	7	0.8504	0.9041	0.8772	0.1334
22	10	0.8436	0.9162	0.8799	0.0959 *
23	28	0.8886	0.8917	0.8901	0.0221 **
24	23	0.8647	0.8654	0.8651	0.0124 **
25	21	0.8765	0.8958	0.8861	0.0356 **
26	35	0.8700	0.8863	0.8782	0.0062 ***
27	32	0.8307	0.9035	0.8671	0.0045 ***
28	328	0.8891	0.8901	0.8896	0.0000 ***
29	31	0.7533	0.7354	0.7443	0.0000 ***
30	25	0.8917	0.8860	0.8888	0.0272 **
31	15	0.9090	0.8693	0.8892	0.0694 *
32	22	0.8738	0.8900	0.8819	0.0276 **
33	47	0.8077	0.8722	0.8399	0.0001 ***
34	50	0.8697	0.8782	0.8740	0.0010 ***
35	199	0.8559	0.8902	0.8731	0.0000 ***
36	319	0.8705	0.8889	0.8797	0.0000 ***
37	84	0.8546	0.8854	0.8700	0.0000 ***
38	229	0.8877	0.8926	0.8902	0.0000 ***
39	26	0.8883	0.8800	0.8841	0.0204 **
40	10	0.8500	0.8139	0.8319	0.0332 **
42	27	0.8384	0.8800	0.8592	0.0055 ***
44	23	0.8240	0.8705	0.8472	0.0055 ***
45	23	0.8206	0.8048	0.8127	0.0009 ***
46	5	0.8467	0.6825	0.7646	0.0351 **
47	11	0.7832	0.8618	0.8225	0.0208 **
48	132	0.8744	0.8889	0.8817	0.0000 ***
49	257	0.8952	0.8803	0.8878	0.0000 ***
50	80	0.8575	0.8765	0.8670	0.0000 ***
51	43	0.8807	0.8796	0.8801	0.0032 ***

Table 2.4: Continued

SIC Code	Sample Size	C^2_{AE}	C^2_{ACF}	C^2_{A}	p-value
52	5	0.8272	0.8212	0.8242	0.0900 *
53	24	0.8791	0.8774	0.8783	0.0195 **
54	25	0.9123	0.8893	0.9008	0.0431 **
55	18	0.8076	0.8906	0.8491	0.0132 **
56	38	0.8550	0.8907	0.8729	0.0033 ***
57	14	0.8574	0.9171	0.8873	0.0730 *
58	39	0.8761	0.8944	0.8852	0.0065 ***
59	47	0.8766	0.8735	0.8750	0.0015 ***
60	13	0.8499	0.8974	0.8736	0.0580 *
61	48	0.8138	0.8945	0.8541	0.0002 ***
62	51	0.8408	0.8831	0.8620	0.0003 ***
63	114	0.7793	0.8835	0.8314	0.0000 ***
64	14	0.8939	0.8974	0.8956	0.0892 *
65	39	0.8948	0.8837	0.8893	0.0083 ***
67	165	0.8740	0.8861	0.8801	0.0000 ***
70	11	0.8272	0.8871	0.8571	0.0512 *
72	12	0.9105	0.8742	0.8923	0.0997 *
73	345	0.8798	0.8874	0.8836	0.0000 ***
75	9	0.8702	0.9378	0.9040	0.1619
78	11	0.9225	0.9038	0.9131	0.1614
79	40	0.8717	0.8832	0.8774	0.0036 ***
80	50	0.9021	0.8894	0.8958	0.0053 ***
82	13	0.8957	0.8918	0.8937	0.0935 *
83	6	0.8614	0.8836	0.8725	0.1435
87	66	0.8868	0.8957	0.8912	0.0011 ***
99	22	0.8711	0.9012	0.8861	0.0323 **
MEAN:	**57**	**0.8579**	**0.8789**	**0.8684**	
MEDIAN:	**25**	**0.8701**	**0.8867**	**0.8778**	
MAX:	**345**	**0.9868**	**1.0000**	**0.9934**	
MIN	**2**	**0.5298**	**0.6825**	**0.6645**	
VAR:	**6447**	**0.0032**	**0.0019**	**0.0019**	

Results using measure two for industry closeness are very similar as when measure one is used. Again, average industry closeness is “none” using Table 1.1 for interpretation of the 0.8684 mean industry closeness. Furthermore, p–values from a hypothesis statistical significance test of whether C^2 is different than 1 are mostly significant at the 10% level or greater (e.g. 58/66 are less than 0.1). Thus measure two provides slightly stronger evidence than measure one that the SIC groups firms whose unexpected fundamentals are correlated over time. Other inferences from the measure one results discussed earlier also hold when measure two is employed. Finally, using the interpretation cutoffs from Table 1.1, measure one and measure two agree 83% (55/66) of the time and never disagreed by more than one cutoff[57].

The main result using measure one and two with unexpected earnings and net operating cash flows discussed above is for the untrimmed sample. Extreme outliers on earnings and/or net operating cash flows in any given firm–year could definitely bias against closeness unless the outliers occur, for each firm in a given industry, in the same year and in the same direction. These outliers could be an error in the data set or actually be correct and due to some firm–specific economic event. Regardless of the reason however I recalculated the results after trimming the sample of firm–year observations such that, for each firm, any observation on earnings or net operating cash flow that was greater than two standard deviations from their respective means was deleted. Results using the trimmed sample are similar to those using the untrimmed sample. Specifically, average SIC industry closeness using measure one with unexpected earnings and net operating cash flows is 0.1520. Using Table 1.1, this result can be interpreted that the SIC groups firms into industries which exhibit, on average, **small** co–movement in unexpected earnings and net operating cash flows if we first delete any firms in each industry which have earnings or net operating cash flows greater than two standard deviations from their respective means over a given time period. Again, measure two yields the same interpretation since average SIC industry closeness using unexpected earnings and net operating cash flows with the trimmed sample is 0.8479 or "small" according to Table 1.1. Furthermore, 29/56 of the SIC industries exhibited closeness statistically different than zero while 27/56 did not using measure one. Also, as with the untrimmed sample, measure two results with the trimmed sample show a higher proportion of industries whose closeness is not statistically different than 1 (e.g. 42/56 of the p–values are less than 0.1).

I have thus far discussed the results for the SIC scheme using both measures of

[57] There was never a case where measure one implied closeness was "none" and measure two implied closeness was "medium" for example.

closeness with unexpected fundamentals. I repeated the analysis using realized earnings and net operating cash flows. Table 2.5 below reports these results for measure one.

Table 2.5: C^1 Measure Results for SIC

SIC Code	**Sample Size**	C^1_E	C^1_{CF}	C^1	**p-value**
1	9	0.0647	0.1128	0.0888	0.1809
2	2	-0.0647	0.1766	0.0559	0.3987
7	2	0.8817	0.7863	0.8340	0.0000 ***
10	98	0.0339	0.0066	0.0203	0.2437
12	9	-0.0499	0.2422	0.0961	0.1616
13	146	0.1424	0.4018	0.2721	0.0000 ***
14	12	0.0338	0.0881	0.0609	0.2344
15	17	0.4108	0.3741	0.3925	0.0000 ***
16	14	0.1140	0.2503	0.1821	0.0090 ***
17	8	0.2503	0.0996	0.1750	0.0441 **
20	90	0.1693	0.2046	0.1869	0.0000 ***
21	7	0.0397	-0.0080	0.0159	0.4432
22	10	0.2080	0.0573	0.1327	0.0745 *
23	28	0.0535	0.1146	0.0841	0.0621 *
24	23	0.1787	0.1484	0.1635	0.0032 ***
25	21	0.1402	0.0565	0.0984	0.0597 *
26	35	0.0977	0.1499	0.1238	0.0055 ***
27	32	0.1189	0.0942	0.1065	0.0185 **
28	328	0.0152	0.0328	0.0240	0.0661 *
29	31	0.4601	0.5169	0.4885	0.0000 ***
30	25	0.0505	0.1829	0.1167	0.0217 **
31	15	0.1195	0.1130	0.1162	0.0602 *
32	22	0.1188	0.1029	0.1109	0.0361 **
33	47	0.2923	0.1490	0.2206	0.0000 ***
34	50	0.0947	0.1096	0.1022	0.0061 **
35	199	0.1344	0.1006	0.1175	0.0000 ***
36	319	0.1165	0.0631	0.0898	0.0000 ***
37	84	0.0875	0.0373	0.0624	0.0238 **
38	229	0.0810	0.1175	0.0992	0.0000 ***
39	26	0.0098	0.0282	0.0190	0.3694
40	10	0.3147	0.3788	0.3467	0.0000 ***
42	27	0.2450	0.2607	0.2529	0.0000 ***

Table 2.5: Continued

SIC Code	Sample Size	C_E^1	C_{CF}^1	C^1	p-value
44	23	0.2730	0.2756	0.2743	0.0000 ***
45	23	0.2909	0.2547	0.2728	0.0000 ***
46	5	0.5991	0.8216	0.7103	0.0000 ***
47	11	0.3575	0.3445	0.3510	0.0000 ***
48	132	0.1187	0.2555	0.1871	0.0000 ***
49	257	0.1699	0.2627	0.2163	0.0000 ***
50	80	0.1762	0.1054	0.1408	0.0000 ***
51	43	0.1292	0.1488	0.1390	0.0008 ***
52	5	0.4266	0.2502	0.3384	0.0039 ***
53	24	0.1238	0.1557	0.1398	0.0088 ***
54	25	0.1529	0.3084	0.2306	0.0000 ***
55	18	0.1411	0.1011	0.1211	0.0378 **
56	38	0.0804	0.2185	0.1494	0.0007 ***
57	14	-0.0169	0.0042	-0.0063	0.5323
58	39	0.0804	0.2342	0.1573	0.0003 ***
59	47	0.1391	0.2066	0.1728	0.0000 ***
60	13	0.3513	0.1088	0.2300	0.0019 ***
61	48	0.1458	0.0448	0.0953	0.0111 **
62	51	0.0892	0.0841	0.0867	0.0160 **
63	114	0.3157	0.1732	0.2444	0.0000 ***
64	14	0.1907	0.1142	0.1525	0.0242 **
65	39	0.0497	0.0079	0.0288	0.2671
67	165	0.0762	0.1459	0.1111	0.0000 ***
70	11	0.0662	-0.0598	0.0032	0.4856
72	12	-0.0535	-0.0216	-0.0375	0.6721
73	345	0.1521	0.1996	0.1758	0.0000 ***
75	9	0.0703	0.2566	0.1634	0.0455 **
78	11	-0.0273	0.0076	-0.0099	0.5446
79	40	0.0698	0.0495	0.0596	0.0961 *
80	50	0.2117	0.3562	0.2840	0.0000 ***
82	13	0.1344	0.1248	0.1296	0.0534 *
83	6	-0.0848	-0.0156	-0.0502	0.6618
87	66	0.1262	0.1533	0.1397	0.0000 ***
99	22	0.0919	0.0986	0.0952	0.0614 *
MEAN:	**57**	**0.1542**	**0.1716**	**0.1629**	
MEDIAN:	**25**	**0.1216**	**0.1354**	**0.1311**	
MAX:	**345**	**0.8817**	**0.8216**	**0.8340**	
MIN	**2**	**-0.0848**	**-0.0598**	**-0.0502**	
VAR:	**6447**	**0.0249**	**0.0260**	**0.0227**	

Table 2.5 shows that SIC industry closeness is slightly greater when realized fundamentals are used in the measures rather than unexpected fundamentals since average industry closeness is 0.1629, up from 0.0918 as seen in Table 2.3. Consistent with this, we also see that 53/66 or 80% of the industries exhibited closeness statistically different than zero. Also, one should notice that the closeness in cash flows (0.1716) above is greater than the closeness in earnings (0.1542). This result is counterintuitive since I would expect average earnings across industries to be closer than average net operating cash flows due to the fact that accruals help earnings to smooth cash flows. Although this difference is observed, a t–test of the difference between these two means yields a p–value of 0.52 which is not enough to reject the null hypothesis that there is a statistical difference between average earnings and net operating cash flow closeness respectively[58].

Table 2.6 following reports the results for the SIC scheme using measure two with realized earnings and net operating cash flows.

