The Pessimism Factor: SEC EDGAR Form 10-K Textual Analysis and Stock Returns

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Abstract

I perform textual analysis on 20,000 annual SEC 10-K Forms, for NYSE, NASDAQ and AMEX stocks, from 1992 until 2015. The textual analysis negative (pessimism) percentage per se, as used in the previous literature, is not a significant determinant of future stock returns. But, monthly portfolios based on the product of annual pessimism change and the previous period returns generate returns in excess of previous winners/losers. Nine months after the filing, the difference is higher than 5%, while it surpasses 7% twelve months after the filing. Negative (positive) previous returns along with positive pessimism changes lead to positive (negative) returns.

JEL classification: G10, G14.

Keywords: SEC Form 10-K, Textual Analysis, Financial Sentiment, NYSE, NASDAQ, AMEX (NYSE MKT).

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1. Introduction

Domestic US companies must submit annual reports on Form 10-K[1]. The significance of Form 10-K is very high, since the federal securities law obliges public companies to provide a "a comprehensive overview of the company's business and financial condition and includes audited financial statements."[2]. Form 10-K provides firms with a unique opportunity to inform investors on an ongoing basis, and for firms' executives to express their expectations for the future, as well as their interpretations of the past, in the most sincere way possible. Given the significance of Form 10-Ks for corporations and investors, a research strand based on content analysis of these forms has emerged in the previous years. Loughran and McDonald (2011) are among the first to study the effect of textual analysis of SEC Form 10-Ks in the subsequent returns of firms. The authors refined the general-purpose Harvard's General Inquirer[3] word lists which Tetlock (2007) used, classifying words in lists so that the words indeed are (as much as possible) positive/negative from a finance perspective. They particularly deal with the filings' effects on stocks during the 4 days window before and after the filing date of a 10-K. Although the short term effects of a few days before and after the filing of the form is indeed a worthwhile research topic, it is also of interest to study for longer effects, in order to examine how the content analysis of 10-Ks can be useful to investors apart from short-term small profits. The previous finance and accounting literature deals with the short-term investor response to Form 10-K filings (Li and Ramesh (2009), Griffin (2003)). Griffin (2003) studies the effect on the day and on one or two days following the filing date.

As far as the literature on content analysis of corporate filings are concerned, Demers, Vega, et al. (2008) makes a distinction between "hard" information (numerical data) and "soft" infor-

[1] https://www.sec.gov/about/forms/form10-k.pdf
[2] http://www.sec.gov/answers/form10k.htm
[3] `http://www.wjh.harvard.edu/~inquirer/`

mation (qualitative verbal communication) and finds an effect on prices up to sixty (60) days after the announcement. Price, Doran, Peterson, and Bliss (2012) analyse quarterly earnings conference calls and finds that textual tone is associated with stock returns up to 60 days after the filing. Davis, Piger, and Sedor (2012) analyse earnings press releases and find that optimistic language is associated with higher future return on assets (ROA). Henry (2008) study the effect of tone of earnings press releases for the days t-1 up to t+1 of the events.

The current analysis is significant for a number of reasons: Firstly, quite surprisingly, none of the papers in the accounting and finance literature have studies the effect of 10-K pessimism on stock returns for the period between the current filing and the next filing. Secondly, to the best of our knowledge, this is the first paper to associate the change in the tone of annual filings with the stock returns for the firm during the period between the previous and the current filing. Thirdly, given the importance of the momentum (Jegadeesh and Titman (1993)) anomaly in finance, the returns of stocks during the previous period can be a significant determinant of their performance during the following period. According to the momentum anomaly, stocks that performed well (badly) in the past tend to continue to perform well (badly) over a three (3) to twelve (12) months holding period. Since companies use their annual filings to disclose information to potential (and current) investors, it is worth examining what are the consequences to future (up to twelve months) stock performance of four (4) scenarios for stocks: Stocks that performed well (badly) in the past and have a positive (negative) change in pessimism (i.e. the t period filing is more (less) pessimistic than the t-1 period filing). Fourthly, textual tone might be more significant when examined within a context that takes into account the previous period's performance, compared to a raw textual tone pessimism as used in the previous literature. Such an analysis that incorporates both the effect of previous stock returns along with the change in pessimism is significant, in the sense that investors might give different attention to stocks that performed good (bad) in the previous period,

along with the fact that they have a higher (lower) pessimism. The previous papers did not study this possibility at all. This is the gap that I attempt to cover with the current analysis. I find that the change in pessimism is more significant than the percentage of negative words used in Loughran and McDonald (2011) and the simple percentage of pessimism. It seems like what matters most is the change in pessimism on a yearly basis for the same firms. Furthermore, the effect of 10-K textual pessimism change is not significant per se above the submission month (the same holds for the raw negative percentage as used in Loughran and McDonald (2011)). But when one employs the interaction of annual pessimism change with the previous period's returns, the is significant for stocks that had negative returns in the previous period. The stocks that perform best in the months after the filing are the ones that had the worst returns in the previous period and had a positive pessimism change. These are the stocks that had the lowest product of returns (when returns are negative) and pessimism change (when pessimism change is positive). I find that this portfolio achieves maximum mean returns nine months after the filing month. These returns are significantly higher (5% to 7%) than what the momentum portfolios would return. These findings are significant both for investors and filing companies, and highlight the importance of combining the effect of multiple factors, in order to achieve results that can not be obtained when every factor is examined on isolation.

According to the model of Barberis, Shleifer, and Vishny (1998), when there is underreaction, news are incorporated slowly into prices. This is a phenomenon that is report in multiple studies such as Hirshleifer, Lim, and Teoh (2009), and is related to the post earnings announcement drift. In the models of DellaVigna and Pollet (2009), investors are risk averse and some of them neglect the information that is contained in firms' latest earnings. In equilibrium there is indirection to earnings surprises, so that on average prices are too low after good news and too high after bad news. Consequently, good news predict high returns to follow and bad news predict low returns

to follow, which is, in other words, the post-earnings announcement drift. Hirshleifer et al. (2009) find that investors' announcement date reactions to earnings news are much slower to earnings news on high-news days (i.e. days with many more announcements on the same day) than on low-news days. As explained in Mendenhall (2004), the post-earnings announcement drift is the phenomenon where a stock's price drifts in the direction of an earnings surprise in the months following an earnings announcement. The drift is also referred as the standardised unexpected earnings (SUE) effect and it seems to be a longstanding feature of stock returns. Three main explanations have been proposed for the drift effect. Some believe has to do with how the studies that report it were conducted, others claim that the drift has to do with not estimating correctly the expected returns after earnings surprises, while others attribute the drift to underreaction to information that is relevant and important for valuation. Ball and Brown (1968) were the first study to present evidence that even after the announcement of earnings, estimated cumulative "abnormal" returns continue to drift up for firms that had "good news" (i.e. firms that had positive earnings surprises) and down for firms that had "bad news", (i.e. firms that had negative earnings surprises). Foster (1977) and Foster, Olsen, and Shevlin (1984) report evidence in favour of an association between the drift and the size of the firm in question. As far as theory and prior research is concerned, these findings to the momentum anomaly (Jegadeesh and Titman (1993)) which appears to be present in multiple assets (Asness, Moskowitz, and Pedersen (2013)), in the sense that I study the future price movements of previous winners/losers. The post-earnings announcement drift (Bernard and Thomas (1989)) and theoretical models of underreaction to news (Barberis et al. (1998)) and the speed of adjustment to news (Hirshleifer et al. (2009)) are also related to our findings, in the sense that the effect takes multiple months after the annual filing to fully develop, and news are incorporated slowly into prices.

The rest of this paper is organized as follows. Section 2 presents the recent textual-analysis

literature. Section 3 presents the data. Section 4 presents the model specification and I explain how I study the effect of SEC EDGAR Form 10-K textual analysis pessimism change along with the previous period returns. Section 5 provides the empirical results. Section 6 concludes.

