Style popularity and the comovement of stocks

Wouters, T.; Plantinga, A.

06E08

Style popularity and the comovement of stocks

T. Wouters* and A. Plantinga*

June 2006

Abstract

We examine to what extent the popularity of an investment style can be attributed to style investing. The style investing hypothesis predicts that assets in the same style show strong comovement with respect to their underlying fundamentals and that reclassifying assets into a new style raises its correlation with that style. We test this prediction by studying how comovement varies with proxies of popularity. We use different kinds of data, such as data on stocks, mutual funds, IPO's and financial analysts. We provide strong evidence that when popularity of a style is high investors base their demand for stocks on an individual stock level. We also find that style popularity is positively related to style performance. The evidence presented here challenges the view that investors base their asset allocation on a style level instead of an individual stock level.

JEL classification: G11, G12, G14

Keywords: Style investing; Comovement; Positive feedback trading

---

* University of Groningen, Faculty of Economics, P.O. Box 800, 9700 AV Groningen, The Netherlands. Tel. +31 50 363 3685. Tessa Wouters is the corresponding author, and can be contacted at t.i.m.wouters@dnb.nl.

1 Introduction

In this paper we link style investing to style popularity. Style investing has become an important issue for institutional as well as for private investors. Many institutional investors claim to follow a particular investment strategy, such as ‘value’ or ‘small-cap’. Investment strategies are often classified in terms of a specific style. A style can be defined as a classification of assets into a category based on common characteristics. Given frequent references to such categories in the media, it is likely that individual investors adopt and use this terminology for their own investing purposes. Meanwhile, the financial services industry has also responded to this terminology. For example, labels such as value and technology, are frequently used to reflect the objective of mutual funds. Barberis and Shleifer (2003) develop a model that explains the impact of style investing on financial markets and security valuation. They combine style-based portfolio selection with a mechanism how investors choose among styles. In the model there are two kind of investors, fundamental traders and switchers. The fundamental traders act as arbitrageurs that try to prevent the price of each asset to deviate too far from its fundamental value. The investment policy of switchers is determined by two distinctive characteristics. Firstly, switchers classify assets into categories where they give each category a label. In this way switchers try to simplify the information processing by making their decisions on a category level rather than an individual asset level. Secondly, the choice for a particular style is dependent on the relative past performance. Good fundamental news about the securities in a style is responsible for a style getting popular.

A consequence of style investing is the emergence of life cycles of investment styles. When a style had a good past performance relative to other styles, switchers allocate to that style and withdraw resources from other styles. If the style matures, good past performance is important to add new resources to a style. The style loses its popularity when bad news arrives or when arbitrage levels out excess returns. These investment cycles show close resemblance with the fashion cycles as described by Shiller (2000).

Barberis and Shleifer (2003) hypothesize that as a consequence of investors applying style investing, comovement in prices (and returns) of styles is induced. Cornell (2004) illustrates this with an example. He shows that labeling increases the chance for investors to make errors when they allocate funds at the level of categories. Companies with different business activities might be linked to the same category. He illustrates this with two Internet companies, Yahoo and Amazon. At the start of the internet bubble the correlation between the price changes of two stocks was low (0.10). After that, the correlation between the returns started to grow to more than 0.80, and stayed above the level of 0.70 for three quarters. At the end it decreased to 0.30. Looking at the fundamentals of both companies it was not clear why these two firms should be highly correlated. Cornell suggests that the temporary popularity of the label 'internet' has caused investors to temporarily consider the two stocks as equivalent investment opportunities. Kumar (2002) studies the relation between style-based investing and stock returns. He divides stocks into opposite styles, value versus growth and large versus small. He uses data on the portfolio composition of the clients from a large discount brokerage house in the US and recommendations of investment newsletters from Hulbert Financial Digest. He finds evidence that individual investors formulate their demands at a style level and re-allocate funds between styles on the basis of past relative performance as well as 'expert advice' from investment newsletters.

Pomorski (2004) examines the relation between mutual fund flows and style attractiveness. He finds that flows are positively related to past returns and negatively related to returns of competing styles. However, at the individual level the pattern disappears. If a fund does well when its style underperforms, the flow of that fund will be negatively related to the past performance of its style. The results support the hypothesis that investors evaluate fund managers both at a style-level and at a fund-level. We find that the popularity of stocks is stock-specific and not dependent on the investment style that the stocks belong to. In addition, we find a size-effect for stocks within styles that are not popular and no size-effect for the popular style stocks. When styles are less popular, the quintile with largest stocks has lower dispersion than the quintile with the smallest stocks. The evidence presented here challenges the view that investors base their asset allocation on a style level instead of an individual stock level. These results support the findings of Pomorski (2004) and contradict empirical work by Kumar (2002), Froot and Teo (2004), Cornell (2004) and Huang (2005). The style investing hypothesis implies that the inflow of resources should be positively related with style popularity. It is likely that style popularity is related to past returns. The representativeness heuristic (Kahneman and Tversky, 1974) implies that investors extrapolate past performance and therefore investors believe that styles that performed well in the past will continue to do that in the future. Popularity should therefore be positively related to past returns. Our findings confirm that popularity is related to good past performance. These results fit closely with the findings of Pomorski (2004),Kumar (2002), Froot and Teo (2004) and Huang (2005).

We also perform some robustness checks to show the life cycles of popularity (which can be compared to the life cycles described by Barberis and Shleifer, 2003). In addition, we perform a regression to test whether the movement in popularity of a particular style leads to comovement in returns between stocks in that style. Our findings show that an increase in popularity leads to a decrease in correlations in returns between stocks in the same style.

The rest of the paper is organized as follows: in the next section we discuss fashion in the context of investing. The reason is that popularity is closely related to fashion. First, popularity may be induced by fashion. Second, fashion and popularity both reflect the collective preferences of individuals and the changes of such preferences over time. In section 3 we describe several variables that measure popularity. In section 4 we present the methodology to form a popularity index and in section 5 we discuss the data and style description. In section 6, we interpret and discuss the results. This is followed with a robustness test in section 7. Finally, we provide concluding remarks in section 8.

2 Fashion

As mentioned in the previous section, the objective of this chapter is to investigate to what extent stock popularity can be attributed to style investing. Fashion may play an important role in the existence of stock popularity. Fashion can be defined as a collective preference that develops through social processes, where the need of identity and the social network are important determinants for market dynamics. In the absence of data on social interaction, fashion is closely related to popularity in the way that it both reflects the collective preferences of individuals and the changes of such preferences over time. In this section, we give a brief overview of fashion and show why it might be important for the decision-making process of investors.

Investing is described in the literature as a process of individuals who choose based on their own opinions about risk characteristics and their prospects of returns rather than on other people's opinion. Then it is less likely that investing should be vulnerable to fashions. However because fashions appear in many areas such as clothes, politics and health, it also is plausible that the fluctuations in fashion appear in the investment industry. The changes in attitude often occur widely in the population without any predictable reason. It is very plausible that fashions in investments also change spontaneously or as a social reaction to some event.

Although we may be inclined to view movements in fashion in cyclical terms, it is also possible to view fashion in terms of permanent changes in collective behavior. As argued by Veblen (1899), changes in fashion are the result of a dynamic social process, where individuals are looking for ways to distinguish themselves from the large majority where the large majority is trying to copy the distinct group of innovative individuals. In

Freeman's (1994) view, fashion has a productive side, since it facilitates a cheap way of introducing innovative productive behavior. In terms of the investment industry, a new innovative way of investing can be used by a small group of elite investors, who use this investment as status enhancing. After a while, others try to copy this strategy. Eventually, this leads to the adoption of an asset class by a large group of investors. A recent example of such a transmission of a new way of investing is the emergence of hedge funds. Hedge funds, in their early stages, were offered to a small minority of investors. The official (most quoted) starting point of hedge funds was in 1949. A. Jones started an equity fund that was organized to provide flexibility in constructing a portfolio (he took long and short positions and used leverage to enhance his performance). Many hedge funds perished during the market downturns, 1969-1970, and 1973-1974. After 1974, hedge funds lost their popularity until the mid-1980s. In 1980, there were 30 hedge funds with an asset value of $193 million. During the 1990s, hedge funds became more accessible to large groups of investors and the industry became more heterogeneous. In 1990, the number of hedge funds grew to 610 with an asset value of $38.9 billion. The last couple of years, regular fund houses start to offer hedge funds to the general public (Ineichen, 2002).

Fashion is strongly related to the adoption cycles described in the marketing literature for product innovations. Everett M. Rogers (1983) makes a distinction between the stages of innovators, early adopters, early majority, and late majority laggards. Rogers associates these adopter groups as differing in their value orientations. Innovators are interested to try new ideas. Early adopters value the respect gained by others for their innovative consumer behavior. The early majority is deliberate in the sense that they considered the innovation carefully before actually adopting it. The late majority is skeptic, and only adopts an innovation after others do. Laggards are conservative or traditional. According to the adoption and diffusion model of Rogers, a fashion cycle starts with a small group of innovators. The demand for the product is low with 2.5% consumers adopting the product. Successively, other individuals start to emulate the fashion leaders and demand for the product is increasing to 16% of the consumers as the fashion cycle progresses. In the next phase the number of consumers that buy the product has grown to 48%. This phase is called the early majority phase. At a certain time, the number of individuals that follows the style reaches a peak. The next 32.5% of the consumers belongs to the late majority. Finally, the last group adopting the style is the laggards, which is 16% of the consumers. In appendix 5A, table 5A.1 shows the different stages of a fashion cycle for internet stocks. It is difficult to recognize when the introduction phase begins, because the small group of fashion leaders is difficult to identify. At this stage, the stocks in the particular style will be neglected by almost all equity analysts. The emulation phase is identified by a growing number of individuals that start to imitate the fashion leaders. In this phase, the face-to-face communication of the individual with friends, family and peers is very important. Some analysts will mention the stocks within a certain style and start to cover them. The investment media (papers, television, internet) may, if attention is given to the style, speed the rate of diffusion. This will lead to the early majority and late majority phase, where the general public starts to follow that particular group of stocks and where analysts become very optimistic about these stocks. The result is that optimism increases, which leads to an inflow in that particular 'fashion' style and an outflow in the rest of the styles. Furthermore, the increase in optimism can be noticed by an increase in volume, turnover and volatility and a decrease in the bid-ask spread. As a result the autocorrelation of the returns of that style and the correlation among stocks within the particular style increases. The number of mutual funds that start in the style and the number of IPO's grow. Finally, the laggards' phase shows a decrease in optimism, which lead to an outflow of resources and an increase in the bid-ask spread.