Table 2.6: C^2 Measure Results for SIC

SIC Code	**Sample Size**	C^2_E	C^2_{CF}	C^2	**p-value**
1	9	0.9080	0.8882	0.8981	0.1474
2	2	0.9958	0.9688	0.9823	0.4677
7	2	0.2226	0.3818	0.3022	0.0000 ***
10	98	0.8535	0.7654	0.8094	0.0000 ***
12	9	0.6956	0.6143	0.6550	0.0001 ***
13	146	0.7806	0.6110	0.6958	0.0000 ***
14	12	0.8965	0.8221	0.8593	0.0463 **
15	17	0.4492	0.7714	0.6103	0.0000 ***
16	14	0.7783	0.8414	0.8099	0.0067 ***
17	8	0.8186	0.9094	0.8640	0.0934 *
20	90	0.7714	0.8037	0.7876	0.0000 ***
21	7	0.7711	0.6855	0.7283	0.0061 ***
22	10	0.8244	0.8903	0.8574	0.0602 *

[58] Analysis of the medians yields similar results and thus the slight skewness of the sample is not enough to change the inferences.

Table 2.6: Continued

SIC Code	Sample Size	C_E^2	C_{CF}^2	C^2	p-value
23	28	0.8067	0.8370	0.8218	0.0005 ***
24	23	0.8388	0.8459	0.8424	0.0043 ***
25	21	0.8536	0.8707	0.8621	0.0143 **
26	35	0.8667	0.8503	0.8585	0.0018 ***
27	32	0.8417	0.8366	0.8392	0.0008 ***
28	328	0.8374	0.8197	0.8285	0.0000 ***
29	31	0.6622	0.5850	0.6236	0.0000 ***
30	25	0.8482	0.8422	0.8452	0.0036 ***
31	15	0.8082	0.8373	0.8228	0.0086 ***
32	22	0.8330	0.8601	0.8465	0.0062 ***
33	47	0.7701	0.8183	0.7942	0.0000 ***
34	50	0.8308	0.8455	0.8382	0.0000 ***
35	199	0.8341	0.8423	0.8382	0.0000 ***
36	319	0.8539	0.8549	0.8544	0.0000 ***
37	84	0.8277	0.8417	0.8347	0.0000 ***
38	229	0.8230	0.8075	0.8153	0.0000 ***
39	26	0.8226	0.8309	0.8267	0.0010 ***
40	10	0.6193	0.5881	0.6037	0.0000 ***
42	27	0.8110	0.7893	0.8001	0.0001 ***
44	23	0.7763	0.7593	0.7678	0.0000 ***
45	23	0.8241	0.7738	0.7990	0.0004 ***
46	5	0.5871	0.3176	0.4524	0.0000 ***
47	11	0.7266	0.7046	0.7156	0.0004 ***
48	132	0.8505	0.7349	0.7927	0.0000 ***
49	257	0.7972	0.7975	0.7974	0.0000 ***
50	80	0.8065	0.8534	0.8300	0.0000 ***
51	43	0.8458	0.8544	0.8501	0.0003 ***
52	5	0.7480	0.7299	0.7390	0.0218 **
53	24	0.8108	0.7479	0.7794	0.0001 ***
54	25	0.7978	0.6792	0.7385	0.0000 ***
55	18	0.7689	0.8314	0.8001	0.0016 ***
56	38	0.8304	0.7938	0.8121	0.0000 ***
57	14	0.7209	0.8202	0.7705	0.0013 ***
58	39	0.8261	0.7424	0.7843	0.0000 ***
59	47	0.7873	0.7780	0.7826	0.0000 ***
60	13	0.6961	0.8450	0.7706	0.0019 ***
61	48	0.8255	0.8552	0.8404	0.0001 ***
62	51	0.8363	0.8641	0.8502	0.0001 ***
63	114	0.7723	0.7928	0.7825	0.0000 ***
64	14	0.7881	0.7572	0.7726	0.0015 ***

Table 2.6: Continued

SIC Code	Sample Size	C_E^2	C_{CF}^2	C^2	p-value
65	39	0.8782	0.8590	0.8686	0.0022 ***
67	165	0.8337	0.7679	0.8008	0.0000 ***
70	11	0.8258	0.9001	0.8630	0.0586 *
72	12	0.9105	0.8523	0.8814	0.0785 *
73	345	0.8257	0.7740	0.7998	0.0000 ***
75	9	0.8880	0.7932	0.8406	0.0497 **
78	11	0.9259	0.7738	0.8498	0.0429 **
79	40	0.8633	0.8400	0.8516	0.0005 ***
80	50	0.7651	0.6789	0.7220	0.0000 ***
82	13	0.7922	0.7150	0.7536	0.0009 ***
83	6	0.8251	0.7845	0.8048	0.0502 *
87	66	0.8230	0.8354	0.8292	0.0000 ***
99	22	0.8637	0.8730	0.8684	0.0162 **
MEAN:	**57**	**0.7969**	**0.7854**	**0.7912**	
MEDIAN:	**25**	**0.8236**	**0.8190**	**0.8110**	
MAX:	**345**	**0.9958**	**0.9688**	**0.9823**	
MIN	**2**	**0.2226**	**0.3176**	**0.3022**	
VAR:	**6447**	**0.0115**	**0.0118**	**0.0100**	

Inferences using measure two to capture SIC industry closeness with realized fundamentals are similar to those using measure one. Specifically average closeness (0.7912) is greater than when unexpected fundamentals were used with measure two (0.8684). Also, average cash flow closeness (0.7854) is slightly greater than average earnings closeness (0.7969) — something I would not expect — however the difference is not statistically significant (p–value 0.54). Furthermore, we see that 64/66 or 97% of the industries had closeness statistically different than 1 (of course remember again that 1 represents no closeness using measure two). Finally, comparing Tables 9 and 10 we see that measure one and two agreed 44/66 or 67% of the time and most of the time they did disagree, measure two reported closeness as "small" while measure one reported closeness as "none" using the cutoffs from Table 1.1.

Tables 9 and 10 report the results for the untrimmed sample. Trimmed sample results however are much stronger in favor of the SIC grouping firms whose fundamentals move together over time. For example, average industry closeness for measures one and two with realized fundamentals for the trimmed sample are 0.3543 and 0.6615 respectively.

Also, a high proportion of industries displayed closeness statistically different than zero at the 10% level or greater (47/56 and 52/56 for measures one and two respectively).

Comparing Tables 7–10 one sees that the SIC scheme groups firms whose realized fundamentals are closer on average than their unexpected fundamentals. Average industry closeness is interpreted as "small" for both measures when realized fundamentals are used ($C^1 = 0.1629$ and $C^2 = 0.7912$) versus "none" for both measures when unexpected fundamentals are used ($C^1 = 0.0918$ and $C^2 = 0.8684$). Also, a higher percentage of industries have closeness statistically different than zero when realized fundamentals are used[59].

2.2.3 GIC Results

Analysis of the industries formed using the GIC scheme yields almost identical results as seen with the SIC scheme. As with the SIC, the GIC scheme groups firms whose realized fundamentals are closer than their unexpected fundamentals both with the trimmed and untrimmed sample. Also, GIC industries are closer on average with the trimmed sample than seen with the untrimmed sample. Furthermore, the proportion of GIC industries which have closeness statistically different than zero follows the same patterns as with the SIC industry results discussed earlier.

2.2.4 Random Sample Results

As discussed earlier, I wanted to know the closeness of randomly selected groups of firms from the sample to see how average SIC/GIC industry closeness compares to this. The following tables report the closeness measure results from selecting 10 random samples of 250 firms each[60] from the trimmed and untrimmed samples respectively.

[59] 53/66 and 64/66 for measures one and two respectively with realized fundamentals versus 37/66 and 58/66 respectively with unexpected fundamentals.

[60] In case the choice of a larger random sample biases against closeness, the measures were also calculated for 10 random samples of 56 firms each with similar results. The average number of firms in an SIC and GIC industry was 56, hence the reason for this choice.

Table 2.7: C_A^1 & C_A^2 Results for Random Sampling Procedure

Sample	N	C_{AE}^1	C_{ACF}^1	C_A^1	**p-value**	C_{AE}^2	C_{ACF}^2	C_A^2	**p-value**
1	250	0.0453	0.0196	0.0325	0.0378 **	0.8862	0.8940	0.8901	0.0000 ***
2	250	0.0452	0.0239	0.0346	0.0292 **	0.8844	0.8941	0.8893	0.0000 ***
3	250	0.0525	0.0249	0.0387	0.0171 **	0.8842	0.8928	0.8885	0.0000 ***
4	250	0.0426	0.0263	0.0344	0.0296 **	0.8869	0.8930	0.8899	0.0000 ***
5	250	0.0499	0.0219	0.0359	0.0246 **	0.8837	0.8875	0.8856	0.0000 ***
6	250	0.0686	0.0364	0.0525	0.0020 ***	0.8808	0.8908	0.8858	0.0000 ***
7	250	0.0561	0.0161	0.0361	0.0241 **	0.8814	0.8911	0.8863	0.0000 ***
8	250	0.0460	0.0253	0.0356	0.0255 **	0.8792	0.8936	0.8864	0.0000 ***
9	250	0.0654	0.0293	0.0473	0.0048 ***	0.8834	0.8942	0.8888	0.0000 ***
10	250	0.0636	0.0289	0.0463	0.0056 ***	0.8793	0.8904	0.8849	0.0000 ***
	MEAN:	**0.0535**	**0.0252**	**0.0394**		**0.8830**	**0.8922**	**0.8876**	
	MEDIAN:	**0.0512**	**0.0251**	**0.0360**		**0.8835**	**0.8929**	**0.8875**	
	MAX:	**0.0686**	**0.0364**	**0.0525**		**0.8869**	**0.8942**	**0.8901**	
	MIN:	**0.0426**	**0.0161**	**0.0325**		**0.8792**	**0.8875**	**0.8849**	
	VAR:	**0.0001**	**0.0000**	**0.0000**		**0.0000**	**0.0000**	**0.0000**	

Table 2.8: C^1 & C^2 Results for Random Sampling Procedure

Sample	N	C_E^1	C_{CF}^1	C^1	**p-value**	C_E^2	C_{CF}^2	C^2	**p-value**
1	250	0.0642	0.0935	0.0789	0.0000 ***	0.8428	0.8188	0.8308	0.0000 ***
2	250	0.0771	0.0936	0.0853	0.0000 ***	0.8386	0.8281	0.8333	0.0000 ***
3	250	0.0746	0.0866	0.0806	0.0000 ***	0.8448	0.8227	0.8337	0.0000 ***
4	250	0.0567	0.0920	0.0744	0.0000 ***	0.8270	0.8067	0.8169	0.0000 ***
5	250	0.0846	0.1057	0.0951	0.0000 ***	0.8283	0.8236	0.8260	0.0000 ***
6	250	0.0936	0.1220	0.1078	0.0000 ***	0.8433	0.8260	0.8347	0.0000 ***
7	250	0.0824	0.1046	0.0935	0.0000 ***	0.8373	0.8066	0.8220	0.0000 ***
8	250	0.0731	0.1189	0.0960	0.0000 ***	0.8376	0.8193	0.8285	0.0000 ***
9	250	0.0837	0.1147	0.0992	0.0000 ***	0.8434	0.8193	0.8314	0.0000 ***
10	250	0.0926	0.1111	0.1019	0.0000 ***	0.8319	0.8271	0.8295	0.0000 ***
	MEAN:	**0.0783**	**0.1043**	**0.0913**		**0.8375**	**0.8198**	**0.8287**	
	MEDIAN:	**0.0798**	**0.1051**	**0.0943**		**0.8381**	**0.8210**	**0.8301**	
	MAX:	**0.0936**	**0.1220**	**0.1078**		**0.8448**	**0.8281**	**0.8347**	
	MIN:	**0.0567**	**0.0866**	**0.0744**		**0.8270**	**0.8066**	**0.8169**	
	VAR:	**0.0001**	**0.0002**	**0.0001**		**0.0000**	**0.0001**	**0.0000**	

Table 2.9: C_A^1 & C_A^2 Results for Random Sampling Procedure (trimmed)