2. Textual Analysis Literature

The study of News Flow has attracted the researchers's interest rather recently with the advent of Data Mining and Sentiment Analysis techniques. The strong interest in this area has been demonstrated by the recent creation of companies and commercial products specialized in the production of financial sentiment (see e.g., RavenPack[4] and Thomson Reuters News Analytics[5]). As far as the finance literature is concerned, the pioneering work of Tetlock (2007) uses textual analysis (based on the Harvard psychosocial dictionary) of a Wall Street Journal column, and associates the content of the news with the Dow Jones returns, using vector autoregressions (VARs). He finds that media pessimism has predictive power on market returns, while reversion effects occur and extreme absolute values of pessimism predict higher trading volumes. Loughran and McDonald (2011) develop finance-oriented word lists by fine-tuning the Harvard dictionary, and correlate textual analysis variables with 10-Ks filing returns, trading volume, volatility and other characteristics. Other studies report evidence of predictive power of stock message boards and major financial columns on volatility, returns and volume (Antweiler and Frank (2004) , Chen, De, Hu, and Hwang (2013)). The related literature also studies the effect of returns on media content Garcıa (2012), the effect of media content on returns during recessions and expansions Garcia (2013)), while a high level of similarity in firm-specific news is found to provoke higher trading aggressiveness of individual investors (Tetlock (2011)). Boudoukh, Feldman, Kogan, and

[4] http://www.ravenpack.com/

[5] http://www.machinereadablenews.com/

Richardson (2013) find that news that can be identified and classified in certain categories have a higher impact on stock markets than unidentified news. The effect on news sentiment during the recent financial crises have been examined in Chouliaras and Grammatikos (2015) for a daily frequency, and in Chouliaras (2015) for the high-frequency (intraday) stock market dynamics, and find that a higher news pessimism is associated with lower stock returns. Another area of research has been the field of corporate earnings, where Tetlock, Saar-Tsechansky, and Macskassy (2008) find that a higher percentage of negative words in news about specific firms predicts lower quarterly earnings. Furthermore, textual analysis has been used for the study of initial public offerings (IPOs). Loughran and McDonald (2013) find that higher uncertainty in filings affect first-day returns and ex post volatility, Jegadeesh and Wu (2013) give different weights on words based on the market reactions that they caused and Li (2010) studies the effect of forward-looking statements in corporate filings on future earnings and liquidity. Finally, Ahern and Sosyura (2014) show evidence of firms manipulating media coverage to achieve better stock prices during mergers and acquisitions negotiations.

3. The Data

3.1. The SEC Form 10-K data

In order to obtain the SEC Form 10-K data, I use a web crawler written in the Python programming language[6], to detect and download the available forms for every firm in the Dow Jones, S&P 500, NYSE, NASDAQ and AMEX (NYSE MKT) stock markets, from 1992 until 2015. In order to download the filings for every firm, one needs to know the ticker of the firm and the central

[6] `https://www.python.org/`

index key (CIK)[7] which is used by SEC EDGAR in order to identify firms in their database. The Form 10-K text files contain huge amounts of html elements, which I strip off using the BeautifulSoup Python library[8]. Furthermore, I notice that the text files also contain great amounts of binary-to-text encoding known as uuencoding. These cover thousands of lines in the text files, and correspond to .xls (Excel files), .zip (Zipped files), .pdf (PDF files), .jpg and .png (both image files formats) that exist in the SEC EDGAR files. To remove these lines I use once more Python. One has to remove the .html and the uuencode lines before proceeding with the Natural Language Processing textual analysis, or else the number of words are artificially increased without any meaningful information, a fact which may distort results since the .html tags and the uuencoding do not contain any meaningful human-read or computer-read information which a parser can capture. The number of 10-Ks per month appears in Figure 2:

Insert Figure 2 here

As one can see from the figure, the number of 10-Ks is significantly higher in the month of March (over 11000 filings in total), followed by February (5525 filings) and April (1042 filings). All other months have less than 1000 filings, with an overall low for October with only 273 filings.This looks quite surprising, but one has to take into account that according to the SEC website[9] the Form 10-K has to be filed at a maximum 60 days after the end of the fiscal year for filers that have $700 Million or more public float, 75 days for filers that have between $75 and $700 Million public float, and 90 days for filers that have $75 Million public float [10].

[7] http://www.sec.gov/edgar/searchedgar/cik.htm

[8] `http://www.crummy.com/software/BeautifulSoup/bs4/doc/`

[9] http://www.sec.gov/answers/form10k.htm

[10] the deadline used to be 75 days for large filers before December 2006, but after December 15, 2006 it was changed to 60 days after the end of the fiscal year

As far as the financial data are concerned, I use the Bloomberg database. I extract stock prices and accounting variables for all available New York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ) and NYSE MKT (formerly known as American Stock Exchange - AMEX) stock markets, from 1992 until 2015.

4. The Methodology

4.1. Combining the 10-K and the financial data

As a first step, I have to combine the financial data obtain from Bloomberg with the 10-K data I obtain from SEC EDGAR. To do this, I use the company names, tickers and central index keys (CIK), and match for every year and every stock index the companies with the appropriate Form 10-K.

4.2. Textual Analysis

As a next step, using textual analysis, based on the Loughran and McDonald (2011) dictionary[11], I measure the positive content of 10-Ks as in Garcıa (2012) and Garcia (2013): $G_i = \sum_i \frac{g_i}{w_i}$, calculated as the percentage of positive words over the total number of words of every 10-K filing. The symbol g_i stands for the number of positive words in the filing, and w_i stands for the total number of words in the filing. I do not count stop words, which are words that are very common and do not really add sentiment to the text. Words such as country names, words such as *a, about, after, again, all, almost, an, and, are, become, can, does, either, elsewhere, has, if, it, is, like, less, often, only, that, they, together, was* and thousands of other words are neglected since they do

[11]The dictionary can be found at `http://www3.nd.edu/~mcdonald/Word_Lists.html`

not offer some significant content in terms of sentiment analysis[12]. Using a regular expression in Python[13], I am able to count only words, excluding numbers, special characters et cetera, which do not provide any textual significance for our sentiment analysis. I do the same for the negative words, obtaining the negative media content as $B_t = \sum_i \frac{b_t}{w_t}$, with b_i denoting the negative words in the filing. Thus, I obtain the *Pessimism* of filing i:

$$Pessimism_i = B_i - G_i \tag{1}$$

The *Pessimism* is calculated for every filing.

The summary statistics of the combination between 10-Ks and financial data appear in Table 2:

Insert Table 2 here

I calculate log-returns for stocks (in this case, the prices are always the ones in the end of every month. The data are annually, which means that the mean yearly return is 6.2%. Furthermore, I calculate the percentage change in pessimism from one year's 10-K to the following year, as well as the percentage of positive and negative words in 10-K filings. I find that the average 10-K has 0.7% positive words, 1.4% negative words, which means 0.7% more negative than positive words (i.e. an average pessimism of 0.7%), while the yearly average pessimism change is 2.5%. I also find that 10-Ks on average have 74796 words.

[12]The stop words can be found at: `http://www3.nd.edu/~mcdonald/Word_Lists.html`
[13]`https://docs.python.org/2/library/re.html`

5. Empirical Results

As a first step in our empirical analysis, I employ a panel data regression analysis to study the effect of 10-K pessimism on stock returns. Firstly, I compare whether the results are more significant for the pessimism percentage as a raw percentage (as used in Garcia (2013)) and as the percentage of negative words (as used in Loughran and McDonald (2011)), versus the percentage change in pessimism from the previous year to this year. The results appear in Table 3 for the return of the submission month:

Insert Table 3 here

The results are straightforward: The negative percentage used in Loughran and McDonald (2011) and the pessimism percentage is not significant for the end of the submission month month returns (both in the univariate and the multivariate cases). But what is significant, is the change in pessimism from the previous year, with a coefficient statistically significant in the 1% significance level both for the univariate and the multivariate cases. The coefficient is negative in both cases, which means that a positive change in pessimism (i.e. if this year the firm has a higher 10-K pessimism than last year) leads to lower returns by the end of the submission month).