Changes in fashion are related to the consumer adoption process. However, the emphasis with fashion is on the social approval of consumption behavior. This social approval is also associated with status. Buying fashion goods yields a status increase for the owner. However, the more people own the particular good, the smaller the status advantage of the particular good gets. Status wears out. Buying fashion goods is risky, since it may be difficult for an individual to make a correct assessment over its future status. An example of the riskiness of buying fashion stocks is the Internet hype. In the Internet bubble, investors tripped over themselves to buy stocks of the next hot internet company. It did not matter how much these companies lost or how awkward the operation activities were, if the name of the company included words like 'internet' or '.com' stock price increases were guaranteed. Cooper, Dimitrov and Rau (2001) show that during the internet hype a corporate name change into dotcom related internet names lead to positive announcement returns on the order of 74% in the ten days surrounding the announcement. However, the E-commerce was still in its infancy and had not developed very much. In 1998, the internet industry was characterized by red marks, which would have made traditional companies desperate, but investors seemed not to care. For example, Amazon.com made a loss of $125 million, but the market price of the shares became worth almost 18 times as much in 1.5 years time. From this example we can conclude that risk is not only in terms of losing money but also in terms of losing status. Investors are not only concerned about the final result, but also about what other people might think when they do not invest in such companies. It seems that the need of identity and the social network are just as well important determinants leading investment decisions.

A large part of the investment literature is based on herding, bubbles and fads. For example, Wermers (1999) investigates the degree in which portfolio managers of mutual funds herd in their trades. This study suggests that herding can result from momentum-following (e.g. buying past winners) or repeating the predominant buy or sell pattern from previous period. While this study tests whether 'too many' portfolio managers appear to make the same choices, it does not directly test the social interaction between portfolio managers. Why do people herd? Fashion could be an additional explanation that clarifies phenomena such as overreaction and underreaction, herding, momentum, etc.
The term fashion covers the three terms: bubbles, herding and fads. For example, bubbles and herding are part of the fashion cycle. Bubbles may start in the third stage of the fashion cycle when the mass starts to adopt the new style. Welch (2000) defines herding as behavior patterns that are correlated across individuals, which can lead to sub-optimal choices in the decision-making process. Many researchers examine the existence of herding in stock markets, but these studies neglect to explain the origin of herding. Reed (1992) compares fads with fashions. The difference between fashions and fads is that a fad has a rapid growth, which sinks into a rapid decline before it ever achieves maturity. In contrast, fashion has a slower growth phase and an observable period of maturity. A fad is a product, which satisfies the single utility of new experience. A fashion is more complex in the way that it satisfies a group with related desires. Fashions are not restricted to essential attributes of the product's design, but are subject to modifications. The effect is that fashions are not independent and isolated, but are consecutive and overlapping. The individual lifecycles of different fashions may be aggregated to one

life-cycle for the main product. For example, a mutual fund is the main product, which has several modifications based on different styles (internet fund, financial fund, etc.).

The analysis of stock markets in terms of fashion is a valuable addition to the behavioral finance theory. Most of the behavioral finance has focused on the investor's cognition and emotions. For example, Barberis, Shleifer and Vishny (1998) develop a model based on the representativeness and conservatism heuristics. It explains the over- and underreaction of investors to new information. Daniel, Hirshleifer and Subrahmanyam (1998) develop a model that is based on investor overconfidence and self-attribution. Their model intends to explain over –and underreaction of stock market prices. Barberis and Shleifer (2003) describe investment styles in terms of cycles, where the origin of the cycle is explained with the representativeness heuristic. In the literature of behavioral finance, social interactions have been (until recently) mostly ignored. To describe the investment process social interactions may be an important aspect to analyze, because social interactions may affect the investor's emotions and biases, and in doing so also investment decisions.

It is difficult to describe the stock market in terms of fashion (cycles), because it is complex to measure the interaction between investors in a social network directly. Without data on social interaction, it is not possible to investigate whether the preferences of individual investors change in the direction of the preferences of friends, families and relatives. Because the aim of this chapter is to investigate to what extent popularity can be attributed to style investing, the focus will be on collective preferences of investors rather than investigating social interaction directly. Since fashion is closely related to popularity in the way that it both reflects the collective preferences of individuals and the changes of such preferences over time, in the next sections, we will concentrate on variables that measure popularity.

3 Measures of style investing and style popularity

In the previous sections, we discussed style investing and its association with fashion cycles. In this section, we will develop a testable model of style investing and style popularity based on our previous discussion. The main focus is to measure to what extent the popularity can be attributed to style investing or to individual stocks in a particular style.

Following Barberis and Shleifer (2003), we define a style as a group of stocks that is classified based on a common characteristic. The process where investors allocate funds among groups of stocks rather than among individual securities is called style investing. This definition of style investing has a number of empirical predictions. When investors apply style investing they will not distinguish between stocks within a style. It may appear that fundamentally unrelated stocks are grouped in the same category, which leads to demand shocks across all stocks in the style. The demand shock across all stocks leads to a higher comovement in prices/returns than implied by their fundamentals. This has consequences for the correlation between stocks in the same style and the correlation between stocks in different styles. When a style becomes popular, the correlation between stocks in the same style will increase. Furthermore, fund inflow by one style drives resources out of competing styles, which leads to negative correlations in prices among styles. In addition, the presence of style switchers leads to positively autocorrelated returns in the short run and negatively autocorrelated returns in the long run. Good performance over the last period relative to other styles pushes the prices up again in the next period inducing positive autocorrelation. Eventually, the price is reversed in the long run inducing negative autocorrelation. The demand for stocks has also implications for the comovement in volumes and turnover ratios. Because stocks in the same style are regarded as the same kind of shares, the demand for these stocks will be equal. Consequently, when investors apply style investing, dispersion (defined as the cross-sectional standard deviation of the turnover ratio) will decrease. In summary, style investing should be reflected in the following measures (Barberis and Shleifer, 2003):

- autocorrelation of returns;
- correlation between stock returns in the same style;
- correlation between stock returns in different styles;
- cross-sectional standard deviation of the stocks' turnover ratios (dispersion);
- relation between past performance and in- and outflows of mutual funds.

Style popularity is based on collective preferences and social pressure, which influence the demand for groups of stocks. This demand-driven approach is potentially very useful to describe cycles in the stock market. Both style popularity and style investing are based on the demand for groups of stocks. However, the definition of style investing is very rigid and makes no distinction between stocks in the same style. Style popularity on the other hand may be based on the popularity of some stocks within a style. For example, style popularity predicts an increase in correlation between some stocks in the same style but this does not necessarily concern the correlations between all stocks in the same style. It is even possible to find some negative correlations between stocks in the same style. In case the popularity of some stocks in the same style increases, the turnover ratio for each asset in the same style will be different. This leads to higher dispersion. Style investing also predicts a positive correlation between the popularity of a style and past returns, resulting in in- and outflow of mutual funds. However, the popularity of a style may also be the result of other factors than past performance. For example, popularity may occur spontaneously or in arbitrary reaction to some widely noted events (Shiller, 2000)

In the next sections, we want to distinguish between the popularity of particular stocks and style investing. As described before, style popularity is based on collective preferences and social pressure, which influence the demand for groups of stocks. It is difficult to test style popularity explicitly, because the relation between the different variables can also be explained by increasing positive expectations about the prospects of a style's fundamentals in the future. Nonetheless, we can examine the collective style popularity, because if a style is popular, many investors and analysts will own or follow the stocks within the style. In the previous paragraph, we listed the measures that reflect style investing. In order to test to what extent popularity can be attributed to style investing, we first have to identify variables that reflect collective preferences for groups of stocks. The following aspects are relevant to describe popularity:

The IPO market is often viewed as a measure of investor enthusiasm. The volume of IPOs displays large variations over time. Shiller's (1990) hypothesis is that IPO markets are subject to fads that affect market prices. Ritter (1991) provides evidence concerning this hypothesis by showing a variation in underperformance year-to-year across industries, with companies that went public in high-volume years faring the worst. This is consistent with a scenario where firms go public when investors are (over)optimistic about the future potential of certain industries. We take the number of IPOs in a style as a measure for popularity.

The mutual fund industry has grown over the past two decades. Stocks under management have grown from 134.8 billion dollar at the end 1979 to 6.8 trillion dollars at the end of 1999 (http://www.sec.gov/news/studies/feestudy.htm). This is an increase of more than 4900%. The number of mutual funds increased from 276 in 1962 to 15644 in 1999, which is an increase of approximately 273% during this period. We take the number of mutual funds applying a specific style that start in a year as a measure of popularity for that particular style.

Liquidity variables can measure the demand of large groups of investors for particular stocks or styles. Baker and Stein (2004) developed a model where an increase in the

market liquidity such as lower bid-ask spreads and high turnover ratio's, may be an indicator for the increase in sentiment in the market. This theory suggests that when the participation of irrational investor increases the market will become more liquid, which results in an increase in volatility and the turnover ratio and a decrease in the bid-ask spread. Ofek and Richardson (2003) illustrate this empirically for the internet industry in the period from January 1998 to February 2000. During this period the turnover ratio and volatility were extremely high and bid-ask spreads were low. For example, the turnover ratio was three times higher for internet companies compared to non-internet companies. Based on the model of Baker and Stein and the empirical study of Ofek and Richardson we assume that liquidity may be a proxy for the sentiment in the market. Because irrational investors also drive fashions in the investment industry, liquidity measures may be good indicators to describe the popularity of stocks. Examples of liquidity measures are volume, turnover ratio, bid-ask spreads, and volatility. In times of mass investment in a particular style or market the turnover ratio will be high because the irrational investors dominate the rational investors. For the same reason should the turnover ratio be low in times when the style is out of fashion.