Sample	N	C_{AE}^1	C_{ACF}^1	C_A^1	**p-value**	C_{AE}^2	C_{ACF}^2	C_A^2	**p-value**
1	250	0.0578	0.0278	0.0428	0.0095 ***	0.8788	0.8920	0.8854	0.0000 ***
2	250	0.0609	0.0336	0.0472	0.0049 ***	0.8847	0.8931	0.8889	0.0000 ***
3	250	0.0812	0.0359	0.0586	0.0007 ***	0.8779	0.8919	0.8849	0.0000 ***
4	250	0.0777	0.0337	0.0557	0.0011 ***	0.8795	0.8918	0.8857	0.0000 ***
5	250	0.0668	0.0281	0.0474	0.0047 ***	0.8824	0.8918	0.8871	0.0000 ***
6	250	0.0652	0.0366	0.0509	0.0027 ***	0.8865	0.8948	0.8907	0.0000 ***
7	250	0.0747	0.0342	0.0544	0.0014 ***	0.8812	0.8910	0.8861	0.0000 ***
8	250	0.0692	0.0331	0.0512	0.0025 ***	0.8818	0.8914	0.8866	0.0000 ***
9	250	0.0556	0.0327	0.0441	0.0078 ***	0.8816	0.8913	0.8864	0.0000 ***
10	250	0.0795	0.0292	0.0543	0.0015 ***	0.8794	0.8910	0.8852	0.0000 ***
	MEAN:	**0.0689**	**0.0325**	**0.0507**		**0.8814**	**0.8920**	**0.8867**	
	MEDIAN:	**0.0680**	**0.0333**	**0.0510**		**0.8814**	**0.8918**	**0.8862**	
	MAX:	**0.0812**	**0.0366**	**0.0586**		**0.8865**	**0.8948**	**0.8907**	
	MIN:	**0.0556**	**0.0278**	**0.0428**		**0.8779**	**0.8910**	**0.8849**	
	VAR:	**0.0001**	**0.0000**	**0.0000**		**0.0000**	**0.0000**	**0.0000**	

Table 2.10: C^1 & C^2 Results for Random Sampling Procedure (trimmed)

Sample	N	C^1_E	C^1_{CF}	C^1	**p-value**	C^2_E	C^2_{CF}	C^2	**p-value**
1	250	0.1111	0.1357	0.1234	0.0000 ***	0.7793	0.7584	0.7688	0.0000 ***
2	250	0.1151	0.1656	0.1404	0.0000 ***	0.7904	0.7658	0.7781	0.0000 ***
3	250	0.1574	0.1946	0.1760	0.0000 ***	0.7749	0.7438	0.7593	0.0000 ***
4	250	0.1352	0.1686	0.1519	0.0000 ***	0.7927	0.7699	0.7813	0.0000 ***
5	250	0.1185	0.1546	0.1365	0.0000 ***	0.7890	0.7584	0.7737	0.0000 ***
6	250	0.1435	0.1749	0.1592	0.0000 ***	0.7917	0.7690	0.7803	0.0000 ***
7	250	0.1524	0.1753	0.1638	0.0000 ***	0.7913	0.7694	0.7803	0.0000 ***
8	250	0.1489	0.1641	0.1565	0.0000 ***	0.7816	0.7618	0.7717	0.0000 ***
9	250	0.1275	0.1860	0.1568	0.0000 ***	0.7880	0.7596	0.7738	0.0000 ***
10	250	0.1651	0.1635	0.1643	0.0000 ***	0.7835	0.7560	0.7697	0.0000 ***
	MEAN:	**0.1375**	**0.1683**	**0.1529**		**0.7862**	**0.7612**	**0.7737**	
	MEDIAN:	**0.1394**	**0.1671**	**0.1566**		**0.7885**	**0.7607**	**0.7738**	
	MAX:	**0.1651**	**0.1946**	**0.1760**		**0.7927**	**0.7699**	**0.7813**	
	MIN:	**0.1111**	**0.1357**	**0.1234**		**0.7749**	**0.7438**	**0.7593**	
	VAR:	**0.0004**	**0.0003**	**0.0002**		**0.0000**	**0.0001**	**0.0000**	

The results from the random sampling procedure in Tables 2.7–2.10 show that even a random sample of firms over the sample time period 1999–2010 displays closeness statistically significantly different than zero. As discussed earlier, the measures do not control for similarity in economic events. To the extent that economic events common to a randomly chosen group of firms have a positive effect on similarity that outweighs the negative effect on similarity of those firm–specific economic events, the measures will be biased upward. Thus, observing closeness measures statistically significantly different than zero for the random samples implies that these firms must be exposed to a set of common economic events (i.e. they all are subject to U.S. macroeconomic conditions) which is biasing the measures upward, away from zero (or downward, away from 1 in the case of measure two).

Also, as expected, 250–firm random samples from the trimmed original sample display larger closeness than random samples from the untrimmed sample. More specifically however comparing Tables 6 and 10 shows that average SIC industry closeness (0.0918) is higher than mean closeness (0.0394) from 10 random samples of firms chosen from the entire sample of firms representing all industries. This can also be seen when comparing Tables 9 and 12 as mean industry closeness of the SIC using realized fundamentals (0.1629) is higher than mean closeness of the 10 random samples (0.0913). These differences between mean industry closeness and mean random sample closeness are all statistically significant at the 1% level. These results hold for closeness measure two as well and also hold when comparing the GIC scheme closeness to the random sample closeness. Taken as a whole, it seems that the SIC and GIC industrial classification schemes do group firms whose fundamentals move together over time to a greater extent than a random grouping of the firms. I would expect this ex ante and thus some validation of the closeness measures is provided.

2.2.5 Interpretation of Results

Combining the results for the untrimmed and trimmed samples using both unexpected and realized earnings and net operating cash flows seems to suggest that both schemes place firms into groups whose fundamentals have low correlation over time. That is, a group of firms' primary generating business activities being similar is not a sufficient condition for their fundamentals to be very correlated over time. Often researchers will control for firm–group similarity (or industry) by using an industrial classification scheme such as the SIC or GIC. The results above imply that this exercise, at best, simply controls for firm–group similarity in primary revenue generating activity and thus exposure to similar demand and supply–side markets. However, it doesn't seem that using one of these schemes controls for similarity in the outcomes (realized and unexpected fundamental firm–performance measures) resulting from being exposed to similar demand and supply–side markets. Researchers should take this into consideration when using these schemes to group "comparable" firms and should not make the assumption that the underlying fundamentals of a given group of firms move similarly simply because a scheme classifies the group as an "industry".

Chapter 3: Accounting Closeness and Information Transfer

3.1 Trading on Information Contained in the Measures

A logical question begs to be asked at this point. Can we trade on information contained in the measures and earn a return above and beyond what we would expect to earn ex ante? It would seem reasonable that we could. Consider the following strategy. First, identify two groups of firms; one (Group A) in which closeness (as measured by C^1 and C^2) is zero and the other (Group B) in which closeness is statistically significantly greater than zero. Next, observe the earnings announcement ($t = 0$) of the leading firm in each portfolio . Suppose that the leaders in both portfolios announce good news. Buy one share of stock in each of the other firms (non–leader firms) in each of the portfolios, hold for a short period of time (i.e. 1-5 days) and then sell. The abnormal return of group B should be greater than the abnormal return of group A. Furthermore, the abnormal return of group B should be statistically significantly greater than zero while the abnormal return of group A should not be statistically significantly greater than zero. The reasoning is as follows. Since portfolio B firms are close, when the leader announces good news, we can expect that, on average[61], the non–leader firms will also subsequently announce good news. At $t = 0$, unless the price of these other firms already incorporates this "closeness" information, the other firms are undervalued and we therefore can buy low and expect to sell high. For portfolio A, when the leader announces good news at $t = 0$ we have no expectation regarding the earnings announcement of the other firms in the portfolio. Since portfolio A has historically zero closeness, we can expect that the effect of the subsequent good news announcers will be offset by the effect of the subsequent bad news announcers. Thus, buying one share of stock in portfolio A firms and selling after 1-5 days should not lead to earning a higher return than expected. Some of these firms are undervalued while some are overvalued at $t = 0$ so buying one share in each will only lead to earning a return lower than expected on some and a return higher

[61] Unless analysts are overly optimistic for the non–leader subsequent earnings announcers.

than expected on some with the expected effect being zero unexpected return.

There are two implicit assumptions that must hold if the proposed strategy above is to work. First, markets are assumed to be inefficient; inefficient in the sense that the price discovery process of a firm subsequent to public information releases is not instantaneous but persists over a short–window (i.e. 1–3 days). Any trading strategy that is a function of publicly available information must start with the assumption of market inefficiency (Otherwise why would a trading strategy be developed?). If markets are efficient then the prices of the non–leader portfolio B firms at $t = 0$ will already incorporate the historical closeness information and thus these firms will already be correctly valued at $t = 0$. Buying a share of each of these firms and selling at a later date should not earn a return higher than expected.

Second, I am assuming zero transaction costs[62]. This assumption is, of course, not completely descriptive of the current trading environment; especially when trading with small balances (i.e. $< \$100,000$). Since the strategy requires making multiple trades, typical individual investors using online brokerage systems (e.g. Scottrade, Ameritrade) will pay a fee of around \$8 per trade. For example, if one invests $\$10,000$ in Portfolio B which consists of 30 companies, then they will pay an \$8 fee for each company (regardless of the amount of shares bought) both for buying and then for selling a few day(s) later. Thus their fee would be $\$8 * 30 * 2 = \$480$. Therefore, in total, the prices of the stocks would need to rise by at least 4.8% over the short–window in order for the individual to break even. If the individual invested $\$100,000$ instead in Portfolio B, the fee would still be \$480. In this situation however, stock price appreciation need only be 0.48% in order for the individual to break even.

In addition to reasoning theoretically, there does exist research whose findings would lend credence to the feasibility of the proposed strategy. Gleason et al. 2008 find that when firms announce bad news at $t = 0$ (in the form of earnings restatements) they experience an abnormal return of, on average, -19.8% over $t = (-1, 1)$. Over the same window, other "peer" firms in the same industry experience abnormal returns, on

[62] I also ignore the tax implications of such a strategy.

average, of about -0.5% ceteris paribus and this is statistically significant at the 1% level. Thus, they find evidence of a contagion effect; the effect of bad news announced by one firm in an industry spills over to the rest of the firms in the form of share price declines.

I believe the very small "contagion" effect documented in Gleason et al. 2008 is due to the assumption that closeness is constant across industries when in fact it isn't. Their effect, I believe, would increase with the closeness (as measured by C^1 and C^2) of the industry in question. In their sample, they have industries with zero closeness and industries with closeness statistically significantly greater than zero lumped together. The effect they find would not be hypothesized for those zero–closeness industries but would be expected for those industries with closeness greater than zero. The net contagion effect was -0.005. Thus, on average, industry closeness must have been statistically greater than zero. This is consistent with the SIC & GIC results I presented earlier in Chapter 2.

Gleason et al. 2008 was not the first paper to examine information transfer. Other papers in this area related to accounting restatements include Foster 1981, Clinch and Sinclair 1987, Pownall and Waymire 1989, Han and Wild 1990, Freeman and Tse 1992, Ramnath 2002 and Palmrose et al. 2004. Information transfer papers related to[63] retailers monthly sales reports, bank loan–loss reserves, bank failures, bankruptcy filings, dividend initiations, internet hacker attacks and nuclear accidents have also been published as well.

3.2 Methodology and Results

To implement the above trading strategy I searched Table 2.4 for the industries which ranked highest and lowest on closeness measure one as a function of earnings and cash flows. To provide the best chance to earn statistically significantly greater abnormal returns on one portfolio versus another I should choose two portfolios which have a large

[63] See, Docking et al. 1997, Aharony and Swary 1983, Bowen et al. 1983, Olssen and Dietrich 1985, Lang and Stulz 1992, Firth 1996, Ferris et al. 1997 and Ettredge and Richardson 2003.

difference in closeness. My decision rule was to find the pair of industries with the highest closeness and lowest closeness respectively subject to the constraint that the leaders of each of the portfolios had to announce good news for 2010[64]. I used Compustat to sort a particular industry–portfolio by the date they announced their earnings for 2010. For a given portfolio, the firm which announced 4th quarter earnings for 2010 first and whose assets were in the top 5% of the portfolio was identified as the "leader". I removed firms which did not have 12/31 fiscal year ends, firms which announced earnings within 3 days of the leader and firms which did not have return information for each day in the window (-2,+3) around the leaders earnings announcement date in CRSP. I defined good news as happening when EPS for 2010 was higher than median analyst forecasted EPS. I used IBES to determine this. Since the industries with the highest and lowest closeness respectively both had leaders which announced bad news for 2010 I moved to the next highest and lowest industries respectively. These also suffered from the same problem and thus one more iteration was needed before I identified a "close" industry and "not close" industry whose leaders announced good news respectively. Thus my two industry–portfolios have the 3rd highest and 3rd lowest closeness respectively from Table 2.5. These industries were SIC 28—Chemicals and Allied Products and SIC 80—Health Services (henceforth "portfolio A" and "portfolio B" respectively). Portfolio A initially consisted of 328 firms and $\{C^1, C^2\} = \{0.0240, 0.8285\}$ while portfolio B consisted of 50 firms and $\{C^1, C^2\} = \{0.2840, 0.7220\}$. I then reduced the sample using the procedure described above and summarized in the following table[65].