As described in Wooldridge (2012), sometimes the partial effect of the dependent variable with respect to an explanatory variable may depend on yet another explanatory variable. For example, in the model

$$Return_{t+12,t} = \beta_0 + \beta_1 \ln PB + \beta_2 \ln \text{Market Cap} + \beta_3 \Delta Pessimism_{t,T} + \beta_4 Return_{t-1,T} + \beta_5 \Delta Pessimism_{t,T} \times \text{Return}_{t-1,T} + u \tag{2}$$

where t stands for the current submission month, T stands for the previous submission month, $Return_{t+12,t}$ stands for the return between the end of the current submission motnh and twelve (12) months in the future, $\Delta Pessimism_{t,T}$ stands for the change in pessimism between the current and the previous filing. I am calculating the returns between the previous filing and one month before the current filing, so that my results are not influenced by the short-term effects of 10-K filings that have been studies in the previous literature. Furthermore, when calculating the future return, I take the price of twelve (12) months after the filing, minus the price of the end of the submission month, so that the results are once again not influenced by the short-term effects of the filings.

The partial effect of $Return_{t-1,t-T}$ on $Return_{t+12,t}$ (holding all other variables fixed) is

$$\frac{\Delta Return_{t+12,t}}{\Delta \text{Return}_{t,t-12}} = \beta_4 + \beta_5 \Delta Pessimism_{t,T} \tag{3}$$

If β_5 is negative, then Equation 2 than an additional increase in pessimism yields a lower return.

A change in the 10-K pessimism can be an important determinant per se, but investors take into account the 10-K pessimism along with what happened to the stock in the period between the previous 10-K filing and the current the filing. There are in total four (4) different scenarios when I examine the 10-K pessimism along with the previous stock returns:

- Positive previous returns and positive change in pessimism (I)
- Positive previous returns and negative change in pessimism (II)

- Negative previous returns and positive change in pessimism (III)
- Negative previous returns and negative change in pessimism (IV)

The results for the effect of the product of pessimism change and previous returns after three (3), six (6), nine (9) and twelve (12) months appear in Table 4:

Insert Table 4 here

The results show a significant coefficient for three out of four periods: 6, 9 and 12 months after the filing. The coefficient is always negative, and becomes more significant (statistically) and higher as time progresses. A negative coefficient means that an increase in the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ will lead stock prices lower in 3, 6, 9 and 12 months after the filing. Such an event happens when either both $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ are positive, or when both $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ are negative (the two minus symbols will cancel out and give a positive outcome). To see more directly the effects, I have to distinguish between positive and negative previous returns, so that I am able to see the effect of $\Delta Pessimism_{t,T}$.

The effect of pessimism on whether the firm had positive or negative returns (separately) appear in Table 5:

Insert Table 5 here

The table shows an interesting finding: the effect of pessimism is almost three times as large (and statistically significant) when previous returns were negative than when they were negative.

The coefficient of -0.143 means that an increase of 1 percent in the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ decreases the subsequent 12-month after filing returns by 0.143%. An increase in the product occurrs when $\Delta Pessimism_{t,T}$ is negative, given the fact that $\Delta Pessimism_{t,T}$ is negative. This means that there is a risk premium for holding stocks that underperformed in the previous period, but have less pessimism in their current 10-K compared to the previous year's filing. The coefficient for positive previous returns is negative and marginally significant when the previous returns were positive, meaning that a higher product leads to lower returns. Once more the product is higher when the $\Delta Pessimism_{t,T}$ is positive, which means that stocks that performed very well in the previous period but have a higher 10-K pessimism in their current filing, tend to underperform in the months after the current 10-K filings. The effect on stocks with negative previous returns is much stronger (significant on the 1% level with a t-stat equal to -3.16) than positive previous returns (not significant with a t-stat equal to -1.59).

The panel data regression results for the four possible scenarios appear in Table 6:

Insert Table 6 here

The coefficient of the interaction between the yearly change in pessimism and the return of the period between the previous and the current filing, is significant only for the two cases of positive previous returns. In column (3), the coefficient is positive when the previous return ($Return_{t-1,T}$) is positive and the change in pessimism ($\Delta Pessimism_{t,T}$) is negative, which means that when the product of previous returns and pessimism becomes higher, returns become higher. In other words, when previous returns are higher or pessimism is lower, subsequent returns (twelve months after submission) are higher. A one percent increase in the product of product of $\Delta Pessimism_{t,T}$ and $Return_{t-1,T}$ increases stock returns by 0.140% 12 months after the filing of the 10-K.

In column (4), the coefficient is negative when $\Delta Pessimism_{t,T}$ is positive and $Return_{t-1,T}$ is positive. This means that a higher product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ reduces stock returns, when previous returns were positive and I have a higher pessimism. In other words, returns are lower for firms that had high stock returns in the previous period but also have a higher pessimism on their current filings. In such an event, a 1 percent in the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ will decrease the firm's stock returns by 14.9% twelve months after the filing. It is worth noting that the interaction of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ is not significant for the two cases where $Return_{t-1,T}$ are negative. It is also worth noting that $\Delta Pessimism_{t,T}$ alone is not significant in none of the four cases, but is significant as an interaction, which makes the case of examining it also previous returns worthwhile. Furthermore, $Return_{t-1,T}$ alone is significant in both cases when $Return_{t-1,T}$ is negative, while it is not significant in both cases where $Return_{t-1,T}$ is positive. Obviously, there is something different happening when previous returns are positive or negative.

As a next step, I create 10 portfolios based on the product of 10-K pessimism and the return of the previous period, and I calculate the mean returns for the 10 quintiles. The results appear in Figure 4 for firms that had negative returns in the previous period:

Insert Figure 4 here

The best results are obtained 9 months after the filing, giving a mean return of over 20% for the best of the 10 portfolios sorted by the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$, when the previous returns were negative.

The results for figures that had positive returns in the previous period appear in Figure 5

Insert Figure 5 here

The mean returns that the portfolios that had positive previous returns, appear to be negative for up to nine (9) months after the filing month, while it they revert to a mean return of almost zero (0), twelve (12) months after the submission month.

The results for firms that had a negative previous return and positive pessimism change appear in Figure 6:

Insert Figure 6 here

The best performing portfolio generates a mean return of close to 15%, 9 months after the submission month. The returns decrease when I get to twelve (12) months after submission, but remain very high. These are the stocks that had underperformed during the previous period, and at the same time have a higher 10-K pessimism. There seems to be a high risk-premium which is awarded to investors that hold these assets, the high-pessimism that underperformed in the previous period.

The results for firms that had negative returns in the previous period and a negative pessimism change (i.e. higher pessimism on this filings versus the previous filing) appear in Figure 7:

Insert Figure 7 here

The results show significantly lower returns for firms that had a negative previous return and negative pessimism change, as shown in Figure 7, than for firms that had a negative previous return and a positive pessimism change that appear in Figure 6. The mean return 9 months after the filing is above 27% for the first case, while it is around 15% for the second case, a return difference equal to 12% in nine (9) months, which is a very big difference in mean returns.

It is worth also examining what the mean returns are when the stocks had positive returns in the previous period. Figure 8 shows the mean returns for portfolios sorted on the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$, in the case where $Return_{t-1,T}$ was positive and $\Delta Pessimism_{t,T}$ was negative:

Insert Figure 8 here

The first portfolio of the ten quintiles performs the worst nine (9) months after the submission month, returning on average -17%, while it goes almost back to zero percent (0%) on the twelve months after submission. On the other hand, the 10th portfolio of the ten quintiles return close to zero percent (0%) for the whole twelve (12) months under examination. Finally, the mean returns for the ten (10) portfolios sorted on the product of $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$, in the case where $Return_{t-1,T}$ and $\Delta Pessimism_{t,T}$ are positive:

Insert Figure 9 here

These portfolios are generating negative mean returns which reach their lowest point nine (9) months after the submission month, while they revert at the twelve (12) months, but still remain

negative.

