INVESTOR SENTIMENT, TRADING PATTERNS AND RETURN PREDICTABILITY

DISSERTATION

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ABSTRACT

Many unanswered questions remain when attempting to determine the motivating factors behind investor trade. Also, contemporary asset pricing models continue to be challenged by seemingly irrational return predictability and additional trading that does not appear to be motivated by information arrival or heterogeneous processing of private and public signals. This dissertation dissects the reasons that investors trade, and also presents evidence of return predictability related to trading and past stock returns.

In the first dissertation essay, I analyze the factors that explain trading volume growth in equity securities. It is found that technical and statistical factors are strong explanatory factors for trading volume growth in the cross-section, while statistical and macro factors are strong sources of time variation.

The second dissertation essay analyzes the first three moments of trading volume growth and determines that there is a link between these moments and future stock returns. It is found that stocks with high mean trading volume growth during the past 12 months experience strong positive excess returns that do not reverse themselves over the next 5 years. This result holds true for both NYSE/AMEX and Nasdaq stocks.

The third dissertation essay analyzes return consistency and determines if consistency is able to predict time-variation in expected returns. I analyze the degree to which return consistency in the past predicts future returns. It is discovered here that consistency is a strong predictor of future returns. In a portfolio context, positively consistent stocks exhibit higher future risk-adjusted returns than other securities in the cross-section, and negatively consistent stocks exhibit lower future risk-adjusted returns. It is also determined that high consistency enhances momentum when the two factors are allowed to interact. Thus, there appears to be strong path dependence in the momentum effect.

Dedicated to my son David, who will never be forgotten. Also dedicated to my mother Robin, this belongs to you.

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CHAPTER 1

INTRODUCTION

This dissertation represents an analysis of changes in investor sentiment, and the implications for trading behavior and stock returns. I determine the factors that drive trading volume growth, as well as break down the relationships between turnover movements and future stock returns. An analysis of return consistency as a predictor of future returns is presented as well.

The first essay works to determine what factors drive cross-sectional variation in trading volume growth. Understanding the variables that drive trading volume growth is critical for creating factor models to describe trading behavior. I analyze the factors that explain trading volume growth in equity securities. It is found that technical and statistical factors are strong explanatory factors for trading volume growth in the cross-section, while statistical and macro factors are strong sources of time variation. Fundamental factors are very weak as sources of time variation, and marginally strong sources of cross-sectional explanatory power. The only exception is January, where fundamentals are much stronger predictors of trading volume growth. Finally, explanatory power of all factors rises in January, so there appears to be a January effect in trading volume that is related to that of stock returns.

The second dissertation essay analyzes the first three moments of trading volume growth and determines if there is a link between these moments and future stock returns. It is found that stocks with high mean trading volume growth during the past 12 months experience strong positive excess returns that do not reverse themselves over the next 5 years. This result holds true for both NYSE/AMEX and Nasdaq stocks. It is also found that all 3 moments of trading volume growth show some ability to predict future returns and trading volume growth, but not in the direction predicted by excess demand. A brief factor model for trading volume growth is presented here to determine whether the first three moments have some ability to act as macro-economic factors for excess volume growth. The model's explanatory power is limited, but the moments show some ability to be priced in a portfolio context. Finally, it is confirmed that the measure used here (Idiosyncratic market-adjusted turnover growth) has a strong contemporaneous relationship with excess returns that have been adjusted for the Fama-French factors, momentum, and a share turnover factor.

The third dissertation essay analyzes return consistency and determines if consistency is able to predict time-variation in expected returns. I analyze the degree to which return consistency in the past predicts future returns. It is discovered here that consistency is a strong predictor of future returns. In a portfolio context, positively consistent stocks exhibit higher future risk-adjusted returns, and negatively consistent stocks exhibit lower future risk-adjusted returns. The results are economically and statistically significant over multiple sub-periods. Also, odd return behavior persists for nearly two years after portfolio formation. Skewness is found to be a strong factor in momentum profits as well. It is also determined that high consistency enhances momentum when the two factors are allowed to interact. Thus, there appears to be strong path dependence in the momentum effect.

CHAPTER 2

What Predicts Volume?

2.1. Introduction and literature review.

The role of trading volume in asset pricing has long been considered an important one, but has yet to be fully understood. What is even more perplexing to academia is why investors trade at all, particularly in the presence of limited new information in the market and/or very little disagreement about that information. The fact that we are also not sure exactly how efficiently investors process new information confuses the issue even further.

In this research, I analyze trading volume and attempt to determine the types of factors that drive volume in the cross-section. The factors are broken into categories: Technical, Fundamental, Statistical, Market and Macro. The goal is to determine a) which of these factors drives cross-sectional variation in trading volume growth, and b) which of these factors serve as potential causes of time-variation. To my knowledge, this has not been done in the literature. Understanding these relationships can be profitable, for there is a clear and well-established contemporaneous relationship between trading volume and stock returns. Thus, understanding volume is pivotal to understanding capital markets, for volume tends to drive movements in price and value.

Trading volume statistics are used in technical analysis, and there is a strong link between stock returns, information and trading volume. Blume, Easley and Ohara (1994) (here after, BEO) argue that trading volume can be used to deduce information about the underlying stock that cannot be found in the price statistic. Campbell, Grossman and Wang (1993) (hereafter, CGW) discuss how trading volume movements can be used to determine the information implications behind stock returns. Their work centers around the idea that high volume transactions may be related to liquidity demands and thus leads to market makers being compensated with changing expected returns. Ultimately, their belief is that a low-volume price movement is less likely to reverse itself than a high volume price movement.

Chordia, Roll and Subrahmanyam (2001) examine whether or not there are systematic liquidity factors in the market. From a microstructure perspective, their analysis reviews various factors that may serve as the underlying sources of market liquidity shocks. Volume is related to liquidity, but not defined by it. Liquidity is more elusive and essentially describes ease of trade. Volume can, in some cases, represent increased liquidity, but it also serves as a measure of information dispersion and investor attention. Understanding both liquidity and volume is important, but the amount of research done to understand volume does not match the amount done to understand liquidity. Also, the connection between trading volume and traditional macroeconomic factors has not been explored in detail. This paper fills that gap.

Lo and Wang (2000) are among the first to thoroughly examine the relationship between portfolio theory and movements in trading volume. They determine that behavior in trading volume leads them to strongly reject the existence of two-fund separation. Also, they find that turnover is well approximated by a two-factor linear structure. Tkac (1998) does an excellent job of discussing systematic variation in trading volume and how it relates to volume movements for individual stocks. Cready and Hurtt (2002) find that in many cases, volume-based metrics provide more clues regarding information response than those based on stock returns. Cremers and Mei (2002) show that there are substantial co-movements between volatility and turnover at systematic levels, and that trading volume may be driven by trading activities associated with both macroeconomic and firm-specific news. Hirshleifer (1988) predicts that for commodity futures markets, the residual risk premium is proportional to the volume of hedging by agents with non-marketable risks.

Karpoff (1986) makes the theoretical argument that trading volume can be driven by information disagreement and dispersion. He also attempts to explain why trade can occur even when there is no information dispersion. He and Wang (1991) make the theoretical argument that information dispersion leads to movements in trading volume. They argue that trading patterns are related to information flow, and that information is revealed through investor trading.

Another factor that is believed to impact movements and levels of trading volume is the popularity or attention that investors pay to a given stock. Miller

(1977) and Mayshar (1983) argue that any shock that increases investor interest in a given stock is going to lead to additional trading in the stock, since the set of potential buyers (and perhaps sellers, assuming there are no short-selling constraints) would then increase. Also, Merton (1987) makes the argument that increases in analyst following for a given stock should lead to price increases, since estimation risk has been reduced. Lee and Swaminathan (2000) also argue that investor attention is the driving force behind changes in trading volume.

While a number of papers have studied the relationship between trading volume and stock returns, none have done a categorical analysis of the underlying determinants of trading volume and its risk sources. This paper makes a contribution to this area by comparing the potential sources of covariation to determine which factors have the strongest cross-sectional and time-varying relationship with trading volume.

This paper has three primary objectives: First, we would like to determine which factors produce volatility of trading volume growth. Second, we would like to know which traditional economic factors do the best job of explaining trading volume in the cross-section. Finally, we would like to perform a categorical comparison of these various factors to determine their relative strength.

The factors used to explain trading volume have been chosen from a relatively agnostic point of view. While there is some theory guiding what should drive trading volume, the theory is not as well developed as that of stock returns.

The variables are analyzed individually, since a multivariate analysis can potentially lead to over fitting and multicollinearity problems. Because there are so many variables and many of them are highly correlated, it is important to find some way of determining which variables are truly strong on their own and which ones are only strong in a multivariate context. For the sake of robustness, a multivariate analysis is done once the list is reduced to a reasonable set of variables that have shown themselves to be strong in a univariate context. The factors are studied for their explanatory power both within and outside the month of January, since January effects in stock returns seem to predict that similar effects hold with trading volume. This extends the work of Sias and Starks (1997) who analyze January trading volume to distinguish between the tax-loss selling hypothesis and the Window Dressing Hypothesis. I too find that trading behavior changes a great deal during January. The underlying sources of volatility remain essentially the same, but there appear to be profit opportunities during this month that are difficult to explain.

It is found that technical and statistical factors are very good at explaining trading volume growth in the cross-section, while statistical and macro factors are sources of volatility for trading volume growth. Fundamental factors are very weak as sources of volatility, and marginally strong explanatory factors for volume differences across stocks. Finally, explanatory power of all factors rises in January, as does the ratio of mean to standard deviation. These results support the idea that investors do trade stocks in response to macroeconomic and market information. Also, trade reactions to these factors increases during the month of January.

These results could also be used to decide if investors are more likely to trade in response to behavioral factors or those having to do with fundamentals and the macro economy. The poor showing of fundamental factors may argue that fundamentals do not play a strong role in the volume growth process relative to the other factors. However, the theory does not support a dichotomy between rational and behavioral factors. For example, 6 month return momentum may be considered a behavioral factor in stock return analysis, but a rational investor would rebalance in response to 6-month return momentum. Thus, this debate is still unresolved. More theory describing exactly what stimuli should lead to trade would help to settle this issue.

Section II presents the factors chosen for the study and motivates their use in this paper. Section III describes the data. Second IV presents univariate tests. Second V presents multivariate tests. Section VI concludes.

2.2. The Factors.

The analysis begins with a description of the factors chosen to explain volume, and exactly what I mean when I refer to trading volume. By trading volume, I am referring to share turnover, which is the number of shares traded, divided by the number of shares outstanding. Share turnover does a good job of eliminating the high association between trading volume and firm size.

According to Datar, Naik and Radcliffe (1998), the correlation between firm size and trading volume is .89, but the correlation between share turnover and firm size is only .11.

Also, rather than explaining the level of share turnover, the factors are measured on their ability to explain turnover growth. This manages the fact that share turnover, like trading volume, is a unit root process. Growth in share turnover is a more transitory measure, and allows us to understand the dynamic nature of trading volume in the cross-section of securities.

Table 1 presents a list of variables and categories for those variables. The factors are chosen from a list of variables that have been long known to affect stock returns. We can logically expect that factors known to impact stock returns may also impact trading volume. Thus, these factors serve as a reasonable starting point to answer difficult questions.

The first category, Macro and Market factors, reflects the fact that there has been a long-established relationship between stock performance and macroeconomic conditions. Macroeconomic variables are considered by many to be directly related to the financial performance of publicly traded firms, which is obviously going to be reflected in the stock price. One potential link between macroeconomic performance and trading volume is that, according to asset pricing theory, investors must rebalance their portfolios to maintain pre-determined asset allocations. Thus, changes in macroeconomic conditions can affect returns, which should affect trading volume as investors rebalance. Lo and

Wang (2001) show how the assumptions of (K+1)-fund separation imply a K-factor linear structure for share turnover. The two macroeconomic factors chosen here are change in industrial production and seasonally-adjusted inflation. There are other factors that could have been included, but these two factors capture the gist of strength determinants in the macro economy.

The second component to the first category includes "Market" factors. These are factors which are expected to affect trading volume because they are related to systematic changes in financial markets. The first set of market factors include equal and value weighted returns on NYSE/AMEX listed firms. The presence of market returns is justified by the relationship between returns and trading volume. Also, the return on the market is typically used in empirical implementations of the CAPM and other asset pricing models.

The second set of market factors include equal and value-weighted trading volume for NYSE/AMEX stocks. These factors are used in Tkac (1998) and Lo and Wang (2001) in their quest to determine if there is a systematic component to trading volume. They both find that market turnover is a meaningful factor, but they do not test for other variables that might explain cross-sectional variation in trading volume growth. I do not use market turnover. Instead, I use percentage growth in trading volume as the factor to represent market trading volume. Standard volume is included here as a market factor, rather than turnover for at least two reasons: First, the standard volume measure is used in many of the seminal studies of trading volume (see Karpoff, 1986 for a review). The inclusion of a market measure of trading volume allows us to measure the importance of trading volume itself, and not just turnover. Secondly, the value-weighted growth in market trading volume factor used here is very similar to the market turnover factor used in Tkac (1998), and achieves many of the same objectives.

The third category consists of “Technical” factors. These factors are given this name because they are based upon technical analysis. This group of factors includes the following variables: lagged return, 6 month return momentum, 60 month return momentum, lagged volume growth, 6 month volume momentum and 60 month volume momentum. Stocks rise and fall in popularity, and there is data to support the notion that increases in visibility have an impact on volume and returns in the future and present[1]. High momentum stocks tend to draw attention from the media and investors, and volume momentum is an even more direct reflection of increases in investor attention. Given that there appears to be a behavioral component to market performance, it would make sense to take a look at these variables.

The fourth set of factors includes “Statistical Factors”. These factors are those that are purely statistical in nature. The statistical factors simply include the first four principal components of the variance-covariance matrix of trading volume growth. Firms are sorted each month into twenty portfolios[2] based upon volume growth for the given month, and then the principal components are

[1] See Lee and Swaminathan (2000), Gervais, Kaniel and Mingelgrin (2001)
[2] The tests are repeated with 10, 15 and 25 portfolios, leading to no material change in the results. There is no reason, to my knowledge that we should consider a number of portfolios that is either less than 10 or more than 25.

created from the eigenvalues of the variance-covariance matrix of mean turnover growth of each of these portfolios. Twenty portfolios are created to ensure that there is a large enough number to rid the data of idiosyncracies of turnover growth. Lo and Wang (2001) find that the first two principal components capture much of the variation in turnover, but they do not study turnover growth. I include the first four principal components here, since there is no cost for doing so, and more than the necessary number of components allows us to capture a greater proportion of the variation in turnover growth.

The next category includes “Fundamental” factors. These are factors that are related to the financial position of the publicly-traded firm. The fundamental factors chosen here are firm size, share price, book to market ratio, earnings to price ratio, cash to price ratio and dividend yield. Firm size is measured as the market capitalization of the firm during the given month. Share price is the price of the firm’s shares at the end of the given month. Book to market is measured as the book value of firm assets as of the end of the prior calendar year, divided by market capitalization at the end of the current month. The earnings price ratio is measured as earnings per share after extraordinary items from the prior fiscal year, divided by the stock price at the end of the current month. The cash to price ratio is measured as cash flow per share from the prior fiscal year, divided by the stock price at the end of the current month. Cash flow per share is measured as net profit plus depreciation, divided by shares outstanding. Dividend yield is the firm’s annual dividend from the prior year, divided by the share price at the end of the current month. These factors are all found to effect stock returns. It is because of this relationship that they are included here. However, the connection between these factors and trading volume has yet to be studied in the literature.

The macroeconomic, market and statistical factors are obviously not idiosyncratic variables. Thus, they can only be studied in a cross-sectional sense via factor sensitivities. The sensitivities for all factors are measured with firm-specfic time series regressions, with a separate regression performed for every potential factor. The regressions include 60 months of turnover growth measurements, and only firms with at least 24 months of turnover growth realizations have their factor sensitivities included in the tests. The only factor sensitivities that are not measured individually are the Principal Components. These coefficients are measured simultaneously.

2.3. The Data.

The tests use monthly data that begin in August, 1962 and end in December, 1999. In order to be included in the sample, a firm had to have a realization for at least one of the variables studied here, as well as a turnover growth realization for the given month. The top and bottom 1% of all variables has been removed. Also, all firms that do not pay dividends are removed from the sample of dividend yields. This is to manage the fact that many firms do not pay dividends for reasons that differ from the factors that determine the cross-section of positive yields. Leaving zero dividends in the sample would unduly truncate the distribution at zero.

Table 2 presents the time series mean of the cross-sectional sample size, mean, median, standard deviation, skewness, 5^{th} percentile, and 95^{th} percentile for every variable used in this study. Additionally, these same statistics are calculated for the turnover growth variable for both the characteristics-based sample and the sample in which sensitivities are estimated. There is a difference in sample size and other statistics between the two samples, since the group in which sensitivities are estimated possesses a more restrictive set of criteria.

Mean turnover growth tends to be positive, but median turnover growth tends to be negative for both groups. The mean monthly sample size is roughly 3 times larger for the characteristics-based group than for the group with factor sensitivities. Firms tend to have a negative sensitivity to inflation growth. While it is not completely clear why this relationship exists, it is plausible that it is the negative relationship between stock returns and inflation that drives this effect. There is a positive relationship (on average) between returns and trading volume, implying that anything that has a positive effect on stock returns is expected to have a positive effect on trading volume as well. A decline in inflation has a positive effect on stock returns. Thus, a decline in inflation should lead to an increase in trading volume.

Growth in industrial production, on average, has a positive relationship with turnover growth. This is also likely to be driven by the positive relationship between industrial production and stock returns, which could lead to a positive relationship between turnover growth and industrial production for the median firm in the economy. Like inflation, the cross section of factor sensitivities with respect to industrial production tends to be positively skewed.

The equal and value-weighted returns on the market tend to have a positive relationship with trading volume growth. Equal and value-weighted trading volume also have a positive effect on turnover growth for the median firm. The median volume beta is 1 for equal-weighted volume growth, but is less than one for value-weighted volume growth. This difference is likely due to data restrictions that are biased against small firms. Also, the dependent variable is turnover growth, while the independent variable is market weighted *volume* growth, which has not by scaled by firm size.

The fundamental variables tend to be positively skewed, other than the earnings to price ratio. The technical factors all tend to be positively skewed as well. The means for the volume-based technical factors tend to be negative. The 1, 6, and 60-month volume momentum factors all have negative means, but the medians are usually higher than the means. Thus, outliers seem to have an impact on this sample as well.

2.4. Univariate Tests.

2.4.1. Univariate tests and sorting procedures.

Table 3 presents the average turnover growth for various groups of stocks, all sorted based upon the magnitude of the given factors and factor sensitivities. The sorts were performed for each month in the sample, and each sorting consists of all firms that possess data on the given variable.

Turnover growth tends to have a U-shaped relationship with macro and market factors. Those firms that have very high and very low sensitivities to the macro and market factors tend to have the highest turnover growth. This is most likely due to the fact that those stocks whose volume growth responds sharply to economic stimuli may have extremely positive or extremely negative factor sensitivities. Thus, the data seem to suggest that it is the *absolute magnitude* of the factor sensitivity that drives volume growth, rather than the sign of the sensitivity. Also, the high sensitivity group has a higher mean turnover growth than the lower sensitivity group for every factor except industrial production.

Turnover growth tends to have a negative relationship with most of the technical factors. The only exception is the 60-month return momentum factor, which has a relatively flat, slightly positive relationship with turnover growth. There is also a strong, negative monotone relationship between turnover growth and lagged volume growth. This is to be expected, since turnover growth for last month's volume growth outliers tends to gravitate back toward the unconditional mean.

All four of the principal components appear to have a strong relationship with trading volume growth. The relationships are positive and somewhat U-shaped, with the exception of the third principal component, which has a negative relationship with trading volume growth. As expected, mean turnover growth for the random factor does not change across quintiles, implying that this is the benchmark for a relationship between trading volume and a factor that has no significance whatsoever. The random factor was created via independent draws from a standard normal distribution. For each month of the time-series, one draw was created for each firm, and this value represents the firm's realization of the random factor. This factor was created so that we could have some reasonable benchmark to help us determine what constitutes a meaningful amount of turnover growth volatility. Obviously, if a factor has a level of volatility that is not significantly greater than that of the random factor, then the factor does not have much explanatory power.

The fundamental factors all have generally positive relationships with trading volume growth. The Book to Market ratio has a relationship that is monotone positive. Those firms that have extreme realizations of book to market, cashflow to price, dividend to price, and earnings to price tend to have strong turnover growth. Thus, value stocks seem to gain a great deal of attention from investors. Share price has a monotone negative relationship with mean turnover growth, since lower priced firms are more liquid and hence, more frequently traded. There is also a negative-monotone relationship between firm size and turnover growth. Thus, large firms are likely to have lower turnover growth than smaller firms.

Table 4 presents the results from "hedge" portfolios, in which the turnover growth for the low group is subtracted from the turnover growth of the high group. This is done for every month of the time series. The mean, t-statistic, standard deviation, skewness, and an additional measure are presented. The additional measure is coined the "V-sharpe" ratio, which is simply a Sharpe Ratio for trading volume growth. Thus, the V-Sharpe is calculated by taking the value of the hedge portfolio outcome and dividing by the time-series standard deviation. The measure allows us to determine which factors tend to have the most consistent and strongest ability to explain trading volume through time. While this is not the focus of the paper, it is a concept that is worth exploring. The factors are ranked by the absolute value of the mean turnover growth spread between the high and low portfolio groups, so the sign is not given in the mean spread. However, the sign of the spread can be extracted from the t-statistics.

Regarding significance, we can see that the macro and market return factors do not have statistically-significant values of hedge portfolio trading volume growth. The only market factors that show some form of statistical significance are equal and value-weighted trading volume, with only equal-weighted trading volume showing strong significance. While this does not eliminate the abilities of these variables to explain trading volume (since explanatory power here is captured by the magnitude of the standard deviations of hedge portfolio turnover growth), it does argue that these factors do not lead to volume premiums between the high and low groups. Hedge portfolios are limited in that they are only able to uncover a linear relationship between the variables, rather than the non-linear one that some factors seem to have with turnover growth. The first three principal components show significance, with the fourth being insignificant. The book to market ratio is the only statistically-significant fundamental factor. The technical factors show strong negative significance, with the exception of the 60-month volume and return momentum factors.

The factors that have negative relationships with turnover growth are: Industrial Production, the second and fourth principal components, lagged return, 6 month return momentum, share price, size, lagged volume growth, and 6 and 60 month volume momentum. Also, only the first principal component, lagged volume, lagged return and firm size have turnover spreads that exceed 10%. Lagged volume has the highest V-sharpe ratio of 106.48%, implying that it is a consistent and strong explanatory factor for turnover growth. Lagged return is second, with a V-sharpe value of 46.87%.

Given that there is a strong January effect in stock returns, it makes sense to do an independent analysis of the month of January to determine how these relationships change at the turn of the year. Table 5 presents the same statistics for the month of January only. Here, statistical significance is more difficult to achieve, since the sample is smaller.

The spread for inflation growth changes sign, going from 1.12% positive to 12.07% negative, although neither value is statistically-significant. However, this alarming change in sign during the month of January may have meaning. The industrial production coefficient gets stronger as well, going from –2% to –7% during the month of January.

The first and fourth principal components increase in magnitude during the month of January. There is a 5-6 fold increase in the turnover growth spread due to value and equal-weighted market trading volume as well. Thus, it appears that market volume has a great deal more explanatory power during the month of January than during other months.