[64]There is no reason to believe that an analogous short–selling strategy wouldn't work if the leader announced bad news

[65]See legend in Appendix E for description of super scripts in Table 3.1.

Table 3.1: Portfolio Sample Selection/Closeness

	Portfolio A	**Portfolio B**
N beg.**(a)**	328	50
C^1 beg.**(b)**	0.0240	0.2840
C^2 beg.**(c)**	0.8285	0.7220
non 12/31 FY end**(d)**	71	6
earnings announced $(0, +3)$**(e)**	12	0
Missing CRSP data **(f)**	74	0
Leader**(g)**	1	1
Leader announcement date**(h)**	1/20/2011	1/25/2011
N final**(i)**	170	43
C^1 final**(j)**	0.0144	0.2922
C^2 final**(k)**	0.8186	0.7043

The closeness of the final portfolio A sample of 0.0144 is not statistically significantly different than zero. The closeness of the final portfolio B sample of 0.2922 is strongly statistically different than zero and the difference in closeness between the portfolios (0.2922 - 0.0144) is strongly statistically significantly different than zero ($p - value < 0.01$). Thus I have two portfolios which are different in terms of closeness. Portfolio A's firms are not close, in the sense that knowing information regarding the earnings and/or cash flows of any one (e.g. the leader) of the firms in portfolio A at time $t = 0$ gives no information aiding in the prediction of the other firms earnings and cash flows. Portfolio B's firms are somewhat close. Using the Table 1.1 interpretation, Portfolio B firms have small closeness as $C^1 = 0.2922$ falls in the interval $[0.1, 0.3)$ and $C^2 = 0.7043$ falls in the interval $[0.6, 0.85)$. Thus knowing information regarding the earnings and/or cash flows of any one of the Portfolio B firms gives some information aiding in the prediction of the other firms earnings and cash flows. Specifically, knowing that the leader in Portfolio B announces good news tells us that the other firms in Portfolio B will, on average, announce good news as well. By, "on average", I don't necessarily mean that the number of non–leader firms which announce good news will necessarily be greater than the number of non–leader firms which announce bad news but that the total magnitude of the good news announcers will exceed the total magnitude of the bad news announcers in terms of the absolute difference between actual earnings and expected earnings. This is all assuming that this historical closeness will persist into the future.

The next step was to determine the windows over which I should measure abnormal returns. I decided on 5 different windows which the prior literature suggests. In case of anticipation of the market regarding the direction of the leaders' earnings announcement I include two windows which capture the market reaction before the date of the leaders' earnings announcement ($[-2, +2], [-1, +1]$). The other three windows I analyze the market reaction around are ($[0, +1], [0, +2], [0, +3]$). The windows which include days before $t = 0$, for the purposes of my trading strategy, are infeasible. An investor who knows that Portfolio B's firms are somewhat close will not be able to predict when the leader will announce earnings and thus will not be able to buy shares of stock in the non–leaders until $t = 0$. I analyze these other windows though following the prior information transfer literature.

Since I desired the abnormal or unexpected return around $t = 0$ for the non–leader firms I needed some measure of expected returns. Once obtained, the difference between actual and expected returns would proxy for the unexpected market reaction over these event windows. The return one can expect to earn on a security depends on the risk of the security ceteris paribus. This risk can be broken down into two parts; systematic and unsystematic. The systematic portion of this risk is commonly proxied for by beta. Beta tells us how the return for security i moves as a function of the overall market return. Betas greater than one imply that, for a one–percent increase(decrease) in the market return, the return on security i also increases(decreases) by one–percent. Thus, betas greater than one represent more risky stocks. Betas less than one but greater than zero imply that, for a one percent increase(decrease) in the market return, the return on security i increases(decreases) by less than one–percent. These are the safe stocks from a risk averse individual's point of view. Finally, betas less than one imply that the return on security i moves opposite that of the market return[66].

The unsystematic portion of risk is usually proxied for by the variance in historical stock returns. I will not attempt to measure this part of the risk as I have no reason to believe that this part would be different, on average, for portfolio A versus portfolio B. However, I do have reason to believe that the systematic portion of this risk would be different.

Portfolio A firms represent SIC industry 28—Chemicals and Allied Products. Portfolio B firms represent SIC industry 80—Health Services. Take for example, Quest Diagnostics, one of the leaders in the Health Services industry. According to their website, they are the world's leading provider of diagnostic testing services for hospitals. They provide tests ranging from routine blood tests, to complex, gene–based, molecular testing. They also are a leading provider of instruments used in these diagnostic tests. They develop and manufacture devices, test kits and reagents used by physicians, hospitals, blood collection centers and other clinical laboratories to help detect, characterize, monitor and select treatment for disease. Based on the description, I am strongly inclined to believe that the price–elasticity of demand for Quests' products and services (as well as the other firms in the Health Services industry) is close to zero. That is, the sensitivity of demand to changes in the prices of the products and services provided by the Health Services industry is likely low. After all, if your physician says you need a special gene test to decide whether or not you have a certain type of cancer, your demand for this test won't change much if the test costs \$1 or \$1,000. My point is, that the firms in the Health Services industry are safer investments from an investors point of view (e.g. lower betas) since the demand for these firms products and services is relatively inelastic with respect to the prices they charge. An educated guess would be that portfolio B firms would experience increases/decreases in returns less extreme than the market (i.e. have betas less than one).

[66]Negative beta stocks are relatively uncommon.

The demand for the products and services provided by SIC 28—Chemicals and Allied Products firms is likely much more responsive to changes in the prices these firms charge. PPG Industries Inc., one of the leaders in this industry, is the world's leading supplier of sealants, coatings, maintenance chemicals, transparencies and application systems for airplanes, automobiles and ships. If PPG decides to raise its price for one of their sealants, the change in demand would likely be greater than Quest raising the price of a diagnostic test which would determine whether you had cancer or not. Since the price elasticity of demand for the products and services provided by firms in portfolio A is likely higher than for portfolio B, I would expect that portfolio A firms are more risky investments ceteris paribusOf course there may be other reasons to believe this as well..

Based on the preceding discussion, the next step was to determine the betas for each of the firms in portfolio A and B. Following prior literature (e.g. Chaney & Philipich 2002) I calculated beta as the coefficient on the market return from the following OLS regression model.

$$R_{id} = \alpha_i + \beta_i R_{md} + \epsilon_{id} \tag{23}$$

Return data for the above regression was obtained from CRSP. I used holding period daily returns from the first trading day of 1999 through the last trading day of 2010. Many studies calculate beta using the regression above but only with daily returns for the previous 250 trading days leading up to the event window of interest. The reason I use 1999–2010 is because the closeness measures were calculated over this time period and I wanted to remain consistent in this respect. For the daily market return, I used the value–weighted NYSE/NASDAQ/AMEX return.

Upon completion of the above procedure I had a vector of 170 betas for the portfolio A firms and 43 betas for portfolio B firms. The mean(median) beta for portfolio A was 0.5749(0.5327) and for portfolio B it was 0.3263(0.3072). This is consistent with my reasoning earlier that portfolio B firms should be less risky than portfolio A firms due to a lower price– elasticity of demand for their products.

The next step was to calculate the abnormal return for each security in each portfolio around each of the 5 event windows $W = [w_1, w_2, w_3, w_4, w_5]$ where w_i is one of the five event windows discussed previously. So, for example, over the window $w_1 = [-2, +2]$ the following formula was used to calculate the abnormal return for security i over event window w_1.

$$AR_{iw_1} = \left(\prod_{d=-2}^{+2} (1 + R_{id}) - 1 \right) - \left(\hat{\alpha}_i + \hat{\beta}_i * \left(\prod_{d=-2}^{+2} (1 + R_{md}) - 1 \right) \right) \tag{24}$$

The first part of (24) represents the actual compound return for security i over window w_1 and the second part represents the expected compound return for security i over window w_1 using the alpha and beta obtained from the historical regression in (23).

Table 3.2 below summarizes the results[67] from implementing the trading strategy described above without controlling for the difference in systematic risk (beta) between the portfolios.

Table 3.2: Event Window Mean Abnormal Returns

Window	Portfolio A	Portfolio B	Portfolio B - Portfolio A
$[-1, +1]$	-0.0346***	0.0191***	0.0537***
$[-2, +2]$	-0.0266***	0.0172***	0.0438***
$[0, +1]$	-0.0164***	0.0154***	0.0318***
$[0, +2]$	-0.0112***	0.0203***	0.0314***
$[0, +3]$	-0.0124***	0.0069*	0.0194***

Table 3.2 provides evidence that one will earn a return less than expected, on average, by implementing the trading strategy described earlier with portfolio A but will earn a return higher than expected, on average, with portfolio B. Thus, one can enjoy statistically significantly greater unexpected returns on portfolio B firms than on portfolio A firms (column 4) over all these windows. This analysis is without controlling for beta however. Since portfolio B firms are of lower risk (have a lower average beta), the

[67] The results were robust to using medians instead of means.

expected return for portfolio B firms will be less than those of portfolio A. Thus the abnormal returns for portfolio B firms should be higher than for portfolio A firms ceteris paribus. This biases in favor of the result. Consequently I control for beta and test to see if the Table 3.2 results persist. To control for differences in beta, I recalculated the event window abnormal returns for portfolio B firms using the mean portfolio A beta in equation (24) instead of $\hat{\beta}_i$. Table 3.3 reports the results from this procedure.

Table 3.3: Mean Abnormal Returns Controlling for Beta

Window	Portfolio A	Portfolio B	Portfolio B - Portfolio A
$[-1,+1]$	-0.0346***	0.0168***	0.0514***
$[-2,+2]$	-0.0266***	0.0142**	0.0408***
$[0,+1]$	-0.0164***	0.0144***	0.0308***
$[0,+2]$	-0.0112***	0.0188***	0.0300***
$[0,+3]$	-0.0124***	0.0091**	0.0215***

As expected, mean event window abnormal returns for portfolio B decreased when abnormal returns for portfolio B were calculated using the mean portfolio A beta in equation (24) instead of firm–specific historical betas. However, the Table 3.2 results are still present. Specifically, adopting the trading strategy proposed earlier leads to one earning a statistically significantly negative abnormal return on portfolio A firms and a statistically significantly positive abnormal return on portfolio B firms. Furthermore, one can earn a statistically significantly higher abnormal return on portfolio B ("close") firms than portfolio A (not "close") firms.

I repeated the strategy above for eight other industry portfolios. These results along with a summary of all the results both for abnormal returns and actual returns are presented in Table F.1 in Appendix F. Table E.1 in Appendix E contains a summary of the portfolio sample selection for each of the 10 portfolios tested.

The trading strategy results summarized in Tables 21 & 22 provide consistent evidence with the strategy described earlier in this Chapter. For example, when leaders announce good news and closeness is reasonably high (i.e. SIC Portfolios 29, 44, 63 and 80 from Table E.1 in Appendix E), abnormal and actual returns are statistically significantly positive over all three realistic trading windows $[0,+1],[0,+2],[0,+3]$ (see Table F.1 in Appendix F). Also, when leaders announce bad news and closeness is reasonably high (i.e. SIC Portfolio 45), abnormal and actual returns are strongly statistically significantly negative over these same windows. Furthermore, when leaders announce good news but closeness is not statistically significantly different than zero (i.e. SIC Portfolios 10, 28 and 39), abnormal and actual returns are either not statistically different than zero or statistically significantly less than zero over these three windows. In addition, when leaders announce good news, closeness is reasonably high, the median beta of the group is high (i.e. SIC Portfolio 15), and the market performs poorly over each of these three windows then abnormal and actual returns are strongly statistically significantly less than zero[68]. Finally, when leaders announce neutral news and closeness is reasonably high (i.e. SIC Portfolio 20), abnormal and actual returns are **not** statistically different from zero over each of these three windows.