5.1. The pessimism-previous factor versus the momentum factor: mean returns

A question that naturally emerges is whether the pessimism risk premium gives indeed extra returns than the standard momentum returns. To answer this question, I plot the mean returns of the momentum quintiles. The results appear in Figure 10:

Insert Figure 10 here

To be able to make comparisons, I plot the mean returns of the momentum (blue line), the product of pessimism and previous returns (red line), and the difference between the two (red line). The results appear in Figure 11:

Insert Figure 11 here

The difference is very big, and is higher than five percent (5%) nine (9) months after the filing, while it becomes equal to 7.61% twelve (12) months after the filing. Indeed, it appears like the product of 10-K pessimism and previous returns gives extra yields than the momentum anomaly does.

6. Conclusion

I perform textual analysis on a sample of over 20,000 annual SEC EDGAR 10-K Forms, for NYSE, NASDAQ and AMEX (NYSE MKT) stocks, from 1992 until 2015. The pessimism change

($\Delta Pessimism_{t,T}$) which measures the change in textual pessimism of the current versus the previous 10-K annual filing for the same firm, appears to be a significant determinant when considered along the returns of the previous period ($Return_{t-1,T}$), i.e. the return between the previous and the current filing. The product of $\Delta Pessimism_{t,T} \times Return_{t-1,T}$ significantly affects stock returns three (3), six (6), nine (9) and twelve (12) months after the submission month. When distinguish between firms that had negative or positive period returns, the effect is more significant when the previous returns were positive. But when I take into account all four possible alternatives for previous returns and pessimism change, the effect is significant for positive previous returns, both for an increase and a decrease in annual 10-K pessimism. Creating monthly portfolios based on the product of 10-K textual analysis pessimism change (the change between the current and the previous filing of the same firm) and the previous period returns (stock returns between the previous and the current filing) one is able to generate returns in excess of what a strategy based on previous winners/losers would return. Nine (9) months after the filing, the difference between the returns of the product compared to the previous period returns is higher than 5%, while it exceeds 7% twelve (12) months after the filing. Firms that had a negative previous return and a positive pessimism change tend to return high positive returns in the twelve (12) months after the filing, while firms that had positive previous returns and a positive pessimism change tend to have negative returns in the twelve (12) months after the filing. The effect is maximum for both cases nine (9) months after the filing. The findings are significant for investors and researchers, and highlight the potential importance of combining the effect of multiple anomalies, compared to creating portfolios sorting only on one factor every time. Our analysis can be associated to both theoretical models of underreaction to news which are incorporated slowly into prices (Barberis et al. (1998)), as well as to the literature about the post announcement drift (Foster (1977), Foster et al. (1984) , Hirshleifer et al. (2009)) and our results contribute to the textual analysis in Finance

literature (Demers et al. (2008), Price et al. (2012), Davis et al. (2012), Loughran and McDonald (2011).

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Table 1: The table shows the total number of filings per year and on March. The number of filings corresponds the number of SEC Form 10-K filings matched with financial data from Bloomberg using the central index key (CIK) as a common identifier. The selected stocks correspond to all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks.

Year	**Number of filings**	**Filings on March**
1994	113	82
1995	80	40
1996	143	95
1997	170	122
1998	187	129
1999	196	131
2000	209	141
2001	955	514
2002	1104	598
2003	1195	777
2004	1271	814
2005	1343	871
2006	1391	878
2007	1411	710
2008	1153	399
2009	1258	509
2010	1158	437
2011	1132	405
2012	1906	794
2013	1201	400
2014	1627	645
2015	1458	778

Fig. 1. Graphical illustration of Table . There is an increasing availability of data starting from 2000. Most of the filings appear to be filed on March, which is reasonable given the fact that many companies use the December 31 as the end of the fiscal year, as the SEC allows 75 to 90 days for the Form 10-K to be filed within EDGAR.

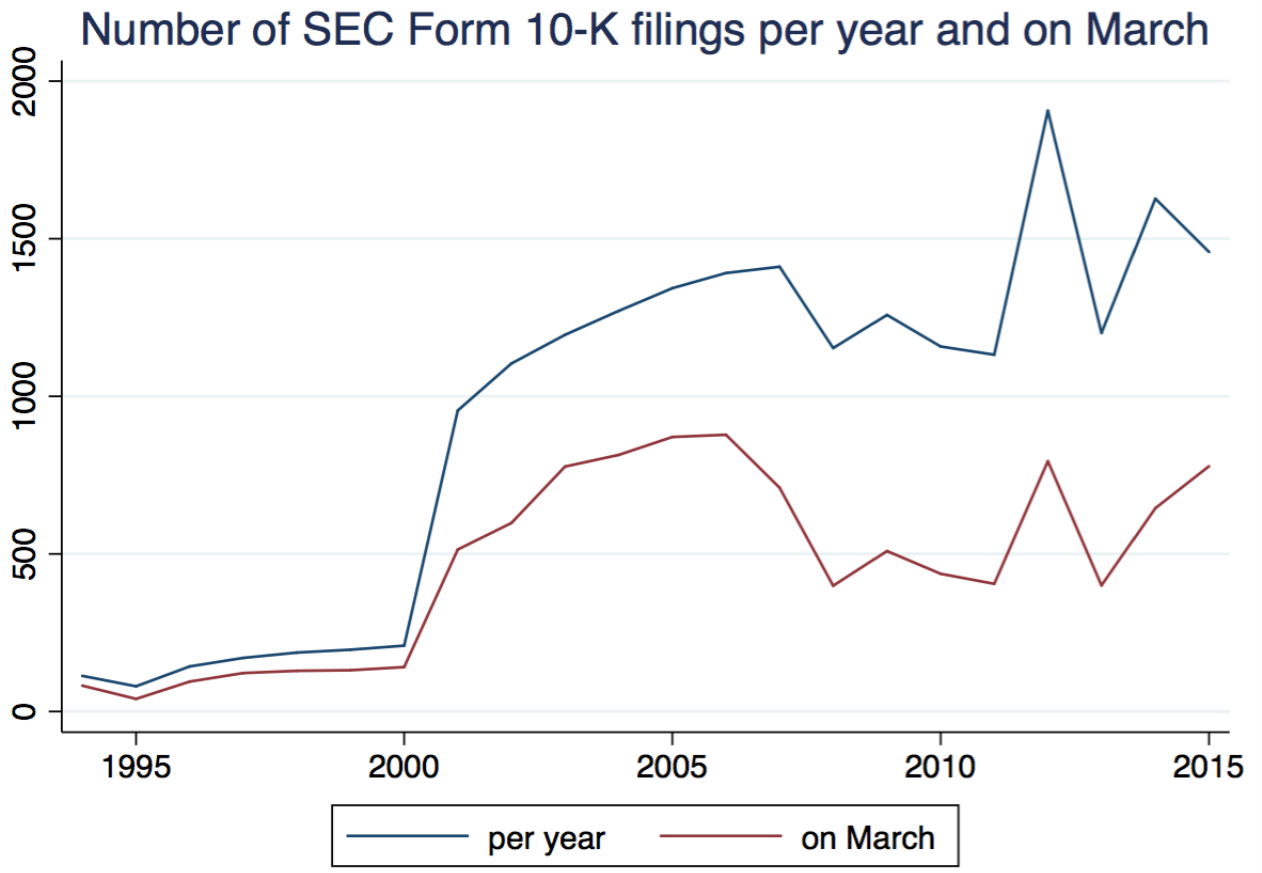

Fig. 2. Number of 10-K filings per month. March appears to be the month of the most filings, as mentioned also in Figure 1. Over 10,000 10-Ks were filed on Marches, followed by 4896 filed on Februaries, and only 904 on Aprils.