A shocking change in strength for the fundamental factors takes place as well. The book to market ratio changes sign during the month of January, going from 5.01% per month to –23.45% per month. Thus, the impact of book to market on turnover growth changes sign during January, and the magnitude also changes a great deal. For all months, high book to market firms tend to have the highest trading volume growth, but during January months, low book to market firms have significantly higher trading volume growth than high book to market firms. Thus, January appears to create a preference for trading glamour stocks. This may serve as evidence of window-dressing by fund managers, but further study would be needed to determine the type of trade taking place. The dividend yield agrees with book to market. During most months, dividend yield turnover premia are small and insignificant, but during the month of January, the premia become large and significantly negative. Thus, those firms with high dividend yields have lower turnover growth than other firms during the month of January. Earnings price and cash flow to price also have much stronger relationships with turnover growth during the month of January. For all months, the relationships are insignificant, but during January, they both have a positive and significant relationship with trading volume growth.

There are many other factors that simply change sign during the month of January. Share price, size, and 60-month volume momentum all change from negative to positive during the month of January. Exactly why this dramatic shift in importance takes place is difficult to determine. Analysis of December premia yields some clues. First, the size and share price turnove premia are extremely negative during the month of December (-46% and –47%, respectively), which explains the high premia that exists during the month of January. But this result remains puzzling for a couple of reasons: First, the positive turnover growth for January is not high enough to compensate for the substantial decline in turnover that takes place during the month of December. We can say that small, low priced stocks are more highly traded during the month of December, but this imbalance is not fully corrected during the month of January. Secondly, it is difficult to understand why this tremendous imbalance between months exists at all.

The peculiar behavior by the earnings price variable during the month of January is puzzling for a different reason. There is indeed a negative turnover premium during the month of December for this variable (-15%). However, the positive premium during January overwhelms the negative premium from the prior month. So, there is a much stronger desire to trade stocks with a high earnings price ratio. This could be related to the fact that earnings information from the prior year may have been released in January for many firms and thus lead investors to trade in those stocks with abnormally high earnings.

The highest V-Sharpe ratio is still held by Lagged Volume Growth, with 6-Month volume Momentum very close behind. Both values exceed the V-Sharpe values for the sorts that are done for all months. Also, unlike before, there are several factors with V-Sharpe ratios that exceed 100%. Thus, many factor mimicking portfolios have turnover growth premia that are much higher during January, with no significant increase in the variance of those premia.

2.4.2. Discussion of Rankings.

We should remember that a high mean, variance and V-Sharpe ratio all imply different things. A high mean states that the factor may be "priced" in the cross-section. High volatility shows that the factor may be a source of comovement for trading volume growth. The factor with a highly volatile relationship with turnover growth obviously presents a source of exposure for this variable. Firms with a high V-Sharpe ratio basically have a high mean spread relative to the variance. So, analysis of the V-Sharpe ratio allows us to determine which factors serve as the most consistent predictors of turnover growth premia in the market.

The highest spreads inTable 4 are possessed by lagged volume, the first principal component, lagged return, size and 6 month return momentum. So clearly, the technical and statistical factors do the best job of explaining changes in turnover growth. The worst explanatory factors are earnings price, dividend yield, inflation, value-weighted market return and equal-weighted market return.

The volatility measure is dominated by the statistical factors. The factor-mimicking variances are strongest for the third, first, second and fourth principal components, respectively. The lowest volatility goes to the book to market, cashflow to price, dividend yield and earnings price factors, respectively. Thus, the fundamental factors do not appear to be sources of risk for turnover growth. With regard to V-Sharpe ratios, we find that lagged volume, lagged return, size, the first principal component and share price are the strongest factors. So, once again, technical, statistical and theoretical factors are very good at explaining turnover growth premia.

Another interesting question is how these rankings change during the month of January. The January effect has been long known to exist in stock returns, so it would not be surprising to find that these relationships change during the first month of the year. Table 4a investigates this issue further. Here, we see that the largest January spreads are produced by share price, earnings price, value-weighted trading volume, equal-weighted trading volume, and lagged return.

These results represent a major move in the rankings for the earnings price ratio, which is near the bottom for the other months of the year. Also, the market volume factors of Tkac (1998) take on major importance during the month of January. Lagged return remains strong. What is also noticeable is that the median spread of the top 5 factors has more than doubled. The median spread for the top 5 factors is 33.33% during January, but only 14.05% for all months of the year. Thus, there is a great deal more cross-sectional explanatory power in the month of January.

The highest volatilities during January are possessed by inflation, the first principal component, industrial production, value-weighted market return, the third principal component and equal-weighted market return. So, in January, the principal components no longer dominate the volatility rankings, as they did before. Also, there is a huge jump in the ranking of macro and market factors, which had much lower rankings during the other months. As a group, there is not a tremendous change in the total volatilities among all factors. The medians are roughly the same as before.

The V-Sharpe ratios are much higher during January for nearly every factor. When all months are included, the highest V-Sharpe ratio is 106.48%. For January only, the highest V-Shape ratio is held by lagged volume growth, with a value of 145.33%. The next four V-Sharpe ratios are: book to market, share price, earnings price, cash price, and size respectively. Thus, the fundamental factors make dramatic improvements in the V-Sharpe rankings during the month of

January. This trend is reflected in many other factors as well. The median V-Sharpe ratio for the 5 highest factors during all months of the year is 45.89%, but it grows to 107.19% during the month of January. The median of mean monthly spreads for all factors grows six-fold from 7.91% to 47.84%. Thus, the ability of the median factor to explain trading volume increases dramatically during the month of January.

2.5. Multivariate Tests.

Robustness dictates that we use multivariate regressions to determine the joint explanatory power of all the factors mentioned in the univariate tests. However, there is the problem that some of the factors may be too highly correlated to include in the same multivariate regression. The correlationTable for the top 10 factors in mean spread and volatility are presented in Tables 6. The Table includes the time-series means of cross-sectional Pearson correlations. The correlation Table for the top factors during the month of January is presented in Table 7. Those variables with correlations that do not exceed 20% are included together in multivariate regressions. If the correlations are greater than this amount, then one of the highly correlated factors is not included in the analysis.

Table 8 presents the results of multivariate regressions. These regressions are important, since they allow us to determine how these factors work in the presence of other factors that are known to affect turnover growth. There are four regressions run in total. In the first regression, the top 6 uncorrelated factors ranked on the absolute value of mean spread are included. The second regression, also in Table 8, includes those factors that ranked in the top 6 in standard deviation. The third and fourth regressions, both included in Table 9, repeat the first and second regressions, but are only done for the month of January. The regressions in Table 9 are done to determine how the meaningfulness of each factor changes during January, and whether or not the joint explanatory power of these factors changes during January months.

The regressions follow the methodology of Fama and Macbeth (1972). The cross-sectional regressions are run for every month of the time-series. The coefficient estimates are then averaged and checked for significance. The first regression, listed in Table 8, includes lagged volume growth, the natural log of firm size, lagged return, 6 month return momentum, share price, and equal-weighted volume growth. All factors are significant statistically, and all maintain the same sign as during the univariate analysis, with the exception of share price, which switches sign from negative to positive.

The second regression includes the factors that rank in the top six in volatility. The list includes the following factors: equal-weighted market return, value-weighted volume growth, inflation growth, growth rate of industrial production, 6 month volume momentum and 6 month return momentum. Not all coefficients are significant here. Equal-weighted market return, inflation growth, and industrial production are not found to be significant. Six-month return momentum is significant, but its sign changes in the multivariate context. The premium is positive in the univariate case, but becomes negative in the presence of other strong factors. The average adjusted r-square is 15.29%, so the joint explanatory power of the high volatility factors exceeds that of the high mean spread factors, even though three factors are statistically insignificant.

There is a second regression on the factors that have high mean spreads, but the regressions are only run during the month of January. The peculiar behavior of trading volume during this month implies that results might change substantially. These results are presented in Table 9. Here, we can see that in January, size is no longer significant. Volume growth is slightly more negative, and still significant. Lagged return and 6 month return momentum are significant, but substantially increase and change sign, going from negative during the regression that includes all months, to positive in the regressions that include only the month of January. Also, share price and equal-weighted volume growth increase and maintain their positive sign. The adjusted r-square increases, relative to the mean spread regressions including all months, from 11.03% to 14.64%. Thus, these factors have greater explanatory power during the month of January.

The second regression in Table 10 includes those factors that rank in the top 6 in standard deviation, but again, the regression is only run in January months. All coefficients maintain the sign that they had in the prior regression, with the exception of equal-weighted market return, which changes sign from negative to positive during the month of January. Equal-weighted return was also not statistically significant during the regression that included all months, but becomes significantly positive during the month of January.

There is a noticeable increase in the coefficient for value-weighted trading volume, which is positive in both January and non-January months, but grows from 1.77% to 8.39% in the month of January. Finally, there is a change in sign for the 6 month return momentum factor, which goes from negative to positive. The joint explanatory power of the high volatility factors increases from 15.29% to 22.45% during the month of January. Thus, the explanatory power of these factors grows as well.

Hence, we can see that throughout the year, most factors maintain their ability to explain the level and changes in trading volume. The primary exceptions are market return, inflation and industrial production. Thus, the market and macro factors are weakened in a multivariate context. We also find that during January, the joint explanatory power of key factors tends to increase. Additionally, many factor coefficients change magnitude and/or sign during the month of January.

2.6. Conclusion.

I analyze the underlying determinants and volatility sources of trading volume growth. It is found that technical and statistical factors are strong explanatory factors for trading volume growth in the cross-section, while statistical and macro factors are sources of comovement for trading volume growth. Fundamental factors are very weak as sources of volatility, and marginally priced. Finally, explanatory power of all factors rises in January, as does the ratio of mean to standard deviation.

Peculiar January effects also exist within the data that cannot be explained. The relationship between trading volume and stock returns implies that this additional explanatory power during the month of January may serve as a source of arbitrage profit. Also, the fact that the relationships change so dramatically during this month seems to show that investor sentiment may not be constant throughout the year.

Future research might include the presentation of a true factor model for trading volume in the cross-section. One could also formalize the link between these premia and stock returns in order to determine if this additional explanatory power truly represents a profit opportunity. Finally, a GARCH model for volatility of trading volume growth premia might be an interesting way to further understand the properties of this process.

CHAPTER 3

Predictable time-variation in investor sentiment: a tale of 3 moments

3.1. Introduction and Literature Review.

Gervais, Kaniel, and Mingelgrin (2001) show that past trading volume growth can predict future stock returns, using short-horizon data. Lee and Swaminathan (2000) argue that volume changes are predictive of future returns, and that these changes also proxy for additional attention being paid to the given security. The relationship between trading volume and returns has become of great interest to economists, since it appears to provide clues into how behavioral mechanisms affect asset prices. However, the nature of this connection is not yet fully understood.

This paper makes contributions on the following fronts. First, there has not been, to my knowledge, a paper that analyzes the combined predictive ability of the first 3 moments of the trading volume growth process. Secondly, there has not been a long-horizon analysis of the predictive ability of turnover growth that has been adjusted for market and firm-specific components. Gervais et al (2002) show that excess demand leads to higher future returns using shorter horizon daily and weekly returns, but they do not confirm that their results hold over longer horizons. Third, there has not been an analysis of long-horizon excess return predictability of these three turnover factors. Here, returns are analyzed for up to 60 months after portfolio formation.

It is found that higher mean trading volume growth from the past leads to higher future stock returns, higher volatility of trading volume growth leads to lower returns, and higher skewness of trading volume growth also leads to lower returns. These results hold for an independent analysis of NYSE/AMEX firms, and for Nasdaq firms as well. The effects are stronger for Nasdaq firms, but they are generally strong for firms in both markets. The returns are strong and persistent through time, lasting up to 5-years into the future when adjusted for the Fama-French factors, a momentum factor and a raw turnover factor.

Also, the first three moments of adjusted turnover growth are predictive of future turnover growth, but the patterns are not those that openly indicate excess demand. High mean market-adjusted turnover growth during the prior 12 months tends to lead to lower idiosyncratic turnover growth the following period. High volatility of market-adjusted turnover growth tends to lead to higher idiosyncratic turnover growth during the following period. Skewness has a negative relationship.

These results are in line with those of Chordia, Subrahmanym and Anshuman (and Gervais et al also make this point) that volume growth may be a proxy for excess demand and attention from investors. Past volume growth serves as a proxy for that additional attention, and volatility of this growth serves as a measure of the consistency of that attention growth. Strong skewness in the volume growth process may imply that extreme increases in volume are quite probable and should be factored into the risk profile of the asset under consideration.

Lakonishok, Shleifer and Vishny (1994) provide evidence that investors tend to over extrapolate past sales growth.[3] Watkins (2002) shows that investors tend to over extrapolate past return consistency. Grinblatt and Moskowitz (2001) report that return consistency leads to higher future returns. If trading volume growth is something that the investor can witness and study as value-increasing, then it is not unreasonable to expect that this variable would also lead to future increases in excess demand. Also, the fact that short-selling constraints tend to lead to positive information being incorporated more readily into the stock price than negative information (Chen, Hong and Stein, 1999) implies that additional trading volume will, on average, lead to increases in demand and price for the security at hand.

Given the aforementioned interpretations of trading volume, there are many potential interpretations of trading volume growth. If one considers trading volume a proxy for the level of interest in a given security, then one would expect that cross-sectionally, those firms that have high mean trading volume growth during a given period are going to have higher returns, both contemporaneously and perhaps also during subsequent periods. More specifically, a rational arbitrageur seeking to speculate on future demand of noise traders might use

[3] This conclusion is contested by Dechow and Sloan (1997), who provide evidence that this extrapolation does not take place.

statistics on past movements in trading volume as a predictor of future changes in excess demand.

I hypothesize (based upon the arguments above) that growth in trading volume, on average, tends to have a positive effect on the price of the firm's shares. We can extend this argument to the next two moments of trading volume growth. If trading volume growth is a "good thing" for the firm's current and future stock price, then it follows that volatility of trading volume growth is a "bad thing". This is due to the fact that simple mean variance optimization dictates that investors would be willing to pay more for a consistent "good thing" than one that is inconsistent. Hence, we would expect that those firms that have highly volatile past growth in trading volume are going to have lower future returns, due to the fact that this historical information is incorporated into the price.

Finally, the argument can be extended to the third moment as well. Positive skewness represents low probabilities of extreme realizations of the random variable. Hence, if turnover growth is a "good thing", then firms with positively skewed turnover growth are going to experience increases in demand from traders and hence, higher returns.

This work extends that of Blume, Easley and O'Hara (1994), who were the first to argue that information can be extracted from the volume process. They explain that the volume process can provide an investor with information that cannot be obtained from the price process alone. They use this argument to rationalize the existence of technical analysis, even when markets appear to be fully efficient.

This work also extends that of Lee and Swaminathan (2000) who provide evidence that past volume interacts with past returns to predict future stock returns. They show that high (low) turnover winner (loser) stocks tend to have lower (higher) future returns, and exhibit many glamour (value) characteristics. Thus, they provide evidence that past turnover growth can be predictive of future returns. However, they do not study all moments of turnover growth together, and they focus on the level of turnover, rather than mean turnover growth.

Lo and Wang (2000) are among the first to thoroughly examine the relationship between portfolio theory and movements in trading volume. Their analysis of trading volume leads to them to strongly reject the existence of two-fund separation. Also, they find that turnover is well approximated by a two-factor linear structure. Tkac (1998) discusses systematic variation in trading volume and how it relates to volume movements for individual stocks. This paper presents a simple factor model designed to attempt to explain idiosyncratic turnover growth for turnover-sorted portfolios. I find that the past moments of trading volume growth have some predictive ability and may be related to market factors. I present them in factor form only as a frame of reference. I do not, however, search for a theoretical motivation for their inclusion in a factor model for trading volume.

Campbell, Grossman and Wang (1993) show that price movements associated with noise trading (proxied by strong increases in trading volume) are more likely to reverse themselves than those associated with informed trades. Again using trading volume to proxy for investor behavior, Llorente et al (1998) also argues that reversals are associated with risk-sharing, and that return continuation is associated with informed speculation.

A theoretical model that is highly applicable to this study is that of De Long, Shleifer, Summers and Waldmann (1990) (hereafter DSSW90). In their model, arbitrageurs can destabilize prices by speculating on the activity of positive feedback traders. Both positive feedback traders and arbitrageurs contribute to price instability in the same direction. Arbitrageurs enter the market before positive feedback traders, and buy based upon a signal that will be made public in later periods. They make the purchase not only because the fundamental value of the asset may have increased, but also because they understand the behavioral patterns of positive feedback traders and their reaction to the realization of the public signal. Basically, they are fully aware that excess demand for the security is going to exist once the security price has increased between periods. This is when the arbitrageurs sell the asset short and remove themselves from long positions.

One of the questions not addressed by the DSSW90 model has to do with the nature of the signal received by arbitrageurs. Of course, positive feedback traders react to price increases, but the critical component of this model has to do with changes in demand that are predictable based upon public information. One could argue that past movements in trading volume may be reliable predictors of future increases in systematic noise trader demand for a given security. If one believes that excess demand can impact stock returns, then this would lead to additional movements in price.

Here, part of the question is answered in that those stocks with odd movements in the first three moments of trading volume tend to have predictable risk-adjusted returns over long horizons. However, the predictability does not appear to show itself as excess trading volume during the following month. In fact, trading volume tends to move in directions that are opposite of those predicted here. Hence, the source of these excess returns is not completely uncovered, although there are interesting patterns of returns and volume in the data. Finally, this paper uses both Nasdaq and NYSE/AMEX stocks in the analysis. Many studies exclude Nasdaq stocks because of double-counting of dealer trades and other institutional differences that add noise to the volume count for Nasdaq securities. I show that when analyzing the moments of market-adjusted volume growth, the processes of both exchanges are fundamentally similar, and that the removal of Nasdaq stocks from these studies results in a disproportionate loss of information.

Section II describes the data. Section III analyzes the contemporaneous relationship between excess volume growth and stock returns in the presence of Fama-French, momentum and turnover-based factors. Section IV analyzes predictability of the trading volume growth moments. Section V analyzes predictability of future turnover growth. Section VI concludes.

3.2. The Data.

The dataset consists of monthly stock returns from the CRSP (Center for Research in Securities Prices) database. The data begins in August, 1962 and end in December, 1999. Nasdaq firms are analyzed in a separate sample for two reasons: First, Nasdaq firms are smaller and more difficult to trade than other firms in the market. Second, volume in this market is over-estimated due to the double counting of dealer trades (Gould and Kleidon, 1994). Thus, any volume-based sorting procedure that includes firms from all three exchanges is going to have comparability problems. Although there are differences in datasets, a separate analysis of Nasdaq stocks is meaningful because there is information to be obtained from volume and price movements within these firms. Double counting may hinder comparisons between exchanges, but Nasdaq firms can be compared with one another. Also, this paper analyzes growth in share turnover, not absolute volume levels. For these reasons, these stocks are not excluded altogether. Diagnostics (below) confirm that the volume processes of both datasets are very similar, and further tests reveal that there is information in the volume process of Nasdaq stocks. Thus, this sample serves as further ground for testing the hypotheses put forth in this research.

Variables are measured monthly, with trading volume being measured by turnover, which is defined as the total number of shares traded for a given month divided by shares outstanding. This measure purges trading volume of size effects, given that there is a very strong correlation between shares outstanding and firm size (Datar, Naike and Radcliff, 1998). According to Datar, Naike and Radcliff (1998), the correlation between trading volume and firm size is .89, but the correlation between turnover and size is .11.

Mean turnover growth for month t is measured as follows:

$$g_t^j = \frac{1}{12}\left\{\sum_{k=t-13}^{t-1} \frac{Vol^j(k) - Vol^j(k-1)}{Vol^j(k-1)}\right\} \tag{1}$$

Where $Vol^j(k)$ is the share turnover for firm j during month k.

To avoid the influence of outliers, the top and bottom 5% of all observations are removed each month. Also, only those shares with share code 10 or 11 are included in the sample. This leads to the exclusion of REITs, ADRs, and closed-end funds. Thus, the analysis is limited to common shares only. Also, only firms with at least 12 months of trading history are included in the sample. Descriptive statistics are listed in Table 10.

The underlying assumption here is that trading volume growth during a given month takes the following form:

$$g_t^i = \overline{g}_t^i + \mu_t^m + \varepsilon_t^i \tag{2}$$

Where g_t^i is the trading volume growth for firm j during month t. $\overline{g}_t^i$ is the 12-month average excess turnover growth for the current month and the prior eleven months. The value-weighted average volume growth for the market has been factored out of this variable. μ_t^m is the value-weighted trading volume growth for the market, which is presented as a component to the entire volume process for a given month. This captures the fact that trading volume growth may very likely have both market-oriented and idiosyncratic components. No distributional assumptions are made for the residual, which is accounted for in later tests. The only distributional assumptions made are those that relate to stock returns, which have more underlying theory to support the analysis.

Market adjusted excess turnover growth is calculated in order to extract the market and firm-specific components of turnover growth for the given month. Thus, this paper focuses on share turnover that is in excess of the market's turnover growth, as well as the mean market-adjusted turnover growth for the firm during the prior 12 months. The calculation for market and firm-adjusted turnover growth is presented as the residual from the market volume growth model presented above:

$$\varepsilon_t = g_t^i - \mu_t^m - \overline{g}_t^i \tag{3}$$

This equation adjusts current trading volume for both market and firm-specific components. The mean turnover growth from the past is only adjusted for the market component, so there is no redundancy in the subtractions above.

A separate analysis for Nasdaq and NYSE/Amex stocks is completed in Table 10, along with a joint analysis consisting of all publicly traded firms meeting the criteria for inclusion. First, we can see that the median share turnover is roughly the same between NYSE/AMEX and Nasdaq stocks. This is primarily due to the restriction of outliers from the sample, since pre-restriction analysis shows that turnover is greater for Nasdaq stocks. Median monthly turnover growth for NYSE/AMEX and Nasdaq stocks are roughly 0% and .1%, respectively. However, the mean turnover growths are 30% and 76% for NYSE/AMEX and Nasdaq stocks, respectively. So, in spite of the removal of outliers, both datasets remain positively skewed.

Table 10 also presents statistics on market and firm-adjusted turnover growth. The mean is roughly zero for both exchanges, and the medians are both negative. Mean 12-month market-adjusted turnover growth is more negative for Nasdaq firms than for NYSE/AMEX securities. The mean of the cross-sectional standard deviations of adjusted turnover growth of NYSE/AMEX stocks is higher than that of Nasdaq stocks. Also, we can see that NYSE/AMEX securities tend to have positive skewness in adjusted turnover growth.

3.3. The Relationship Between Excess Turnover Growth and Stock Returns.

The first objective is to confirm that there is a positive contemporaneous relationship between trading volume and stock returns. This relationship must be reconfirmed for three reasons. First, the risk-factors known to describe stock returns have changed over time. When seminal volume studies were completed, the Fama-French 3-Factor Model had not yet been created, and the momentum effect had not yet been uncovered. Thus, we should determine if turnover and turnover growth are priced in stock returns in the presence of these variables. Secondly, this question determines whether or not trading volume measures can be used to capture the behavioral aspects of financial market factor analysis. Third, it allows us to confirm the strength of the idiosyncratic turnover growth measure in the presence of raw turnover.