These results imply that the return earned over a specific window, as a result of implementing the trading strategy described, is a function of the closeness of the group, the level and magnitude of news that the leader announces and the market return. This function appears to be somewhat linear from the results that were found. However the SIC industry–portfolio 15 results are one reason to believe this function may not be linear because this group had relatively high closeness ($C^1 = 0.5437$) and announced good news (1% higher than expected) but experienced negative returns over all three windows because the market return was negative over two of these windows and the median beta of the group was high ($\beta = 2.1180$). However, for nine of the ten SIC–industry portfolios tested, the median beta was less than one and since the function appears to be somewhat linear from the results found for these nine the return results from all three realistic trading windows ($[0,+1],[0,+2],[0,+3]$) were combined into 27

[68]Providing evidence that the mean portfolio return is more sensitive to the market reaction than to the closeness of the portfolio when beta is "high".

observations for these SIC industry–portfolios and the following OLS regression was calculated to examine the relationship described above.

$$RET_{i,w} = \gamma_1 + \gamma_2 C_i^1 + \gamma_3 \%News_i + \gamma_4 C_i^1 * \%News_i + \gamma_5 MR_w + \epsilon_{i,w} \tag{25}$$

where $RET_{i,w}$ is the mean actual or mean abnormal return earned over window w for SIC industry–portfolio i, C^1 is the historical closeness of portfolio i, $\%News_i$ is the percentage deviation of 2010 actual earnings per share from the median consensus analyst forecast (from IBIS and shown in Table E.1 in Appendix E) for the leader of portfolio i and MR_w is the market return over window w. The interaction of C^1 with $\%News$ is necessary since returns move in opposite directions depending on the direction of the news and this effect is hypothesized to be increasing in the closeness of the firm–group whose leader announces such news.

Results are presented below in Table 3.4 both when the dependent variable is actual returns and abnormal returns (column i represents the i'th coefficient from equation (25)).

Table 3.4: Return Regression Results

$\mathbf{Ret_{i,w}}$	i	γ_i	$\mathbf{t-stat_i}$	$\mathbf{p-value_i}$	$\mathbf{R^2(Adj\ R^2)}$
Actual	1	-0.0015	-0.1672	0.8687	0.7705(0.7287)
	2	-0.0284	-0.6835	0.5014	
	3	-0.1870	-1.1462	0.2640	
	4	3.1129	3.5764	0.0017	
	5	1.0605	2.4811	0.0212	
Abnormal	1	-0.0023	-0.2497	0.8052	0.7516(0.7065)
	2	-0.0427	-0.9883	0.3337	
	3	-0.5376	-3.1709	0.0044	
	4	3.7432	4.1391	0.0000	
	5	0.9378	2.1117	0.0463	

Table 3.4 provides strong evidence that closeness interacts with the leaders' news announcement to exacerbate firm–group short window actual and abnormal returns. The strongly statistically significant γ_4 indicates that the short–window portfolio return is increasing in the earnings surprise announced by the leader at $t = 0$. Furthermore, this effect is increasing in the closeness of the group. Specifically from Table 3.4, a one–percent increase in $\%News$ leads to a $(3.1129 * C^1 - 0.1870)$ percent increase in the short window portfolio actual return. Thus since $3.1129 * C^1 - 0.1870$ is a statistically significantly increasing function of C^1 one can correctly interpret that closeness interacts with the news announcement to exacerbate the contagion effect. Interestingly, when $C^1 \lesssim 0.06$ the coefficient on $\%News$ is negative and no contagion effect is observed on average. This result helps to specify a lower bound on how close a firm–group must be before a contagion effect from a news announcement is observed. Finally, both the actual and abnormal return are strongly positively statistically significantly correlated with the market reaction over window w as expected. Finally, the independent variables in the model explain over 70% of the variation in the short window returns; with the IV's explaining more variation in actual returns (73%) than in unexpected returns (70%).

A couple of things should be noted however regarding the equation (25) analysis. First, the sample size is rather small (i.e. $n = 27$) and thus the sampling distribution of the each of the coefficients is not guaranteed to be normal (hence the use of the t–tests). As a result, $t - stat_i$ and $p - value_i$ may be somewhat noisy approximations of the true relationship between the IV's and DV's given. Second, OLS regression assumes a linear relationship between the dependent variable and the coefficients. To the extent that the data is non–linear, OLS regression lines will not precisely describe the relationship being analyzed.

Overall, the results suggest that returns to the trading strategy described above are higher for those closer portfolios versus those portfolios exhibiting historically low closeness. That is, in historically "close" industries, when leaders announce good news, the strategy generates statistically significantly positive (and higher) abnormal and actual returns[69] than in industries exhibiting zero–to–low historical closeness. Also I find evidence that when leaders in "close" industries announce bad news, the strategy generates statistically significantly negative abnormal and actual returns. The negative contagion effect of leaders announcing bad news seems to be greater than the positive one when leaders announce good news (See SIC industry–portfolio 45 results). Results also suggest however that one should pay careful attention to the average beta of the portfolio. Close firm portfolios whose leaders announce good news might not generate positive returns if the included companies have high betas ($\beta > 1$) and the market performs poorly over one or more trading window days. The contagion effect of the good news leader earnings announcement is offset by the extra sensitive reaction to the market for firms with high betas[70]. Thus, closeness should be the first screening criteria for determining the portfolio of choice, followed by an assessment of the firm betas. High average portfolio firm betas pose a much greater risk to investors since a small negative move for the market will be amplified for these firms. High closeness portfolios with average betas less than one are ideal. Positive contagion effects from leaders' good news earnings announcements in "close" industries tend to offset a negative market move when the firms have low betas since the firm–specific returns are not affected as much (See the results SIC industry–portfolios 29, 44 and 80) . Of course, positive market moves exacerbate these positive contagion effects for firms with betas greater than zero.

3.3 Discussion

These results have interesting implications. First, we see that, at time $t = 0$ the market underprices portfolio B firms and a simple strategy of buying low and selling high earns a return higher than expected for these firms. This is in direct contrast to the semi–strong efficient markets hypothesis which predicts that, at time $t = 0$, all publicly available information will be captured in the price of a firm thus leaving no opportunity

[69]This fact provides evidence that the expected returns model I used in equations (23) and (24) is a reasonable description of returns. If this wasn't true then abnormal returns wouldn't necessarily be in a consistent direction with actual returns.

[70]See the results for SIC industry portfolio 15 in Appendices E & F.

to buy low and sell higher than expected.

Second, the contagion effect of firm information announcements is present subsequent to "good news" announcements. Previous literature has focused more on "bad news" announcements (e.g. earnings restatements, bankruptcy filings, internet hacker attacks, nuclear disasters etc.).

Third, this contagion effect is not independent of the fundamental accounting "closeness" of the announcing leader firms' group. Specifically, we could have hypothesized, from Gleason et al. 2008, that portfolio A firms would also see statistically significantly positive abnormal returns since the leader announced good news and the firms belong to the same industry. The reasoning would have been[71] that the leaders' good news earnings announcement is an indication of the overall prospects for the industry and a contagion effect should be observed whereby the other non–announcing "peer" firms in the industry experience share price increases at time $t = 0$. The evidence in Table 3.2 however, provides evidence against this hypothesis. In fact, the market reaction to the leaders' good news earnings announcement is negative for those non–announcing peer firms over all 5 windows!

3.4 Conclusion

Closeness in an accounting information sense cannot be universally defined since any definition depends on which elements in the set of accounting information one wants to base closeness on and who the users are. In this study I have defined closeness between a group of firms as the correlation in their ex post financial statement information.

In Chapter 1 I introduced two measures that I believe to be good proxies for closeness as defined in the study. The first measure is the equally–weighted average correlation in abnormal earnings and cash flows between each pair of firms in a group. The second measure is the equally–weighted average determinant of the abnormal earnings and cash flow correlation matrices between each pair of firms in a group. Through simulation I

[71]Following the reasoning in Gleason et al. 2008.

have shown that both measures do a good job of capturing closeness since groups of firms one would expect ex ante to not be as close rank lower on the closeness measures than those firms one would expect ex ante to be closer. That is, I find that the measures of firm–group closeness are decreasing in the variability (i.e. randomness) of the earnings process for that particular group of firms. Additionally, C^2 is more sensitive than C^1 to changes in the randomness of a firms' earnings process. Finally, I find that both measures seem to coincide with each other well. That is, both measures agree most of the time on the magnitude of closeness between a group of firms.

In Chapter 2 I used the measures to evaluate the two most widely used industrial classification schemes in regards to their ability to group firms whose fundamentals move together over time. Evidence shows that both the SIC and GIC schemes do a decent to poor job of grouping firms whose fundamentals co–vary over time. Researchers should take this into consideration when using these schemes to group "comparable" firms. Industrial classifications group firms with similar primary revenue generating business activities. This methodology however does not always translate into firm–groups whose fundamentals move similarly over time. Prior research has shown that the industrial classification schemes do a relatively good job at grouping firms whose share prices move similarly. This should imply that these schemes also group firms whose unexpected fundamentals move similarly assuming that firm value is equal to discounted unexpected fundamentals. Results in this study imply that this assumption should be tempered to allow for investor bias and/or noise to enter into the firm value formula. This is consistent with Lee (2001) who argues that firm value is a function of discounted unexpected fundamentals and investor bias and/or noise.

Finally, in this chapter, I use information contained in the measures to develop a simple trading strategy which generates statistically significant abnormal returns. I also provide evidence that within–industry contagion effects to firm information announcements are increasing with the closeness of that particular industry.

Appendix A: Transitivity of Correlation

Here I will prove the following Theorem stated in section 1.5.2. The proof is similar to Langford et al. (2001).

Theorem. *Suppose that X, Y and Z are random variables and that X and Y, and Y and Z are positively correlated with correlations $r_{X,Y}$ and $r_{Y,Z}$ respectively. Suppose further that $r_{X,Y}^2 + r_{Y,Z}^2 > 1$. Then X and Z are positively correlated.*

Proof. I will first assume that the random variables X, Y and Z each assume only finitely many distinct values. Formally, X, Y and Z are functions defined on the following set $\Omega = \{a_1, a_2, a_3, \ldots, a_n\}$. Now X can be identified with a vector in n–dimensional Euclidean space via the correspondence

$$X \leftrightarrow \mathbf{X} = (X(a_1), X(a_2), \ldots, X(a_n))$$

and similarly for Y and Z. If one assumes that the set Ω is equipped with a uniform probability measure[72] then the correlations of X, Y and Z will be captured in the geometric properties of the corresponding vectors $\mathbf{X}$, $\mathbf{Y}$ and $\mathbf{Z}$. I will further assume that $E(X) = E(Y) = E(Z) = 0$. I can do this without loss of generality since variances and covariances (and hence correlations) are translation invariant. That is the correlation between two vectors will not change if the two vectors are shifted by a constant. From vector analysis one may recall that the dot product of two vectors, $\mathbf{X}$ and $\mathbf{Y}$, in n–dimensional Euclidean space is given by the formula $\mathbf{X} \cdot \mathbf{Y} = |\mathbf{X}||\mathbf{Y}|cos(\theta_{XY})$, where θ_{XY} is the angle between $\mathbf{X}$ and $\mathbf{Y}$ and *cos* represents the cosine function. Since $\mathbf{X} \cdot \mathbf{Y} = \sum_{i=1}^{N} x_i y_i$ and $|X| = \sqrt{\sum_{i=1}^{N} x_i^2}$ then …

[72] As is the case when we are dealing with "data".

$$cos(\theta_{XY}) = \frac{\mathbf{X} \cdot \mathbf{Y}}{|\mathbf{X}||\mathbf{Y}|} = \frac{\sum_{i=1}^{N} x_i y_i}{\sqrt{\sum_{i=1}^{N} x_i^2} * \sqrt{\sum_{i=1}^{N} y_i^2}} = r_{X,Y}$$

and thus $r_{X,Y}$ is just the cosine of the angle θ_{XY} between the vectors $\mathbf{X}$ and $\mathbf{Y}$. Although I am in n–dimensional space, since there are three vectors, I can restrict my focus to only the 3–dimensional subspace spanned by the vectors $\mathbf{X}$, $\mathbf{Y}$ and $\mathbf{Z}$ and I can thus use a geometric argument to prove the theorem. Now, given the domain of the cosine function below (in degrees) ...

$$cos(\theta_{XY}) = \begin{cases} (0,1] \text{ for } 0 \leq \theta_{XY} < 90° \\ 0 \text{ for } \theta_{XY} = 90° \\ [-1,0) \text{ for } 90° < \theta_{XY} < 180° \end{cases}$$

one can see that two random variables will have positive correlation if the angle between their corresponding vectors is acute, negative if the angle is obtuse and zero if their corresponding vectors are perpendicular (i.e. form a right angle). If the angle is zero then the two variables have correlation 1 and if the angle is 180 degrees the two variables have correlation -1.