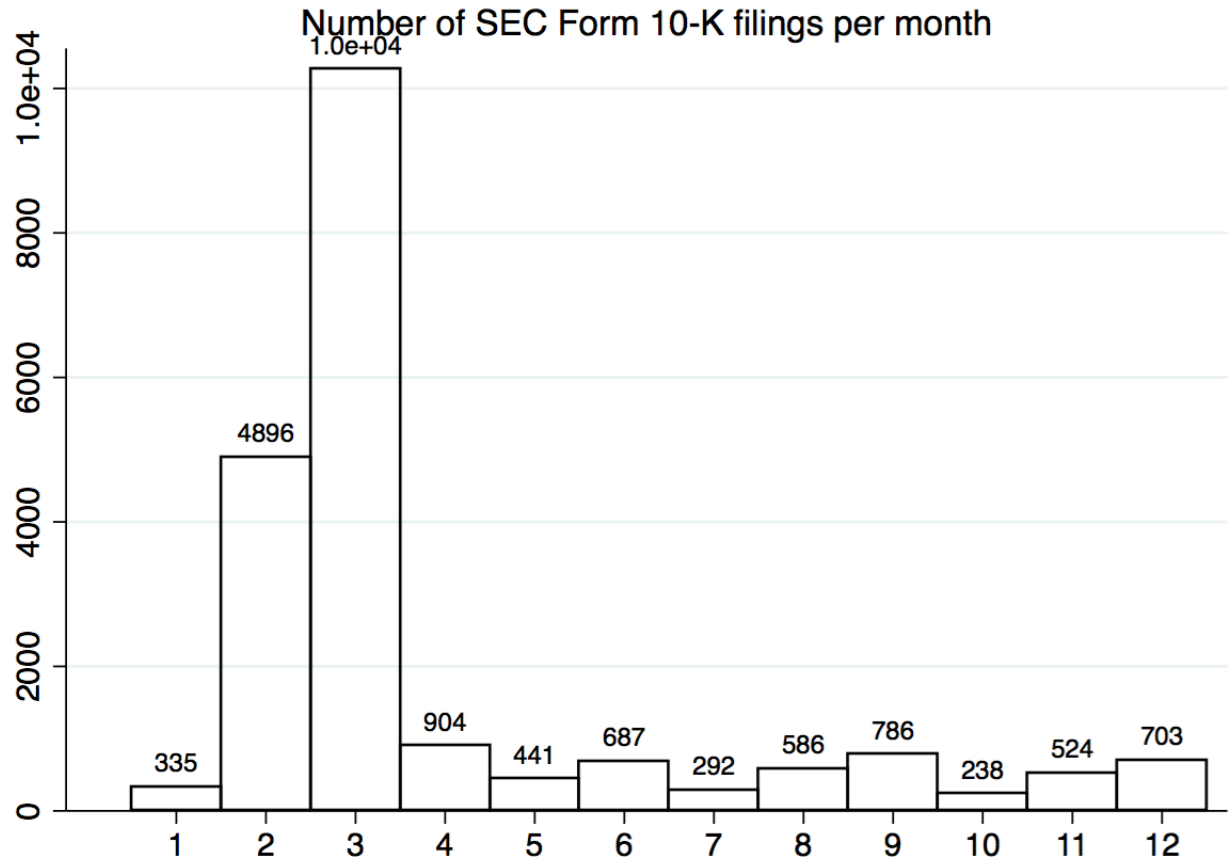

Fig. 3. Number of 10-K filings per day of the month. There seem to be two spikes, on in the middle of the month (1044, 1165 and 1191 filings on days 14, 15, 16 respectively) and on close to the end of the month (1062, 1304, 1496 filings on days 26, 27, 28 respectively)

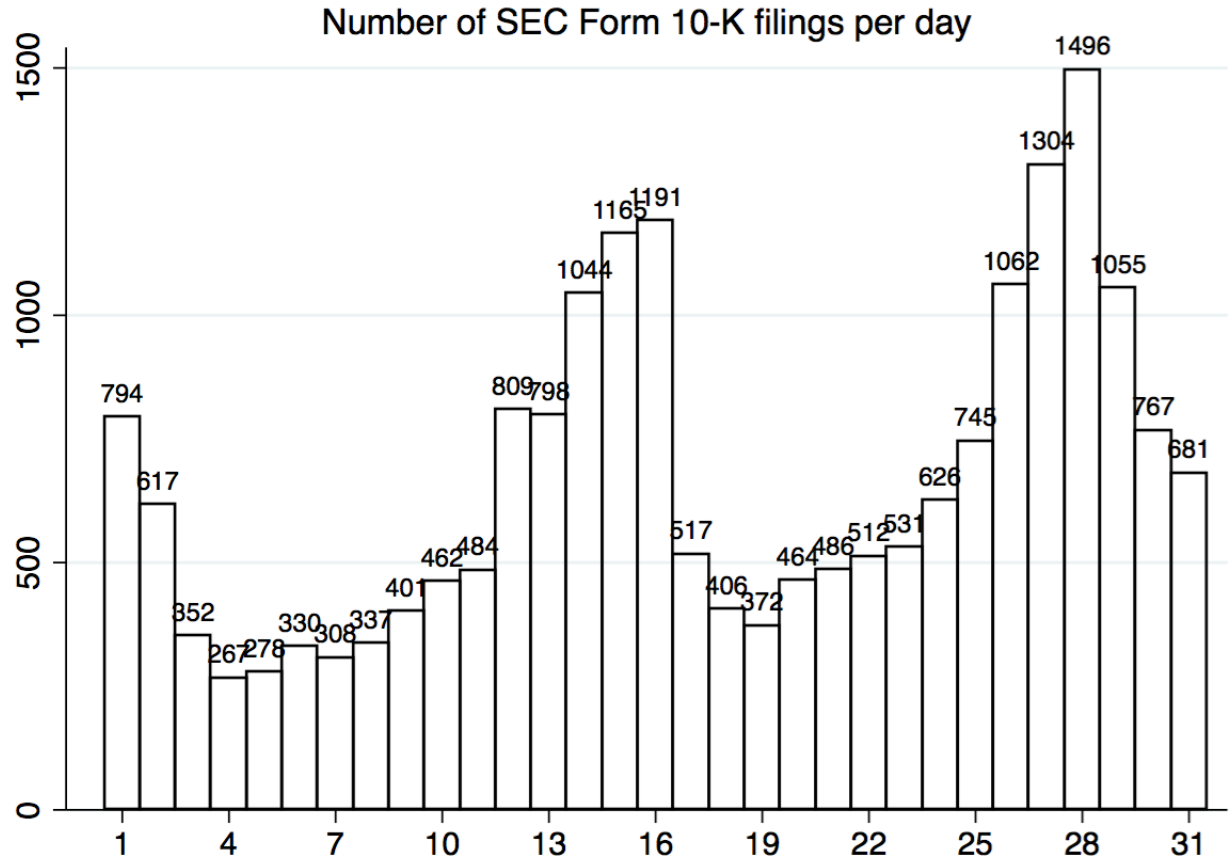

Table 2: Summary statistics table. T stands for the previous submission month while t stands for the current submission month. $\Delta Pessimism_{t,T}$ measures the change in pessimism between the previous Form 10-K filing (T) and one month before the current filing (t-1). $\Delta Pessimism_{t,T} \times Return_{t,T}$ captures the product of pessimism change between the previous (T) and the current period (t), times the return between the previous and the current filing ($Return_{t,T}$). $Return_{t,t-1}$ captures the return between the end of the filing month and the previous month. $Return_{t+1,t}$ captures the return between one month after submission minus the submission month. Similarly I calculate $Return_{t+3,t}$, $Return_{t+6,t}$, $Return_{t+9,t}$, $Return_{t+12,t}$ for the returns 3, 6, 9 and 12 months after submission. I always get the price at the end of the submission month, in order to avoid dealing with the short-term effects that were studies in the previous literature. Finally, I calculate the percentage of positive words (Positive$_t$), negative words Negative$_t$, pessimism Pessimism$_t$ using the Loughran and McDonald (2011) word lists, and the summary statistics for the total number of words $Words_t$at each Form 10-K filing. Selected stocks are all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks from 1992 to 2015.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
$\Delta Pessimism_{t,T} \times Return_{t,T}$	-0.001	0.256	-5.389	3.778	14145
$Return_{t-1,T}$	0.034	0.422	-3.394	3.097	15673
$Return_{t,t-1}$	0.01	0.128	-1.241	1.989	19757
$Return_{t+1,t}$	0.012	0.153	-1.688	3.482	19933
$Return_{t+3,t}$	0.018	0.247	-2.241	2.938	19544
$Return_{t+6,t}$	0.006	0.349	-2.69	3.466	19193
$Return_{t+9,t}$	0.022	0.41	-3.149	4.025	15794
$Return_{t+12,t}$	0.044	0.441	-3.394	3.156	16005
$\Delta Pessimism_{t,T}$	0.025	0.690	-6.736	5.285	14698
Positive$_t$	0.007	0.002	0	0.02	20661
Negative$_t$	0.014	0.005	0	0.217	20661
Pessimism$_t$	0.007	0.006	-0.013	0.212	20661
$Words_t$	74796.751	66134.272	122	747663	20661