This question is addressed in Table 11. For every month of the time-series, 10 portfolios are formed based upon excess market-adjusted turnover growth. Thus, turnover is not only adjusted for the market component, but also for the firm-specific component of market-adjusted turnover growth. The returns from these portfolios in excess of the t-bill rate are then regressed on the size, book to market, and market factors from the models of Fama and French (1996). Additionally, a momentum and share turnover factor were added to the regression. The momentum factor was created by sorting all NYSE stocks into 3 groups based upon 12-month momentum every month. The return to the low momentum portfolio is then subtracted from that of the high momentum portfolio. This hedge portfolio return is included in the regression as the momentum factor.

The turnover factor was created using the same approach as that used to create the momentum portfolios, also using the same number of groups. The mean monthly return for hedge portfolios sorted on turnover is 2.97% per month. As expected, the raw contemporaneous positive relationship between raw turnover and stock returns still exists. The analysis is done separately for NYSE/AMEX and Nasdaq stocks.

In Table 11, we should first note that the Gibbons, Ross, Shanken F-test rejects the null hypothesis that the intercepts are 0 at the 1% level. Secondly, we can see that the intercept for the low excess turnover growth portfolio is both economically and significantly negative, presenting a startling risk-adjusted return of –3.24% per month. Thus, those stocks with high/low excess turnover tend to have high/low excess returns contemporaneously. The same is true for Nasdaq stocks, where the spread is even greater. The low idiosyncratic excess turnover growth portfolio has an excess return of –4.51% per month, while the high excess turnover growth portfolio has an excess return that is roughly 0% per month. This relationship has not previously been confirmed in the presence of these risk factors.

For both Nasdaq and NYSE/AMEX stocks, the intercepts are monotone increasing in the level of excess turnover growth. This is true for both NYSE/AMEX and Nasdaq stocks.

The portfolios all tend to load positively on the size and distress factors. The relationship tends to be U-shaped for both SMB and HML. The most extreme relationship with both factors occurs for those stocks in the highest decile of excess turnover growth.

The turnover factor is significant for every portfolio and priced positively for every portfolio as well. The turnover factor certainly has a presence on both exchanges. However, the magnitude of the turnover coefficient is not as strong as that for the other factors, and is usually a little more than half the size of the coefficient on the distress factor, which is the highest of all. The magnitude of this factor coefficient does exceed the size of the market return factor coefficient when included in the same regression. The highest realization of the turnover factor coefficient occurs in the high excess turnover growth portfolio group, in which case, the turnover factor has the highest coefficient of all factors included in the model.

Nasdaq firms show some similarities to NYSE/AMEX securities, but not every result is the same. The adjusted r-squares are much lower for the Nasdaq sample, ranging from .36 to .54. The highest and lowest adjusted r-squares are obtained for the highest and lowest excess turnover growth groups, respectively. This again confirms the fact that these factors do the best job of explaining the returns of securities with high idiosyncratic turnover growth.

As in the NYSE/AMEX sample, the GRS F-test rejects the null hypothesis that all of the intercepts are zero at the 1% significance level. The portfolios all tend to have positive loadings on the size and distress factors, and once again, the strongest loadings are for the portfolio with the highest excess turnover growth. Therefore, it appears that high excess turnover stocks tend to be small stocks with high book to market ratios.

3.4. Return Predictability of Volume Growth Moments.

The next objective is to determine whether or not past moments of excess trading volume growth show any ability to predict *future* stock returns. There is a clear and strong contemporaneous relationship, but there has not been, to date, any confirmation that monthly realizations in idiosyncratic turnover growth are predictive of future stock returns. Lee and Swaminathan analyze long horizon volume movements and find that there is an interaction between past trading volume and returns to momentum investing. However, they do not explore idiosyncratic trading volume growth per se, and instead focus on levels of trading volume[4]. They also do not explore higher order moments in the volume growth proces. Gervais et Al (2001) find predictability in shorter-horizon data.

This question is answered here in two ways. The first method is via cross-sectional Fama-Macbeth regressions, which allow returns to be regressed cross-sectionally on characteristics expected to have an impact on future stock returns. The second method is a portfolio approach that allows expected returns to co-vary with macroeconomic factors.

The cross-sectional regression performed is of the following form:

[4] They do make reference to 4 year changes in trading volume as a robustness test.

$$r_{t+1}^{j} = \alpha + \beta_1(mean_t) + \beta_2(Var_t) + \beta_3(skew_t) + \beta_4(\log(size)) + \beta_5(mom12) + \varepsilon_{t+1} \quad (4)$$

where r_{t+1}^{j} is the market-adjusted return on the stock in excess of the t-bill rate, "mean" is the 12-month mean excess turnover growth for the stock, "Var" is the 12-month standard deviation of excess turnover growth, "skew" is the skewness of excess turnover growth during the past 12 months, "log(size)" is the log of firm size during month t, and "mom12" is the 12-month cumulative return on the stock up through and including month t-1.

The regressions are run cross-sectionally every month, and the coefficients are averaged and checked for significance. The averages are checked over three separate time periods: 1963 - 1979, 1980 – 1989, and 1990 – 1999, and the analysis is replicated for NYSE/AMEX and Nasdaq stocks separately. The results are presented in Table 12.

The one-month cross sectional tests show that the first moment of excess turnover growth tends to have strong predictive ability for future returns. The coefficients are relatively stable through time, and consistently positive across exchanges. Also, the coefficient is significant for all three time periods for both Nasdaq and NYSE/AMEX securities. The magnitudes of the coefficients tend to be similar across exchanges, and no exchange has a stronger effect than the other for all time periods. The relationship is not as strong during the 1990s as during the 1963-1979 period, but both periods dominate the 1980s.

The volatility coefficients are all negative, with one exception. During the 1980 – 1989 time period, Nasdaq stocks do not exhibit a negative relationship, in which case the coefficient is reliably positive. The coefficients for NYSE/AMEX firms are stable and negatively significant for all sub-periods. The coefficients for Nasdaq stocks are significantly negative for the first and final sub-period. The magnitude of Nasdaq coefficients declines substantially between the first and last sub-periods as well.

The skewness coefficient is significantly negative for the first and second sub-period for NYSE/AMEX stocks. The coefficient for the last period is not negative, but is statistically insignificant. The average coefficient for all time periods is significantly negative. The skewness coefficients for Nasdaq stocks are negative for the first two periods and positive during the 1990s, as is the case for NYSE/AMEX stocks. The coefficients are only significant during the second and third sub-period. The coefficient for the entire period is negative and not-statistically significant.

Figure 3 takes a time series regression approach to analyzing the long-horizon impact of the first three moments of excess turnover growth. For every month in the cross-section, stocks are sorted into portfolios based upon the realization of the mean, standard deviation and skewness of excess turnover growth during the past 12 months. The mean return for the lowest group is then subtracted from that of the highest group, creating the return on a zero investment hedge portfolio. The hedge portfolio return is then calculated for months 1 through 60 after the investment period, in order to analyze the long-run effects of each factor on excess returns. The goal is to determine if the excess returns created by the first three moments of trading volume are due to overreaction and correction or by under reaction. The analysis is done separately for NYSE/AMEX and NASDAQ stocks.

We can see that the excess returns from the mean volume growth hedge portfolios are positive, where they remain for the entire 5-year period. This is true for both exchanges, although there is a marked decline in the magnitude of the excess returns for Nasdaq stocks over longer horizons. The highest returns for the NYSE/AMEX stocks occur during the first year, and then decline thereafter. However, they remain positive throughout. The excess returns for Nasdaq stocks starts off twice as high as that for NYSE/AMEX securities, at an annualized 19.2% per year. The alphas then begin to decay over time, but remain as high as 4.8% per year in month 60. The cumulative return for the Nasdaq portfolio is higher than that for the NYSE/AMEX group. NASDAQ 5-year excess returns are 68.21% vs. 15.51% for NYSE/AMEX stocks.

The results on volatility (Figure 4) are also in line with prior sections on volume growth. For both NYSE/AMEX and NASDAQ stocks, the returns to hedge portfolios sorted on volatility of excess volume growth are negative, where they remain negative for the entire time horizon. Returns for NYSE/AMEX securities begin very low, at roughly -7.2% per year, and then gradually increase toward zero, remaining negative. NASDAQ returns are predominantly negative also, and much more volatile. The returns begin at –3.24% per year in month one, decline to -6.24% per year in month 6 and then show a sea-saw effect over time, but remain predominantly negative. Over long horizons, the pattern does not change, leading to a cumulative loss on this portfolio of 21.68% over the next five years.

The effects of skewness (Figure 5) tend to be negative for both NYSE/AMEX and Nasdaq securities. The negative effects are more persistent for Nasdaq stocks, since NYSE stocks show some form of mild reversal. Excess returns for the hedge portfolios on NYSE/AMEX stocks become positive in month 41, but are negative for earlier months and show another decline in month 55. Nasdaq stock hedge portfolio returns are reliably negative throughout, but the magnitude declines over time. The buy and hold return for the NYSE/AMEX portfolio is not very strong, but negative during the first year, averaging –1.27% per year. The 5-year buy and hold excess return is –4.16%. While the sign of this return verifies prior results related to skewness of turnover growth and excess demand implications, it is difficult to argue that these returns exceed reasonable transactions costs. Nasdaq stocks tell a different story. The 1-year buy and hold risk-adjusted return for Nasdaq skewness hedge portfolios is negative 12.49%, while the 5-year cumulative risk-adjusted return is –32.87%. Like before, Nasdaq securities show a strong reaction to the moments of trading volume growth. NYSE/AMEX securities show strong reaction to the first two moments of trading volume growth, but not the third.

The reason for this relationship between past volume growth and future returns is not apparent. There is little formal theory driving this result, so one is left to wonder why those securities that have experienced high excess trading volume growth in the past are going to have higher returns in the future. The volatility and skewness results are also without a clear answer. Each hedge portfolio tends to have a negative loading on the distress factor, implying that they have a positive relationship with glamour stocks. This could provide clues into herding effects that may take place within the market. The mean and skewness portfolios have negative loadings on the size factor, indicating a positive correlation with small stocks. The standard deviation hedge portfolio has a positive loading on the size factor. Finally, the first and third moment portfolios have positive loadings on the market factor, and the standard deviation portfolio has a negative loading on the market factor. So, when the market does well, stocks with a high standard deviation of excess turnover growth tend to have strong negative returns.

Gervais et al (2001) present an argument that securities which experience extremely high trading volume growth are the victims of excess demand, leading to higher returns. One way to determine if this is the case for longer-horizons is to analyze excess volume growth in the future as a function of prior realizations of the first 3 moments. This is not a perfect measure, since additional trading may not represent excess demand. However, it is a place to begin, and it would also be interesting to determine if these moments have the ability to predict future idiosyncratic volume growth. This is done in the next section.

3.5. Predicting Turnover Growth.

The next objective is to determine if moments of turnover growth are reliable predictors of future growth in trading volume. If this is the case, then it is plausible that a rational investor would use this information from the past as a predictor of future changes in investor sentiment. The ability to predict shifts in investor sentiment (here proxied by turnover growth) has been shown to lead to excess returns. This issue is investigated in two ways: via cross-sectional regressions using firm-specific information, and via time-series regressions using turnover-sorted portfolios. To answer this question in a cross-sectional context, the following regression model was estimated:

$$g_{t+1}^{j} = \alpha + \beta_1(g_t^j) + \beta_2(mean_t) + \beta_3(Var_t) + \beta_4(skew_t) + \beta_5(\log(size)) + \beta_6(mom12) + \varepsilon_t \qquad (5)$$

where g_{t+1}^{j} is firm-specific excess trading volume growth from month t to month t+1. Again, volume growth is adjusted for market volume growth during the given month, as well as the firm-specific average of market-adjusted volume growth during the past 12 months. The lag is included to account for the nature of the excess volume growth process, and to account for time-dependencies that still exist. Firm size is accounted for by the log of market value during month t, 12-month momentum is also added in the regression to account for any momentum trading effects which might exist. The regressions are performed using the Fama-Macbeth methodology and each regression is performed cross-sectionally for every month of the time-series. GMM is used for each month of the time-series, in order to minimize distributional assumptions on regression residuals. The White estimator is used for the estimated asymptotic covariance matrix. The coefficients are then averaged and checked for significance. For robustness, three separate time periods are analyzed: 1963 – 1979, 1980 – 1989, and 1990 – 1999. The goal is to determine if the first three moments of turnover growth serve as reliable predictors of future movements in trading volume growth. The results from these tests are presented in Table 13.

The outcome is somewhat surprising. There is a strong pattern between prior trading volume growth and future trading, but it does not go in a direction that implies that excess trading is taking place for stocks that exhibit higher past volume growth. The coefficient on the 12-month mean excess trading growth variable is negative on average. Also, it is significantly negative for both exchanges for each time period. The coefficients are relatively stable across exchanges and through time, leading one to infer that the first moment of trading volume growth from the past is a reliable predictor of firm-specific market-adjusted volume growth for the following month.

The volatility coefficient has a significantly positive sign for both exchanges and across all time periods. The coefficients are relatively stable between the Nasdaq and NYSE/AMEX groups, and appear to grow significantly during the 1990s. The same is true for the coefficient on the mean. One could consider this to be evidence of a growing influence of past trading volume during the exuberant market of the 1990s. The positive sign of this coefficient is again in contrast to expectation, or at the very least, is not indicative of lower trading volume growth resulting from strong volatility of growth in the past. Excess demand may still be a driving force, but there is certainly mean reversion in trading volume growth as a function of the variables presented here.

The skewness coefficient presents a mixed bag of outcomes. The coefficients are not always significant in every period, and tend to show a great deal more volatility than those for the other moments. For NYSE/AMEX stocks, the mean coefficient is slightly negative and significant. It is negative for the 1990s, but positive for other periods. Also, it is not significant from 1980 – 1989. For Nasdaq stocks, the skewness coefficient is negative for 2 of 3 time periods, and significant for each period up to 1989. However, it is not significant during the 1990s. The mean coefficient estimate is negative and significant.

The results for mean and standard deviation seem to argue that past volume growth has strong predictability for future returns and volume growth. Skewness is not as clear and varies by exchange. These results hold when various measures of trading volume are used in the left hand side of the regression[5].

Why this is the case is not clear. What may be happening is that those stocks with high mean trading volume growth are somehow perceived to be have an increase in risk, leading to higher returns for these securities. One could also make the interpretation that perhaps they are actually less risky than previously

[5] The regression is repeated using growth in turnover, excess turnover that is not firm-specific, as well as unadjusted turnover and turnover growth. The outcomes are similar in all cases.

perceived, and the price reaction is a response to a higher firm valuation. The type of risk is not specified here, and is left to future research. Chen, Hong and Stein (1999) make reference to the idea that skewness can be induced into the returns distribution as a result of momentum or consistent trading patterns. Given that securities with high mean and skewness of trading volume growth have experienced strong positive return patterns in the recent past, this is also a possibility.

The second test of turnover growth predictability is macro in nature. A simple factor model was completed in order to understand whether these factors mentioned in the paper may proxy for aggregate shifts in investor sentiment. The methodology derives from that of Fama and French (1996), but in no way should be interpreted as being driven by a formal theoretical model.

The factors chosen for representation here are those that are expected to have an impact on idiosyncratic turnover growth for a firm in the cross-section. First, there is the obvious search for a market factor, two of which are chosen for this test. The first market factor is the value-weighted level of market turnover for all publicly traded securities. This factor would be biased if Nasdaq firms are included, since their turnover levels are overestimated. To deal with this issue, only NYSE/AMEX firms are included in its measurement. The second market factor is value-weighted idiosyncratic excess turnover growth for all NYSE/AMEX firms. This factor has excluded both firm-specific and market components of expected turnover growth, leaving only surprise. If investors are entering and leaving the market at a high rate during a given point in time, then this factor is going to have a high or low value in response to these trading flows.

The other 3 factors in the model are the mean, standard deviation and skewness of excess turnover growth. Hedge portfolio returns were created for each factor by sorting all NYSE firms into 3 groups based upon their realization for each of the first three moments of excess turnover growth. The idiosyncratic turnover growth for the low portfolio is subtracted from that of the high portfolio, creating the hedge portfolio volume realization.

This will allow us to determine if these factors have an impact on all stocks at an aggregate level. All firms are sorted each month into 10 portfolios based upon the level of turnover during the given month. The number of portfolios was chosen to maximize statistical power when using the F-statistics of Gibbons, Ross and Shanken (1989). However, the only formal statistical tests being done here relate to the value of the coefficients, and we are not doing a formal test on intercepts, since there is no theoretical restriction to apply in the analysis of trading volume portfolios. The results are presented in Table 14.

The factors based on prior moments of trading volume growth tend to be significant in nearly every portfolio. The coefficient for the mean turnover growth factor tends to be negative for all portfolios, with low turnover stocks having the most negative coefficient on both exchanges. Thus, low turnover stocks tend to have trading volume movements that are correlated with those securities that have had low trading volume growth during the past 12 months.

Conversely, high turnover stocks tend to have much weaker correlations with those securities that have not had very high volume growth in the past. These results are a bit obvious, given that low/high turnover securities are the ones that have had very low/high turnover growth during the past 12 months. This is not always the case, however, since there are some securities that can have extraordinarily low turnover growth and still be relatively high turnover stocks. The general idea is to measure whether or not these factors have broad cross-sectional influence on a variety of securities with various forms of trading behavior. Also, we can find out if the moments of trading volume growth are sufficiently strong predictors of time-variation in trading volume growth.

The coefficient on the volatility of volume growth factor is positive for all portfolios. The mean reaction in the cross-section appears to be that excess trading volume growth is higher for all stocks during periods that high volatility securities receive more trading. The coefficients decline in magnitude as we go from the low turnover groups to the high ones. The decline in this coefficient seems to suggest that low turnover stocks have a great deal in common with those securities that have had strong volatility in excess turnover growth during the past 12 months. The highest turnover groups also have positive correlations with stocks with high turnover growth volatility, but their correlation is much lower.

The factor loadings are significant for the every turnover decile for both the mean and volatility factors. There are a couple of exceptions, however. High turnover Nasdaq stocks do not tend to load strongly on either factor, and high turnover NYSE/AMEX stocks only load strongly on the volatility factor. The mean turnover growth factor is not significantly different from zero for high turnover stocks in either group of exchanges. Besides the top decile, however, the mean turnover growth factor has a very strong presence.

The skewness factor is the only one that does not show strong explanatory power in a portfolio context. It is also the only factor that changes sign as we go from low turnover to high turnover groups. For both NYSE/AMEX and Nasdaq stocks, the loading on this factor changes sign from positive to negative. This is still meaningful evidence, in spite of the fact that the coefficients are not significantly different from zero. The fact that the coefficient patterns are monotone and display the same behavior across exchanges makes them worth studying. The positive sign for low turnover stocks implies that these securities have a positive relationship with the skewness factor, and tend to have high excess turnover when the skewness factor does well. The coefficient changes sign for high turnover stocks, implying that these securities have a positive relationship with those stocks that have had low skewness in trading volume growth during the past 12 months.

The Wald, Likelihood Ratio and Lagrange Multiplier tests all reject (at the 1% level) the null hypothesis that the mean and volatility coefficients are zero across portfolios. We cannot reliably reject the null hypothesis that the skewness coefficients are not equal to zero. Therefore, as a general volume factor, skewness portfolios do not make a strong appearance.

The adjusted r-squares for the NYSE/AMEX stocks are higher than those for Nasdaq securities, although the explanatory power of the model leaves much to be desired. These sentiment factors show themselves to have strength, as would a value or glamour factor. However, there are many other determinants of trading volume growth left to be uncovered. Finally, the market factor for excess turnover growth has a strong presence in the model for NYSE/AMEX stocks. The coefficients are strong positive throughout, and a little less than one. The market turnover factor has a weak presence, and does not appear to provide much explanatory power in the presence of other factors. Hence, it's ability to explain excess turnover growth appears to be limited.

3.6. Conclusion.

This paper studies the first three moments of trading volume growth as predictors of future stock returns. Stocks with high mean trading volume growth during the past 12 months experience reductions in excess trading volume during the following month, but tend to have strong positive excess returns that do not reverse themselves over the next 5 years. This result holds true for both NYSE/AMEX and Nasdaq stocks.

It is also found that all 3 moments of trading volume growth show strong ability to predict future returns and trading volume growth. Predictability is weakest for skewness, but still provides information. All three moments predict very clear patterns in future stock returns, and these returns do not exhibit reversal over long horizons. The negative excess returns for skewness and volatility of volume growth tend to argue that there may be a consistency effect in trading volume growth that is captured by these two variables.

There is also a brief factor model for trading volume growth presented here to determine whether the first three moments have some ability to act as macro-economic factors in the presence of volume factors for turnover and excess turnover growth. The model's explanatory power is limited, but the moments show some ability to be priced in a portfolio context. This factor model is not driven by theory, however, and should only be considered a framework with which to think about ways of modeling shifts in investor sentiment.

Chapter 4

Does consistency predict returns?

4.1. Background and Extended Literature Review.

Jegadeesh and Titman (1993) document medium-term momentum in stock returns. They determine that by forming portfolios based on deciles of prior mean returns, excess profits can be earned by purchasing the stocks in the highest return decile and selling those in the lowest return decile. They show that the profits cannot be explained by the unconditional CAPM, nor by delayed price reaction to common factors. Generally speaking, no asset-pricing model has been able to explain the momentum effect.

Data snooping biases have been discussed as a potential explanation for this effect. However, Asness, Liew and Stevens (1996) and Richards (1996) study momentum at the country index level and find that medium term continuation exists outside of the United States. Rowenhourst (1998), studying international data at the firm-specific level, also determines that momentum exists around the world, which weakens data-mining as a potential explanation for this effect. He also argues that since medium term continuation of the international portfolio is correlated with continuation in the United States, there may very well be a common factor driving this effect.

This paper analyzes the importance of *consistency* of future stock returns, controlling for momentum effects and any other variable that might lead to return predictability. Here, I define consistency as the relative frequency of positive or negative returns during a given period. More specifically, consistency is measured by dummy variables that account for whether or not the stock has had a run of positive or negative returns during the prior 6 months and count variables that cumulate the number of positive or negative returns during the pre-investment period. Count variables are used for long horizons during which few securities have had consistently positive or negative returns. The consistency question is a logical one that should be answered, given that return momentum without alluding to the consistency of those returns would be incomplete. If one were to analyze the technical side of the momentum phenomenon, it might be meaningful to determine if investors are reacting simply to the magnitude of past returns, or if they are reacting to the consistency with which those returns are realized. Does a stock that has 6 straight months of consistent returns receive preferential treatment over a stock that has simply had one very strong return that has skewed its mean for the pre-investment period? This is the question that this paper attempts to answer.

An analysis of consistency might also provide clues regarding whether or not there is a risk-based explanation for the momentum effect. If one were to believe that there is a risk-based explanation for momentum, then uncovering path dependence in the process leaves more to be explained. Path dependence is a technical phenomenon, and is not based upon fundamentals. However, discovery of these relationships does not preclude the possibility of a risk-based explanation.

We must keep in mind, however, that investor sentiment can be considered a macroeconomic risk factor as well, and path dependence in the momentum effect may imply that sentiment changes through time, depending upon the consistency of a stock's recent performance.

If we recall the standard physics definition of momentum, which is the mass of an object multiplied by its velocity, then many stocks that we consider to be momentum stocks do not truly display this feature. For example, in figure 3, we have 3 stocks: A, B and C. Each of these securities may be considered high momentum stocks, based upon the definitions used in Jegadeesh and Titman (1993). However, the paths of these securities are very different. The charts include the price of the stock on the Y-axis and the month after investment on the X-axis. So, we can consider the chart to measure the buy and hold return for the security over a given time horizon.