Now, referring to Figure 3, it is known from geometry that the angle between $\mathbf{X}$ and $\mathbf{Z}$ (i.e. $\angle XOZ$) is less than or equal to the sum of the angle between $\mathbf{X}$ and $\mathbf{Y}$ ($\angle XOY$) and the angle between $\mathbf{Y}$ and $\mathbf{Z}$ ($\angle YOZ$). Since these angles are given by $cos^{-1}(r_{X,Z})$, $cos^{-1}(r_{X,Y})$ and $cos^{-1}(r_{Y,Z})$ respectively, and since $cos^{-1}(r_{X,Y})$ and $cos^{-1}(r_{Y,Z})$ are acute because $r_{X,Y}$ and $r_{Y,Z}$ are positive, it follows that $r_{X,Z}$ will be positive whenever ...

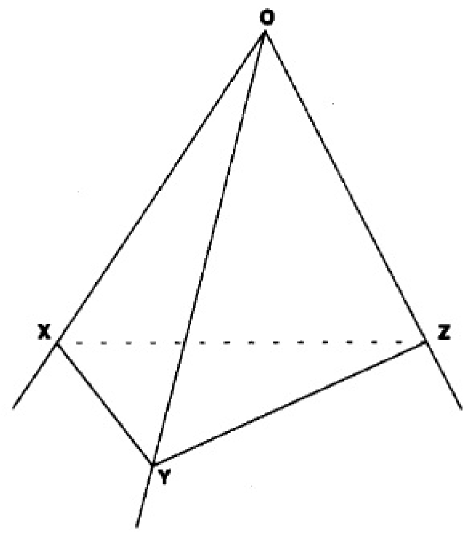

Figure A.1: Three Vectors in Three Dimensional Space

$$cos\left(cos^{-1}(r_{X,Y}) + cos^{-1}(r_{Y,Z})\right) > 0$$

Expanding the left–hand side out by the addition formula for the cosine function, we see that this is equivalent to ...

$$cos\left(cos^{-1}(r_{X,Y})\right) cos\left(cos^{-1}(r_{Y,Z})\right) - sin\left(cos^{-1}(r_{X,Y})\right) sin\left(cos^{-1}(r_{Y,Z})\right) > 0$$

$$r_{X,Y}r_{Y,Z} - \sqrt{(1-r^2_{X,Y})(1-r^2_{Y,Z})} > 0$$

Rearranging, squaring both sides and then simplifying yields the equivalent condition

$$r^2_{X,Y} + r^2_{Y,Z} > 1$$

$\square$

Appendix B: Alternative Weighting Scheme for C^1 and C^2

Although I initially assign equal weights to earnings and cash flows in C^1 and C^2 it should be pointed out that earnings tend to smooth cash flows and thus have a smaller variance over time than cash flows. During periods where this is the case for each firm, the pair–wise earnings across firms should be correlated more than pair–wise cash flows. Thus, assigning equal weights to C_E^1 and C_{CF}^1 (C_E^2 and C_{CF}^2) will only bias C^1 (C^2) downward. Therefore, as a robustness test, closeness measures were calculated for the industries using an alternative weighting scheme described below[73].

First, the standard deviation of earnings (σ_e and σ_{cf}) and cash flows was calculated within–industry for the sample time period (1999–2010). Then the following system of equations was solved to obtain the weights placed on C_E^1 (C_E^2) and C_{CF}^1 (C_{CF}^2).

$$\alpha + \beta = 1 \tag{1}$$

$$\frac{\alpha}{\alpha + \beta} = 1 - \frac{\sigma_E}{\sigma_E + \sigma_{CF}} \text{ when } \sigma_E < \sigma_{CF} \tag{2}$$

Equation (1) tells us that the weight assigned to earnings (α) plus the weight assigned to cash flows (β) should equal one. Equation (2) tells us that ratio of the weight assigned to earnings to the sum of the weights should equal to one less the ratio of the standard deviation of earnings to the sum of the standard deviations of earnings and cash flows. The latter ratio represents the relative percent of the total standard deviation of earnings and cash flows that can be attributed to earnings. The former ratio represents the relative percent of the total weights that can be attributed to earnings. It makes sense to choose the weights in a manner consistent with the relative variances of earnings and cash flows. The more inherent volatility in the ex post summary performance measure, the less weight that should be placed on it when measuring closeness across firms over time. When cash flows have lower variance than earnings Equation (2) would be of the following form...

[73]See Appendix D for a concise summary of the results. Notice that the results are rather similar using the alternative weighting scheme rather than equally weighting earnings and cash flows.

$$\frac{\beta}{\alpha+\beta} = 1 - \frac{\sigma_{CF}}{\sigma_E + \sigma_{CF}} \text{ when } \sigma_{CF} < \sigma_E \tag{3}$$

Solving the pair of equations gives the following ...

$$\alpha = \begin{cases} \frac{\sigma_{CF}}{\sigma_E+\sigma_{CF}} & \text{for } \sigma_E < \sigma_{CF} \\ \\ \frac{\sigma_E}{\sigma_E+\sigma_{CF}} & \text{for } \sigma_{CF} < \sigma_E \end{cases}$$

$$\beta = 1 - \alpha$$

Appendix C: The Determinant of the Correlation Matrix

To visualize C^2, first note that C^2 is a function of $|CORR_X(i,j)|$ where X is a random variable whose mean and variance exist and are finite[74]. $CORR_X(i,j)$ is a two by two matrix whose (i,j)'th entry is the sample Pearson Product moment correlation between X_i and X_j where (i,j) represents a firm–pair as seen below.

$$CORR_X(i,j) = \begin{bmatrix} r_{ii} & r_{ij} \\ r_{ji} & r_{jj} \end{bmatrix}$$

We can then form a parallelogram with the two row vectors of $CORR_X(i,j)$ as shown below ...

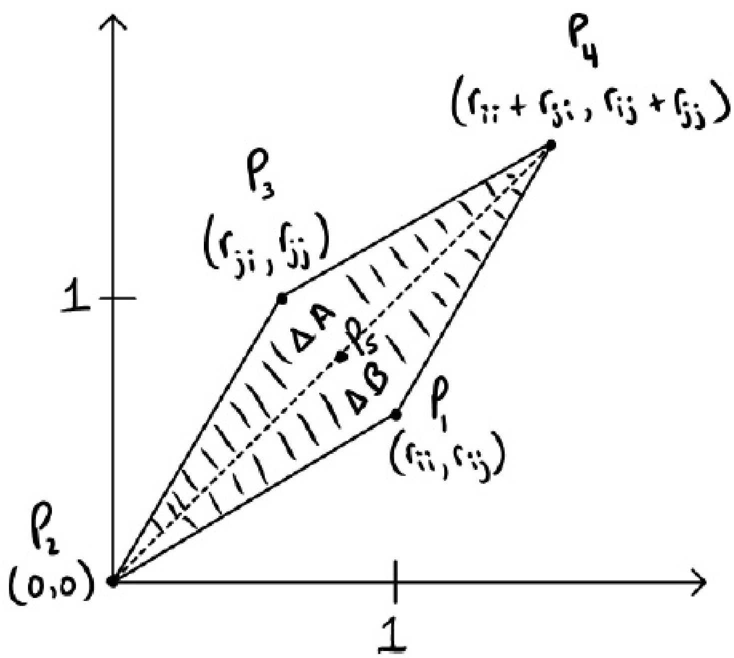

Figure C.1: Parallelogram formed from row vectors of correlation matrix

Above, we see that row one of $CORR_X(i,j)$ is given by vector $\overrightarrow{P_2P_1} = (r_{ii}, r_{ij})$. Row two of $CORR_X(i,j)$ is given by vector $\overrightarrow{P_2P_3} = (r_{ji}, r_{jj})$. We then use these vectors to form

[74]Recall that X is either earnings, unexpected earnings, cash flows or unexpected cash flows in this study.

parallelogram $P_1P_2P_3P_4$ [75]. It turns out that the determinant of $CORR_X(i,j)$ gives the area ("volume" in dimensions higher than two) of this parallelogram. The closer the area is to zero, the smaller the angle formed by the two vectors and thus the closer the vectors are to each other. When the determinant is zero, the parallelogram has zero area and thus the row vectors lie on top of each other and are perfectly correlated. Keep in mind that the row vectors are the correlation of each firm both with itself and with the other firm over time. Thus, the closer the vectors are to being superimposed on each other, the closer the firms are to each other in terms of their outputs moving similarly over time.

A generalization of the following theorem was stated for all n–dimensional matrices in section 1.4.2 but will be proven for the special two–dimensional correlation matrix case.

Theorem. *The determinant of a 2×2 correlation matrix $CORR_X(i,j)$ is equal to the area of the parallelogram formed by the row vectors of $CORR_X(i,j)$.*

Proof. First note that, by definition, $det(CORR_X(i,j)) = |CORR_X(i,j)| = r_{ii} * r_{jj} - r_{ij} * r_{ji}$. We know however, from the properties of the Pearson Product moment correlation, that $r_{ii} = r_{jj} = 1$ and that $r_{ij} = r_{ji}$. That is, a random variable is perfectly correlated with itself and the Pearson Product moment correlation displays symmetry. This immediately implies that $|CORR_X(i,j)| = 1 - r_{ij}^2$.

Now I will show that the area of the parallelogram formed by the row vectors of $CORR_X(i,j)$ is equal to $1 - r_{ij}^2$. Such a parallelogram can be depicted as in Figure 4. The diagonal $\overrightarrow{P_2P_4}$ cuts the parallelogram in half such that half of the area of the parallelogram lies above $\overrightarrow{P_2P_4}$ (or $\triangle A$) while half of the area lies below $\overrightarrow{P_2P_4}$ (or $\triangle B$). This implies the following, where D represents the distance ...

[75] $\square P_1P_2P_3P_4$ represents the area of parallelogram $P_1P_2P_3P_4$.

$$
\begin{aligned}
\square P_1P_2P_3P_4 &= \triangle A + \triangle B = 2(\triangle A) \\
&= 2 * \frac{1}{2} * D(P_2, P_4) * D(P_5, P_3) \\
&= 2 * \frac{1}{2} * D(P_2, P_4) * \frac{1}{2} D(P_1, P_3) \\
&= \frac{1}{2} * D(P_2, P_4) * D(P_1, P_3) \\
&= \frac{1}{2}\sqrt{(1 + r_{ji})^2 + (1 + r_{ij})^2}\sqrt{(1 - r_{ji})^2 + (1 - r_{ij})^2} \\
&= \frac{1}{2}\sqrt{(1 + r_{ij})^2 + (1 + r_{ij})^2}\sqrt{(1 - r_{ij})^2 + (1 - r_{ij})^2} \\
&= \frac{1}{2}\sqrt{2(1 + r_{ij})^2}\sqrt{2(1 - r_{ij})^2} \\
&= \frac{1}{2}\sqrt{2}(1 + r_{ij})\sqrt{2}(1 - r_{ij}) \\
&= (1 + r_{ij})(1 - r_{ij}) \\
&= 1 - r_{ij}^2
\end{aligned}
$$

$\square$

Appendix D: Industrial Classification Results Summary

Below are two tables summarizing the results from applying the measures to the sample of firms described earlier. The first table summarizes the mean results using an equal weighting scheme (i.e. $\frac{1}{2}$ weight assigned to earnings and cash flows in C^1 and C^2) while the second table summarizes the mean results using the alternative weighting scheme described in Appendix B.