Table 3: The effect of Form 10-K pessimism on stock returns for the end of the submission month. Selected stocks are all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks from 1992 to 2015. I am studying the effect of the percentage of negative words (Negative$_t$, as used in Loughran and McDonald (2011)) versus the change in pessimism between the current and the previous Form 10-K ($\Delta Pessimism_{t,T}$) and the Pessimism Percentage (Pessimism$_t$).

	(1) $Return_{t,t-1}$	(2) $Return_{t,t-1}$	(3) $Return_{t,t-1}$	(4) $Return_{t,t-1}$	(5) $Return_{t,t-1}$	(6) $Return_{t,t-1}$
$\ln PB$	0.0164***		0.0183***		0.0183***	
	(5.40)		(6.48)		(6.48)	
$\ln Market\,Cap$	0.00982***		0.00892***		0.00894***	
	(3.24)		(3.29)		(3.30)	
$\Delta Pessimism_{t,T}$	-0.00484***	-0.00583***				
	(-3.14)	(-3.32)				
Pessimism$_t$			-0.0352	-0.204		
			(-0.21)	(-1.13)		
Negative$_t$					0.0113	-0.160
					(0.06)	(-0.84)
Constant	-0.181***	0.0264**	-0.212***	-0.0235***	-0.213***	-0.0230***
	(-2.96)	(2.21)	(-4.03)	(-4.12)	(-4.04)	(-3.85)
R-squared	0.0503	0.0376	0.0416	0.0279	0.0416	0.0279
N	13247	14124	18303	19757	18303	19757
Fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Std. errors clustering by firm	✓	✓	✓	✓	✓	✓

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: The effect of Form 10-K pessimism on stock returns, three (3), six (6), nine (9) and twelve (12) months after the submission month. Selected stocks are all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks from 1992 to 2015. I am studying the effect of the change in pessimism between the current and the previous Form 10-K ($\Delta Pessimism_{t,T}$), the effect of the stock return between the previous and the current filing ($Return_{t-1,T}$), as well as the effect of $\Delta Pessimism_{t,T} \times Return_{t-1,T}$, which is the interaction of the stock returns between the previous and the current filing ($Return_{t-1,T}$), times the change in pessimism between the previous and the current filing ($\Delta Pessimism_{t,T}$).

	(1) $Return_{t+12,t}$	(2) $Return_{t+9,t}$	(3) $Return_{t+6,t}$	(4) $Return_{t+3,t}$
$\ln PB$	0.225***	0.186***	0.136***	0.0705***
	(11.58)	(11.61)	(11.88)	(9.94)
$\ln MarketCap$	0.000907	0.0661***	0.0524***	0.0320***
	(0.06)	(4.85)	(5.01)	(4.59)
$Return_{t-1,T}$	-0.285***	-0.397***	-0.245***	-0.115***
	(-21.52)	(-25.49)	(-18.27)	(-15.88)
$\Delta Pessimism_{t,T}$	0.00438	0.00151	-0.000306	0.00914***
	(0.90)	(0.32)	(-0.08)	(3.20)
$\Delta Pessimism_{t,T} \times Return_{t-1,T}$	-0.0541***	-0.0443**	-0.0279*	-0.0157
	(-3.32)	(-2.09)	(-1.81)	(-1.54)
Constant	-0.0574	-1.420***	-1.142***	-0.652***
	(-0.19)	(-5.28)	(-5.51)	(-4.71)
R-squared	0.350	0.303	0.278	0.199
N	10994	11153	13008	12947
Fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Std. errors clustering by firm	✓	✓	✓	✓

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The effect of Form 10-K pessimism on stock returns, twelve (12) months after the submission month. Selected stocks are all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks from 1992 to 2015. I am studying the effect of the change in pessimism between the current and the previous Form 10-K ($\Delta Pessimism_{t,T}$). Finally, I am examining the effect of $\Delta Pessimism_{t,T} \times Return_{t-1,T}$, which is the interaction of the stock returns between the previous and the current filing ($Return_{t-1,T}$), times the change in pessimism between the previous and the current filing ($\Delta Pessimism_{t,T}$). In this table, I am studying the two possible scenarios for the previous period returns ($Return_{t-1,T}$), which are (1) previous returns ($Return_{t-1,T}$) are negative and (2) previous returns ($Return_{t-1,T}$) are positive.

	(1) $Return_{t+12,t}$ If $Return_{t-1,T} < 0$	(2) $Return_{t+12,t}$ If $Return_{t-1,T} > 0$
$\ln PB$	0.268***	0.185***
	(7.90)	(9.68)
$\ln MarketCap$	0.0123	-0.0299*
	(0.42)	(-1.94)
$Return_{t-1,T}$	-0.476***	-0.105***
	(-14.08)	(-4.65)
$\Delta Pessimism_{t,T}$	-0.0246*	0.00609
	(-1.77)	(0.72)
$\Delta Pessimism_{t,T} \times Return_{t-1,T}$	-0.140***	-0.0446
	(-3.16)	(-1.59)
Constant	-0.432	0.606**
	(-0.75)	(1.97)
r2	0.513	0.266
N	4536	6446
Fixed effects	✓	✓
Year fixed effects	✓	✓
Std. errors clustering by firm	✓	✓

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The effect of Form 10-K pessimism on stock returns, twelve (12) months after the submission month. Selected stocks are all available (on Bloomberg) NYSE, NASDAQ and AMEX (NYSE MKT) stocks from 1992 to 2015. I am studying the effect of the change in pessimism between the current and the previous Form 10-K ($\Delta Pessimism_{t,T}$). Finally, I am examining the effect of $\Delta Pessimism_{t,T} \times Return_{t-1,T}$, which is the interaction of the stock returns between the previous and the current filing ($Return_{t-1,T}$), times the change in pessimism between the previous and the current filing ($\Delta Pessimism_{t,T}$). In this table, I am studying all four possible scenarios, which are (1) previous returns are negative and change in pessimism is negative, (2) previous return is negative and change in pessimism is positive, (3) previous returns are positive and change in pessimism is negative, (4) previous returns are positive and change in pessimism is positive.

	(1)	(2)	(3)	(4)
	$Return_{t+12,t}$	$Return_{t+12,t}$	$Return_{t+12,t}$	$Return_{t+12,t}$
	If $Return_{t-1,T} < 0$		If $Return_{t-1,T} > 0$	
	If $\Delta Pessimism_{t,T} < 0$	If $\Delta Pessimism_{t,T} > 0$	If $\Delta Pessimism_{t,T} < 0$	If $\Delta Pessimism_{t,T} > 0$
$\ln PB$	0.281***	0.259***	0.189***	0.160***
	(6.54)	(5.09)	(6.81)	(5.81)
$\ln MarketCap$	-0.0501	0.0424	-0.0345	-0.0174
	(-1.25)	(0.98)	(-1.31)	(-0.86)
$Return_{t-1,T}$	-0.377***	-0.559***	-0.0208	-0.0201
	(-5.59)	(-9.17)	(-0.46)	(-0.44)
$\Delta Pessimism_{t,T}$	0.0221	0.00598	-0.00829	0.0197
	(0.64)	(0.22)	(-0.45)	(0.96)
$\Delta Pessimism_{t,T} \times Return_{t-1,T}$	-0.0121	-0.0513	0.143**	-0.151***
	(-0.11)	(-0.61)	(2.16)	(-2.63)
Constant	0.954	-1.151	0.678	0.292
	(1.22)	(-1.33)	(1.31)	(0.70)
r2	0.442	0.567	0.285	0.270
N	2117	2419	3148	3298
Fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Std. errors clustering by firm	✓	✓	✓	✓

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fig. 4. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing) were negative.