Which of these stocks truly exhibits momentum? Some might not consider stock A to be a high momentum stock, even though its return for the past 6 months is the same as the others. Some might even consider stock C to be a negative momentum stock. Stock B appears to have the most consistent improvement in returns, given that its price each month exceeds the price from the prior month. Analyzing this situation is not simply a manipulation of the pre-investment horizon, but rather a focus on path dependence. Understanding whether the market treats each of these securities differently might help provide clues regarding exactly why the market prices momentum, and why it might make sense that investors place a higher value on high momentum stocks than low momentum stocks. Also, it allows us to understand if it is the mean return itself that drives price continuation, or the consistency with which that mean is established.

The predictability of consistency may be driven by herding behavior of momentum traders, or it may be related to some form of "slow information leakage" by the firm over time, implying that investors may expect that good news is likely to be followed by more good news. Also, a high momentum stock with strong consistency is more likely to fit with theories of under and overreaction to information, implying that we might expect that price consistency, in and of itself, contains information about future returns *above and beyond* the information obtained by simply analyzing mean returns. Whether this information relates to fundamental changes in value or predictable time-variation in noise trader sentiment is another question.

Chan, Jegadeesh and Lakonishok (1996) study earnings momentum as a potential explanation for return continuation, but earnings and return momentum are found to be distinct from one another. However, they do find that analysts are slow to adjust earnings forecasts to past news, and this leads Chan et al to argue that the market is slow to adjust to new information. So, although earnings and return momentum are correlated, one phenomenon is not subsumed by the other.

Jegadeesh and Titman (2000) also shows that momentum has continued to persist in the 1990s, and that it tends to reverse itself over long horizons, which further weakens the belief that cross-sectional variation in unconditional means leads to return momentum. This evidence argues that momentum could be the result of overreaction and subsequent reversal, whether it be firm-specific or macroeconomic. It also tends to support some of the various behavioral theories that have been proposed as potential explanations for return momentum (see Daniel, Hirshleifer and Subramanyam (1998), Barberis, Shleifer and Vishny (1998) and Hong and Stein (1998)). Chordia and Shivakumar (2000) propose a conditional asset-pricing model that supports cross-sectional variation in conditional means as an explanation for the momentum effect in stock returns. They argue that a) there are distinct industry and individual stock components to returns momentum, and b) both of these components have distinct relationships to the macroeconomy. One promising attribute of their approach is the evidence that autocorrelation most responsible for momentum profits covaries with macroeconomic factors. This makes it more difficult to argue that irrational bubbles in asset prices are responsible for returns momentum. Griffin, Ji and Martin (2002) refute the conclusions of Chordia and Shivakumar. Using multi-country data, they conclude that momentum profits do not co-vary with macroeconomic factors, and that co-movement in momentum profits across countries is too weak to support a risk-based explanation.

Another potential explanation based on a more widely-accepted asset pricing structure is presented by Harvey and Siddique (2000). While they do not completely explain momentum, they find that the addition of a co-skewness factor to the Fama-French three factor model does a much better job of explaining this anomaly. Their use of the model is driven by the fact that firms which exhibit return momentum also tend to have the greatest degree of co-skewness in their returns distribution. The connection the authors make between skewness in the returns distribution and momentum in stock prices is an interesting one. However, this paper takes an additional step that is related to skewness: rather than assuming that return continuation is related to the *presence* of skewness during the investment period, I argue that return continuation is also related to the *lack of skewness* during the pre-investment/evaluation period. However, as Coval and Hirshleifer (2001) argue, this consistency (or lack of skewness) during the portfolio formation period can produce informational effects leading to conditional skewness during the investment period. Chen, Hong and Stein (2000) analyze daily stock returns and find that firms that have had strong returns and volume increases in the past tend to have negative conditional skewness in their daily returns distribution.

Grinblatt and Moskowitz (2002) is the only paper, to my knowledge, that has analyzed return consistency and its interaction with momentum. Analyzing securities from 1963 through 1999, they find a consistent winners effect over medium-term horizons, and that the sign of past returns matters when predicting future returns. This paper takes the additional steps of analyzing security returns in sub-periods from 1927 through 1999. Additionally, I find that there is a strong and robust loser consistency effect that maintains itself over the following two years.

Here it is found that consistency leads to greater predictability in stock returns over short, medium and long-term investment horizons. Also, it is found that there is a strong interactive effect between momentum and consistency that appears to overwhelm the effects of both individual factors. The interaction between the factors is such that momentum has a positive interaction with the positive consistency measure, and a negative interaction with the negative consistency measure, implying that a winner (loser) security is likely to have higher (lower) future returns if the returns of the past have been realized in a highly consistent fashion. Hence, one can conclude that an arbitrageur might use return consistency as an additional predictor of future changes in investor sentiment.

These results support the theoretical predictions of Grinblatt and Han (2001). In their paper, they argue that a “disposition effect”, in which investors are less likely to sell securities which have amassed capital losses, leads to path dependence in the momentum effect. The presence of a strong consistent winner and losers effect may very well point to a behavioral explanation for momentum.

Section II describes the data and variables used in the paper. Section III revisits the Jegadeesh and Titman (1993) study. Section IV presents results from empirical tests. Section V concludes.

4.2. The Data and Variable Descriptions.

Stock returns were gathered from the Center for Research in Securities Prices (CRSP) database for the time period covering January, 1927 through December, 1999. Securities with less than 24 months of returns history are eliminated from the sample. Also, the security must have data available on each of the variables for the test in which the security is included. This time period was chosen to coincide with the availability of all variables needed for the study.

The first and primary measure of return consistency involves analyzing those securities that have had 6 months of consecutive price increases or declines. A stock that possesses a high number of consecutive price increases must have positive returns during every month of the entire pre-investment period. Six months is chosen for the length of the pre-investment period, since it is long enough to draw some inference, yet not so long that there are no stocks that can meet the criterion. It is seen in Table 15 that roughly 1 – 1.5% of all securities during a given month have had six consecutive months of positive returns. The breakdown by decade shows that the percentage is relatively stable, with the maximum occurring during the 1980 – 1989 time period, during which 1.75% of all firms met the criterion. The minimum is the 1927 – 1939 time period, with only .86% of all firms reaching the standard.

Negative runs have roughly the same likelihood as positive ones. The overall average is only slightly lower than the positives (1.32% vs. 1.12%), so these variables have a surprisingly strong negative autocorrelation through time.

The maximum average (not surprisingly) occurs during the great depression, and the minimum occurs during the 1980s, which is the same time period that the maximum occurs for positives. The number of firms meeting the standard is low. Even during the decades with the greatest number of publicly-traded securities, less than 40 stocks per year are included in the strong consistency group. Count variable models are included later to account for effects that are uncovered and to ensure that the effects are genuine.

When analyzing consistency over 12 and 24-month time horizons, a count variable is used. The variables simply count the total number of price increases during a given pre-investment period. Conditional upon the level of return momentum, a stock with a greater number of price increases during the pre-investment period has witnessed more consistent increases in its market value. Analogously, I define a measure of negative consistency in the following way: Rather than counting the number of price increases during the pre-investment period, I count the number of price *decreases* during the pre-investment period (the pre-investment and investment periods are going to be defined shortly).

To see these definitions in equation form, we have the following:

$$\text{PmomK(t)} = \sum_{j=t-1}^{t-K} \lambda_j \quad \text{where} \qquad \lambda_j = \begin{cases} 1 \ \forall \ r_j > 0, \text{j} = \text{t-1,....,t-K} \\ 0 \ \ else \end{cases} \qquad (6)$$

$$\text{PlmomK(t)} = \sum_{j=t-1}^{t-K} \delta_j \quad \text{where} \qquad \delta_j = \begin{cases} 1 \ \forall \ r_j < 0, \text{j} = \text{t} - 1, \ldots, \text{t} - \text{K} \\ 0 \ \ \mathit{else} \end{cases} \tag{7}$$

$$\text{PcmomK(t)} = 1_k \quad \text{where} \qquad 1_K = \begin{cases} 1 \ \text{if } r_{t-1} \ldots, r_{t-K} > 0 \\ 0 \ \ \text{else} \end{cases} \tag{8}$$

$$\text{PclmomK(t)} = 1_k \quad \text{where} \qquad 1_K = \begin{cases} 1 \ \text{if } r_{t-1}, \ldots, r_{t-K} < 0 \\ 0 \ \ \text{else} \end{cases} \tag{9}$$

r_j makes reference to the return during period j, where j is the (t-j)th realization in the return generating process. PMOMK and PLMOMK are the variables that count the number of price increases and decreases, respectively, during the K-month pre-investment period. PCMOMK (PCLMOMK) is a dummy variable taking the value of 1 if all returns during the prior K periods are positive (negative), 0 otherwise. These variables are formulated for every month of the time series and for every stock in the cross-section.

Table 15 contains other descriptive characteristics of the dataset as well. The mean, median, standard deviation and skewness of each variable is calculated cross-sectionally for every month of the time-series. The time-series mean of each of these variables is then calculated by decade, presented alongside the overall average. These statistics are calculated for the consistency dummies (6 months only), and the count variables, which are used for 12 and 24 month horizons.

The positive and negative count variables tend to have very similar means and medians. They also both have some degree of negative skewness. As expected, the dummy variables have positive skewness over time, since the percentage of firms that meets the criterion is not very high. Using both count variables and dummies allows us to explore the dynamic nature of this effect, including both rare cases, as well as cases that include all stocks in the cross-section. All securities that possess observations on all variables are included in the study.

4.3. Jegadeesh and Titman, revisited.

As a first step in this process, a replication of the Jegadeesh and Titman momentum results appears to be in order. While I do not consider consistency to be a direct derivative of the momentum literature, it is, in some ways, a natural benchmark. To recall, Jegadeesh and Titman (1993) finds that there exists medium-term continuation in stock returns. Their most inexplicable results appear when they analyze the six-month portfolio formation and six-month investment period. Thus, this is the investment horizon that I focus on here.

Unlike Jegadeesh and Titman, who only explore the 1965-1989 time period, I analyze all stock returns from 1927 through 1999. This expansion of the dataset can take place for two reasons: First, I use monthly returns, rather than aggregating daily data, as they do in their paper. Secondly, several years have passed since the publication of their study, so additional data is available[6]. The portfolio formation procedure is replicated for the six month-six month strategy for the entire time period, since this is where the authors find their meaningful results. In order to analyze the robustness of their findings, I break the analysis into 3 sub-periods: 1927 – 1965, 1965 – 1989 (the Jegadeesh and Titman (1993) period) and 1989 – 1999.

Stocks were sorted each month based upon cumulative buy and hold returns during the prior six months, including the current month. The stocks are then held for six months, starting with the subsequent month. So, the portfolio formation is based upon returns for months t, t-1,…., t-5, and the holding period consists of months t+1, t+2, …., t+6. For each month t, the portfolio goes long in the top decile of six-month performers, and short in the bottom decile of performers.

In order to use standard t-statistics that do not need to be adjusted for autocorrelation, the portfolio return for a given month is a weighted average of the returns from stock groupings created during each of the prior 6 months. For example, 1/6 of the return during month t comes from the stocks selected during month t-1, 1/6 comes from the stocks selected during month t-2, etc. This method, following the convention of their original paper, was done for all three sub-periods mentioned, as well as the entire period. The results are presented in Table 16.

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[6] Although they do write another paper in 2000 that uses later data. However, this dataset expands that which is used in their subsequent paper, and analysis from another angle can prove beneficial.

As expected, the results for 1965 – 1989 are nearly identical to those of Jegadeesh and Titman (1993), with t-statistics very close as well. What is more interesting is the transitory nature of momentum profits. In both the pre-1965 and post 1989 sub-periods, momentum profits are not statistically-significant. While one can argue that wide-spread knowledge of momentum kept it from being profitable during the 1990s, it is difficult to make the same argument before 1965. There can be some comfort in the fact that the mean monthly return to the strategy is positive during all periods, implying that winners tend to always outperform losers for medium-term investment horizons. Also, if the null hypothesis is that the structural tendency toward momentum is constant for all time periods, then we would expect time-variation in the significance of their results. What is most peculiar, however, is the fact that the mean return to the momentum strategy would have been 30% lower had this out of sample data been included in the original study. If all available data had been included, the mean return would have been roughly 25% lower, with a 40% reduction in the t-value[7].

It appears that the strong performance of the momentum strategy during the 1965-1989 sub-period is primarily due to the asymmetrically poor performance of losers relative to winners. During this period, both winners and losers had their worst performance, but losers suffered much more than winners, creating momentum profits.

[7] This assumes the use of CRSP monthly data, which is all that is available for the pre-1965 time period.

Three additional stylized facts can be extracted from an analysis of the momentum trading strategy:

1) The pre-1965 period appears to have a highly volatile and negatively-skewed spread, much more so than during any other period. This is driven by the strong positive skewness of the losers (leading to strong negative skewness for the W-L portfolio). The losers are also much more volatile than the winners during this period.

2) In every period, losers are more volatile than winners. Also, for the two later periods, the losers have positive skewness, and the winners have negative skewness. This leads to tremendous negative skewness in the momentum strategy. Given that there is a debate regarding the relevance of higher order moments in the momentum trading strategy, it is quite plausible that negative skewness may be the cause of momentum profits.

3) Throughout the entire CRSP history, the median momentum profit during a given month (1.15%) has exceeded the mean (.6%), further evidence of the impact of strong negative skewness. The strategy loses nearly 1% per month one-fourth of the time, and as much as 4.2% per month 10% of the time. So, there are many months during which the strategy is not profitable at all.

More importantly, however, is the fact that it may not make sense to analyze momentum as a source of profit that appears from the continuation of both winner and loser stocks. While it is true that winners have stronger performances than losers, most of the momentum profits are the result of poor performances by losers relative to winners during the Jegadeesh and Titman (1993) sample period. Although the returns during the pre-1965 time period were reasonably strong (roughly 6% per year), this period is also accompanied by high volatility and extremely strong negative skewness for winner stocks. The high volatility is reflected in the non-significance of the t-statistic, but the extreme negative skewness is not. The positive skewness for loser stocks very likely has an impact on lower returns for these stocks. Similarly, the negative skewness of winner stocks is likely to have an impact on their high return. However, the asymmetric nature of this effect is what appears to create momentum profits.

Given the extreme negative skewness in momentum profits during the Jegadeesh and Titman (1993) sample period, it is quite likely that there may indeed be a risk-based explanation for momentum. In fact, consider the negative skewness of hedge portfolio profits during the Jegadeesh and Titman sample period (-1.60). This value is more negative than the negative skewness of winner stocks during this same period (-.67). The problem, however, is that the return to hedge portfolios is lower than that of winner stocks, which should lead to less negative skewness for these securities, since there should be a reward for bearing additional skewness risk. So, if returns should be higher for assets that have greater negative skewness, then the momentum portfolios are not a very good investment[8]. An investor could do just as well, or better during this period by borrowing at the risk-free rate and investing in high-momentum stocks. The average return on t-bills during this period (6.72% per year or .56% per month) would lead to a profit of 1.1% per month or 13.2% per year. Not only does this return exceed that which is earned during this period on the momentum strategy (.92% per month, or 11.04% per year), but it also gets rid of the positive skewness of loser stocks, which is a source of risk for momentum profits. So, it appears that skewness plays a role in momentum profits on multiple levels. Namely, the returns to momentum portfolios may very well be a compensation for skewness risk, and the reward is not the most efficient available.

4.4. Results from Empirical Tests.

4.4.1. Consistency-based trading strategies.

The first test involves analyzing consistency for medium-term horizons through the use of dummy variables. All firms during a given month that have 6 months of positive returns during months t-1 through t-6 are sorted into a portfolio, and the equal-weighted mean return for these firms is calculated. The equal-weighted return for all other stocks in the cross-section is then calculated and subtracted from the mean of the high consistency group. This time series of

[8] One could argue that the higher volatility of winner stocks (6.87% vs. 4.31%) is the driving force behind higher returns. While this is plausible, one should consider that the difference in volatility (2.56%) is being rewarded by a return differential of roughly .74% per month, or 8.84% per year. This would imply that one could get an 8.84% return on an asset with a volatility level of roughly 2.56% per year, which is highly unlikely, given Sharpe Ratios that have tended to exist historically (this Sharpe ratio would be roughly 3.45, vs. 2.899 for winner stocks and 2.56 for the momentum portfolio). The impact of this outcome is magnified when compounded with the fact that skewness is nearly three times more negative for the hedge portfolio than for winner stocks only.

returns is then regressed on the monthly realization of the size, book to market and market factors of the Fama-French 3 factor model. Additionally, a January dummy is included, along with a momentum factor. The momentum factor is calculated as follows: all NYSE firms are sorted into high, medium and low categories based upon the buy and hold return for months t-1 through t-12. The difference between the month t return of the high group and that of the low group is considered to be the momentum factor realization for month t.

The intercepts from this regression serve as a measure of excess returns incurred from engaging in the consistency strategy. The procedure is noisy, given that such a small number of firms are included in the high or low consistency category. This is going to affect the significance level of the risk-adjustments in the time-series regressions (since N is not very large, relative to the standard deviation of coefficient estimates). However, analyzing the sign and magnitude of the intercepts will serve as one piece of evidence regarding the impact of return consistency on future stock returns. The time-series regressions are performed for three periods: 1927 – 1964, 1965 – 1989 (The Jegadeesh and Titman period), and 1990 – 1999. The coefficient for all time periods is also included.

In Table 17, it can be seen that for every sub-period, the excess returns for positive consistency portfolios are positive. Low power keeps them from being significant in every time period, but the signs are consistently positive, and the intercept is significant for the overall time period. Excess returns are at their highest during the 1965 – 1989 time period, during which returns average 10.8%

per annum. The lowest excess return average is during the 1990 – 1999 time period, with an average of 2.04% per year. The average across all periods is .7% per month, or 8.4% per year.

The negative consistency effect is much stronger than that for positive consistency. For every sub-period, the excess returns for negatively consistent stocks is negative and significant at the 5% level. The overall excess return estimate for these firms is roughly 12% per year, and the peak occurs in the 1990s, during which excess returns average -16.2% per year. The minimum is during the 1927 – 1939 time period, during which excess returns average –8.4% per year. So, the returns to negative consistency are economically significant, even when they have been at their weakest.

The bottom panel of Table 17 compares the high consistency firms to the low consistency firms. The mean return each month for the low firms is subtracted from that of the high firms. This will determine if the effects covary positively or negatively with one another. A positive intercept in the regression would imply that positive consistency has an impact that strongly exceeds negative consistency, implying that those firms with negatively consistent returns are perceived differently by the market than those with positive consistency.

For every sub-period, the excess return to those firms with positive consistency significantly exceeds those of firms with negative consistency. Also, the hedge portfolio excess returns are both economically and statistically significant. The average through time is nearly 24% per year. The maximum excess return takes place during 1965 – 1989 sub-period, where the hedge portfolio averages 28.14% per year. The minimum occurs during the 1990 – 1999 sub-period, with an average of 16.92% per year. The consistency effect appears strong and robust through all time periods. It also shows itself to be strong for both winner and loser stocks.

4.4.2. Long Horizon Effects of consistency.

The apparently strong presence of consistency effects for monthly returns naturally leads to questions about long-horizon effects. The presence or non-presence of long-horizon reversals might provide clues regarding the nature of consistency effects. There is the chance that investors are overreacting to consistency, and there is also the chance that the presence of consistency involves underreaction to firm-specific information.

This question is analyzed in Table 18. Here, stocks are again sorted each month into groups based upon negative and positive consistency. Again, the high consistency group consists of those securities that have had 6 months of positive returns. The negative consistency group consists of those stocks that have had 6 months of negative returns. There are three hedge portfolios formed (one for each panel of the table): the first panel compares those stocks that do and do not have high positive consistency, the second panel compares those that do and do not have high negative consistency, and a final panel that compares those firms with positive consistency with those that have negative consistency.

The buy and hold returns for each hedge portfolio are calculated during months t+1 through t+6, t+7 through t+12, t+13 through t+18 and t+19 through t+24. The returns are orthogonalized, implying that there is no overlap in the investment horizons or return calculations. This allows us to see what the return is for a given portfolio during each of these investment periods. Risk-adjustments are not quite reasonable when analyzing semi-annual returns for portfolios formed during the past, so these results are calculated for raw hedge portfolio returns only. If the magnitude of return differences is strong, then it is nearly infeasible to determine that the difference in risk between the high and low consistency portfolios drives the entire return difference. Additionally, these results are provided in order to give hints on the performance of these portfolios up to two years into the future. If reversals take place after two years, they are obviously not captured here.

The positive consistency hedge portfolios receive most of their gains during the first 6 months. The mean return for high consistency stocks during the first six months is roughly 13.5% per year, giving a hedge portfolio return of 6.68% per year. The return difference between high consistency stocks and all other stocks is only about 1% per year for months 7 - 12, and it is actually lower than other stocks during months 13 – 18. Surprisingly, the return difference becomes positive again during the months 19 – 24.

The positive consistency results are puzzling, without simple interpretation. What is clear is that there is a definite reversal that takes place during months t+13 through t+18. The slightly higher return during the last 6 months of this 2 year period may show that the correction is yet another overreaction within itself. One thing to note, however, is that the return difference during months t+19 through t+24 is not statistically significant. Hence, one could argue that perhaps the positive consistency effect is at least in part due to an overreaction. But this statement has the caveat that returns are not analyzed beyond 2 years.

The results on negative consistency tell a different story. There is no sign of reversal during the first two years, during which returns to these stocks are always lower than those of other securities in the cross-section. The most negative hedge portfolio returns occur during the first six months, averaging –9.88% per year, during which time negatively consistent stocks have average returns of –4.18% per year. The negative performance of these firms continues during months t+7 through t+12, during which time hedge portfolio returns are negative 6.46% per year. The returns to negatively consistent stocks themselves are roughly zero at this time, so they have leveled off. However, they still severely under-perform other stocks in the market.

During months t+13 through t+24, there is less than 2% per year difference between the negatively consistent stocks and other stocks in the cross-section. But no reversal is apparent during the time period analyzed. Thus, there is some evidence here that the consistent losers effect may be due to underreaction. There is also the possibility that these stocks may be experiencing long-horizon corrections to previous overreaction.

The positive minus negative hedge portfolio is analyzed in the final panel of Table 18. As before, the differences between the returns on consistent winners and losers is extremely strong early, averaging over 19% per year during the first six months. The difference continues during months 7 – 12, at roughly 7.5% per year. The fact that these are zero investment hedge portfolios makes the result that much more significant.

The difference between the returns of each group is insignificant during months t+13 through t+18. This is when both groups of stocks underperform other stocks in the market. Finally, the difference is positive again during months t+19 through t+24, when winners start to outperform and losers underperform.

4.4.3. Conditional sorts and stronger momentum controls.

Prior results suggest that consistency has an impact on stock returns. The impact is strong and present through all time periods. There is an even stronger contrast between those stocks with strong positive consistency and those with strong negative consistency. A deeper question that has been partially answered in prior results is whether or not momentum works independently of consistency. The presence of a momentum factor in time series regressions is an adjustment for the macroeconomic presence of momentum, but it does account for firm-specific momentum. If the theory of Grinblatt and Han (2001) is to be supported, it is expected that there would be an interaction between momentum and consistency.

Table 19 addresses part of this question. Momentum is controlled for through conditional sorting procedures that compare consistent stocks with those securities that are already in the given momentum quintile of the same security. Analyzing 6-month consistency dummies is not feasible here, since 6 months of positive or negative returns is a relatively rare occurrence. Conditional sorting procedures makes the occurrence of 6 months of positive or negative returns extremely rare within a given momentum quintile.