Table D.1: Industry Closeness with Equal Weighting Scheme

	Measure	SIC	GIC	Random
Untrimmed	C_A^1	0.0918 (37/66)	0.0943 (46/68)	0.0394 (10/10)
	C_A^2	0.8684 (58/66)	0.8724 (63/68)	0.8876 (10/10)
	C^1	0.1629 (53/66)	0.1570 (57/68)	0.0913 (10/10)
	C^2	0.7912 (64/66)	0.8061 (66/68)	0.8287 (10/10)
Trimmed	C_A^1	0.1520 (29/56)	0.1455 (42/63)	0.0507 (10/10)
	C_A^2	0.8479 (42/56)	0.8570 (41/63)	0.8867 (10/10)
	C^1	0.3543 (47/56)	0.2973 (52/63)	0.1529 (10/10)
	C^2	0.6615 (52/56)	0.6751 (61/63)	0.7737 (10/10)

For example, applying closeness measure one with abnormal earnings and cash flows to the untrimmed sample and calculating the mean SIC industry closeness over the time period 1999-2010 gives 0.0918. The fraction after each reported measure is the proportion of industries (or groups in the case of the random samples) whose closeness was statistically significantly different than 0 (1 for closeness measure two) at the 10% level or better. Thus, for example, 37 out of the 66 SIC industries represented in the sample had C_A^1 statistically significantly different from 0 at the 10% level or greater[76]. From Table 3.4 one sees that the SIC and GIC scheme perform very similarly in regards to the two measures. That is, the difference between the measures applied to the SIC and GIC scheme is practically zero. The only exception to this is in the trimmed sample where C^1 is 0.3543 for the SIC but equal to 0.2973 for the GIC scheme.

[76] i.e. The p–value from a hypothesis test of whether C_A^1 is different than zero was ≤ 0.1 for 37 out of the 66 SIC industries represented in the sample.

Table D.2 on the following page summarizes the results using the alternative weighting scheme described in Appendix B where the weight placed on the earnings and cash flow variables is proportional to their relative variances over the sample period by industry[77]. Note that the results are very similar to the results when equal weights were given to earnings and cash flow variables. It is interesting to note that the industry variance of earnings was less than the industry variance of cash flows for every industry (regardless of the classification scheme used) over the sample period[78].

Table D.2: Industry Closeness with Alternative Weighting Scheme

	Measure	**SIC**	**GIC**	**Random**
Untrimmed	C_A^1	0.0983 (40/66)	0.1005 (45/68)	0.0405 (10/10)
	C_A^2	0.8654 (57/66)	0.8699 (63/68)	0.8872 (10/10)
	C^1	0.1615 (52/66)	0.1576 (57/68)	0.0919 (10/10)
	C^2	0.7921 (64/66)	0.8071 (66/68)	0.8307 (10/10)
Trimmed	C_A^1	0.1635 (30/56)	0.1520 (40/63)	0.0529 (10/10)
	C_A^2	0.8422 (45/56)	0.8529 (42/63)	0.8860 (10/10)
	C^1	0.3555 (47/56)	0.2955 (51/63)	0.1479 (10/10)
	C^2	0.6624 (49/56)	0.6793 (61/63)	0.7693 (10/10)

The following eight figures are histograms of untrimmed industrial classification closeness for both the SIC & GIC scheme using both unexpected fundamentals and realized fundamentals[79]. Normal curves are superimposed over the histograms to give the reader an idea of the shape of the closeness distribution in relation to an equal–mean normal distribution.

[77] The mean weight given to earnings and cash flows respectively was around $(0.61, 0.39)$.

[78] Also, the industry variance of earnings was, on average, 33% less than the industry variance of cash flows.

[79] The histograms appear similar for the trimmed sample but the means are a little higher (shifted to the right) for C^1 and a little lower (shifted to the left) for C^2 consistent with the results presented in the paper.