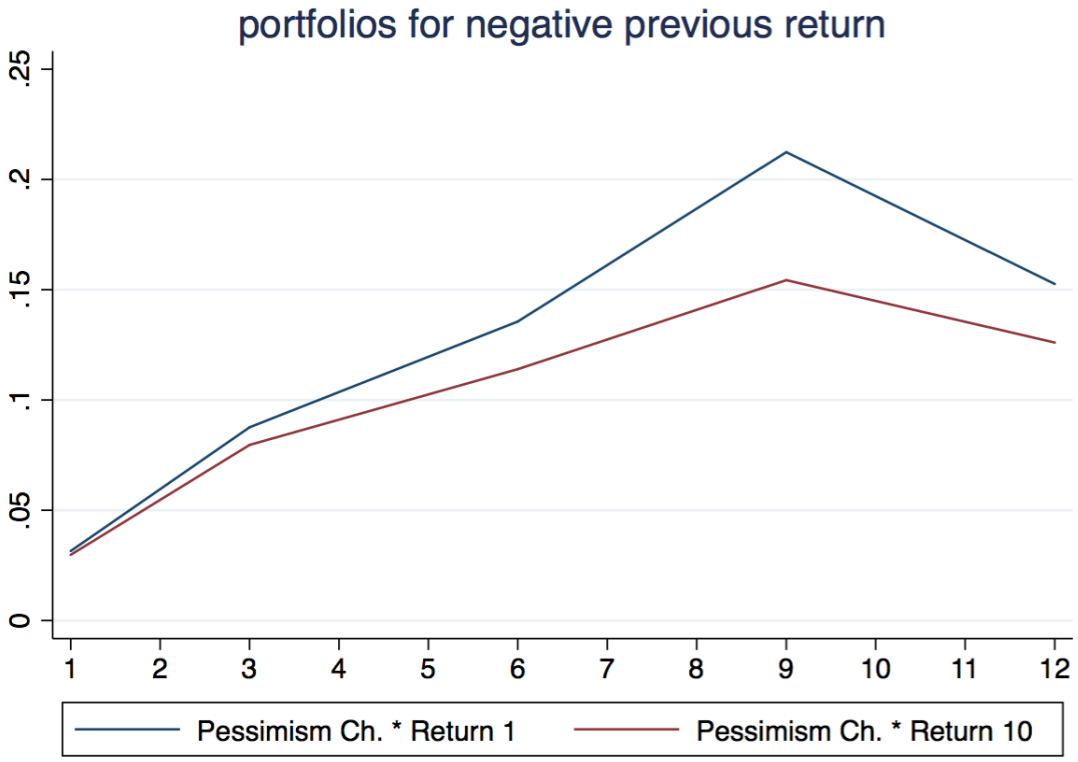

Fig. 5. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing) were positive.

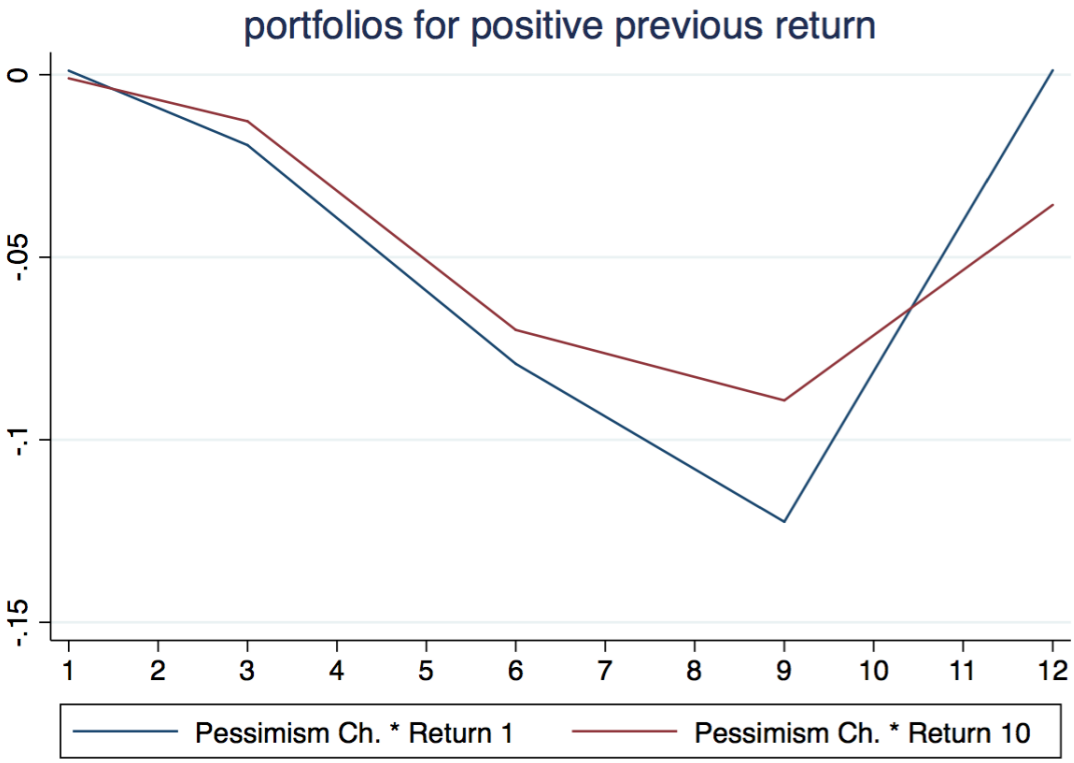

Fig. 6. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing, $Return_{prev}$) were negative, while the change in pessimism ($\Delta Pessimism_{t,T}$) was positive.