Table 19 also allows us to analyze consistency measures over longer horizons, while controlling more directly for momentum effects. We can see if stocks that have had long horizons of return consistency continue to have positive or negative returns, once momentum is accounted for. The horizons are 12 and 24 months, and count variables are used, rather than dummies.

The procedure is as follows: for every month of the time-series, all securities in the cross-section are sorted into quintiles based upon the buy and hold returns for the prior K months. K is the number that matches the time horizon over which consistency is accounted for. So, for example, if K = 24, that means that the consistency measure has been created over a 24 month time horizon. The consistency measure is simply a count of the number of positive or negative returns the firm has experienced during this time interval. So, for K = 12, firms are first sorted into quintiles based upon buy and hold returns during the prior 12 months. Additionally, within each momentum quintile, firms are again sorted into quintiles based upon 12-month positive or negative consistency (both are calculated here).

The hedge portfolio return is then calculated by taking the average return across all high consistency quintiles and subtracting the average return for all low consistency quintiles. There are, for example, 5 high consistency quintiles every month, with each high consistency quintile belonging to a different momentum quintile. Thus, the high minus low return is simply (average ((5,1), (5,2), (5,3), (5,4), (5,5)) – average ((1,1), (1,2), (1,3), (1,4), (1,5)), where the first digit refers to the consistency quintile within the given momentum quintile, and the second digit refers to the momentum quintile. Firms must be first sorted by momentum and then by consistency (and not the other way around) because the first variable sorted by is the one being held constant.

The mean monthly return on the hedge portfolio is calculated in the same manner as that of Jegadeesh and Titman (1993). The return for, say, a six month investment horizon is the mean return obtained from holding the securities in the portfolio for six months, with the return to the portfolio for a given month simply being the average of the return for each portfolio formed during the prior six months (see Jegadeesh and Titman (1993)). The same procedure was used in the section of this paper in which the Jegadeesh and Titman (1993) results were replicated. This process has been shown to reduce autocorrelation in t-statistics.

Over long horizons and when controlled for momentum in this fashion, winners do not show strong consistency effects. Most of the coefficients are not significant for any time period. This holds for all sub-periods analyzed as well. Therefore, there does not appear to be a positive consistency effect when consistency is measured during the prior 12 months.

Table 19 also shows that losers during the prior 12 months have a strong independent consistency effect, even when momentum is controlled for. Monthly returns to hedge portfolios are negative and significant for every time horizon and every sub-period. This is true for both 12 and 24-month negative consistency. The highest monthly returns are for the 12-month consistency hedge portfolio when held over the following 6 months. The hedge portfolio for this strategy produces a statistically significant return of -6.48% per year.

The results from Table 19 seem to show the consistency may not always have an independent impact beyond that of momentum. But this is to be expected if the two are linked. If one supports a behavioral explanation for return momentum, then it would be logical to conclude that behavioral reactions to momentum are more likely to occur when the returns are also consistent. Additionally, one could argue that behavioral reactions to consistency are more likely to reveal themselves in the presence of momentum.

This question is analyzed in Table 20. Here, we wish to determine if there is an interaction between momentum and return consistency. It is also plausible that this question can be answered with the following cross-sectional regression:

$$r_i^{t+1} = \alpha + \hat{\beta}(mom_i^t) + \beta_2(cons_i^t) + \beta_3(vol_i) + \beta_4(skew_i) + \beta_5(mom_i^t * cons_i^t) + \varepsilon \quad (10)$$

where r_i^{t+1} is the one-month return on the stock, in excess of the risk-free rate. mom_i^t is the buy and hold return for the stock during the prior K months (K = 6, 12, 24, regressions are performed for each value). $cons_i^t$ is the consistency measure during the prior K months. The consistency horizon is matched with the momentum horizon. vol_i^t is the volatility of the security throughout its life, including periods both before and after month t. $skew_i^t$ is the skewness of the firm's returns throughout its life. $mom_i^t * cons_i^t$ is the interactive term between momentum and consistency. The interactive term serves as the focal point of the cross-sectional regressions. However, the volatility and skewness terms are not only included as additional controls, but also to ensure that the consistency and momentum effects are not simply volatility effects in disguise. The momentum and consistency coefficients, in the presence of an interactive term serve as unconditional coefficients, which answers the following question: What effect does momentum have when consistency is not present? The question is reversed for consistency.

The belief is that positive consistency should interact positively with momentum, while negative consistency should interact negatively with momentum. This is because a stock with high positive consistency and high momentum should have higher returns than other stocks in the cross-section. Similarly, a stock with high negative consistency and low momentum should have lower returns than other stocks in the cross section. Thus, the coefficient on the interaction between negative consistency and momentum should be negative (the higher this value, the lower is the expected return). Another way of stating this would be to say that momentum is enhanced by consistency and that consistency is enhanced by momentum.

We can also write the answer to this question in equation form. For positive consistency, we expect that $\frac{\partial^2 E(R_{t+1})}{\partial P_t \partial M_t} > 0$. P (in this case) represents the positive consistency measure and M represents the momentum measure. For negative consistency, we expect that $\frac{\partial^2 E(R_{t+1})}{\partial N_t \partial M_t} < 0$, where N represents the negative consistency measure.

Table 20 runs the cross-sectional regression above for every month of the time series. There are regressions both with and without volatility. Also, consistency and momentum effects are analyzed for pre-investment periods of 6, 12 and 24 months. Count variables are used for consistency, and buy and hold returns for the same time interval are used for momentum.

The cross-sectional regressions support the idea that consistency and momentum have strong interactions with one another. For every regression using positive consistency, the coefficient is positive and significant. For every regression using negative consistency, the coefficient on the interactive term is both negative and significant. This significance holds true for those cases both with and without volatility.

What is also interesting are the signs of the unconditional consistency coefficients in the presence of momentum and an interactive term. For all positive cases, the consistency coefficient is negative. Thus, the unconditional impact of consistency here is negative, implying that the predictive ability of return consistency (at least during the following month, and in cross-sectional regressions) is driven by its relationship with momentum. What appears to take place during prior sections is that the positive interaction between momentum and consistency leads to a positive reward for positive consistency and a negative impact for negative consistency.

When the pre-investment period is extended to 12 and 24 months, it can be seen that the unconditional consistency coefficient is negative. So, for long-horizon pre-investment periods, negative consistency has a negative unconditional impact. Once again, the interactive term is negative for consistent losers over long horizons.

The results here seem to argue that consistency and momentum strongly interact and that these two factors strengthen one another. Consistency in itself, does not lead to return continuation, but it does so in the presence of strong return magnitude. This fits intuition in that a behavioral explanation for consistency might lead one to conclude that high consistency leads to a positive price reaction if that consistency is accompanied by high returns. Additionally, this can be interpreted as evidence that momentum effects are, at the very least, impacted in some way by path dependence.

4.5. Conclusion.

I analyze return continuation and its impact on future stock returns. I find that there is a clear and strong consistency effect in stock returns. This effect is stronger in the negative direction than the positive, and continues to persist for the following 2 years. Consistent winners strongly outperform all other stocks, and they also outperform consistent losers. This effect appears to be robust through time and various risk-adjustments.

There is some reversal for winners over the next two years, but no reversal for the losers. It is also determined that this effect is driven primarily by its interaction with momentum. The only exception is long-horizon consistency, in which the effect leads to unconditional continuation in the negative direction. What is generally concluded is that consistency (according to cross-sectional tests) and momentum are enhanced by one another. The fact that consistent winners(losers) have stronger returns than inconsistent winners(losers) seems to point to a potential explanation for the momentum effect. This supports the theory of Grinblatt and Han, and implies that a behavioral bias may be the cause of momentum.

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APPENDIX A

TABLES

Table 1: List of factors under study.

This table consists of the factors analyzed in this paper. They have been sorted into categories that describe their origin. Inflation is the percentage growth rate in seasonally-adjusted inflation during the given month. Industrial production is the percentage change in industrial production. EW mkt return and VW mkt return are the equal and value-weighted returns on the market, respectively. EW volume growth and VW volume growth are the equal and value-weighted growth in trading volume of the market, respectively. Lagged return is the return on the security during the prior month. 6 month return momentum and 60 month return momentum are the cumulative return on the given security during the past 6 and 60 months, not including the prior month. Princomp 1, Princomp 2, Princomp 3 and Princomp 4 are the first, second, third and fourth principal components of the variance covariance matrix of turnover growth portfolios. Size is market capitalization during the given month. Book to market ratio is the ratio of book value during the prior fiscal year to market value during the given month. Earnings price ratio is the ratio of earnings per share, excluding extraordinary items during the prior fiscal year to price during the given month. Cash price ratio is the ratio of cash flow during the prior year to price during the current month. Dividend yield is the dividend during the prior fiscal year divided by the share price during the given month. Share price is the price of the firm's stock during the given month.

Table 1: List of factors under study.

MACRO	MARKET	TECHNICAL	STATISTICAL	FUNDAMENTAL
inflation	EW mkt return	1 month return momentum	Princomp 1	Size
industrial production	VW mkt return	6 month return momentum	Princomp 2	Book to market ratio
	EW volume growth	60 month return momentum	Princomp 3	Earnings price ratio
	VW volume growth	1 month volume momentum	Princomp 4	Cash price ratio
		6 month volume momentum		Dividend yield
		60 month return momentum		Share price

Table 2: Descriptive statistics of volume factors.

This table presents the time series average of the cross-sectional sample size, mean, median, standard deviation, skewness, 5^{th} percentile, and 95^{th} percentile of every factor used in the study. Also, statistics of turnover growth for both the sample that requires sensitivities and the sample based on firm characteristics is also presented. The data span the time period of August, 1962 through December, 1999.

Table 2: Descriptive statistics of volume factors.

VARIABLE	N	MEAN	MEDIAN	STD DEV	SKEWNESS	5th Percentile	95th percentile
INFLATION	3,677.62	-11.77	-10.46	635.99	0.17	-128.54	98.75
INDUSTRIAL PRODUCTION	3,677.62	0.10	0.17	30.74	0.47	-34.35	33.93
EW MKT RETURN	3,677.62	1.26	1.18	4.22	-0.01	-4.01	6.68
VW MKT RETURN	3,677.62	1.61	1.57	5.64	0.55	-5.23	8.33
PRINCOMP 1	3,677.62	0.76	0.71	5.48	-0.73	-4.56	6.03
PRINCOMP 2	3,677.62	-0.68	-0.67	7.71	-0.15	-8.96	7.80
PRINCOMP 3	3,677.62	1.51	1.52	15.33	0.33	-11.94	14.94
PRINCOMP 4	3,677.62	0.43	0.53	16.22	0.32	-13.68	14.00
EW VOL GROWTH	3,677.62	1.02	1.00	1.26	-0.30	-0.55	2.67
VW VOL GROWTH	3,677.62	0.87	0.86	1.09	-0.09	-0.64	2.47
BOOK TO MARKET	878.28	0.75	0.65	0.48	0.96	0.17	1.66
CASH PRICE	841.94	0.06	0.09	0.16	-1.32	-0.23	0.25
DIV PRICE	391.14	0.03	0.03	0.02	1.25	0.01	0.08
EARN PRICE	898.88	-0.01	0.05	0.19	-2.44	-0.39	0.13
LAGGED RETURN	8,897.37	0.01	0.00	0.09	0.10	-0.15	0.16
6 MONTH RET MOM	8,388.53	0.06	0.05	0.25	0.32	-0.33	0.50
60 MONTH RET MOM	4,047.82	0.57	0.40	0.87	0.94	-0.51	2.29
SHARE PRICE	7,485.66	16.84	14.46	11.44	0.77	2.79	39.51
RANDOM	4,711.57	0.00	0.00	1.00	0.00	-1.64	1.65
LAGGED VOLUME	8,867.63	0.06	-0.04	0.49	0.79	-0.58	1.03
6 MONTH VOL MOM	8,427.76	0.01	-0.14	0.68	1.04	-0.80	1.39
60 MONTH VOL MOM	4,522.73	-0.23	-0.67	1.04	1.81	-1.00	2.07
SIZE (IN MILLIONS)	8,290.95	478.01	59.89	2,349.29	17.54	4.08	1,771.99

TURNOVER GROWTH	N	MEAN	MEDIAN	STD DEV	SKEWNESS	5th Percentile	95th percentile
SAMPLE WITHOUT SENSITIVITIES	10,191.60	6.88%	-11.73%	82.38%	201.46%	-82.89%	165.00%
SAMPLE WITH SENSITIVITIES	3,691.48	18.47%	-0.83%	78.71%	218.69%	-64.06%	172.55%

Table 3: Rankings of turnover growth by factor.

This table presents the results of sorts based upon the average level of turnover growth for each month in the time series. Each month, the firms are sorted into equal-sized groups based upon the given factors. The level of turnover growth for each group is then averaged and presented here. RANK represents the quintile of the factor that is being referred to and averaged in the given row. For example, RANK = 1 refers to the row giving the mean monthly turnover growth for the lowest quintile of every variable listed below.

Table 3: Rankings of turnover growth by factor.

Statistical Factors

rank	Princomp 1	Princomp 2	Princomp 3	Princomp 4	Random
1	15.33%	27.62%	20.92%	24.39%	6.97%
2	13.52%	17.97%	15.64%	17.17%	6.91%
3	15.34%	15.14%	15.28%	15.22%	6.84%
4	19.72%	15.38%	17.40%	16.27%	7.05%
5	31.51%	19.43%	26.73%	21.92%	6.99%

Macro and Market Factors

rank	Inflation	Industrial Prod.	EW Mkt. Return	VW Mkt Return.	volgrow	wvolgrow
1	22.11%	23.40%	21.35%	21.49%	18.72%	20.02%
2	17.50%	17.07%	16.53%	16.43%	16.14%	16.59%
3	15.47%	15.60%	15.87%	15.86%	16.13%	16.05%
4	16.38%	17.01%	17.80%	17.74%	18.59%	17.92%
5	23.23%	21.36%	22.77%	22.84%	24.20%	23.45%

Technical Factors

rank	1-Mth Ret. Momentum	6-Mth. Ret. Momentum	60 - Mth. Ret. Momentum	1-Mth. Vol Momentum	6-Mth. Vol Momentum	60-Mth Vol. Momentum
1	8.38%	3.75%	2.30%	17.73%	2.34%	4.55%
2	11.15%	8.33%	1.98%	12.16%	4.54%	2.49%
3	5.12%	7.98%	1.70%	5.95%	5.39%	4.17%
4	0.25%	2.98%	2.83%	-3.84%	2.77%	3.88%
5	-5.67%	-5.42%	3.97%	-15.42%	-2.25%	2.80%

Fundamental Factors

rank	Book to Market	Cash Price	Div Price	Earn Price	Share Price	Size
1	17.16%	19.59%	17.75%	20.34%	22.64%	25.44%
2	17.20%	17.24%	17.24%	17.93%	21.89%	23.71%
3	18.36%	19.02%	19.16%	17.69%	18.80%	19.42%
4	20.16%	18.54%	16.43%	17.88%	18.97%	17.47%
5	21.88%	21.44%	19.11%	21.43%	14.84%	12.18%

Table 4: Turnover growth hedge portfolios.

This table presents the results of turnover growth premia resulting from hedge portfolios formed based upon the level of the given factors. Firms are sorted each month into equal-sized groups based upon the level of each factor listed below. The average turnover growth for the month for the low group is then subtracted from the average turnover growth for the high group. The mean, t-statistic, standard deviation skewness, and V-Sharpe ratio are presented below. The V-Sharpe ratio is the ratio of the absolute value of the mean and the time-series standard deviation. Chi-square tests reveal that all factors have standard deviations that are significantly greater than that of the random portfolio.

Table 4: Turnover growth hedge portfolios.

VARIABLE	MEAN SPREAD	T-STATISTIC	VARIABLE	STD DEV	VARIABLE	V-SHARPE
LAGGED VOLUME GROWTH	33.15%	-23.47	PRINCOMP 3	48.56%	LAGGED VOLUME GROWTH	106.48%
PRINCOMP 1	16.18%	10.64	PRINCOMP 1	47.73%	LAGGED RETURN	46.87%
LAGGED RETURN	14.05%	-9.5	PRINCOMP 2	47.39%	SIZE	45.89%
SIZE	13.28%	-9.21	PRINCOMP 4	45.12%	PRINCOMP 1	33.89%
6 MONTH RET MOMENTUM	9.15%	-6.7	EW MKT RETURN	44.59%	SHARE PRICE	28.50%
PRINCOMP 2	8.19%	-40.69	VW MARKET RETURN	43.48%	6 MONTH RET MOMENTUM	26.51%
SHARE PRICE	7.80%	-6.04	VW MKT VOL GROWTH	43.41%	BOOK TO MARKET	20.61%
PRINCOMP 3	5.80%	4.16	EW MKT VOL GROWTH	43.33%	PRINCOMP 2	17.29%
EW MKT VOL GROWTH	5.48%	3.31	INFLATION GROWTH	40.30%	6 MONTH VOL MOMENTUM	14.46%
BOOK TO MARKET	5.01%	3.52	INDUSTRIAL PRODUCTION	39.22%	EW MKT VOL GROWTH	12.64%
6 MONTH VOL MOMENTUM	4.59%	-2.66	6 MONTH RET MOMENTUM	34.51%	PRINCOMP 3	11.95%
VW MKT VOL GROWTH	3.43%	2.13	6 MONTH VOL MOMENTUM	31.75%	VW MKT VOL GROWTH	7.91%
PRINCOMP 4	2.34%	-1.47	LAGGED VOLUME GROWTH	31.14%	CASHPRICE	7.48%
INDUSTRIAL PRODUCTION	2.04%	-0.99	LAGGED RETURN	29.98%	60 MONTH RET MOMENTUM	6.73%
CASHPRICE	1.84%	0.89	SIZE	28.93%	60 MONTH VOL MOMENTUM	6.31%
60 MONTH RET MOMENTUM	1.84%	0.85	60 MONTH VOL MOMENTUM	27.69%	INDUSTRIAL PRODUCTION	5.21%
60 MONTH VOL MOMENTUM	1.75%	-0.75	SHARE PRICE	27.37%	PRINCOMP 4	5.19%
EW MKT RETURN	1.42%	0.63	60 MONTH RET MOMENTUM	27.34%	DIVPRICE	4.14%
VW MARKET RETURN	1.35%	0.59	EARNINGSPRICE	26.42%	EARNINGSPRICE	3.71%
INFLATION GROWTH	1.12%	0.54	DIVPRICE	25.19%	EW MKT RETURN	3.18%
DIVPRICE	1.04%	0.49	CASHPRICE	24.63%	VW MARKET RETURN	3.10%
EARNINGSPRICE	0.98%	0.51	BOOK TO MARKET	24.30%	INFLATION GROWTH	2.77%
RANDOM	0.02%	0.01	RANDOM	4.27%	RANDOM	0.52%

Table 5: Turnover growth hedge portfolios (January only)

This table presents the results of turnover growth premia resulting from hedge portfolios formed based upon the level of the given factors. Firms are sorted each month into equal-sized groups based upon the level of each factor listed below. The average turnover growth for the month for the low group is then subtracted from the average turnover growth for the high group. The mean, t-statistic, standard deviation skewness, and V-Sharpe ratio are presented below. The V-Sharpe ratio is the ratio of the absolute value of the mean and the time-series standard deviation. The results include only the month of January. Chi-square tests reveal that all factors have standard deviations that are significantly greater than that of the random portfolio.

Table 5: Turnover growth hedge portfolios (January only).

VARIABLE	MEAN SPREAD	T-STATISTIC
SHARE PRICE	34.90%	9.11
EARNINGSPRICE	33.41%	7.79
VW MKT VOL GROWTH	33.33%	10.04
EW MKT VOL GROWTH	31.47%	7.59
LAGGED VOLUME GROWTH	28.95%	-46.09
SIZE	27.50%	5.14
PRINCOMP 1	24.60%	5.57
BOOK TO MARKET	23.45%	-3.67
60 MONTH RET MOMENTUM	15.83%	3.12
DIVPRICE	15.19%	-2.09
PRINCOMP 4	12.93%	-2.75
INFLATION GROWTH	12.07%	-4.28
CASHPRICE	12.02%	2.67
60 MONTH VOL MOMENTUM	11.71%	1.65
LAGGED RETURN	9.71%	-1.35
PRINCOMP 3	7.81%	1.13
INDUSTRIAL PRODUCTION	7.35%	-1.01
6 MONTH RET MOMENTUM	4.02%	-0.7
6 MONTH VOL MOMENTUM	2.11%	-0.25
VW MARKET RETURN	2.10%	0.29
EW MKT RETURN	1.47%	0.21
PRINCOMP 2	1.43%	0.16
RANDOM	0.07%	0.01

VARIABLE	STD DEV
INFLATION GROWTH	53.34%
PRINCOMP 1	51.42%
INDUSTRIAL PRODUCTION	47.69%
VW MARKET RETURN	43.84%
PRINCOMP 3	43.68%
EW MKT VOL GROWTH	43.13%
EW MKT RETURN	42.84%
VW MKT VOL GROWTH	42.70%
PRINCOMP 4	41.36%
6 MONTH RET MOMENTUM	38.33%
SIZE	34.90%
PRINCOMP 2	34.19%
SHARE PRICE	32.56%
EARNINGSPRICE	32.48%
LAGGED RETURN	30.44%
6 MONTH VOL MOMENTUM	25.73%
60 MONTH RET MOMENTUM	24.98%
60 MONTH VOL MOMENTUM	21.67%
DIVPRICE	21.01%
BOOK TO MARKET	20.16%
LAGGED VOLUME GROWTH	19.92%
CASHPRICE	12.61%
RANDOM	3.77%

VARIABLE	V-SHARPE
LAGGED VOLUME GROWTH	145.33%
BOOK TO MARKET	116.31%
SHARE PRICE	107.19%
EARNINGSPRICE	102.87%
CASHPRICE	95.34%
SIZE	78.78%
VW MKT VOL GROWTH	78.07%
EW MKT VOL GROWTH	72.97%
DIVPRICE	72.33%
60 MONTH RET MOMENTUM	63.39%
60 MONTH VOL MOMENTUM	54.05%
PRINCOMP 1	47.84%
LAGGED RETURN	31.89%
PRINCOMP 4	31.26%
INFLATION GROWTH	22.62%
PRINCOMP 3	17.89%
INDUSTRIAL PRODUCTION	15.40%
6 MONTH RET MOMENTUM	10.48%
6 MONTH VOL MOMENTUM	8.22%
VW MARKET RETURN	4.79%
PRINCOMP 2	4.18%
EW MKT RETURN	3.44%
RANDOM	1.86%

Table 6: Pearson correlations of volume factors.

This table presents the time-series average of cross-sectional Pearson correlations for all variables of the top 10 variables for mean spread and spread volatility. INFLATION is the percentage growth rate in seasonally-adjusted inflation during the given month. INDPROD is the percentage change in industrial production. EW RET and VW RET are the equal and value-weighted returns on the market, respectively. EW VOL GRWTH and VW VOL GRWTH are the equal and value-weighted growth in trading volume of the market, respectively. LAGGED RETURN is the return on the security prior month. 6 MTH RET MOM and 60 MTH RET MOM are the cumulative return on the given security at the end of the past 6 and 60 months, not including the prior month. Princomp 1, Princomp 2, Princomp 3 and Princomp 4 are the first, second, third and fourth principal components of the variance covariance matrix of turnover growth portfolios. Size is market capitalization at the end of the given month. BOOKMKT is the ratio of book value at the end of the prior fiscal year to market value at the end of the given month. EARNPRICE is the ratio of earnings per share, excluding extraordinary items at the end of the prior fiscal year to price at the end of the given month. CASHPRICE is the ratio of cash flow at the end of the prior year to price at the end of the current month. DIVPRICE is the dividend at the end of the prior fiscal year divided by the share price at the end of the given month. PRICE is the price of the firm's stock at the end of the given month.