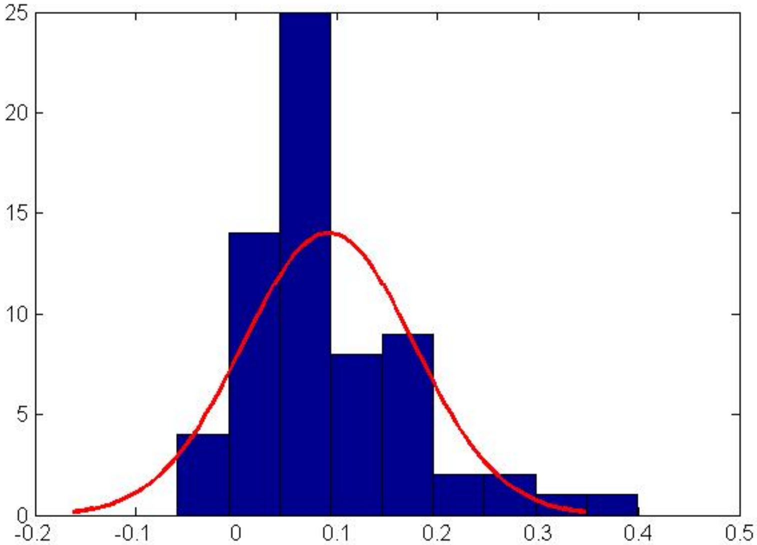

Figure D.1: Histogram of C_A^1 for SIC scheme

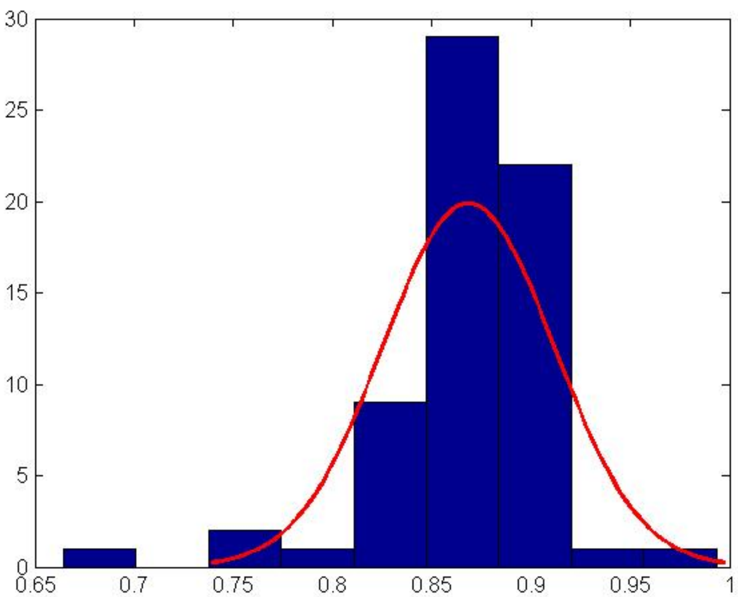

Figure D.2: Histogram of C_A^2 for SIC scheme

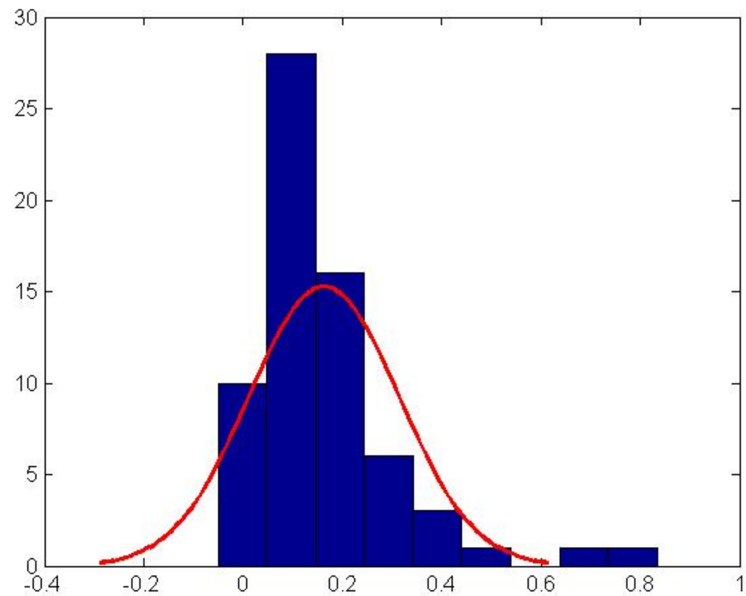

Figure D.3: Histogram of C^1 for SIC scheme

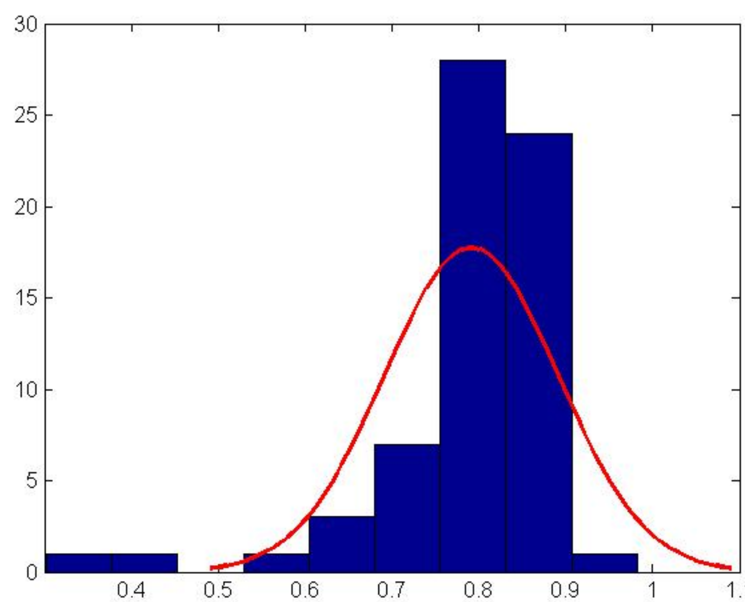

Figure D.4: Histogram of C^2 for SIC scheme

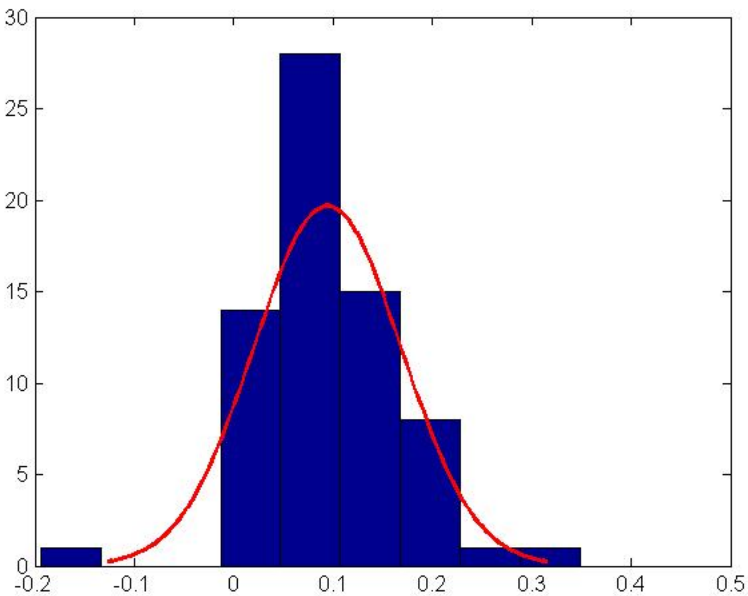

Figure D.5: Histogram of C_A^1 for GIC scheme

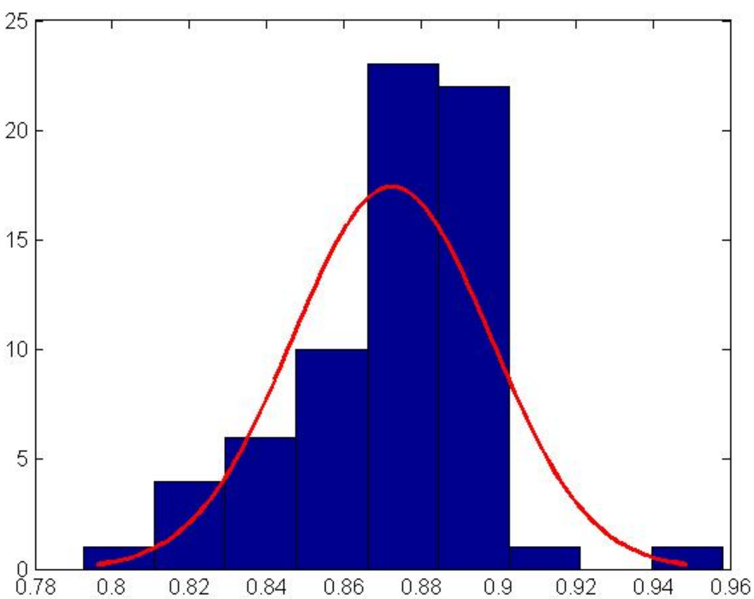

Figure D.6: Histogram of C_A^2 for GIC scheme

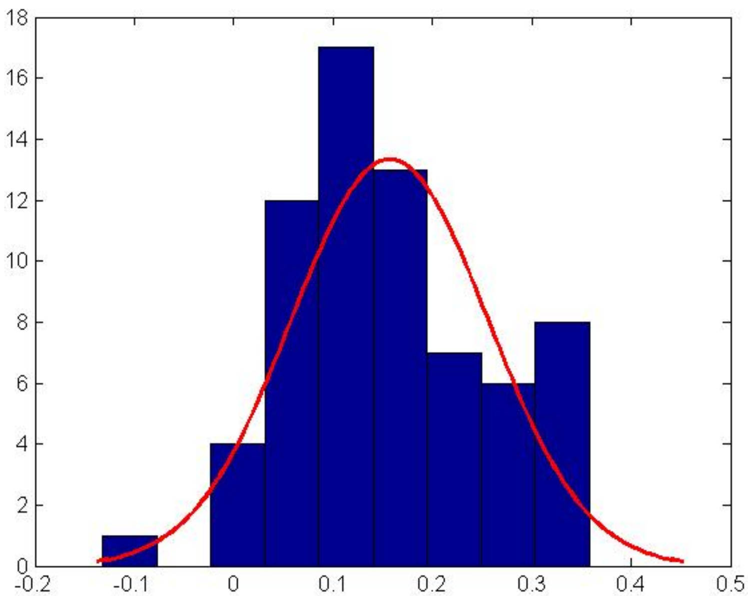

Figure D.7: Histogram of C^1 for GIC scheme

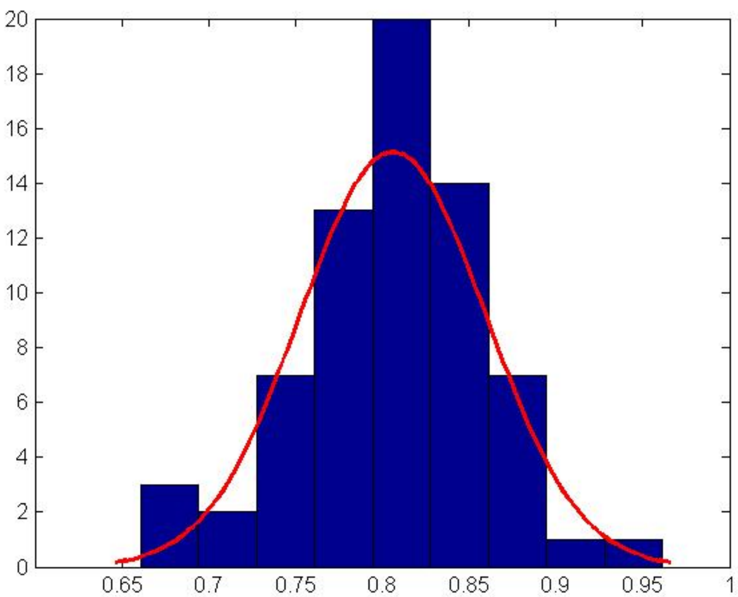

Figure D.8: Histogram of C^2 for GIC scheme

Appendix E: Portfolio Sample Selection Summary

Table E.1 summarizes the sample selection procedure and summary statistics for each SIC industry–portfolio tested.

Table E.1: Portfolio Sample Selection and Summary Statistics

SIC Industry	**10**	**39**	**15**	**20**	**28**
N beg.**(a)**	98	26	17	90	328
C^1 beg.**(b)**	0.0203	0.0190	0.3925	0.1869	0.024
C^2 beg.**(c)**	0.8094	0.8267	0.6103	0.7876	0.8285
non 12/31 FY end**(d)**	22	10	6	39	71
earnings announced $(0, +3)$**(e)**	2	3	1	2	12
Missing CRSP data **(f)**	35	3	3	20	74
Leader**(g)**	1	1	1	1	1
Leader announcement date**(h)**	1/20/11	2/2/11	1/27/11	2/2/11	1/20/11
N final**(i)**	$\underline{\underline{38}}$	$\underline{\underline{9}}$	$\underline{\underline{6}}$	$\underline{\underline{28}}$	$\underline{\underline{170}}$
C^1 final**(j)**	0.0321	0.0165	0.5437	0.24	0.0144
C^2 final**(k)**	0.7592	0.8536	0.5721	0.7424	0.8186
mean pair–wise corr. **(l)**	0.1354	0.2422	0.5867	0.1486	0.07
EPS**(m)**	\$4.64	\$1.86	\$33.42	\$2.55	\$5.18
Expected EPS**(n)**	\$4.26	\$1.84	\$33.03	\$2.55	\$5.04
News**(o)**	\$0.38	\$0.02	\$0.39	\$0	\$0.14
Median Beta**(p)**	0.7598	0.4252	2.118	0.557	0.5327
Avg. Total Assets**(q)**	\$11.55	\$0.21	\$2.84	\$11.62	\$5.78

Table E.1: Continued

SIC Industry	29	80	44	45	63
N beg.[(a)]	31	50	23	23	114
C^1 beg.[(b)]	0.4885	0.284	0.2743	0.2728	0.2444
C^2 beg.[(c)]	0.6236	0.722	0.7678	0.7990	0.7825
non 12/31 FY end[(d)]	3	6	3	5	1
earnings announced $(0, +3)$[(e)]	14	0	2	3	9
Missing CRSP data [(f)]	2	0	7	5	22
Leader[(g)]	1	1	1	1	1
Leader announcement date[(h)]	1/31/11	1/25/11	1/27/2011	1/18/11	1/25/11
N final[(i)]	$\underline{\underline{11}}$	$\underline{\underline{43}}$	$\underline{\underline{10}}$	$\underline{\underline{9}}$	$\underline{\underline{81}}$
C^1 final[(j)]	0.5185	0.2922	0.347	0.2309	0.2813
C^2 final[(k)]	0.5817	0.7043	0.7244	0.7846	0.7656
mean pair–wise corr.[(l)]	0.6969	0.4400	0.5162	0.2581	0.405
EPS[(m)]	\$6.22	\$4.05	\$2.13	1.71	\$6.26
Expected EPS[(n)]	\$5.95	\$3.98	\$2.07	1.79	\$6.08
News[(o)]	\$0.27	\$0.07	\$0.06	\$(0.08)	\$0.18
Median Beta[(p)]	0.8907	0.3072	0.5895	0.8515	0.8864
Avg. Total Assets[(q)]	\$104.69	\$3.14	\$2.17	\$10.89	\$85.32

Legend for Tables 3.1 & E.1

(a) Beginning sample size.

(b),(c) Closeness of beginning sample over the historical time period 1999–2009.

(d) Number of firms with non 12/31 fiscal–year ends.

(e) Number of firms with earnings announced within 3 trading days of leader.

(f) Number of firms with missing CRSP returns for at least one of the six days in the window (-2,+3) around leaders earnings announcement ($t = 0$).

(g) The firm which announces 4th quarter earnings for 2010 first.

(h) Date in which leader announced 4th quarter earnings for 2010.

(i) Final sample size.

(j),(k) Closeness of final sample over the historical time period 1999–2009.

(l) Mean pair–wise Pearson correlation in earnings between leader and other portfolio firms over time period 1999–2009.

(m) Industry "leader" actual 2010 Earnings per share.

(n) Industry "leader" expected earnings per share for 2010 using IBES data.

(o) Difference between expected earnings per share and actual earnings per share.

(p) Median beta of the portfolio firms where beta is measured as described in the paper.

(q) Average 2010 total assets (in \$billions) for portfolio firms.

Appendix F: Portfolio Return Results Summary

Table F.1 on the following page summarizes the results of applying the trading strategy described in Chapter 3 to ten of the two–digit SIC industry portfolios from Table 2.4. Average unexpected returns (AR) as well as actual returns (R) are given along with the market return (MR) over each window (W)[80] for each SIC industry–portfolio (SICP). Additionally, OP represents the price paid for one share of each security in the portfolio. This is obtained by summing the opening prices of the securities at the starting day of the window. Finally, CP represents the price that would have been received by selling one share of each security in the portfolio at the close of the last trading day in the window.

The portfolio abnormal return (PAR) is also given for each of the ten industry–portfolios tested. This is calculated by first assigning weights to each security in proportion to how far security i's beta is from one. I assume a risk neutral investor and thus the weight assigned to security i (i.e. share of investment given to security i) is decreasing in the quantity $(1 - \beta_i)$. The weight thus is given as the following where N is the number of securities in the portfolio.

$$w_i = \frac{1}{N} + \left(\frac{1}{N} - \left(\frac{|1 - \beta_i|}{\sum_{i=1}^{N} |1 - \beta_i|} \right) \right) \tag{4}$$

The intuition for the above equation is the following. From a risk neutral investors' standpoint it seems intuitive that they want to invest in securities with betas equal to one. Investment in securities with betas different than one should be decreasing in the magnitude of the difference. The above equation assures that this holds and also insures that the sum of the weights is equal to one. Intuitively, the above equation assigns

[80] Actual returns are only given over the windows that would be feasible to implement the trading strategy.

weight w_i to security i in proportion to how much $|1 - \beta_i|$ contributes to the sum of all of the security beta deviations from one. Securities with betas deviating very little from one contribute less to the total deviation and thus are assigned greater weight.

Table F.1: SIC Industry–Portfolio Return Results

SICP	W	OP	CP	CP−OP	R	MR	AR	PAR
10	[0,+1]	$869.54	$855.98	$(13.56)	−1.56%	−0.26%	−3.72%	−4.56%
	[0,+2]	$869.54	$855.97	$(13.57)	−1.56%	0.37%	−5.29%	−6.34%
	[0,+3]	$869.54	$847.02	$(22.52)	−2.59%	0.33%	−6.40%	−7.82%
15	[0,+1]	$107.64	$103.52	$(4.12)	−3.83%	−1.51%	−1.04%	−1.06%
	[0,+2]	$107.64	$103.53	$(4.11)	−3.82%	−0.76%	−3.07%	−2.92%
	[0,+3]	$107.64	$105.84	$(1.80)	−1.67%	0.93%	−4.25%	−3.88%
20	[0,+1]	$896.05	$893.69	$(2.36)	−0.26%	0.07%	−0.07%	−0.32%
	[0,+2]	$896.05	$896.53	$(0.48)	0.05%	0.29%	0.20%	0.10%
	[0,+3]	$896.05	$897.53	$1.48	0.17%	0.90%	0.31%	0.09%
28	[0,+1]	$4075.80	$4031.70	$(44.10)	−1.08%	−0.26%	−1.64%	−1.71%
	[0,+2]	$4075.80	$4066.00	$(9.80)	−0.24%	0.37%	−1.12%	−1.30%
	[0,+3]	$4075.80	$4075.80	$0.00	0.00%	0.33%	−1.24%	−1.28%
29	[0,+1]	$488.23	$509.15	$20.92	4.28%	0.95%	2.84%	4.26%
	[0,+2]	$488.23	$507.32	$19.09	3.91%	−0.79%	3.02%	3.98%
	[0,+3]	$488.23	$507.44	$19.21	3.93%	−0.03%	3.21%	3.66%
39	[0,+1]	$78.28	$78.17	$(0.11)	−0.14%	0.07%	−0.77%	−0.55%
	[0,+2]	$78.28	$78.17	$(0.11)	−0.14%	0.29%	−0.73%	−0.96%
	[0,+3]	$78.28	$78.97	$0.69	0.88%	0.90%	−0.26%	−0.16%
44	[0,+1]	$327.70	$335.70	$8.00	2.44%	−1.51%	2.20%	2.67%
	[0,+2]	$327.70	$332.78	$5.07	1.55%	−0.76%	0.90%	0.58%
	[0,+3]	$327.70	$336.85	$9.15	2.79%	0.01%	0.43%	−0.42%
45	[0,+1]	$268.30	$258.23	$(10.07)	−3.75%	−1.01%	−4.24%	−4.57%
	[0,+2]	$268.30	$252.22	$(16.08)	−5.99%	−1.39%	−5.39%	−5.16%
	[0,+3]	$268.30	$247.82	$(20.48)	−7.63%	−1.26%	−6.93%	−6.92%
63	[0,+1]	$3573.60	$3638.90	$65.30	1.83%	0.69%	0.85%	1.22%
	[0,+2]	$3573.60	$3653.10	$79.50	2.22%	0.90%	1.13%	1.46%
	[0,+3]	$3573.60	$3582.00	$8.40	0.24%	−0.83%	0.33%	0.52%
80	[0,+1]	$958.09	$972.10	$14.01	1.46%	0.69%	1.54%	1.56%
	[0,+2]	$958.09	$991.55	$33.46	3.49%	0.90%	2.03%	2.01%
	[0,+3]	$958.09	$984.37	$26.28	2.74%	−0.83%	0.69%	0.72%

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