As described above, popularity is a process of adopters and imitators. Both are influenced by two means of communication: mouth-to-mouth and mass media. The media may speed the rate of diffusion of opinions among investors. Analyst recommendations are one of the media channels in the investment industry. Style attractiveness could be measured in terms of the coverage of analysts and the number of analysts' up- and downward revisions. The number of analysts' up- and downward revisions is a measure for analysts' sentiment. In the context of style popularity, the ratio of up- and downward revisions should vary positively with the style attractiveness. When analysts become more optimistic (pessimistic) about a particular style the number of analysts and the ratio of upward divided by downward revisions will increase (decrease).

In summary, number of IPO's and the number of mutual funds that start in a year, liquidity and communication channels can express style popularity. To distinguish between the popularity of particular stocks and style investing, the main focus in the next sections will be to test to what extent investors apply style investing. Firstly, we generate a popularity index by using the principal component analysis. Secondly, we test with a regression analysis whether popularity is based on a style level or on an individual stock level. We use the cross-sectional standard deviation of the turnover ratio as proxy for style. If a style becomes popular, the dispersion in the turnover ratio will become lower.

In addition, we test whether the popularity of investment styles is related to past performance. Finally, we make some robustness checks where we first show the movement of popularity through time and then test whether the movement in popularity of investment styles leads to co-movement in prices/returns.

4 Methodology

In this section we describe the methodology used to test whether popularity of stocks takes place on a style or an individual level. The variables that measure style popularity is explained in section 4.1 and in section 4.2 the dispersion measure is described. In section 4.3 we explain the model we use to test whether dispersions are significantly lower than average during periods of style popularity.

4.1 Style popularity measures

In section 3 we described different variables that reflect the popularity of investment styles and stocks. According to our hypothesis the following variables measure popularity:

- number of IPOs ($Nipo_{X,t}$);
- number of mutual funds that start in a year ($Nmf_{X,t}$);
- turnover ratio ($Turn_{X,t}$);
- bid-ask spread ($Spread_{X,t}$);
- analyst optimism ($Updn_{X,t}$);
- analyst coverage ($Analyst_{X,t}$).

The number of IPOs is the number of IPOs in the specific style (X) in period t. The number of mutual funds is the number of funds applying the style under consideration that start in period t. The turnover ratio is the average daily turnover of all stocks within a style and is defined as the volume divided by the number of outstanding shares. The bid-ask spread is the average of daily spreads in a month for each stock in a style. The spread is the difference between the ask and bid price divided by the mid price. To measure style popularity among analysts, we use analyst coverage and analyst optimism. For analyst optimism, we use the number of upward revisions divided by the number of downward revisions for all stocks in style X at time t:

$$Updn_{X,t} = \frac{\sum_{i=1,t} UP_{X,t}}{\sum_{i=1,t} DOWN_{X,t}}, \tag{1}$$

where $UP_{X,t}$ is the number of upgrades and $DOWN_{X,t}$ is the number of downgrades for all stocks in style X during period t. For each period we express analysts' coverage as the log of the number of different analysts that cover style X at time t.

With the six variables described above we create the following popularity index:

$$\begin{aligned} P_{X,t} = {} & b_0 Nipo_{X,t} + b_2 Nmf_{X,t} + b_3 Turn_{X,t-1} + b_4 Spread_{X,t-1} + \\ & b_5 Updn_{X,t} + b_6 Analyst_{X,t-1} \end{aligned}, \tag{2}$$

where $P_{X,t}$ is the level of popularity for style X for a given period t. The coefficients of the popularity index are obtained using a principal component analysis. This analysis composites an index based on variables that capture a common factor (see section 6.1 for a further explanation). The unit of time is measured in terms of months. The number of mutual funds that start in a period is based on annual data. Therefore, for each month in a specific year the number of mutual funds is the same.

4.2 Dispersion measure: stock or style popularity

We follow the same methodology of Christie and Huang (1995) to test to what extent stock popularity can be attributed to style investing. We use the dispersion of the turnover ratio as proxy for style investing. If all stocks within a style become popular within the same period, the turnover ratio of stocks within a style will commove to each other. This will lead to a decrease in dispersion of the turnover ratio. The cross standard deviation of the turnover ratio is:

$$\sigma_{X,t} = \sqrt{\frac{\sum_{i=1}^{n} \left(Turn_i - \overline{Turn}\right)^2}{n-1}} , \tag{3}$$

where $Turn_i$ is the observed turnover ratio of stock i and $\overline{Turn}$ is the cross-sectional average of the n turnovers in a style. $\sigma_{X,t}$ is an indicator of dispersion of stock popularity across the style category, i.e. a decrease of $\sigma_{X,t}$ means more "uniform" popularity.

4.3 Regression model

With the following regression we want to test to what extent investors apply style investing. During abnormal levels of popularity, style investing is likely to be more pronounced. Specifically, style investing suggests that securities (belonging to that style) do not differ in their sensitivity to popularity and therefore it predicts that periods of high popularity induce decreased levels of dispersion. In contrast style popularity translates into an increased level of dispersion. To differentiate between the two hypothesis, we isolate the level of dispersion, $\sigma_{X,t}$, in the extreme tail of the distribution of popularity and test whether it differs significantly from the average levels of dispersion that exclude the extreme level of popularity. To test the style investing hypothesis we perform the following regression:

$$\sigma_{X,t} = a + b_1 P_{X,t} + \varepsilon_{X,t}, \tag{4}$$

where $P_{X,t}$ is the extreme level of popularity for style X. We use a dummy for the level of extreme popularity ($\overline{P_X} + \sigma_{p_X}$). We adopt this criterion for extreme levels of popularity because extreme levels of popularity are arbitrary. The dummy is one if the level of popularity in month t lies in the extreme tail of the popularity and zero otherwise. The a coefficient denotes the average dispersion of the sample excluding the region covered by a dummy variable for extreme levels of popularity. For each variable in this regression we determine whether they are stationary. If necessary, we take the first difference of the variables in this regression to obtain stationary series. If investors apply style investing, an increase in popularity of a style will lead to a lower level of dispersion. This implies that style investing predicts a significantly negative coefficient for b_1. If investors differentiate between stocks within the style, an increase in stock popularity will lead to an increase in the level of dispersion. Therefore, positive estimates for b_1 would be consistent with popularity on an individual stock level.

5 Data

To test whether a style becomes popular we try to find independent measures that can be used to label a style or sector. Examples of style dimensions are value/growth, small/large capitalization, industries and global regions. We have chosen to study eleven different industries. We have not chosen to study value and growth styles, because value and growth are defined using market variables. The stocks that are labeled as growth in one year will not necessarily be growth stocks in the next year. Styles based on industries or countries do not experience such difficulties, because for example a technology stock is labeled as technology and continues to be a technology stock in future, unless the nature of the firms operations changes due to acquisitions. We sort stocks into industries based on SIC codes using the 12 industry portfolio classification form French's data library on the internet[1]. We use the list composed by Morgan Stanley[2] with pure internet-related companies to form an internet portfolio.

In our study, we include all NYSE, AMEX and NASDAQ stocks for the period 1982 to 2004. Real estate investment trusts (REITs), American Depository Receipts (ADRs), closed end mutual funds, foreign stocks, unit investment trusts and Americus trusts are excluded from our sample. We use the returns of the CRSP database and the accounting data of COMPUSTAT. We use CRSP to collect daily bid and ask prices and monthly data for SIC codes, market capitalization, returns, and volume trading. We use I/B/E/S to obtain the number of up- and downward revisions and the number of analysts that cover a particular style. We take the number of IPOs in a given month from Bloomberg.

The mutual fund data is extracted from the CRSP Survivor-Bias Free US Mutual Fund Database. There are two different types of style-related objective codes in the CRSP database for the post-1991 period: the ICDI Fund Objective Codes and the Strategic Insight Objective Codes. We selected funds that only invest in US stocks. Each fund must have at least 70% of common stocks. For each industry we found mutual funds that invest in equity shares of companies engaged in that particular industry. For the health, financial, technology, energy and utility industry mutual funds exist that explicitly invest

[1] http://www.mba.tuck.darthmouth.edu/pages/faculty/ken.french/

[2] http://www.morganstanley.com/institutional/research/research_reports.html?page=research).

in stocks of that particular industry. For the manufacturing, retail, chemicals and consumer (non-)durable good industries we use the ICDI and SI objective codes. Because both the ICDI and SI objective codes do not distinguish between internet telecom and technology, we subdivide the mutual funds with the objective technology into internet, telecom and technology. We subdivide funds into name-based categories, which is in line with the idea that investors base there asset allocation on categories to make the choice easier. We assume that investors infer from the name of a mutual fund the objective of the mutual fund. Mutual funds with the following words in the name are defined as internet funds: Internet, NetNet, Wireless and www. For telecom funds we use the word telecommunication. We use the internet to verify whether the objective of each fund is in line with the labels we chose.

6 Results

In section 3 and 4 we described a couple measures that reflect popularity. Table 1 shows some descriptive statistics over the period 1983 to 2004. The sample contains 276 months (*N*).

Table 1: Descriptive statistics (1983-2004)

N is the number of months that is included in our sample. $Nipo_t$ is the number of IPO's in a month. Nmf_t is the average number of mutual funds that start in a month. $Turn_{t-1}$ is the log of the turnover ratio. $Spread_{t-1}$ is the average bid-ask spread. $Updn_{t-1}$ is the number of upward revisions against the number of downward revisions and $analysts_t$ is the log of number of analysts that cover the market in a month.