Table 6: Pearson correlation of volume factors.

	BOOKMKT	CASHPRICE	INFLATION	INDPROD	EW RET	LAGGED RETURN	6 MTH RET MOM
BOOKMKT	1.00	0.20	-0.01	0.01	-0.07	-0.06	-0.17
CASHPRICE	0.20	1.00	0.00	0.01	-0.01	0.06	0.08
INFLATION	-0.01	0.00	1.00	0.05	-0.06	0.00	0.01
INDPROD	0.01	0.01	0.05	1.00	-0.03	-0.01	0.00
EW RET	-0.07	-0.01	-0.06	-0.03	1.00	0.00	0.01
LAGGED RETURN	-0.06	0.06	0.00	-0.01	0.00	1.00	0.06
6 MTH RET MOM	-0.17	0.08	0.01	0.00	0.01	0.06	1.00
PRICE	-0.17	0.20	0.04	0.00	-0.04	0.13	0.22
SIZE	-0.09	0.08	0.02	0.00	-0.04	0.02	0.04
LAGGED VOL	0.01	0.01	0.00	0.00	0.00	0.12	-0.05
6 MTH VOL MOM	-0.06	0.01	0.01	0.00	-0.01	0.02	0.11
60 MTH VOL MOM	-0.10	0.03	0.03	-0.02	-0.01	0.02	0.00
EW VOL GRWTH	0.00	0.04	-0.08	-0.06	0.13	-0.01	-0.04
VW VOL GRWTH	-0.06	0.03	-0.12	-0.03	0.08	0.01	0.01

	PRICE	SIZE	LAGGED VOL	6 MTH VOL MOM	60 MTH VOL MOM	EW VOL GRWTH	VW VOL GRWTH
BOOKMKT	-0.17	-0.09	0.01	-0.06	-0.10	0.00	-0.06
CASHPRICE	0.20	0.08	0.01	0.01	0.03	0.04	0.03
INFLATION	0.04	0.02	0.00	0.01	0.03	-0.08	-0.12
INDPROD	0.00	0.00	0.00	0.00	-0.02	-0.06	-0.03
EW RET	-0.04	-0.04	0.00	-0.01	-0.01	0.13	0.08
LAGGED RETURN	0.13	0.02	0.12	0.02	0.02	-0.01	0.01
6 MTH RET MOM	0.22	0.04	-0.05	0.11	0.00	-0.04	0.01
PRICE	1.00	0.33	0.01	0.09	0.22	-0.02	0.05
SIZE	0.33	1.00	0.00	0.04	0.18	-0.02	0.01
LAGGED VOL	0.01	0.00	1.00	-0.17	0.02	-0.01	0.00
6 MTH VOL MOM	0.09	0.04	-0.17	1.00	0.05	0.01	0.00
60 MTH VOL MOM	0.22	0.18	0.02	0.05	1.00	0.01	0.00
EW VOL GRWTH	-0.02	-0.02	-0.01	0.01	0.01	1.00	0.53
VW VOL GRWTH	0.05	0.01	0.00	0.00	0.00	0.53	1.00

Table 7: Pearson correlations of volume factors (January only)

This table presents the time-series average of cross-sectional Pearson correlations for all variables of the top 10 variables for mean spread and spread volatility. Only the month of January is included here. INFLATION is the percentage growth rate in seasonally-adjusted inflation during the given month. INDPROD is the percentage change in industrial production. EW RET and VW RET are the equal and value-weighted returns on the market, respectively. EW VOL GRWTH and VW VOL GRWTH are the equal and value-weighted growth in trading volume of the market, respectively. LAGGED RETURN is the return on the security during the prior month. 6 MTH RET MOM and 60 MTH RET MOM are the cumulative return on the given security during the past 6 and 60 months, not including the prior month. Princomp 1, Princomp 2, Princomp 3 and Princomp 4 are the first, second, third and fourth principal components of the variance covariance matrix of turnover growth portfolios. Size is market capitalization during the given month. BOOKMKT is the ratio of book value during the prior fiscal year to market value during the given month. EARNPRICE is the ratio of earnings per share, excluding extraordinary items during the prior fiscal year to price during the given month. CASHPRICE is the ratio of cash flow during the prior year to price during the current month. DIVPRICE is the dividend during the prior fiscal year divided by the share price during the given month. PRICE is the price of the firm's stock during the given month.

Table 7: Pearson correlation of volume factors (January only).

	BOOK TO MARKET	CASHPRICE	INFLATION	INDUSTRIAL PROD	DIVPRICE	EARNPRICE	LAGGED RETURN	6 MTH RET MOM
BOOK TO MARKET	1.00	0.21	-0.01	0.04	0.25	0.00	-0.08	-0.18
CASHPRICE	0.21	1.00	0.00	0.01	0.10	0.81	0.14	0.17
INFLATION	-0.01	0.00	1.00	0.20	0.00	0.02	0.02	0.02
INDUSTRIAL PROD	0.04	0.01	0.20	1.00	0.00	0.00	0.00	0.01
DIVPRICE	0.25	0.10	0.00	0.00	1.00	0.00	-0.06	-0.14
EARNPRICE	0.00	0.81	0.02	0.00	0.00	1.00	0.17	0.27
LAGGED RETURN	-0.08	0.14	0.02	0.00	-0.06	0.17	1.00	0.14
6 MTH RET MOM	-0.18	0.17	0.02	0.01	-0.14	0.27	0.14	1.00
60 MTH RET MOM	-0.21	0.08	0.01	-0.04	-0.16	0.19	0.05	0.04
SHARE PRICE	-0.15	0.23	0.03	0.00	-0.06	0.35	0.18	0.30
SIZE	-0.08	0.08	0.03	0.00	0.03	0.10	0.04	0.06
LAGGED VOL	0.07	-0.02	-0.02	-0.03	0.05	-0.05	0.03	-0.19
6 MTH VOL MOM	-0.06	0.02	0.02	0.00	0.05	0.03	0.03	0.08
EW VOL GRWTH	-0.03	0.04	-0.17	-0.09	-0.05	0.05	-0.02	-0.02
VW MKT RET	-0.02	0.02	-0.05	0.01	-0.02	0.02	-0.02	0.00
VW VOL GRWTH	-0.07	0.05	-0.13	-0.06	-0.05	0.07	0.05	0.04

	60 MTH RET MOM	SHARE PRICE	SIZE	LAGGED VOL	6 MTH VOL MOM	EW VOL GRWTH	VW MKT RET	VW VOL GRWTH
BOOK TO MARKET	-0.21	-0.15	-0.08	0.07	-0.06	-0.03	-0.02	-0.07
CASHPRICE	0.08	0.23	0.08	-0.02	0.02	0.04	0.02	0.05
INFLATION	0.01	0.03	0.03	-0.02	0.02	-0.17	-0.05	-0.13
INDUSTRIAL PROD	-0.04	0.00	0.00	-0.03	0.00	-0.09	0.01	-0.06
DIVPRICE	-0.16	-0.06	0.03	0.05	0.05	-0.05	-0.02	-0.05
EARNPRICE	0.19	0.35	0.10	-0.05	0.03	0.05	0.02	0.07
LAGGED RETURN	0.05	0.18	0.04	0.03	0.03	-0.02	-0.02	0.05
6 MTH RET MOM	0.04	0.30	0.06	-0.19	0.08	-0.02	0.00	0.04
60 MTH RET MOM	1.00	0.23	0.08	-0.05	0.02	0.07	0.01	0.04
SHARE PRICE	0.23	1.00	0.34	-0.14	0.09	-0.01	-0.01	0.05
SIZE	0.08	0.34	1.00	-0.05	0.05	-0.02	-0.03	0.02
LAGGED VOL	-0.05	-0.14	-0.05	1.00	-0.20	0.02	0.04	-0.01
6 MTH VOL MOM	0.02	0.09	0.05	-0.20	1.00	-0.01	-0.02	-0.03
EW VOL GRWTH	0.07	-0.01	-0.02	0.02	-0.01	1.00	0.11	0.47
VW MKT RET	0.01	-0.01	-0.03	0.04	-0.02	0.11	1.00	-0.01
VW VOL GRWTH	0.04	0.05	0.02	-0.01	-0.03	0.47	-0.01	1.00

Table 8: Cross-sectional regression results.

This table presents the results of a regression of turnover growth on the factors that ranked in the top six in a) mean turnover growth premia of the factor-mimmicking portfolio and b) standard deviation of turnover growth premia. The regressions are done following the methodology of Fama-Macbeth (1972). The regression is run cross-sectionally for every month of the time-series, and the coefficients are averaged and checked for significance. The mean, t-statistic, standard deviation and skewness of each coefficient is presented. The Mean Group presents regression results for those firms that ranked in the top six in mean spread, and the Volatility Group presents results from those factors that rank in the top six in Volatility of spread. Statistical factors were not included, and neither were those that are too highly correlated with those factors in the regression model (i.e. equal and value weighted market trading volume were not included together).

Table 8: Cross-sectional regression results.

MEAN GROUP - ALL MONTHS

VARIABLE	MEAN	T-STATISTIC	STD DEVIATION	SKEWNESS
INTERCEPT	46.97%	13.20	74.30%	0.73
LAGGED VOLUME GROWTH	-30.25%	-47.06	13.42%	0.13
LOG SIZE	-1.87%	-10.22	3.82%	-0.84
LAGGED RETURN	-37.78%	-13.33	59.19%	-1.65
6 - MONTH RET. MOMENTUM	-13.03%	-10.18	26.73%	-1.51
SHARE PRICE	0.11%	4.75	0.49%	-0.28
EW VOLUME GROWTH	3.22%	5.36	12.56%	2.28
ADJUSTED R-SQUARE	11.03%	28.08	8.20%	4.52

VOLATILITY GROUP - ALL MONTHS

VARIABLE	MEAN	T-STATISTIC	STD DEVIATION	SKEWNESS
INTERCEPT	6.82%	8.32	17.11%	0.82
EW MKT RETURN	-0.22%	-0.85	5.51%	0.09
VW VOLUME GROWTH	1.77%	2.03	18.26%	0.65
INFLATION GROWTH	0.01%	0.74	0.25%	-0.16
INDUSTRIAL PRODUCTION	-0.02%	-0.47	0.78%	0.14
6 - MONTH VOLUME MOMENTUM	-3.03%	-5.07	12.50%	-1.09
6 - MONTH RET. MOMENTUM	-10.97%	-5.64	40.64%	-0.34
ADJUSTED R-SQUARE	15.29%	24.69	12.94%	1.71

Table 9: Cross-sectional regression results (January only).

This table presents the results of a regression of turnover growth on the factors that ranked in the top six in a) mean turnover growth premia of the factor-mimmicking portfolio and b) standard deviation of turnover growth premia. The regressions are done following the methodology of Fama-Macbeth (1972). The regression is run cross-sectionally for every month of the time-series, and the coefficients are averaged and checked for significance. The mean, t-statistic, standard deviation and skewness of each coefficient is presented. The Mean Group presents regression results for those firms that ranked in the top six in mean spread, and the Volatility Group presents results from those factors that rank in the top six in Volatility of Mean spread. Statistical factors were not included, and neither were those that are too highly correlated with those factors in the regression model (i.e. equal and value weighted market trading volume were not included together).

Table 9: Cross-sectional regression results (January only).

MEAN GROUP - JANUARY ONLY

VARIABLE	MEAN	T-STATISTIC	STD DEVIATION	SKEWNESS
INTERCEPT	-4.46%	-0.32	83.58%	0.35
LAGGED VOLUME GROWTH	-25.88%	-14.57	10.66%	-0.34
LOG SIZE	0.53%	0.72	4.41%	0.03
LAGGED RETURN	13.00%	1.72	45.24%	-0.72
6 - MONTH RET. MOMENTUM	25.58%	6.24	24.62%	0.29
SHARE PRICE	0.36%	4.75	0.45%	-0.50
EW VOLUME GROWTH	10.38%	3.69	16.89%	2.64
ADJUSTED R-SQUARE	14.64%	9.10	9.65%	1.96

VOLATILITY GROUP - JANUARY ONLY

VARIABLE	MEAN	T-STATISTIC	STD DEVIATION	SKEWNESS
INTERCEPT	-4.28%	-1.85	13.91%	0.04
EW MKT RETURN	4.69%	3.81	7.38%	2.18
VW VOLUME GROWTH	8.39%	2.24	22.51%	2.50
INFLATION GROWTH	0.06%	1.57	0.22%	1.53
INDUSTRIAL PRODUCTION	-0.11%	-0.68	0.97%	0.74
6 - MONTH VOLUME MOMENTUM	-1.11%	-0.50	13.42%	0.17
6 - MONTH RET. MOMENTUM	25.87%	3.22	48.24%	-0.39
ADJUSTED R-SQUARE	22.45%	8.79	15.32%	1.12

Table 10: Descriptive statistics.

The table below gives descriptive statistics on the variables in this study. Turnover is the number of shares traded during the month, divided by the number of shares outstanding. Turnover growth is the market-adjusted percentage change in turnover from month t to month t+1. Mkt and firm adjusted turnover growth is turnover growth from month t to t+1, minus the average turnover growth for the market, minus the mean market-adjusted turnover growth for the prior 12 months. Mean turnover growth is the average turnover growth from the past 12 months. Standard deviation of turnover growth is the standard deviation of turnover growth during the past 12 months. Skewness of turnover growth is the skewness of turnover growth from the past 12 months. The mean of cross-sectional medians for each variable is presented, the mean of the cross-sectional standard deviation is presented, and the cross-sectional average of firm-specific volatility is presented as well. The data span the entire time series, which runs from August, 1962 through December, 1999.

Table 10: Descriptive statistics.

All Firms

Variable	median	mean	min	max	p25	p75
Share Turnover	0.03	0.05	0.00	7.16	0.01	0.06
Turnover growth	0.00	0.54	-0.99	813.31	-0.31	0.48
Mkt and firm adjusted turnover growth	-0.11	0.02	-1.09	2.31	-0.38	0.24
mean 12 mth adj. Growth	-0.29	-0.20	-0.43	0.33	-0.42	0.00
std. 12 mth adj. Growth	0.36	0.49	0.25	1.17	0.25	0.68
skewness 12 mth adj. Growth	-0.08	0.26	-0.42	2.06	-0.42	0.84

NYSE/AMEX firms only

Variable	median	mean	min	max	p25	p75
Share Turnover	0.03	0.04	0.00	2.41	0.02	0.05
Turnover growth	0.00	0.30	-0.98	104.27	-0.29	0.43
Mkt and firm adjusted turnover growth	-0.10	0.01	-1.09	2.21	-0.40	0.26
mean 12 mth adj. Growth	-0.08	-0.13	-0.43	0.33	-0.41	0.06
std. 12 mth adj. Growth	0.43	0.51	0.25	1.17	0.25	0.72
skewness 12 mth adj. Growth	0.34	0.45	-0.42	2.06	-0.41	1.11

NASDAQ firms only

Variable	median	mean	min	max	p25	p75
Share Turnover	0.03	0.06	0.00	5.66	0.01	0.07
Turnover growth	0.01	0.76	-0.89	743.20	-0.34	0.56
Mkt and firm adjusted turnover growth	-0.14	0.01	-1.07	2.16	-0.39	0.25
mean 12 mth adj. Growth	-0.32	-0.27	-0.43	0.33	-0.43	-0.16
std. 12 mth adj. Growth	0.37	0.45	0.25	1.17	0.25	0.62
skewness 12 mth adj. Growth	-0.13	0.05	-0.42	2.06	-0.41	0.39

Table 11: Analysis of the volume-return premium.

The table here presents a portfolio analysis of the volume-return premium. For each month from August, 1962 through December, 1999, firms are sorted based upon excess market-adjusted turnover growth, which is defined as turnover growth during month t, minus the value-weighted turnover growth for the market, minus the 12-month average of market-adjusted turnover growth, including the current one. There are five portfolios created, and the mean return in excess of the t-bill rate is regressed on the HML, SMB, and MKT factors from the Fama-French 3-Factor model, along with a momentum and turnover factor that were created in the following way: each month, all NYSE stocks are sorted based upon the magnitude of the given factor (Momentum = 12 month buy and hold returns, Turnover = number of shares traded during month t, divided by number of shares outstanding). Three groups are then created. The one-month return for the low group is then subtracted from the one-month return for the high group, creating a hedge portfolio return for the given month. This return is then included in the model as the factor realization for month t. The mean return for each of the five portfolios is then regressed on the realizations of the five factors presented here. The coefficients, t-statistics, adjusted r-square values, and Gibbons, Ross and Shanken F-statistics are all presented below.

Table 11: Analysis of the volume-return premium.

NYSE/AMEX STOCKS (ALL COEFFICIENTS ARE MULTIPLIED BY 100)

	COEF 1	T-STAT 1	COEF 2	T-STAT 2	COEF 3	T-STAT 3	COEF 4	T-STAT 4	COEF 5	T-STAT 5
INTERCEPT	-3.24	-2.87	-2.18	-1.81	-1.46	-1.27	-0.94	-0.74	-0.31	1.04
HML	43.21	33.50	31.36	31.37	22.61	25.47	28.77	32.24	39.14	54.91
SMB	55.37	42.81	50.25	36.93	38.70	35.40	38.03	42.66	53.35	79.33
MKT	-13.54	-14.43	-7.35	-8.00	-8.56	-5.81	-4.87	-9.21	-15.15	-31.06
MOMENTUM	-44.18	-36.68	-25.91	-32.75	-25.17	-30.85	-31.61	-33.94	-42.19	-54.03
TURNOVER	2.77	14.45	6.82	16.33	16.23	19.02	22.27	31.78	45.83	79.72
Adj R-Square	0.79	0.77	0.76	0.80	0.80	0.79	0.83	0.84	0.83	0.76

GRS - P-value
< .001

NASDAQ STOCKS

	COEF 1	T-STAT 1	COEF 2	T-STAT 2	COEF 3	T-STAT 3	COEF 4	T-STAT 4	COEF 5	T-STAT 5
INTERCEPT	-4.51	-4.37	-4.36	-3.55	-2.40	-1.51	-2.00	-0.93	-0.07	1.83
HML	34.02	28.25	12.99	26.04	21.87	10.24	10.14	28.52	34.75	54.98
SMB	87.59	91.95	88.67	94.55	79.61	103.61	88.33	93.16	114.64	148.57
MKT	-21.78	-11.62	-8.62	-8.26	-11.64	3.43	-25.46	-7.92	-16.89	-27.89
MOMENTUM	-4.91	-16.66	-22.29	-17.30	-29.82	-26.92	-14.49	-35.81	-34.81	-38.68
TURNOVER	-16.78	-9.55	-2.43	6.73	10.66	-23.38	43.09	21.90	40.54	59.44
Adj R-Square	0.37	0.54	0.49	0.49	0.47	0.38	0.44	0.51	0.66	0.54

GRS - P-value
< .001

Table 12: Cross-sectional regressions.

For every month from August, 1962 through December, 1999 stock returns in excess of the t-bill rate for month t+1 are regressed on the mean, standard deviation and skewness of market-adjusted trading volume growth for the past 12 months, ending at month t. The log of firm size, and 12 month return momentum from month t are also included in the regression. Size is the log of market value during month t+1, and 12 month return momentum is measured as the buy and hold return on the security for 12 months, ending at month t. The regression is performed cross-sectionally, with the average coefficients and significance levels given for four periods: 1963 – 1979, 1980 – 1989, 1990 – 1999, and 1963 – 1999. The first table presents results for NYSE/AMEX firms, and the second table presents results for Nasdaq securities only.

Table 12: Cross-sectional regressions.

NYSE/AMEX (all coefficients are multiplied by 100)

	1963 - 1979		1980 - 1989		1990 - 1999		OVERALL	
VARIABLE	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**
INTERCEPT	-2.38	-2.76	-4.68	-5.10	-8.03	-7.66	-4.53	-8.14
MEAN MKT ADJ TURNOVER GROWTH	13.40	13.30	9.78	10.25	11.58	11.86	11.93	20.06
STD DEV MKT ADJ TURNOVER GROWTH	-2.73	-6.38	-1.41	-2.63	-2.34	-5.13	-2.27	-8.27
SKEWNESS MKT ADJ TURNOVER GROWTH	-0.20	-3.16	-0.19	-2.41	0.04	0.75	-0.13	-3.31
SIZE	0.32	5.36	0.42	6.84	0.59	9.75	0.42	11.57
12 MONTH MOMENTUM	-0.16	-0.55	0.32	1.03	0.04	0.15	0.03	0.15

NASDAQ

	1963 - 1979		1980 - 1989		1990 - 1999		OVERALL	
VARIABLE	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**
INTERCEPT	6.41	5.05	14.70	18.03	17.38	14.71	-11.63	-15.79
MEAN MKT ADJ TURNOVER GROWTH	17.77	8.92	5.19	5.40	13.94	12.37	13.32	12.99
STD DEV MKT ADJ TURNOVER GROWTH	-4.27	-4.20	2.77	3.59	-2.20	-4.04	-1.80	-3.28
SKEWNESS MKT ADJ TURNOVER GROWTH	-0.12	-0.66	-0.60	-3.73	0.21	2.14	-0.16	-1.62
SIZE	0.76	8.32	1.13	17.36	1.40	16.60	1.03	19.76
12 MONTH MOMENTUM	-1.20	-3.19	-0.36	-1.72	1.12	4.54	-0.95	-4.90

Table 13: Cross-sectional predictors of idiosyncratic turnover growth.

This table presents a regression of the idiosyncratic turnover for month t+1 regressed on the first three moments of turnover growth for the prior 12 months, along with firm size and momentum. The first three moments of turnover growth include the mean, standard deviation and skewness of market-adjusted turnover growth for the prior 12 months, not including the current month. The size variable is the log of firm size during the prior month, and momentum is the 12 month buy and hold return for the prior 12 months, not including the current month. The regressions are performed cross-sectionally, for ever month from August, 1963 through December, 1999. The coefficients are then averaged and checked for significance. The analysis is done over 3 disjoint time periods: 1963 – 1979, 1980 – 1989 and 1990 – 1999. Also, results are presented for the overall time period.

Table 13: Cross-sectional predictors of idiosyncratic turnover growth.