	N	*Mean*	*Std. Deviation*
$Nipo_t$	276	13	12
Nmf_t	276	66	81
$Turn_{t-1}$ *(log)*	276	0.894	0.204
$Spread_{t-1}$	276	5.955	1.343
$Updn_{t-1}$	276	0.767	0.325
$Analysts_t$ *(log)*	276	3.125	0.100

The number of IPOs is the number of IPOs in the respective sectors or styles in a month. The average number of IPOs in a month during this period was 13. The average number of mutual funds that started in a month was 66. The bid-ask spread is the average of daily spreads in a month for each stock in a style. The spread is the difference of the bid- and ask price divided by the mid price. The average bid-ask spread is 5.96%. The turnover ratio is the average monthly turnover and is defined as the volume divided by the number of outstanding shares. The average monthly turnover (log) was 0.89.The average number of analysts per stock on the US stock market during 1983 and 2003 was 3.125.

Table 2 shows the monthly summary statistics for every industry over the period January 1983 to December 2004. The average turnover ratio is 1.157 for the business sector and 0.933 for the health sector. The average number of mutual funds that start in the business sector is 18 compared to 55 for the health sector. Also the number of analysts that cover both sectors is high. Utility and the chemical sector were not very popular during this period. The turnover was the lowest with 0.731 and 0.162, respectively. Furthermore, the number of IPOs was on average zero and the number of analysts that covered the sectors was the lowest. In the next section we test whether popularity is focused on a style or individual stock level. Before we test the style investing hypothesis, we first present our findings for the average popularity of each investment style.

Table 2: Descriptive popularity statistics for each sector over the period 1983 to 2004

N is the number of months that is included in our sample. $Nipo_t$ is the number of IPO's in a month. Nmf_t is the average number of mutual funds that start in a month. $Turn_{t-1}$ is the log of the turnover ratio. $Spread_{t-1}$ is the average bid-ask spread. $Updn_{t-1}$ is the number of upward revisions against the number of downward revisions and $analysts_t$ is the log of number of analysts that cover the market in a month. P_t is the average standardized popularity. The average popularity for the Internet sector is over the period 1993 to 2004.

Industries	IPO_t	Nmf_t	$Turn_{t-1}$	$Spread_{t-1}$	$Updn_{t-1}$	$Analysts_t$	P_t
Manufacturing	0	0	1.871	5.233	74.612	5.944	0.358
Consumer durables	0	0	1.881	5.015	86.119	4.799	0.378
Consumer non durables	1	1	1.863	5.026	76.713	5.312	0.437
Financials	2	6	1.622	4.703	94.167	5.731	0.459
Health	3	55	2.352	7.049	84.871	5.392	0.436
Telecom	1	1	2.181	5.863	75.807	4.774	0.413
Utility	0	8	1.487	2.133	91.152	4.597	0.375
Business	3	18	2.513	7.398	82.043	6.241	0.410
Wholesale	0	0	1.854	4.867	81.479	5.882	0.443
Chemicals	2	1	2.134	6.016	84.666	4.752	0.299
Energy	1	6	1.799	8.671	108.942	4.898	0.461
Internet	3	5	3.429	6.975	315.714	1.368	0.682

6.1 Popularity index

Following the procedure of section 4.1 the level of popularity is created by making an index of the different popularity measures described in section 3. The procedure is as follows. The model is estimated by using first principal component analysis. The first principal component of the six variables with their lags is estimated[3]. This gives a first-stage index with twelve loadings, one for each of the current and lagged variables. We then compute the popularity index with six variables, lead or lag, based on the Kaiser-Meyer-Olkin measure (the one which gives the highest value). This leads to the following the coefficients of our popularity index (cf. section 4.1):

$$\begin{aligned} P_{X,t} = 0.110 Nipo_{X,t} + 0.234 Nmf_{X,t} + 0.295 Turn_{X,t-1} - 0.212 Spread_{X,t-1} + \\ 0.211 Updn_{X,t-1} + 0.286 Analyst_{X,t} \end{aligned}, \tag{5}$$

where $Nipo_t$ is the number of IPO's in a month, Nmf_t is the number of mutual funds that start in a year, $Turn_{t-1}$ is the log of the monthly turnover ratio, $Spread_{t-1}$ is the average monthly bid-ask spread, $Updn_{t-1}$ is the number of upward revisions divided by the number of downward revisions in the given month for all stocks in style X and $Analyst_t$ is the log of number of analysts that cover a sector in a particular month. Table4 presents the Kaiser-Meyer-Olkin measure, which is 0.710, meaning that the principal component analysis gives useful results (if the value is above 0.60, the factors extracted will account for a fare amount of variance). Moreover, Bartlett's test of sphericity is significant, indicating a good fit. This is confirmed by the correlation matrix in table 3, which shows that most of the correlations between the variables are statistically significant at a 1% level. Table 5 shows that the first principal component explains 51.3% of the standardized sample variance, and only the first eigenvalue is above 1.00. Figure 1 confirms that only one factor captures the common variance. The correlation between the twelve-term first stage index and the Popularity index is 0.99, suggesting that little information is lost in dropping six terms.

[3] Other variables such as inflow and outflow of mutual funds and number of stopped analysts reduced the Kaiser-Meyer-Olkin measure.

Table 3: Correlation scheme for variables

	$NIPO_t$	Nmf_{t-1}	$Turn_{t-1}$	$Spread_{t-1}$	$Analysts_t$	$Updn_{t-1}$	P_t
$NIPO_t$	1						
Nmf_t	.208(**)	1					
$Turnover_{t-1}$ *(log)*	.304(**)	.609(**)	1				
$Spread_{t-1}$	-.229(**)	-.154(**)	-.550(**)	1			
$Analysts_t$ *(log)*	.170	.613(**)	.812(**)	-.470(**)	1		
$Updn_{t-1}$	.0.07(*)	.364(**)	.414(**)	-.386(**)	.487(**)	1	
P_t	.338(**)	.721(**)	.907(**)	-.651(**)	.880(**)	.650(**)	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4: Kaiser-Meyer-Olkin measure and Bartlett's Test of sphericity

Kaiser-Meyer-Olkin measure tests whether the partial correlations among variables is small. Bartlett's test of sphericity tests whether the correlation matrix is an identity matrix which would indicate that the factor model is inappropriate. The *df* is the number of degrees of freedom and Sig. is the probability value which measures whether the value is statistically significant.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.710
Bartlett's Test of Sphericity	Approx. Chi-Square	684.090
	df	15
	Sig.	.000

Figure 1: Scree plot

A scree plot is a graphical method where the eigenvalues are plotted against the component number.

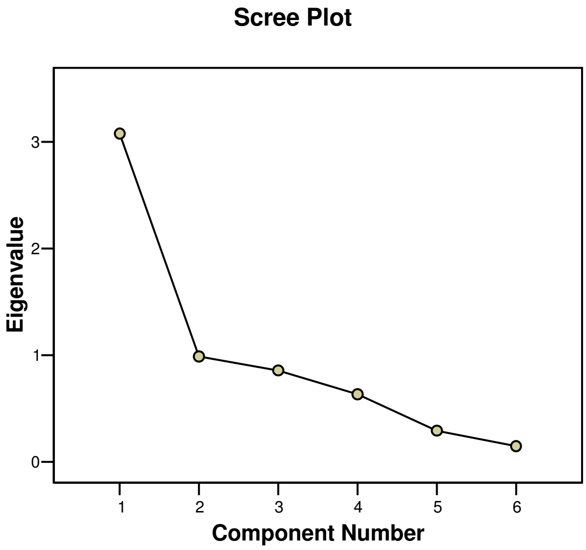

Table 5: Total Variance Explained

This table presents the results form the principal component analysis. The variances extracted by the factors are called the *eigenvalues*. The first column (Total) contains the *Eigenvalue*s. It shows the total variance that is extracted by each factor. The second column (% of Variance) contains the percent of total variance accounted for by each factor. The third column (Cumulative %) contains the cumulative variance extracted for the current and preceding factors.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.077	51.287	51.287	3.077	51.287	51.287
2	.989	16.477	67.764			
3	.858	14.294	82.058			
4	.635	10.579	92.637			
5	.293	4.888	97.525			
6	.148	2.475	100.000			

Extraction Method: Principal Component Analysis.

The coefficients in equation 5 are intuitively appealing. Firstly, the variables have the expected sign. As expected, the variables (except for bid-ask spreads) show a positive relation with popularity. As one of these variables increases, the level of popularity tends to increase as well. If the level of popularity of a style or stock increases, the bid-ask spread will also decrease. Secondly, the proxies enter with the expected timing. Investor behavior such as liquidity leads to firm supply variables. More generally, proxies that involve firm supply responses ($Nipo_t$ and Nmf_t) are likely to lag proxies that are based on investor demand ($Spread_{t-1}$ and $Turn_{t-1}$). In addition, the timing of the variable $Updn_{t-1}$ and $Analyst_t$ suggests that a fraction of analysts have to become optimistic before more analysts start to cover a sector or stock.

The coefficients obtained from this model are used to calculate a popularity index for each individual sector. For each sector the obtained popularity index will be regressed against the dispersion variable.

6.2 Popularity at a style or stock level

Using equation 5, we obtain a popularity index for each sector. Table 5 (column right-hand side) shows the average monthly popularity index for every industry over the period January 1983 to December 2004. The average popularity is the highest for the financial and internet sector with 0.459 and 0.682, respectively. The manufacturing and the chemical sector have the lowest average popularity with 0.358 and 0.299, respectively. These values conceal the cyclical nature of popularity (which can be compared to the fashion cycles mentioned in section 2). In section 7.1, we will further investigate the movement in popularity for each sector through time.

When investors apply style investing there should be a negative relation between style popularity and the cross standard deviation of the turnover ratios. The turnover ratios of all stocks in the same style should comove, which lead to a decrease in the standard deviation of the stocks' turnover ratios. Table 6 provides the average level of turnover dispersion for each sector. The average level of turnover dispersion is 17.9 percent a month across all stocks. Across the industries, the level of turnover dispersion ranges from a low of 4.0 percent for utilities to 19 percent for business sector in the period 1983 to 2004. Although, we show averages for popularity and dispersion, it seems that there is a positive relation between style popularity and dispersion.

Table 6: Dispersion in turnover ratios over period 1983 to 2004

Dispersion is the cross standard deviation of the turnover ratio. The average dispersion for the Internet sector is over the period 1993 to 2004.

Industries	Dispersion
All stocks	17.900
Manufacturing	11.412
Consumer durables	8.038
Consumer non durables	9.741
Financials	9.180
Health	15.039
Telecom	15.152
Utility	3.981
Business	19.340
Wholesale	14.082
Chemicals	8.084
Energy	8.859
Internet	35.075

Equation 4 was estimated using the coefficients obtained from the first principal component analysis (equation 5). Table 7 provides the regression estimates across industries over the period 1983 to 2004. Under the dispersion in turnover ratio as a dependent variable, the coefficient estimates are reliable and uniformly positive. Therefore, the popularity of stocks cannot be attributed to style investing. The sectors financials and energy, which have the highest popularity during this period, exhibit positive coefficients. The business sector has the highest average dispersion after excluding the region by the dummy variable (as indicated by the constant). The utility sector exhibits the lowest dispersion during this period and has a very low coefficient. The results show that the popular sectors have the highest dispersion and positive coefficients. This suggests that popularity is on an individual stock level instead of a style level.

Table 7: Regression analysis with as independent variable dispersion in turnover over period 1983 to 2004

The independent variable is a dummy for extreme movements in popularity. If necessary, we take the first difference of the variables to obtain stationary series. It is one when the value is above mean+standard deviation and otherwise zero. The dependent variable is the standard deviation of the turnover ratio. The detrended levels are obtained by taking the first difference. Newey-west is used to adjust the *t*-statistics for heteroskedasticity and autocorrelation.

Industries	constant	b_1	t(constant)	$t(b_1)$	adj. R^2
Manufacturing	0.098	0.081	13.952	2.596	0.100
Consumer durables	0.077	0.027	21.319	3.838	0.056
Consumer non durables	0.090	0.063	16.525	3.873	0.116
Financials	0.083	0.049	9.093	2.330	0.024
Health	0.135	0.093	14.195	5.097	0.103
Telecom	0.112	0.223	13.001	3.611	0.165
Utility	0.039	0.014	19.138	3.417	0.062
Business	0.168	0.199	12.354	5.891	0.171
Wholesale	0.118	0.145	11.777	3.822	0.113
Chemicals	0.078	0.014	19.639	1.519	0.019
Energy	0.080	0.045	8.068	4.407	0.026
			Detrended levels		
Financials	0.084	0.042	13.196	1.174	0.018
Health	0.148	0.028	12.806	2.243	0.006
Business	0.194	0.039	9.749	2.002	0.006
Energy	0.086	0.015	9.039	1.630	0.002

To show that the results are not dependent on the period we chose, we also perform regressions over the period 1992 to 2004. Table 8 presents the outcomes of the regression. The results are consistent with the results of table 7. The coefficient estimate for the internet sector is negative, which implies that the popularity can be attributed to style investing. However, the heteroskedasticity consistent *t*-statistics shows that this result is not reliable.

When we use the full sample period, we find that the popularity index shows non stationary series for the financial, health, business and energy sector. When we either restrict the sample period to the 1992-2004 period or detrend the data, the relationship between the level of (detrended) popularity and the level of dispersion is still positive. Although the coefficients are still positive and the two out of four coefficients are statistically significant, detrending makes a considerable difference in the explanatory power. The adjusted R-squares of these regressions range from 0.002 to 0.018, which is lower than the adjusted R-squares of the regressions without detrending, which ranges from 0.024 to 0.171.

To summarize, our findings show that the level of dispersion is high when popular is high, which indicates that popularity is stock specific and not style-specific.

Table 8: Regression analysis with as independent variable dispersion in turnover over the period 1992 to 2004

The independent variable is a dummy for extreme movements in popularity. If necessary we take the first difference of the variables to obtain stationary series. It is one when the value is above mean+standard deviation and otherwise zero. The dependent variable is the standard deviation of the turnover ratio. Newey-west is used to adjust the t-statistics for heteroskedasticity and autocorrelation.

Industries:	constant	b_1	t(constant)	$t(b_1)$	adj. R^2
Manufacturing	0.131	0.074	13.221	2.190	0.084
Consumer durables	0.088	0.018	18.951	2.393	0.035
Consumer non durables	0.116	0.038	14.927	2.218	0.051
Financials	0.088	0.044	23.902	2.296	0.121
Health	0.180	0.048	12.631	2.599	0.032
Telecom	0.166	0.169	15.679	2.730	0.092
Utility	0.041	0.010	12.983	2.425	0.038
Business	0.246	0.121	13.474	3.779	0.079
Wholesale	0.164	0.099	10.178	2.511	0.053
Chemicals	0.093	0.000	17.907	0.014	0.000
Energy	0.113	0.012	6.318	0.714	0.002
Internet	0.369	-0.080	14.115	1.389	0.015

To detect size-effects in the dispersion of stocks within a style, we divide stocks into quintiles and run the regression again for each size-group within the sectors. Table 9 show the effect of size conditional on dispersion. We find a size-effect for most of the less popular industries. Sectors like consumer durables, chemicals, and utility show from small-size to the large-size a pattern of decreasing coefficients. When one of these sectors becomes more popular, the demand for large caps will increase. This results in a lower dispersion in turnover. For the popular sectors, financials and health, we cannot find size-effects. If one of these styles is popular, dispersion will be high independent of size. For the internet sector, we perform the regression over the period 1998 to 2004. The reason is that the internet sector has its origin in 1992 and, therefore, has a small number of stocks over the period 1992 to 1997. The results for the internet sector show from small-size to the large-size a pattern of increasing coefficients. This implies that when this sector becomes more popular, the demand for small caps increases, resulting in a lower level of dispersion. The low number of stocks in some of the quintiles may influence the results in the way that one stock may have a larger impact on the outcome. Therefore, we also divide stocks into three size portfolios (30%-40%-30%) and perform the same regression. We find similar results as is shown in table 9.

Table 9: regression analysis: industries divided into size quintiles over period 1983 to 2004

For each sector we form quintiles on market capitalization. Market capitalization is calculated at the end of each year and equals the number of shares outstanding times its market price. The independent variable is a dummy for extreme movements in popularity. It is one when the value is above mean+standard deviation and otherwise zero. The dependent variable is the standard deviation of the turnover ratio. In panel B, we take the first difference of the variables to obtain stationary series. For the internet sector, we perform the regression over the period 1998 to 2004. Number is the average number of stocks in each size portfolio. Newey-west is used to adjust the *t*-statistics for heteroskedasticity and autocorrelation.

Panel A: Levels

Industries:		number	constant	b_1	t(constant)	$t(b_1)$	adj. R^2
Manufacturing	small	317	0.087	0.051	11.534	2.289	0.037
	s2	91	0.090	0.045	17.748	3.732	0.119
	s3	56	0.115	0.183	10.089	2.122	0.119
	s4	48	0.078	0.042	12.094	3.452	0.080
	large	32	0.076	0.025	10.776	2.445	0.025
Consumer durables	small	40	0.074	0.023	20.428	2.499	0.037
	s2	8	0.070	0.031	11.912	2.128	0.033
	s3	5	0.058	0.020	9.002	1.576	0.007
	s4	4	0.040	-0.011	9.361	-2.116	0.008
	large	4	0.035	0.006	15.766	1.741	0.013
Consumer non durables	small	167	0.086	0.087	13.426	3.715	0.135
	s2	39	0.099	0.018	15.237	1.408	0.012
	s3	31	0.073	0.028	20.612	3.730	0.077
	s4	24	0.055	0.010	22.723	2.233	0.027
	large	28	0.037	0.009	16.267	1.875	0.024
Financials	small	526	0.082	0.045	6.530	1.894	0.011
	s2	131	0.077	0.058	20.867	2.061	0.113
	s3	81	0.070	0.050	19.430	3.502	0.147
	s4	66	0.072	0.062	13.982	5.310	0.171
	large	57	0.050	0.024	23.410	2.174	0.099
Health	small	269	0.127	0.093	11.906	3.596	0.068
	s2	57	0.138	0.067	13.965	3.962	0.080
	s3	29	0.140	0.041	18.546	2.446	0.045
	s4	20	0.118	0.088	13.001	4.157	0.145
	large	24	0.070	0.031	12.580	2.162	0.055
Telecom	small	35	0.127	0.093	11.906	3.596	0.068
	s2	15	0.138	0.067	13.965	3.962	0.080
	s3	14	0.140	0.041	18.546	2.446	0.045
	s4	13	0.118	0.088	13.001	4.157	0.145
	large	21	0.070	0.031	12.580	2.162	0.055
Utility	small	35	0.030	0.010	16.895	1.520	0.026
	s2	28	0.031	0.013	14.409	2.099	0.030
	s3	35	0.035	0.018	15.198	2.204	0.048
	s4	38	0.039	0.005	16.043	0.979	0.005
	large	31	0.028	0.000	11.552	-0.050	0.000