NYSE/AMEX

	1963 - 1979		1980 - 1989		1990 - 1999		OVERALL	
VARIABLE	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**
INTERCEPT	15.95	3.60	0.06	0.01	20.51	5.31	12.85	4.86
1-MTH LAG	-28.61	-34.11	-28.39	-28.03	-25.10	-18.44	-27.60	-45.84
12-MTH MEAN EXC TURNOVER GROWTH	-152.01	-19.40	-174.50	-16.70	-238.39	-47.84	-181.51	-35.91
12-MTH STD DEV EXC TURNOVER GROWTH	19.85	6.63	37.07	7.98	64.40	27.30	36.58	17.02
12-MTH SKEWNESS EXC TURNOVER GROWTH	1.65	3.09	-0.33	-0.42	-6.15	-17.17	-1.00	-2.70
SIZE	-2.22	-6.74	-1.76	-5.45	-3.12	-11.22	-2.34	-12.23
12 MONTH RETURN MOMENTUM	-5.92	-5.08	-0.92	-0.73	3.34	3.69	-2.06	-2.92

NASDAQ

	1963 - 1979		1980 - 1989		1990 - 1999		OVERALL	
VARIABLE	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**	**COEFFICIENT**	**T-STAT**
INTERCEPT	5.46	1.12	22.80	3.05	8.51	1.12	14.23	3.37
1-MTH LAG	-25.80	-21.11	-30.08	-21.95	-25.33	-17.77	-27.63	-33.96
12-MTH MEAN EXC TURNOVER GROWTH	-131.84	-13.41	-126.23	-10.97	-226.91	-21.82	-155.02	-22.61
12-MTH STD DEV EXC TURNOVER GROWTH	15.63	2.57	7.05	1.18	72.65	8.85	27.14	6.60
12-MTH SKEWNESS EXC TURNOVER GROWTH	-0.91	-0.85	1.07	1.08	-10.95	-5.97	-2.72	-3.53
SIZE	-1.11	-3.65	-2.16	-3.84	-2.15	-4.24	-1.87	-6.16
12 MONTH RETURN MOMENTUM	1.67	2.02	-1.88	-0.98	3.18	1.75	0.45	0.44

Table 14: Factor-based analysis of the first three moments of turnover growth.

For every month from August, 1963 through December, 1999, firms are sorted by the level of share turnover. Ten portfolios are formed all together . The mean excess market-adjusted turnover growth for each portfolio is then calculated. The realizations of excess market adjusted turnover growth are then regressed on the factors representing the first three moments of market adjusted turnover growth, value-weighted excess market-adjusted turnover, and value- The factors based upon the first three moments of turnover growth were created by sorting all NYSE stocks each month based upon the mean, standard deviation and skewness of market adjusted excess turnover growth for the prior 12 months, not including the current month. The excess market adjusted turnover growth for the low groups is subtracted from that of the high group, creating a hedge portfolio excess turnover growth realization. This realization is included in the time-series regression as an independent variable. The value weighted excess turnover and turnover factors were created by value-weighting the excess market adjusted turnover and raw turnover for all NYSE/AMEX stocks. The analysis is done separately for NYSE/AMEX and Nasdaq stocks and presented below.

Table 14: Factor-based analysis of the first three moments of turnover growth.

NYSE/AMEX

VARIABLE	PORTFOLIO 1	T-STAT	PORTFOLIO 2	T-STAT	PORTFOLIO 3	T-STAT	PORTFOLIO 4	T-STAT	PORTFOLIO 5	T-STAT
INTERCEPT	0.28	17.28	0.19	15.81	0.14	12.64	0.09	8.38	0.05	5.78
MEAN EXC TURNOVER GRWTH	-0.26	-4.06	-0.16	-3.31	-0.20	-4.90	-0.18	-4.50	-0.21	-5.33
STDEV EXC TURNOVER GRWTH	0.88	5.08	0.62	5.09	0.60	6.31	0.56	5.51	0.56	5.96
SKEW EXC TURNOVER GRWTH	0.12	0.75	0.09	0.77	0.09	0.96	0.08	0.84	0.07	0.93
MKT EXC TURNOVER GROWTH	0.88	7.82	0.87	7.77	0.88	8.76	0.94	9.90	0.96	10.15
MKT TURNOVER	1.96	5.81	0.86	3.68	0.41	1.91	0.40	2.23	-0.14	-0.77
Adjusted R-square	0.36		0.35		0.38		0.39		0.43	

VARIABLE	PORTFOLIO 6	T-STAT	PORTFOLIO 7	T-STAT	PORTFOLIO 8	T-STAT	PORTFOLIO 9	T-STAT	PORTFOLIO 10	T-STAT
INTERCEPT	0.00	0.38	-0.04	-3.79	-0.08	-8.29	-0.14	-13.42	-0.29	-22.87
MEAN EXC TURNOVER GRWTH	-0.20	-5.26	-0.22	-5.20	-0.22	-5.48	-0.16	-4.04	-0.09	-1.53
STDEV EXC TURNOVER GRWTH	0.52	5.52	0.53	5.83	0.51	5.34	0.51	5.35	0.41	4.05
SKEW EXC TURNOVER GRWTH	0.06	0.63	0.07	0.84	0.05	0.65	-0.09	-1.08	-0.19	-2.04
MKT EXC TURNOVER GROWTH	0.95	10.65	0.89	6.98	0.84	8.57	0.83	4.54	0.85	3.50
MKT TURNOVER	-0.11	-0.61	-0.18	-0.85	-0.40	-1.95	-0.46	-2.15	-0.27	-0.85
Adjusted R-square	0.39		0.37		0.34		0.30		0.16	

NASDAQ

VARIABLE	PORTFOLIO 1	T-STAT	PORTFOLIO 2	T-STAT	PORTFOLIO 3	T-STAT	PORTFOLIO 4	T-STAT	PORTFOLIO 5	T-STAT
INTERCEPT	0.35	9.24	0.28	6.78	0.19	5.20	0.07	2.11	0.05	1.33
MEAN EXC TURNOVER GRWTH	-0.49	-4.02	-0.38	-3.31	-0.45	-4.25	-0.50	-5.07	-0.57	-5.06
STDEV EXC TURNOVER GRWTH	1.40	3.80	1.35	3.77	1.20	3.79	1.18	3.58	1.14	3.51
SKEW EXC TURNOVER GRWTH	0.14	0.40	0.10	0.25	0.09	0.30	-0.09	-0.25	0.07	0.22
MKT EXC TURNOVER GROWTH	0.25	0.70	0.77	1.95	0.88	3.20	1.51	5.49	1.00	2.54
MKT TURNOVER	4.63	6.91	1.40	2.41	0.27	0.50	0.67	1.26	-0.35	-0.67
Adjusted R-square	0.24		0.19		0.18		0.17		0.16	

VARIABLE	PORTFOLIO 6	T-STAT	PORTFOLIO 7	T-STAT	PORTFOLIO 8	T-STAT	PORTFOLIO 9	T-STAT	PORTFOLIO 10	T-STAT
INTERCEPT	-0.02	-0.77	-0.10	-3.67	-0.13	-5.21	-0.23	-8.65	-0.35	-13.33
MEAN EXC TURNOVER GRWTH	-0.39	-4.30	-0.41	-4.57	-0.39	-4.57	-0.26	-3.23	-0.08	-1.07
STDEV EXC TURNOVER GRWTH	1.02	3.29	0.77	2.64	0.70	2.52	0.66	2.36	0.40	1.57
SKEW EXC TURNOVER GRWTH	0.04	0.12	-0.06	-0.21	0.10	0.35	-0.09	-0.34	-0.25	-0.95
MKT EXC TURNOVER GROWTH	0.67	1.41	1.18	3.68	0.68	3.05	0.25	0.90	0.69	1.84
MKT TURNOVER	0.74	1.67	0.25	0.51	0.09	0.20	0.64	1.44	0.57	1.40
Adjusted R-square	0.17		0.11		0.11		0.08		0.04	

Table 15**:** Descriptive statistics.

All stocks in the CRSP universe from January, 1927 through December 1999 were analyzed for every month during this time frame. The percentage of stocks with 6 months of consecutive positive or negative returns were calculated and averaged across decades below. Also, count variables were created, one of them counting the total number of positive/negative returns during the prior 12 months, and another calculating the number of positive or negative returns during the prior 24 months. The time-series mean of the cross-sectional mean, median, standard deviation, skewness and sample size are presented below. The results are presented for the entire time period, as well as by decade.

Table 15: Descriptive statistics.

MEAN

VARIABLE	1927 - 1939	1940 - 1949	1950 - 1959	1960 - 1969	1970 - 1979	1980 - 1989	1990 - 1999	OVERALL
N	669.98	818.05	994.62	1297.50	1922.23	2019.85	2680.66	1486.13
6 MTH POS DUMMY	0.86%	1.10%	1.72%	1.29%	1.12%	1.75%	1.38%	1.32%
6 MTH NEG DUMMY	1.33%	0.96%	0.87%	1.35%	1.59%	0.70%	1.02%	1.12%
12 MTH POS COUNT	5.41	5.80	6.09	5.81	5.44	6.07	5.94	5.80
24 MTH POS COUNT	10.78	11.68	11.99	11.79	10.82	12.16	11.98	11.60
12 MTH NEG COUNT	6.08	5.63	5.35	5.77	5.96	5.38	5.44	5.66
24 MTH NEG COUNT	12.23	11.19	10.89	11.36	12.01	10.76	10.75	11.31

MEDIAN

VARIABLE	1927 - 1939	1940 - 1949	1950 - 1959	1960 - 1969	1970 - 1979	1980 - 1989	1990 - 1999	OVERALL
6 MTH POS DUMMY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6 MTH NEG DUMMY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12 MTH POS COUNT	5.38	5.85	6.11	5.82	5.48	6.11	6.02	5.82
24 MTH POS COUNT	10.79	11.70	12.09	11.75	10.84	12.34	12.03	11.65
12 MTH NEG COUNT	6.12	5.65	5.40	5.79	6.00	5.38	5.42	5.68
24 MTH NEG COUNT	12.31	11.22	10.84	11.38	12.10	10.69	10.64	11.31

STANDARD DEVIATION

VARIABLE	1927 - 1939	1940 - 1949	1950 - 1959	1960 - 1969	1970 - 1979	1980 - 1989	1990 - 1999	OVERALL
6 MTH POS DUMMY	0.06	0.07	0.10	0.09	0.08	0.11	0.10	0.09
6 MTH NEG DUMMY	0.09	0.07	0.07	0.09	0.09	0.07	0.09	0.08
12 MTH POS COUNT	1.52	1.45	1.62	1.65	1.62	1.70	1.72	1.61
24 MTH POS COUNT	2.29	2.15	2.41	2.47	2.47	2.60	2.63	2.43
12 MTH NEG COUNT	1.47	1.39	1.56	1.59	1.59	1.62	1.64	1.55
24 MTH NEG COUNT	2.17	2.01	2.27	2.34	2.38	2.40	2.42	2.28

SKEWNESS

VARIABLE	1927 - 1939	1940 - 1949	1950 - 1959	1960 - 1969	1970 - 1979	1980 - 1989	1990 - 1999	OVERALL
6 MTH POS DUMMY	14.39	14.33	13.27	14.87	17.80	11.96	11.74	14.05
6 MTH NEG DUMMY	12.45	16.09	16.55	13.84	15.86	17.13	12.55	14.92
12 MTH POS COUNT	0.05	-0.10	-0.07	-0.04	-0.09	-0.22	-0.10	-0.08
24 MTH POS COUNT	0.02	-0.28	-0.19	-0.14	-0.32	-0.47	-0.23	-0.23
12 MTH NEG COUNT	-0.17	-0.05	0.00	-0.04	-0.32	-0.02	0.07	-0.08
24 MTH NEG COUNT	-0.22	-0.16	-0.08	-0.10	-0.59	-0.14	0.06	-0.18

Table 16: Jegadeesh and Titman, revisited.

From July, 1927 through December, 1999, all stocks are sorted into monthly deciles based upon buy and hold returns during the prior 6 months. All securities selected during the given month are held for six months, and the portfolio return for the given month is calculated as a weighted average of the returns of securities selected during each of the prior 6 months. The time-series of portfolio returns is then averaged over time and checked for significance, produced here in this table. The results are broken into the 1927 – 1965 time period, the 1965 – 1989 period, and the post 1989 period. The mean, t-statistic, standard deviation and skewness are presented here as well.

Table 16: Jegadeesh and Titman, revisited.

High Portfolio Returns (Monthly)

period	Mean	T-statistic	Std. Deviation	Skewness
Pre-1965	1.81%	4.41	8.74%	1.26
1965 - 1989	1.66%	4.18	6.87%	-0.67
Post 1989	1.85%	3.59	5.62%	-0.71
overall	1.76%	6.72	7.76%	0.74

Low Portfolio Returns (Monthly)

	Mean	T-statistic	Std. Deviation	Skewness
Pre-1965	1.32%	2.27	12.39%	3.10
1965 - 1989	0.74%	1.60	8.05%	0.81
Post 1989	1.60%	2.22	7.85%	0.89
overall	1.16%	3.26	10.51%	2.83

High - Low Portfolio Returns (Monthly)

	Mean	T-statistic	Std. Deviation	Skewness
Pre-1965	0.49%	1.43	7.30%	-4.59
1965 - 1989	0.92%	3.68	4.31%	-1.60
Post 1989	0.25%	0.59	4.57%	-1.27
overall	0.60%	2.94	6.08%	-4.42

Table 17: Risk-adjusted returns to positive or negative consistency portfolios.

For every month from January, 1927 through December, 1999, all stocks in the CRSP universe were sorted based upon the number of positive/negative returns during the prior 6 months (months t-1 through t-6). The mean return for the group of securities that have had six continuous months of positive/negative returns is then calculated, forming a time-series of raw stock returns. This mean monthly return is then compared with the mean monthly return for all other securities that did not have 6 months of consecutive positive/negative returns, creating a hedge portfolio return. This time series of hedge portfolio returns is then regressed on the size, book to market and market factors of the Fama-French 3 factor model, as well as a January dummy. The first table includes a hedge portfolio that only includes the returns of positively consistent firms compared to all others, the second table repeats the process for negatively consistency firms, the third table creates a hedge portfolio return that consists of the returns of positively consistent stocks, minus those that are negatively consistent. The results are presented for three subperiods, as well as for the entire time-horizon.

Table 17: Risk-adjusted returns to positive or negative consistency portfolios.

Positive consistency dummy (6 months) Coefficient estimates are multiplied by 100

	1927 - 1964		1965 - 1989		1990 - 1999		Overall	
Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Intercept	0.73	1.54	0.90	2.40	0.17	0.43	0.70	2.59
ssmb	19.12	1.16	-15.95	-1.28	11.08	0.79	8.42	0.92
shml	-2.19	-0.14	-28.67	-1.98	-10.65	-0.69	-8.93	-1.01
smkt	-16.47	-1.62	-5.53	-0.67	-17.74	-1.71	-10.40	-1.84
momhedge	-9.82	-0.85	1.17	0.09	-2.83	-0.19	-10.11	-1.36
jan	0.77	0.46	0.32	0.25	-0.79	-0.58	0.01	0.01

Negative consistency dummy (6 months)

	1927 - 1964		1965 - 1989		1990 - 1999		Overall	
Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Intercept	-0.70	-2.10	-1.33	-3.90	-1.35	-2.60	-1.04	-4.83
ssmb	32.82	3.16	-17.23	-1.50	-1.71	-0.09	11.37	1.63
shml	-6.60	-0.68	-9.34	-0.69	-2.11	-0.10	-3.72	-0.57
smkt	2.02	0.35	9.00	1.19	3.70	0.27	4.23	1.08
momhedge	3.39	0.51	3.12	0.31	10.97	0.57	1.70	0.33
jan	0.26	0.22	1.04	0.86	1.12	0.64	0.50	0.65

Positive minus Negative

	1927 - 1964		1965 - 1989		1990 - 1999		Overall	
Variable	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Intercept	1.661	2.8	2.345	4.01	1.41	1.93	1.947	5.34
ssmb	-97.031	-4.71	-8.12	-0.41	16.476	0.63	-35.264	-2.89
shml	28.643	1.41	-17.788	-0.79	-6.89	-0.24	0.991	0.08
smkt	9.037	0.73	-8.51	-0.67	-18.787	-0.97	-1.519	-0.2
momhedge	-29.741	-1.89	-0.176	-0.01	-14.967	-0.55	-12.441	-1.16
jan	-0.535	-0.24	-0.722	-0.37	-0.801	-0.32	-0.673	-0.53

Table 18: Long-horizon implications of consistency portfolios.

For every month from January, 1927 through December, 1999, stocks are sorted into groups based upon whether or not they've had 6 consecutive months of postive returns. The mean return for these stocks is then analyzed during months t+1 – t+6, t+7 – t+12, t+13 - t+18, and t+18 – t+24. Each of these returns is then compared to the buy and hold return for the same time period for those securities that did not have 6 consecutive months of positive returns. The hedge portfolio buy and hold returns are presented below. This process is then repeated for those securities that have had 6 consecutive months of negative returns (Negative consistency dummies). Finally, the mean return each month for those stocks that have had 6 consecutive months of negative returns is subtracted fro those that have had 6 months of positive returns, creating the "Positive minus negative" portfolio. This is presented in the third panel below.

Table 18: Long-horizon implications of consistency portfolios.

Positive consistency dummy (all coefficients are multiplied by 100)

Horizon	Hedge	T-stat	Positive	T-stat	Non-positive	T-stat
Months 1 - 6	3.34	6.74	7.43	10.20	3.40	5.45
Months 7 - 12	0.53	1.16	3.76	5.43	3.49	5.57
Months 13 - 18	-0.74	-1.86	2.62	3.54	3.51	5.58
Months 19 - 24	0.52	1.20	3.67	4.77	3.51	5.57

Negative consistency dummy

Horizon	Hedge	T-stat	Negative	T-stat	Non-negative	T-stat
Months 1 - 6	-4.94	-9.97	-2.09	-2.49	3.48	5.58
Months 7 - 12	-3.23	-6.92	-0.04	-0.05	3.53	5.64
Months 13 - 18	-0.83	-1.75	2.54	3.15	3.51	5.57
Months 19 - 24	-0.89	-1.72	2.63	2.93	3.51	5.57

Positive minus Negative

Horizon	High - Low	T-stat	High	T-stat	Low	T-stat
Months 1 - 6	9.57	12.50	7.43	10.20	-2.09	-2.49
Months 7 - 12	-0.08	-0.11	2.62	3.54	2.54	3.15
Months 13 - 18	1.65	2.02	3.67	4.77	2.63	2.93
Months 19 - 24	3.75	4.92	3.76	5.43	-0.04	-0.05

Table 19: Conditional sorting on consistency and momentum.

The table here produces the results of portfolio sorts based on both return momentum and consistency. For each month from January, 1927 through December, 1999, stocks are first sorted into quintiles based upon return momentum for the prior 3, 6, 12 and 24 months. Within each momentum quintile, stocks are sorted again on return consistency for the prior 3, 6, 12, and 24 months. The high (low) return is the cross-sectional average of the high consistency returns (across momentum quintiles), and the high-low return is the difference between the high and low groups. The holding periods also range from 3 to 12 months and returns are calculated in the same manner as JT (1993). Count refers to the fact that the securities are sorted into quintiles based upon the number of positive or negative returns that the security has had during the prior K months.

Table 19: Conditional sorting on consistency and momentum.

12 MONTH WINNERS (COUNT)

Portfolio	period	3 MONTH	T-STAT	6 MONTH	T-STAT	12 MONTH	T-STAT	24 MONTH	T-STAT
High	1927 - 1964	1.31%	3.30	1.32%	3.27	1.28%	3.08	1.48%	3.43
Low	1927 - 1964	1.50%	3.38	1.43%	3.18	1.32%	2.95	1.60%	3.56
High - Low	1927 - 1964	-0.19%	-1.40	-0.11%	-0.84	-0.04%	-0.37	-0.12%	-1.20
High	1965 - 1989	1.26%	3.67	1.28%	3.76	1.25%	3.70	1.17%	3.58
Low	1965 - 1989	1.40%	4.03	1.31%	3.82	1.28%	3.79	1.30%	3.92
High - Low	1965 - 1989	-0.14%	-1.27	-0.03%	-0.27	-0.03%	-0.35	-0.14%	-1.60
High	1990 - 1999	1.26%	3.22	1.31%	3.36	1.29%	3.43	1.25%	3.68
Low	1990 - 1999	1.36%	3.13	1.34%	3.23	1.35%	3.47	1.38%	4.16
High - Low	1990 - 1999	-0.10%	-0.49	-0.03%	-0.18	-0.06%	-0.38	-0.13%	-1.01

24 MONTH WINNERS (COUNT)

Portfolio	period	3 MONTH	T-STAT	6 MONTH	T-STAT	12 MONTH	T-STAT	24 MONTH	T-STAT
High	1927 - 1964	1.26%	3.05	1.25%	2.96	1.37%	3.15	1.58%	3.67
Low	1927 - 1964	1.48%	3.24	1.43%	3.13	1.54%	3.37	1.79%	3.96
High - Low	1927 - 1964	-0.22%	-1.43	-0.18%	-1.20	-0.17%	-1.22	-0.21%	-1.52
High	1965 - 1989	1.23%	3.66	1.23%	3.67	1.18%	3.56	1.12%	3.48
Low	1965 - 1989	1.46%	4.12	1.39%	3.97	1.36%	3.92	1.39%	4.11
High - Low	1965 - 1989	-0.23%	-1.84	-0.16%	-1.35	-0.18%	-1.62	-0.27%	-2.50
High	1990 - 1999	1.21%	3.08	1.23%	3.17	1.23%	3.22	1.23%	3.61
Low	1990 - 1999	1.58%	3.73	1.52%	3.71	1.47%	3.86	1.43%	4.34
High - Low	1990 - 1999	-0.37%	-1.91	-0.29%	-1.51	-0.25%	-1.42	-0.20%	-1.27

12 MONTH LOSERS (COUNT)

Portfolio	period	3 MONTH	T-STAT	6 MONTH	T-STAT	12 MONTH	T-STAT	24 MONTH	T-STAT
High	1927 - 1964	1.26%	3.03	1.18%	2.84	1.13%	2.68	1.42%	3.33
Low	1927 - 1964	1.49%	3.55	1.53%	3.60	1.46%	3.37	1.63%	3.65
High - Low	1927 - 1964	-0.24%	-2.61	-0.35%	-4.02	-0.32%	-4.24	-0.21%	-3.16
High	1965 - 1989	1.11%	3.07	1.04%	2.92	1.05%	3.00	1.11%	3.26
Low	1965 - 1989	1.51%	4.61	1.52%	4.66	1.46%	4.55	1.36%	4.37
High - Low	1965 - 1989	-0.40%	-4.42	-0.47%	-5.60	-0.41%	-5.55	-0.25%	-4.05
High	1990 - 1999	1.10%	2.32	1.08%	2.35	1.12%	2.57	1.20%	3.22
Low	1990 - 1999	1.60%	4.63	1.62%	4.74	1.54%	4.71	1.41%	4.79
High - Low	1990 - 1999	-0.50%	-2.76	-0.54%	-3.38	-0.42%	-3.05	-0.21%	-1.99

24 MONTH LOSERS (COUNT)

Portfolio	period	3 MONTH	T-STAT	6 MONTH	T-STAT	12 MONTH	T-STAT	24 MONTH	T-STAT
High	1927 - 1964	1.25%	2.92	1.18%	2.75	1.30%	3.00	1.60%	3.73
Low	1927 - 1964	1.52%	3.40	1.51%	3.31	1.59%	3.45	1.76%	3.89
High - Low	1927 - 1964	-0.27%	-2.53	-0.32%	-3.03	-0.29%	-2.87	-0.16%	-1.92
High	1965 - 1989	1.13%	3.05	1.09%	2.99	1.11%	3.09	1.16%	3.34
Low	1965 - 1989	1.51%	4.68	1.50%	4.68	1.43%	4.55	1.35%	4.39
High - Low	1965 - 1989	-0.39%	-4.10	-0.41%	-4.64	-0.32%	-3.87	-0.19%	-2.50

Table 20: Interactive effects via cross-sectional regressions.

This table presents the results of a linear regression of raw returns on momentum, consistency, volatility, skewness, and an interactive term. Momentum is measured as the buy and hold return of the stock during the prior K months. Positive (negative) consistency is measured as the number of positive (negative) returns on the stock during the prior K months. Volatility is the volatility of the stock during its entire history. Skewness is the skewness of the stock's returns during its entire history. K is measured differently for each panel. K = 6, 12 and 24 months, with K varying between panels. Also, the value of K is the same for the momentum and consistency measures in the same regression. The regressions are run cross-sectionally for every month from January, 1927 through December, 1999. The time-series of coefficients is then averaged and checked for significance. For each value of K, the regression is run twice: once with volatility and skewness included in the regression and again without volatility and skewness included in the regression. T-statistics are included as well.

Table 20: Interactive effects via cross-sectional regressions.

6 month positive consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
MODEL 1	0.756	7.91	-0.677	-1.61	-0.228	-5.98	.	.	.	
MODEL 2	0.694	9.02	-0.465	-1.46	-0.198	-7.36	0.010	0.70	0.120	3.79

12 month positive consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
MODEL 1	0.293	6.22	-0.376	-0.97	-0.081	-3.10	.	.	.	
MODEL 2	0.263	6.94	-0.292	-1.01	-0.053	-2.82	0.016	1.13	0.117	3.61

24 month positive consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
MODEL 1	0.150	6.43	-1.322	-3.85	-0.039	-2.08	.	.	.	
MODEL 2	0.131	6.84	-1.121	-4.17	-0.031	-2.10	0.012	0.86	0.109	3.33

6 month negative consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
Without volatility	-0.431	-4.64	0.023	7.07	0.101	3.37	.	.	.	.
With volatility	-0.367	-4.68	0.023	7.59	0.111	4.02	0.018	1.23	0.116	3.62

12 month negative consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
Without volatility	-0.157	-3.91	0.018	6.10	-0.044	-2.01	.	.	.	
With volatility	-0.129	-3.58	0.016	6.09	-0.044	-2.24	0.025	1.70	0.109	3.30

24 month negative consistency (count)

MODEL	INTERACTIVE	T-STATISTIC	MOMENTUM	T-STAT	CONSISTENCY	T-STAT	VOLATILITY	T-STAT	SKEWNESS	T-STAT
Without volatility	-0.062	-3.11	0.007	2.64	-0.057	-3.67	.	.	.	
With volatility	-0.048	-2.63	0.006	2.49	-0.044	-3.21	0.022	1.48	0.100	3.02

APPENDIX B

FIGURES

Figure 1: Characteristics of the share turnover variable.

The following three charts provide the autocorrelation, inverse autocorrelation and partial autocorrelation functions for the share turnover variable. NYSE/Amex (Nyseam) firms are presented, as well as Nasdaq (Nas) firms. Turnover is calculated as shares traded during the month, divided by shares outstanding. The variable being graphed is the cross-sectional mean for each variable across all firms in the CRSP universe.

Figure 1: Characteristics of the share turnover variable.

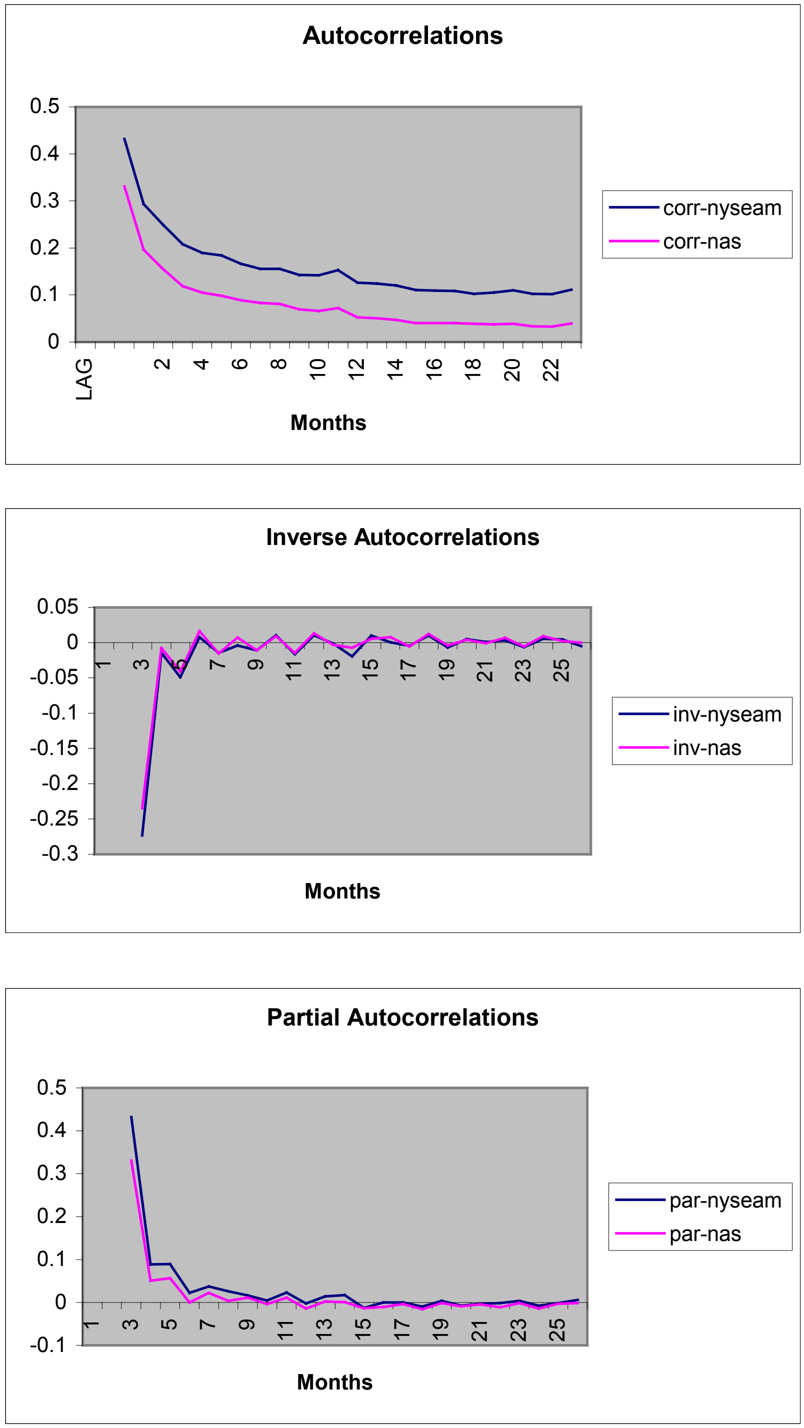

Figure 2: Characteristics of raw turnover growth.

The following three charts provide the autocorrelation, inverse autocorrelation and partial autocorrelation functions for the raw turnover growth variable. NYSE/Amex (Nyseam) firms are presented, as well as Nasdaq (Nas) firms. Turnover is calculated as shares traded during the month, divided by shares outstanding. The variable being graphed is the cross-sectional mean for each variable across all firms in the CRSP universe.

Figure 2: Characteristics of raw turnover growth.

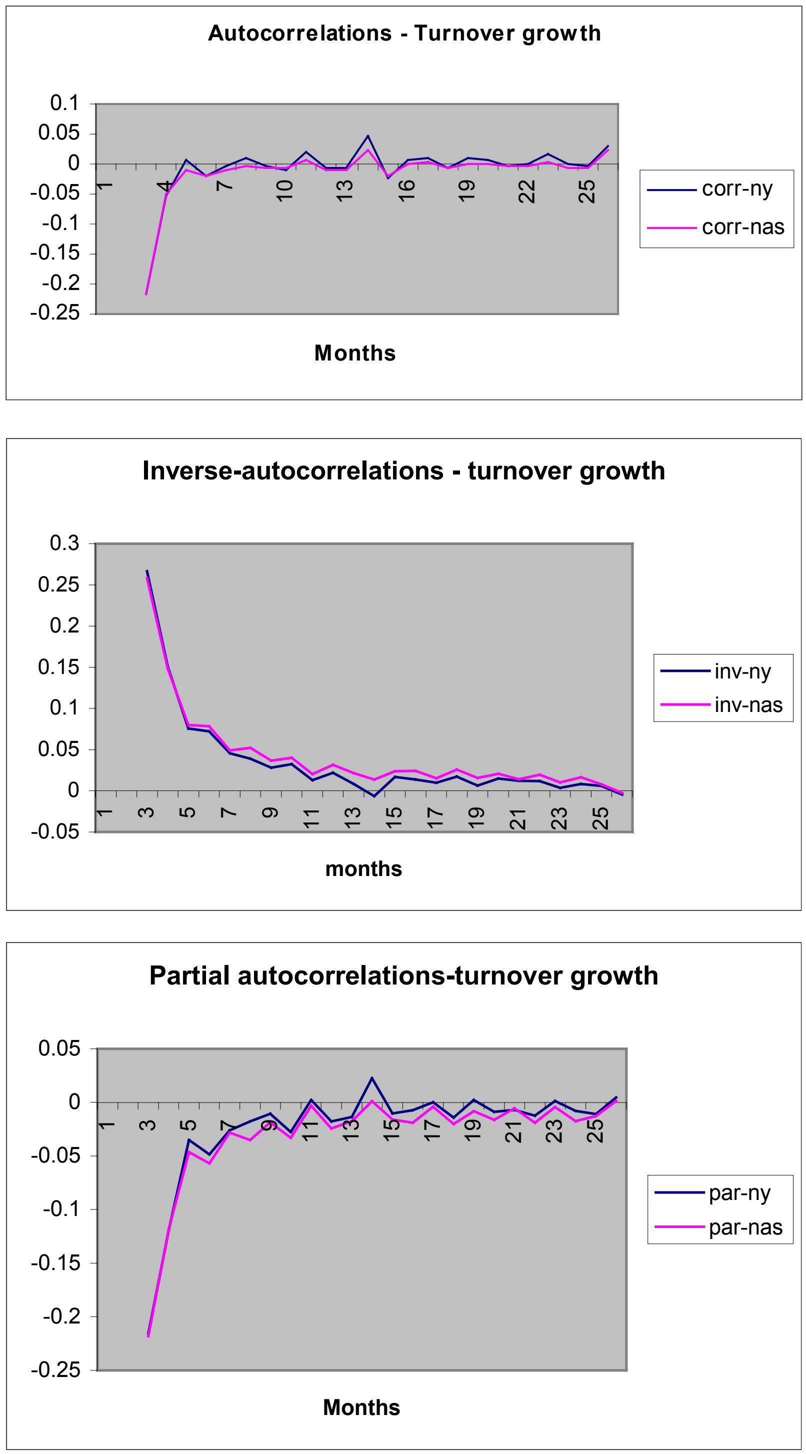

Figure 3: Long-horizon excess returns to the first moment of turnover growth.

This figure presents a chart of the intercepts in regressions of the excess returns of portfolios sorted on the first three moments of market-adjusted turnover growth on SMB, HML, MKT, as well as a momentum and share turnover factor. The regression is performed for NYSE/AMEX and Nasdaq stocks separately. For each month k, the one-month return for month t+k was regressed on the factor realizations for month t+k, producing the intercept that is charted below. The charts on the left plot the value of the intercept for 60 months, and the chart on the right plots the cumulative value of the intercept, interpreting the intercept as the risk-adjusted one-month return. The tests were done for all months from August, 1963 through December 1999. Figure 2a form portfolios based upon 12 month mean market adjusted turnover growth, figure 2b form portfolios based upon the standard deviation of 12 month market-adjusted turnover growth, and figure 2c form portfolios based upon the skewness of 12-month market-adjusted turnover growth.

Figure 3: Long-horizon excess returns to the first moment of turnover growth.

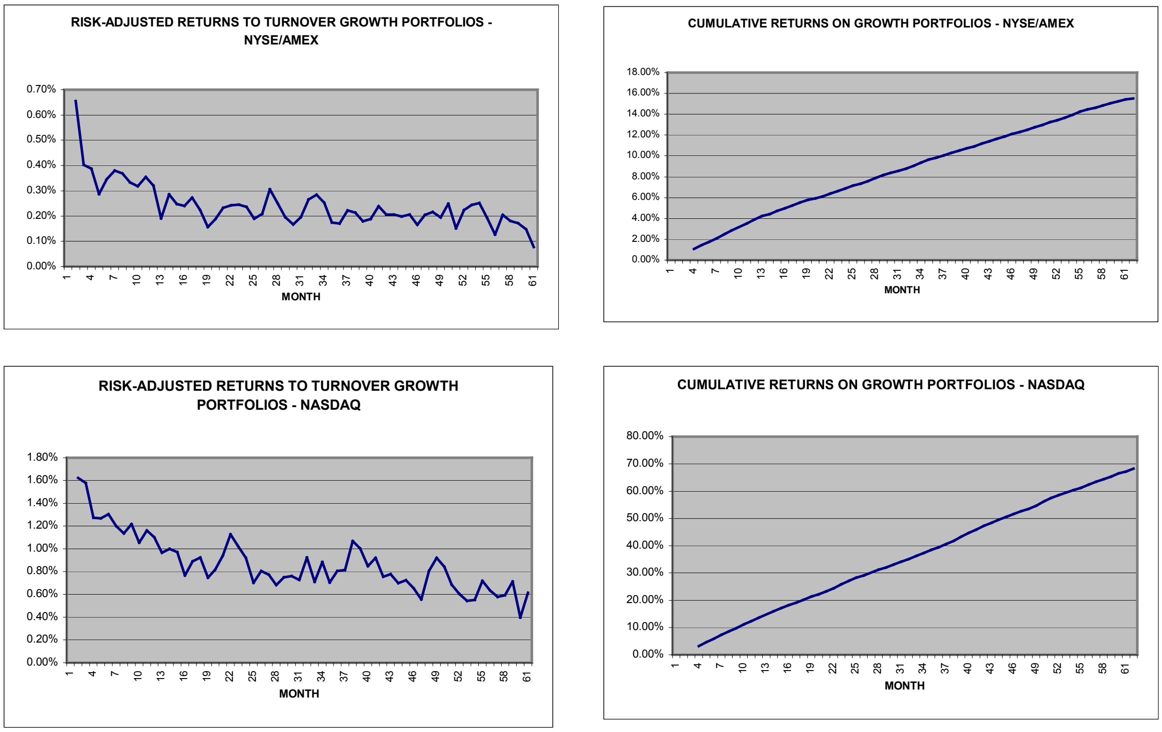

Figure 4: Long-horizon excess returns to the second moment of turnover growth.

This figure presents a chart of the intercepts in regressions of the excess returns of portfolios sorted on the first three moments of market-adjusted turnover growth on SMB, HML, MKT, as well as a momentum and share turnover factor. The regression is performed for NYSE/AMEX and Nasdaq stocks separately. For each month k, the one-month return for month t+k was regressed on the factor realizations for month t+k, producing the intercept that is charted below. The charts on the left plot the value of the intercept for 60 months, and the chart on the right plots the cumulative value of the intercept, interpreting the intercept as the risk-adjusted one-month return. The tests were done for all months from August, 1963 through December 1999. Figure 2a form portfolios based upon 12 month mean market adjusted turnover growth, figure 2b form portfolios based upon the standard deviation of 12 month market-adjusted turnover growth, and figure 2c form portfolios based upon the skewness of 12-month market-adjusted turnover growth.

Figure 4: Long-horizon excess returns to the second moment of turnover growth.

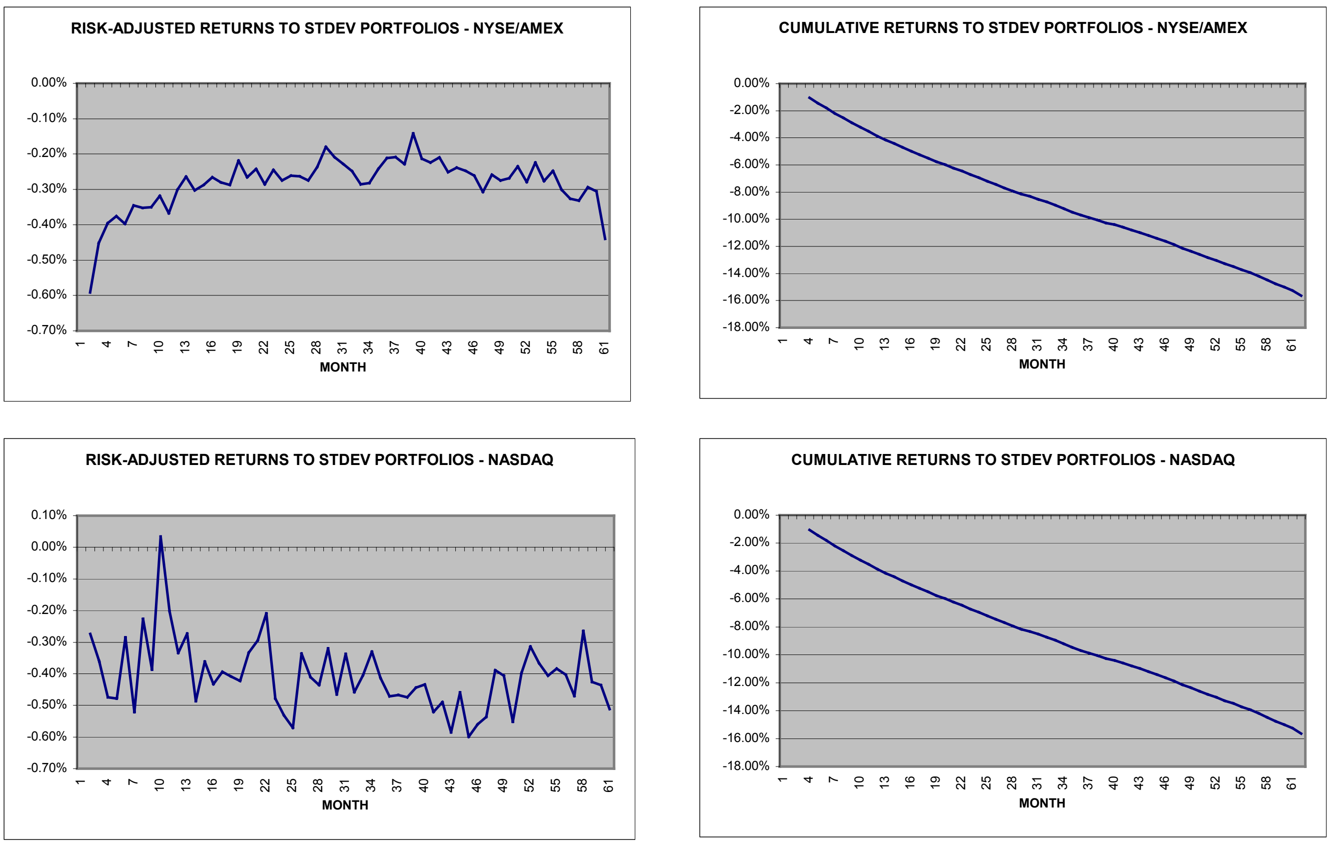

Figure 5: Long-horizon excess returns to the third moment of turnover growth.

This figure presents a chart of the intercepts in regressions of the excess returns of portfolios sorted on the first three moments of market-adjusted turnover growth on SMB, HML, MKT, as well as a momentum and share turnover factor. The regression is performed for NYSE/AMEX and Nasdaq stocks separately. For each month k, the one-month return for month t+k was regressed on the factor realizations for month t+k, producing the intercept that is charted below. The charts on the left plot the value of the intercept for 60 months, and the chart on the right plots the cumulative value of the intercept, interpreting the intercept as the risk-adjusted one-month return. The tests were done for all months from August, 1963 through December 1999. Figure 2a form portfolios based upon 12 month mean market adjusted turnover growth, figure 2b form portfolios based upon the standard deviation of 12 month market-adjusted turnover growth, and figure 2c form portfolios based upon the skewness of 12-month market-adjusted turnover growth.

Figure 5: Long horizon excess returns to the third moment of turnover growth.

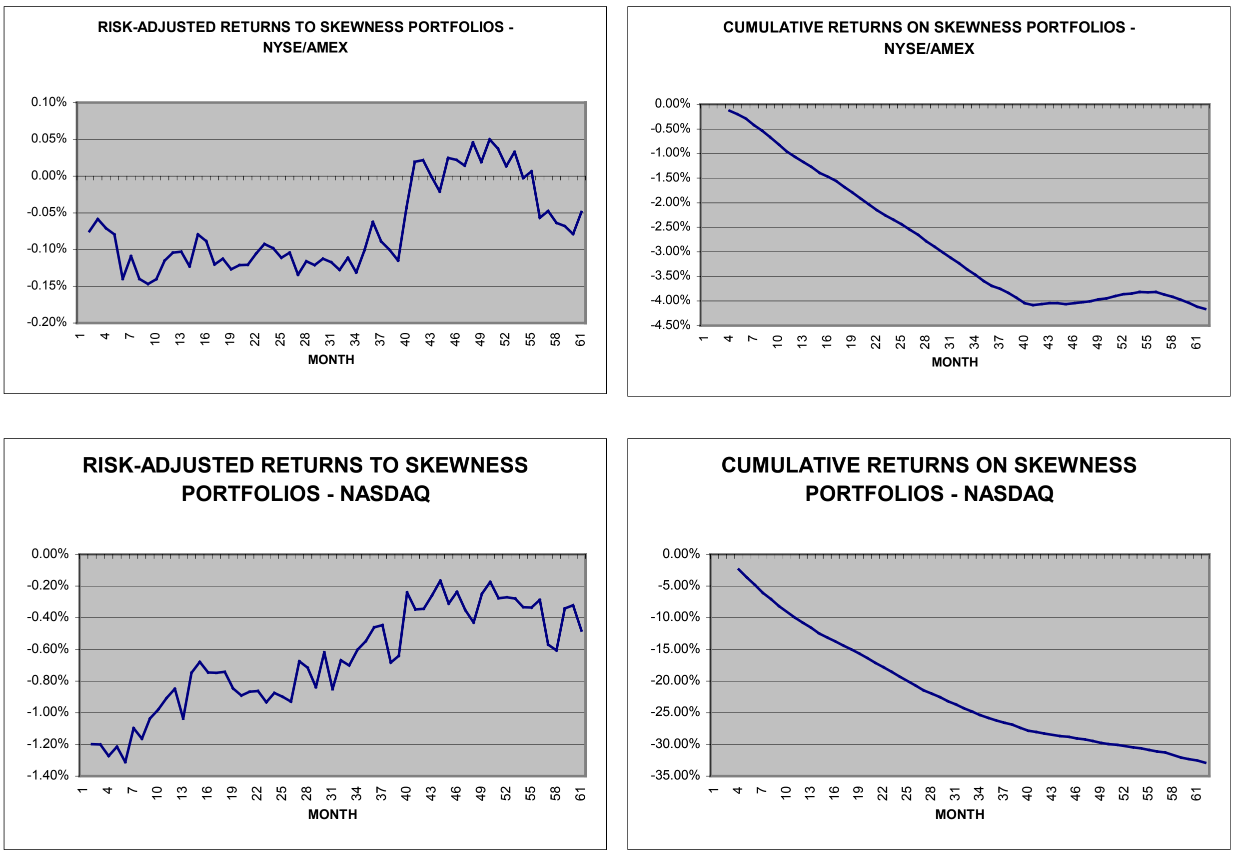

Figure 6: Three ways to characterize momentum.

This set of figures consists of the price series of three stocks over a given 6-month period. On the x-axis lies the given month after investment, and on the y-axis lies the price of the stock. The value on the Y-axis is simply the normalized price of the stock for the given month. These charts are designed to show multiple ways to characterize momentum.

Figure 6: Three ways to characterize momentum.