Business	small	493	0.135	0.205	11.214	5.143	0.175
	s2	98	0.163	0.118	15.519	5.031	0.177
	s3	58	0.187	0.098	17.501	5.151	0.137
	s4	42	0.199	0.060	13.209	3.452	0.037
	large	30	0.159	0.104	13.703	5.389	0.150
Wholesale	small	310	0.112	0.169	9.505	3.328	0.092
	s2	75	0.111	0.110	15.410	4.154	0.166
	s3	47	0.112	0.096	14.283	3.569	0.102
	s4	39	0.077	0.043	20.255	6.079	0.176
	large	26	0.055	0.072	10.819	4.493	0.210
Chemicals	small	47	0.070	0.021	20.871	2.377	0.039
	s2	14	0.069	0.045	16.843	2.267	0.080
	s3	17	0.078	-0.014	9.075	-1.373	0.005
	s4	14	0.069	-0.011	6.880	-0.907	0.003
	large	14	0.037	-0.004	22.703	-0.853	0.005
Energy	small	117	0.082	0.056	5.494	3.757	0.017
	s2	25	0.070	0.049	17.505	5.339	0.203
	s3	16	0.059	0.044	15.234	6.185	0.169
	s4	16	0.058	0.025	12.136	4.305	0.057
	large	19	0.044	0.025	12.146	4.823	0.094
Internet	small	84	0.290	-0.127	5.419	-1.900	0.035
	s2	30	0.281	-0.075	9.768	-2.422	0.036
	s3	20	0.333	-0.089	8.626	-2.253	0.026
	s4	18	0.367	-0.029	7.490	-0.464	0.002
	large	11	0.240	0.129	7.678	2.612	0.091
Panel B: Detrended levels							
Financials	small	526	0.089	0.020	7.910	0.724	0.000
	s2	131	0.087	-0.004	12.254	-0.363	0.000
	s3	81	0.079	0.012	16.294	1.332	0.002
	s4	66	0.083	0.012	12.545	0.833	0.001
	large	57	0.054	-0.002	17.196	-0.327	0.000
Health	small	269	0.141	0.087	11.817	1.809	0.012
	s2	57	0.149	0.030	15.876	1.227	0.003
	s3	29	0.146	0.046	21.116	1.712	0.012
	s4	20	0.132	0.052	13.766	1.911	0.010
	large	24	0.074	0.037	13.245	1.987	0.016
Business	small	493	0.166	0.088	9.557	1.702	0.005
	s2	98	0.180	0.104	16.040	4.620	0.019
	s3	58	0.201	0.144	19.346	2.540	0.041
	s4	42	0.208	0.077	15.532	3.820	0.009
	large	30	0.175	0.074	15.176	4.633	0.011
Energy	small	117	0.091	0.036	6.698	1.397	0.002
	s2	25	0.078	0.011	17.108	0.922	0.002
	s3	16	0.065	0.052	16.169	1.859	0.052
	s4	16	0.063	0.009	14.209	1.308	0.002
	large	19	0.049	0.014	13.658	1.668	0.006

As we mention before, the popularity index shows non stationary series for the financial, health, business and energy sector. For these sectors, we take the first difference to obtain stationary series. Panel B of table 9 shows similar results as panel A, with the exception that only for the business sector the coefficients are statistically significant.

Baker and Wurgler (2004), show that size-effects exist in low-sentiment conditions only. They define sentiment as a force that drives the relative demand for speculative investments. Investors' sentiment has strong effects on the cross-section of stock prices. If popularity is not related to the style's fundamentals, popularity will be driven by investors' sentiment. Although we do not know whether popularity is driven by investors' sentiment or by fundamentals, our findings show close resemblance to the outcomes of Baker and Wurgler (2004).

Barberis and Shleifer (2003) argue that an investment cycle starts after good information in terms of good past performance. Pomorski (2004) show this empirically. He finds that flows are positively related to past returns and negatively related to returns of competing styles. We want to test the relationship between the change in popularity ($\Delta P_{X,t}$) and past returns. Firstly, we perform the Granger Causality test for each sector to test whether both variables, change in popularity and monthly returns, play a role in the determination of each other. The Granger probabilities show that there is causal relationship between the change in popularity and returns for the most popular sectors. Specifically, quarterly returns Granger cause popularity (see table 10).

Table 10: Granger causality test: quarterly returns and popularity over the period 1983 to 2004

For each quarter we calculated returns and the change in popularity. The change in popularity is reflected by $\Delta P_{X,t}$. The significance levels are presented with stars, where ** is 1% and * is 5% significance level.

Granger causality tests[4]	Obs	F-statistic	probability
Manufacturing			
Return does not Granger Cause $\Delta P_{X,t}$	85	16.171**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		0.082	0.921
Consumer durables			
Return does not Granger Cause $\Delta P_{X,t}$	85	19.875**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		1.234	0.297
Consumer non durables			
Return does not Granger Cause $\Delta P_{X,t}$	85	15.030**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		0.282	0.755
Financials			
Return does not Granger Cause $\Delta P_{X,t}$	85	4.145**	0.019
$\Delta P_{X,t}$ does not Granger Cause Return		1.591	0.210
Health			
Return does not Granger Cause $\Delta P_{X,t}$	85	24.884**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		3.333	0.041
Telecom			
Return does not Granger Cause $\Delta P_{X,t}$	85	17.773**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		1.839	0.166
Utility			
Return does not Granger Cause $\Delta P_{X,t}$	85	0.731	0.485
$\Delta P_{X,t}$ does not Granger Cause Return		1.443	0.242
Business			
Return does not Granger Cause $\Delta P_{X,t}$	85	11.701**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		7.091**	0.001
Wholesale			
Return does not Granger Cause $\Delta P_{X,t}$	85	8.753**	0.000
$\Delta P_{X,t}$ does not Granger Cause Return		0.865	0.425
Chemicals			
Return does not Granger Cause $\Delta P_{X,t}$	85	6.119**	0.003
$\Delta P_{X,t}$ does not Granger Cause Return		0.016	0.985
Energy			
Return does not Granger Cause $\Delta P_{X,t}$	85	3.859**	0.025
$\Delta P_{X,t}$ does not Granger Cause Return		1.085	0.343
Internet			
Return does not Granger Cause $\Delta P_{X,t}$	44	6.522**	0.004
$\Delta P_{X,t}$ does not Granger Cause Return		3.583*	0.038

[4] We include 8 lags for the Granger test. This lag length corresponds to a reasonable belief about the time in which past returns could predict popularity.

Because the Granger causality runs one-way from past returns to popularity and not the other way, we perform a regression to test the relation between the change in popularity and past performance:

$$\Delta P_{X,t} = c_t + \beta_1 R_{X,t-1} + \beta_2 \Delta P_{X,t-1} + \varepsilon_t , \tag{6}$$

where $\Delta P_{X,t-1}$ is the change in quarterly popularity and $R_{X,t-1}$ is the quarterly return for style X at time t-1. With equation 6 we test whether the change in popularity of a style is the result of good past performance or popularity. If the change in popularity influences the change in popularity in the next period, b_2 should be positive implying that there is persistence in popularity time series. If the popularity of a style depends on past performance, b_1 should be positive. The outcomes of the regression are presented in table 11.

Table 11: Regression analysis with as dependent variable popularity over period 1983 to 2004

This table shows the results of equation 6. The dependent variable is the change in popularity and the independent variables are the past quarterly return and change in past popularity. Newey-west is used to adjust the *t*-statistics for heteroskedasticity and autocorrelation.

Industries:	constant	b_1	b_2	t(constant)	t(b_1)	t(b_2)	adj. R^2
Manufacturing	-0.037	2.069	-0.276	-1.107	6.348	-2.828	0.321
Consumer durables	-0.034	2.048	-0.370	-0.798	7.853	-3.854	0.313
Consumer non durables	-0.021	2.175	-0.369	-0.572	7.083	-4.745	0.292
Financials	-0.022	1.478	-0.518	-0.560	3.145	-6.832	0.248
Health	-0.041	1.913	-0.431	-1.282	6.112	-5.552	0.367
Telecom	-0.028	1.535	-0.317	-0.671	5.254	-3.847	0.297
Utility	0.009	0.640	-0.306	0.247	1.102	-2.922	0.086
Business	-0.007	1.093	-0.455	-0.182	5.163	-2.945	0.304
Wholesale	-0.001	1.532	-0.472	-0.025	3.650	-4.258	0.308
Chemicals	-0.035	1.786	-0.339	-0.827	4.707	-3.826	0.234
Energy	0.018	0.861	-0.406	0.499	3.321	-5.335	0.194
Internet	-0.016	0.250	0.062	-0.286	1.387	0.393	0.055

As can be seen from the table, we find that lagged popularity (difference) and lagged returns influence current changes in popularity. Past returns seems to have a positive influence on popularity independent of the average popularity of a style. This implies that changes in popularity are induced by past performance in stock returns. That is, investors buy stocks from a style that have performed well in the past.

These results are consistent with Barberis and Shleifer (2003), who suggest that an investment cycle starts with good past performance. These results also fit closely with the literature on the positive-feedback trading of institutional investors. Grinblatt, Titman and

Wermers (1995) and Carhart (1997) show that institutional investors tend to buy stocks that performed well in the past.

Overall, our results suggest that stock popularity cannot be attributed to style investing. We show a positive relation between dispersion and extreme levels of style popularity. This means that in periods of high style popularity, we cannot find comovement in trading activity within styles. This implies that only a fraction of stocks belonging to that style is popular. The fraction of popular stocks may be related to particular size groups. We have therefore tested for size-effects, to check whether popularity is centered on particular size groups. For most of the less popular sectors (from small size to the large size) we find a decreasing pattern of coefficients. However, most of the coefficients are still positive, which points to the existence of popularity at a stock level instead of a style level. Finally, we test whether changes in popularity are related to past performance in returns and find a positive relation.

7 Robustness analysis

In section 6.2, we present an average popularity score for each sector over the period 1983 to 2004. This is a static value, which does not show the life cycles of popularity (which can be compared to the fashion cycles mentioned in section 2) and the movement in popularity through time. In section 7.1, we present the cyclical nature of popularity for each sector.

The empirical analysis in section 6.2 shows evidence inconsistent with the predictions of style investing theory. A possible alternative explanation for our findings is that we investigate the comovement in turnover ratios rather than the comovement in prices/returns as is shown by a series of recent studies (Cornell (2004), and Barberis, Shleifer and Wurgler (2005)). Another explanation for our findings in section 6.2 is that we focus on the extreme level of popularity rather than the change in popularity. Hence, to explore whether movements in popularity lead to comovement in returns, we test the impact of the change in popularity on the comovement in returns for each sector in section 7.2.

7.1 Movement in popularity

Barberis and Shleifer (2003) describe style investing in terms of life-cycles. The birth of a style starts after good fundamental news about the securities in a style. If the style matures, good past performance in style returns is important to add new resources to a style. The style loses its popularity when bad news arrives or when arbitrage levels out excess returns. After a while, the cycle may start all over again. In this section, we show the movement in style popularity through time. Before we show the movement in popularity through time for the eleven different industries, we first present the movement in popularity for the internet sector. In appendix A we describe the internet sector in terms of a popularity cycle. The popularity cycle is divided into different stages based on the model of E. Rogers (1983). In appendix A we present a further outline of the procedure followed. Table A.3 shows the different stages of the popularity cycle for internet sector with the corresponding popularity. Popularity shows a low value in the leader stage and reaches a peak in the late majority stage. The right-hand column in table A.3 shows that dispersion reaches its peak in the early majority phase. This implies a positive relation between dispersion and popularity.

In order to show the movement in popularity for the other eleven sectors, we calculate a 2.5-year rolling average popularity. Figure 2 shows that popularity of sectors is changing through time. For example, the popularity of the business sector was relatively low during the eighties and started to increase in the nineties. On the other hand, the popularity of the utility sector was relatively high over the period 1988 to 1993 and declined after 1994. We also calculate the 2.5-year rolling average dispersion. Figure 2 shows that dispersion moves in a similar way as popularity. For the business sector dispersion shows an increasing pattern, while dispersion for the utility sector shows a decreasing pattern in the mid-nineties.

Figure 2: The 2.5-year rolling average popularity and the 2.5-year rolling average dispersion over the period 1983 to 2004

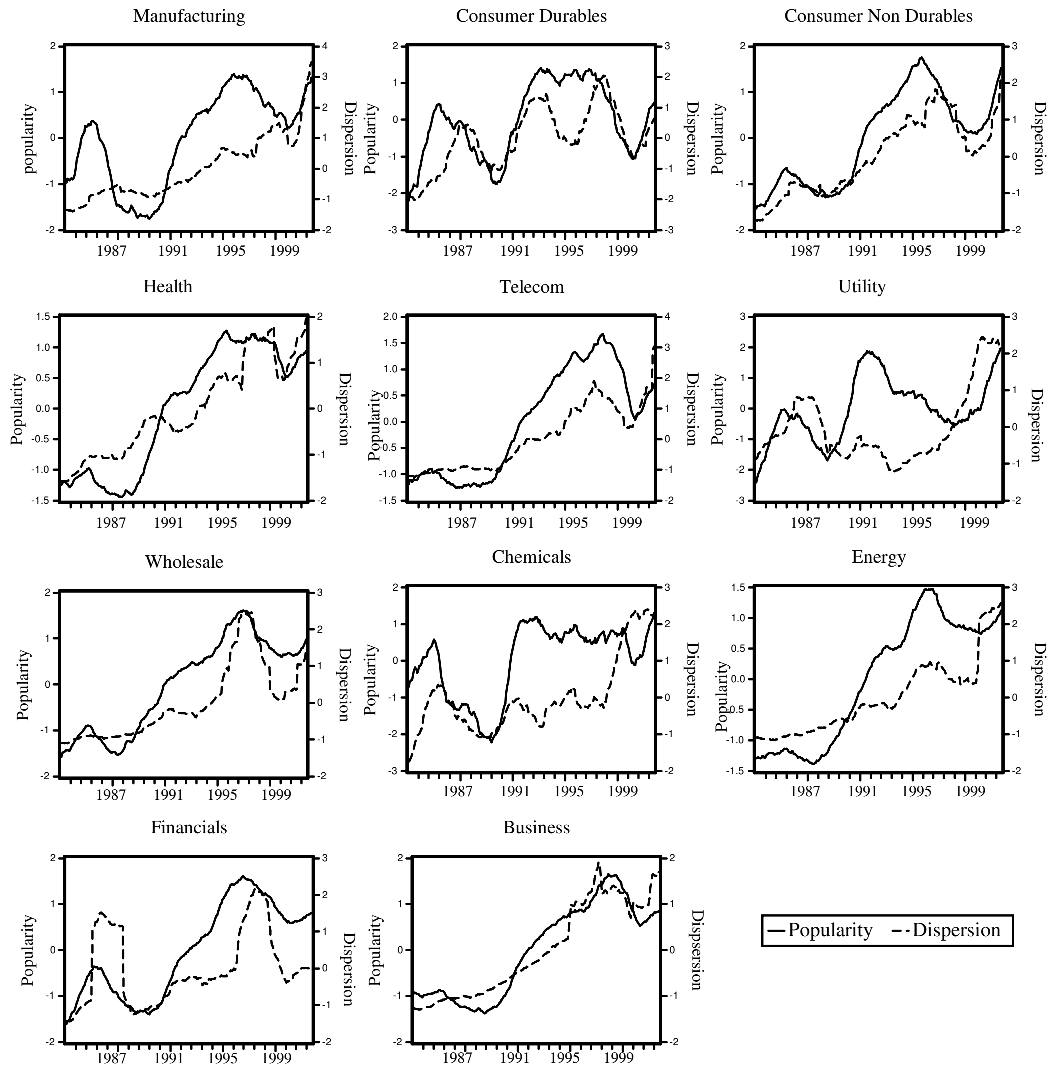

Table 12 presents the average popularity for four different periods. The numbers confirm our analysis of figure 2. The utility sector is popular during the eighties and becomes less popular in the nineties. Other sectors, like business and energy, are not popular during the eighties but increase in popularity during the nineties. Overall, figure 2 and table 12 show that the movement in popularity shows close resemblance with the fashion cycles as described in section 2.

Table 12: Average popularity over different horizons

	Average popularity				
Industries:	1983-1986	1987-1990	1991-1994	1995-1999	2000-2004
Manufacturing	0.149	-0.493	-0.070	0.733	0.702
Consumer durables	-0.129	0.077	0.207	0.728	0.373
Consumer non durables	-0.530	-0.455	0.122	1.047	0.771
Financials	-0.578	-0.583	-0.204	1.041	1.057
Health	-0.616	-0.834	0.284	0.978	1.058
Telecom	-0.461	-0.597	0.045	0.939	0.949
Utility	-0.150	-0.025	0.706	0.397	0.482
Business	-0.482	-0.797	-0.040	0.846	1.216
Wholesale	-0.591	-0.602	0.292	0.908	0.942
Chemicals	0.194	-0.199	0.313	0.481	0.495
Energy	-0.807	-0.790	0.129	1.139	1.099

7.2 Popularity and the comovement in prices/returns

In section 7.1, we show the movement in popularity through time. In this section, we explore whether the movement in popularity leads to comovement in returns. If investors apply style investing, they will not distinguish between stocks within a style. Stocks that may be fundamentally unrelated are grouped to the same category, which lead to demand shocks across all stocks in the style, resulting in comovement in returns. The correlation between returns is a good indicator to distinguish between style popularity and stock popularity. If investors apply style investing the returns across all stocks in the style will be highly correlated.

Before we test for the eleven sectors whether the movement in popularity leads to comovement in returns, we first analyze the comovement in returns of internet stocks. In appendix A, table A.4 shows the average correlations in returns between internet stocks for different stages in the cycle. As subperiods we use the different stages of the fashion cycle which are defined in appendix A. The internet sector does not show the same high correlations in returns as the results of Cornell (2004). The correlation increases slightly in the emulation and mass phase, but is even lower than Cornell's correlation of 30% at the end of the boom. Table A.5 in appendix A presents the distribution of the 60-day rolling correlation through time over the period 1994 to 2003. We calculate for each sub period and correlation group the average and median fraction of 60-day rolling correlation between all pairs of stocks. This table shows that there is a very low fraction of stocks that was highly correlated with each other. For 4.5 % of the cases the 60-day correlation increases to above 40% in the introduction period, 0.5% in the emulation period and 0.4% in the mass phase. We also calculate the 60-day rolling correlations between Yahoo and Amazon and calculated the average and median (between the brackets) correlation for each sub period. The average correlations were in the emulation period 56% (56%) and for the mass phase 66% (70%). Another note that can be made on the correlations is that fifty percent of the stocks are negatively or not (0%) related with each other (in all five phases). Comparing these results with the results of Cornell (2004) we believe that the results of Cornell are a result of chance instead of evidence for the style investing hypothesis. He chose just those two internet stocks that show high comovement in returns. An explanation for the results found by Cornell may be stock popularity. Both stocks, Yahoo and Amazon, could have been popular during this period.

In order to test for comovement in returns for the other eleven industries, we perform the following regression:

$$\Delta corr_{X,t} = a_t + \beta_1 \Delta P_{X,t} + \varepsilon_t, \tag{7}$$

where $\Delta corr_{X,t}$ is the change in percentages of correlations between daily returns in a quarter that fall between –0.20 and 0.20 and $\Delta P_{X,t}$ is the change in popularity. Table 13 provides the estimates of the coefficient across industries. The third row contains the estimates of β_1 and shows that the coefficients are uniformly positive. This implies that correlation between returns is decreasing when a style shows an increase in popularity, although, the heteroskedasticity consistent *t*-statistics show that the results are not reliable.

In summary, using the comovement in returns rather than the comovement of turnover ratios, we find similar results as in section 6.2. Notably, the comovement in returns decreases with an increase in popularity. However, the adjusted R-squares of these regressions range from 0.000 to 0.093, lower than the adjusted R-squares of the regressions with comovement in turnover ratios, which, as reported in table 7, ranges from 0.024 to 0.171. Nevertheless, the coefficients are uniformly positive, which points to the existence of popularity at an individual stock level instead of a style level. Taken together the results of 6 and 7, our findings are consistent with the predictions of stock popularity hypothesis instead of the predictions of the style investing hypothesis.

Table 13: Regression coefficients: correlation between returns and the change in popularity over period 1983 to 2004

This table shows the results of equation 7, where the dependent variable is the number of stocks that have a correlation in returns between –0.20 and 0.20. Correlations are calculated for each quarter over daily returns over the period 1983 to 2004. The independent variable is the change in popularity. Newey-west is used to adjust the *t*-statistics for heteroskedasticity and autocorrelation.

Industries:	constant	b_1	t(constant)	$t(b_1)$	adj. R^2
Manufacturing	0.031	0.015	0.128	0.008	0.000
Consumer durables	-0.229	2.825	-3.555	0.800	0.007
Consumer non durables	-0.115	3.046	-0.306	1.327	0.020
Financials	-0.066	2.022	-0.260	1.555	0.017
Health	-0.113	2.088	-0.411	0.842	0.019
Telecom	-0.389	10.868	-0.590	3.491	0.093
Utility	-0.088	5.795	-0.172	1.380	0.025
Business	0.012	2.627	0.023	1.391	0.039
Wholesale	0.005	2.019	0.029	0.644	0.006
Chemicals	-0.175	4.186	-0.371	1.557	0.037
Energy	0.103	0.740	0.295	0.247	0.001

8 Conclusion

This paper provides evidence that popularity is at an individual stock level instead of a style level. Because popularity is closely related to fashion, we discuss fashion in the context of investing in section 2. Fashion and popularity are related in the way that they both reflect the collective preferences of individuals and the changes of such preferences over time. The chapter uses different sources of data, such as data on stocks, mutual funds, IPOs and analysts to reflect the collective preferences of investors. With the different sources of data we compose a popularity index. The popularity index is obtained with principal component analysis. This analysis constructs an index based on variables that capture a common factor. We find strong evidence that style popularity cannot be attributed to style investing. That is, popularity is stock-specific rather than style-specific. Styles that are less popular show size-effects. Investors choose for large caps when a style is less popular. Barberis and Shleifer argue that an investment cycle starts after good information in terms of good past performance. Our findings show that popularity is positively related to past returns. These findings are closely related to the literature on positive feedback trading (momentum traders). Grinblatt, Titman and Wermers (1995 and 1997) and Carhart (1997) show that institutional investors tend to buy stocks that performed well in the past.

Finally, we perform some robustness checks to show the life cycles of popularity which can be compared to fashion cycles as is described in section 2. In addition, we perform a regression to test whether the change in popularity of a particular style leads to comovement in returns between stocks in that style. Our findings show that an increase in popularity leads to a decrease in correlations in returns between stocks in the same style.

Taken together, our findings are consistent with the predictions of stock popularity hypothesis instead of the predictions of the style investing hypothesis.

Appendix A: Fashion cycle for the internet sector

Everett Rogers developed the diffusion of innovation model to help understand the social process through which a change or innovation is accepted. Rogers states that "diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system." This process has proven effective in a variety of situations from deciding on a plan of action in a small social gathering to introducing **a new product** in the market place.
Rogers suggests that trying to quickly and massively convince a group to adopt a new idea usually results in failure. He, therefore, determined that any group could be divided into five categories, based on the idea that certain individuals are more accepting of new ideas (i.e. are more innovative) and others are less accepting and may never adopt or embrace new ideas. The five adopter categories are: innovators, early adopters, early majority, late majority and laggards.

Classification of analysts into categories following five segments of individual innovativeness by Rogers (1983):
Innovators: up to 2.5% participants
Early adaptors: up to 13.5% participants
Early majority: up to 34% participants
Late majority: more than 34% participants
Laggards: less than 16% participants

Table A.1: Classification of analysts into categories following five segments of individual innovativeness by Rogers (1983) for internet stocks

	Total number of brokers in internet sector	Total number of brokers in I/B/E/S	Brokers internet sector in % of total number of brokers in I/B/E/S	Fashion cycle based on the model of Rogers
1992	3	221	1.4%	Innovators
1993	10	221	4.5%	
1994	14	237	5.9%	Early adopters
1995	24	253	9.5%	
1996	40	280	14.3%	
1997	66	336	19.6%	
1998	96	365	26.3%	
1999	136	356	38.2%	Early majority
2000	154	341	45.2%	
2001	157	326	48.2%	
2002	154	293	52.6%	Late majority
2003	161	380	42.4%	

Because the internet sector had its origin in the nineties it was completely new, we can express this sector in terms of fashion cycles. We use the adoption and diffusion model of Rogers (1983) to divide the internet cycle in different stages. Table A.2 presents the level of popularity among investors reported by popularity measures described in section 4.1. Table A.2 shows the different stages of the fashion cycle with the corresponding values of the different variables for the internet sector.

Table A.2: Descriptive statistics for the internet sector over the period 1993 to 2003

The adoption and diffusion model by Rogers (1983) is used to divide the internet period in different stages. Turnover ratio is style volume divided by the style's number of outstanding shares. Nmf_t is the number of mutual funds that is organized during the period. *Avg. Inflow* is the average in –and outflow per mutual fund on an annual basis. Analyst coverage is the total number of analysts with respect to the total number of analysts in period t that follows internet stocks. N_{up}/N_{down} is ratio with the number of upgrades with respect to the number of downgrades.

		Number of IPO's	Turnover	Avg. bid-ask spread	Mutual funds		Analyst	N_{up}/N_{down}
					Nmf_t	Avg. Inflow (%)	*Coverage*	
1993	Leaders	1	2.378	4.667	0	0	0.00%	0
1994-1996	Early adopters	33	1.624	5.288	2	0.506	4.90%	1.083
1997-1999	Early majority	261	4.044	7.493	36	153.751	12.10%	0.901
2000-2003	Late majority	123	2.533	8.474	26	0.003	18.70%	2.501

The fashion cycle of internet stocks started in 1992 where the first internet firm, America Online, went public. The first mutual fund that specializes in internet stocks started trading in 1996. The number of IPO's grew to 261 in the early majority phase, which was between 1997 and 1999 and fell to 123 in the period 2000 to 2003. At the same time the average percentage of inflow for each mutual fund in a year reached its peak with 153.75%. Liquidity increased in the same period, the average turnover ratio increased to 4.0. The number of analysts that cover internet stocks in the early majority phase is 12% and reaches its peak in the late majority phase with 18.7% of all analysts covering the internet sector. The measures that reflect optimism reach their peak in the early majority phase.

Table A.3 presents the average level of return and turnover dispersion for the internet sector. The average level of return dispersion grows from 16.5 percent in the leaders phase to 26 % in the late majority phase. The standard deviation of the turnover ratio across the assets is 17.4% in the leader phase and grows to 52.2% in the late majority phase. This is a positive relation between dispersion and popularity, which implies that investors do not choose stocks on a group basis but on an individual level within the group.

Table A.3: Popularity and dispersion for the internet sector for the different stages of the fashion cycle

For each phase we calculated the average standardized popularity and the cross standard deviation of the turnover ratio (see equation 3 and 5 in section 4.2 and 6.1).

		Average popularity	Average turnover dispersion
1993	Leaders	0	0.174
1994-1996	Early adopters	-0.057	0.298
1997-1999	Early majority	0.521	0.522
2000-2003	Late majority	1.299	0.284

Table A.4 presents the style investing measures, the average correlations in returns between stocks and the autocorrelation, for different stages in the cycle. The internet sector does not show the same high correlations in returns as the results of Cornell shows.

Table A.4: Style investing measures

The autocorrelation with one lag is calculated for the time series of returns of the internet sector. For each pair of internet stocks we calculated the correlation and then we calculated the average correlation of all pairs.

		Style investing	
		Correlation among stocks	Auto-correlation
1993	Leaders	-	-0.047
1994-1996	Early adopters	0.008	0.258
1997-1999	Early majority	0.013	-0.820
2000-2003	Late majority	0.011	-0.787

Other sectors already existed for a long time and are difficult to express in terms of the five stages used by Rogers. We calculate the different stages of the fashion cycle for the other ten sectors. Our findings suggest that all ten sectors were in their early and late majority in the nineties.

Table A.5: The average and median (between the brackets) fraction of 60-day rolling correlations for each correlation group and phase in the fashion cycle.

For each pair of stocks we calculated the 60-day rolling correlation. For each phase we calculated the average rolling correlation for each pair and then calculated the fraction of correlations that belongs to the different correlation groups.

	The fraction of correlations that belong to each correlation interval							
	<-40%	-40% - -21%	-20%-0%	1-20%	21-40%	41-60%	61-80%	81%-100%
Subperiod								
1994.1-1997.6	5.5% (5.8%)	13.8% (13.9%)	31.2% (30.9%)	30.5% (29.9%)	12.7% (13.5%)	3.7% (3.4%)	0.8% (0.7%)	0.1% (0.1%)
1997.7-1998.6	0.5% (0.3%)	7.9% (7.6%)	42.0% (42.4%)	40.2% (40.4%)	7.3% (7.2%)	0.4% (0.3%)	0.1% (0.0%)	0.0% (0.0%)
1998.7-2000.6	0.3% (0.2%)	5.0% (6.1%)	45.5% (44.2%)	42.4% (41.4%)	4.7% (5.7%)	0.4% (0.3%)	0.0% (0.0%)	0.0% (0.0%)
2000.7-2001.6	0.0% (0.0%)	0.9% (0.9%)	51.2% (51.2%)	45.7% (45.8%)	0.6% (0.4%)	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
2001.7-2003	0.1% (0.1%)	2.5% (2.7%)	49.2% (49.2%)	44.4% (43.8%)	2.1% (2.1%)	0.1% (0.1%)	0.0% (0.0%)	0.0% (0.0%)