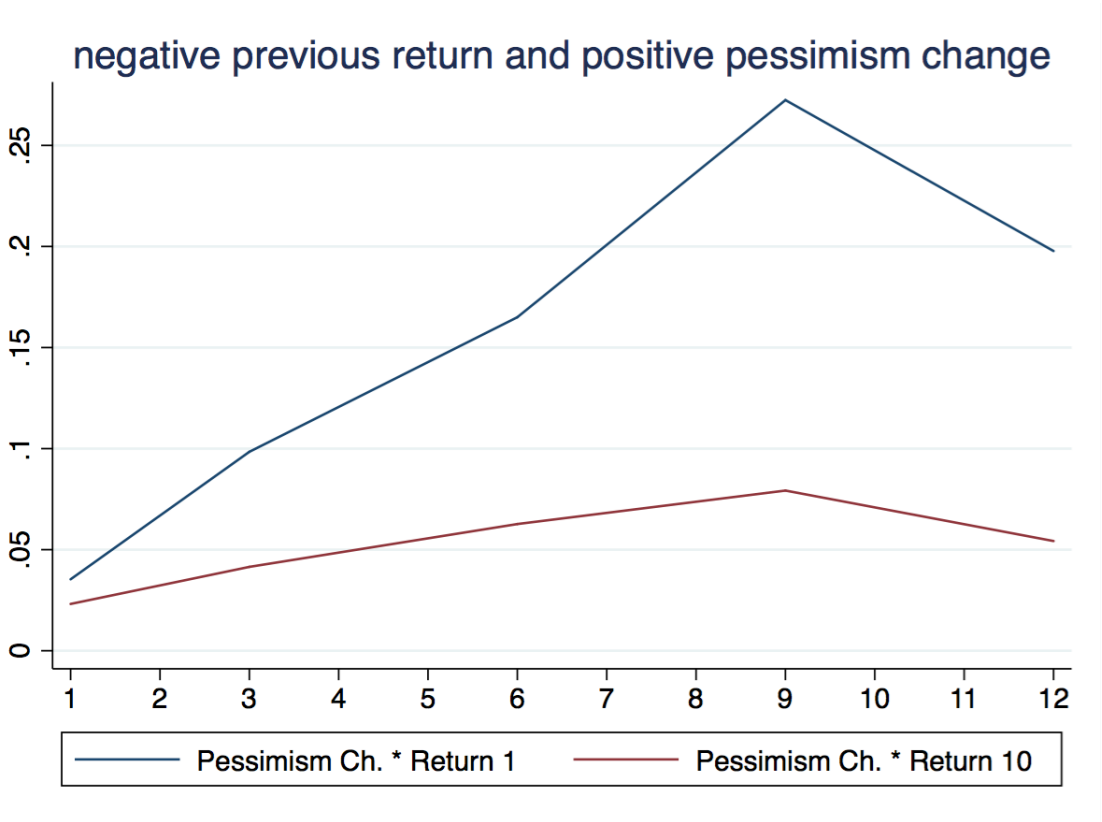

Fig. 7. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing, $Return_{prev}$) were negative, while the change in pessimism ($\Delta Pessimism_{t,T}$) was negative.

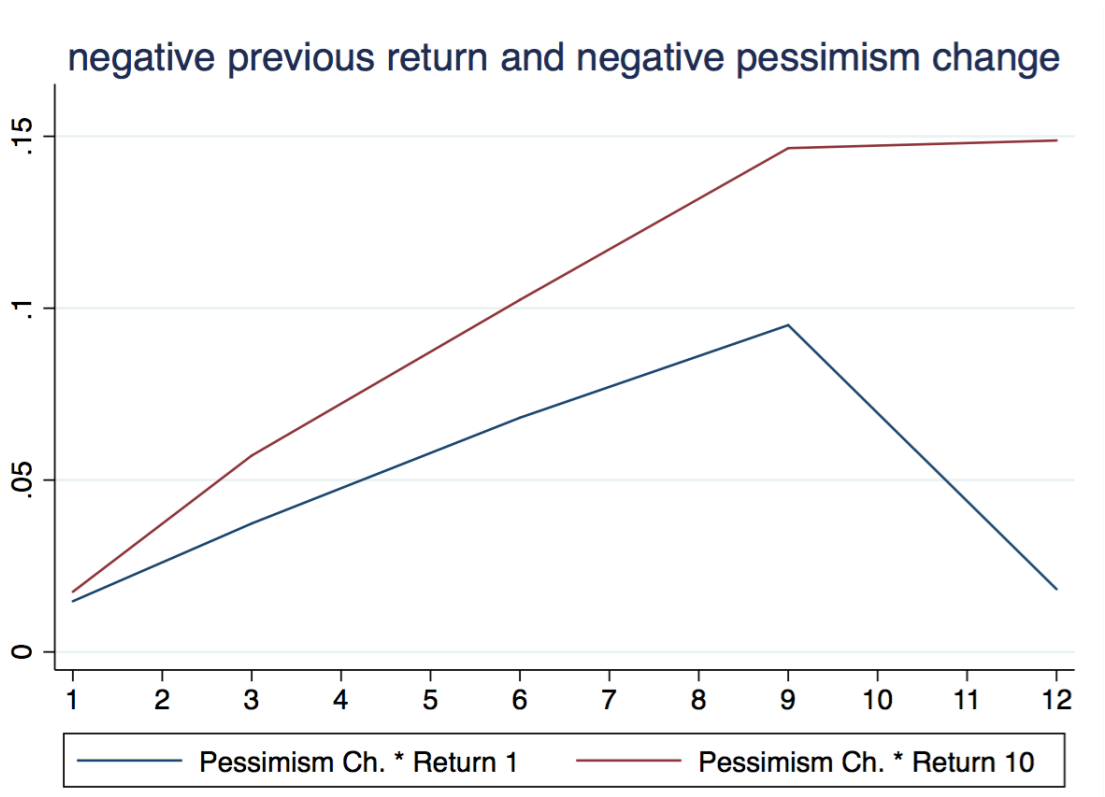

Fig. 8. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing, $Return_{prev}$) were positive, while the change in pessimism ($\Delta Pessimism_{t,T}$) was negative.

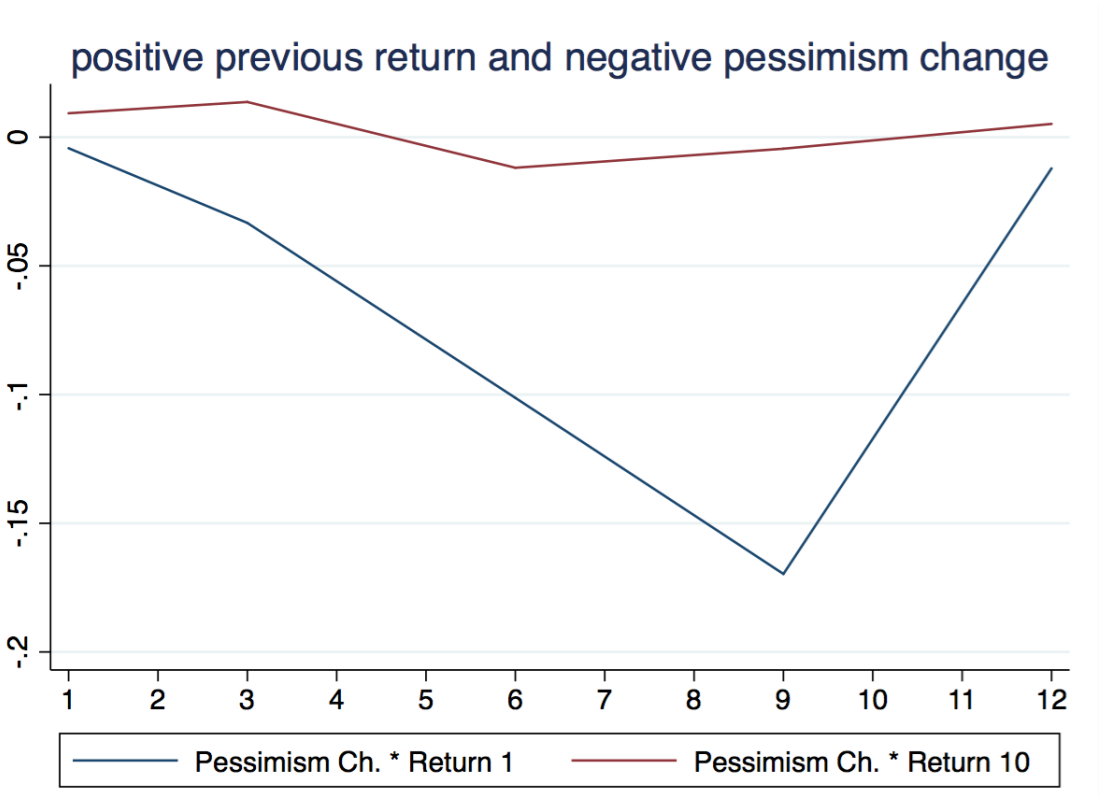

Fig. 9. On every month of every year, 10 portfolios are created, based on the product of $\Delta Pessimism_{t,T} \times Return_{prev}$ (i.e. the product between the change in pessimism between the current and the previous filings, $\Delta Pessimism_{t,T}$, and the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, while "Pessimism Ch. * Return 10" corresponds to the portfolios that had the highest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month. In both cases, the stock returns for the previous period (i.e. the period between the previous and the current filing, $Return_{prev}$) were positive, while the change in pessimism ($\Delta Pessimism_{t,T}$) was positive.

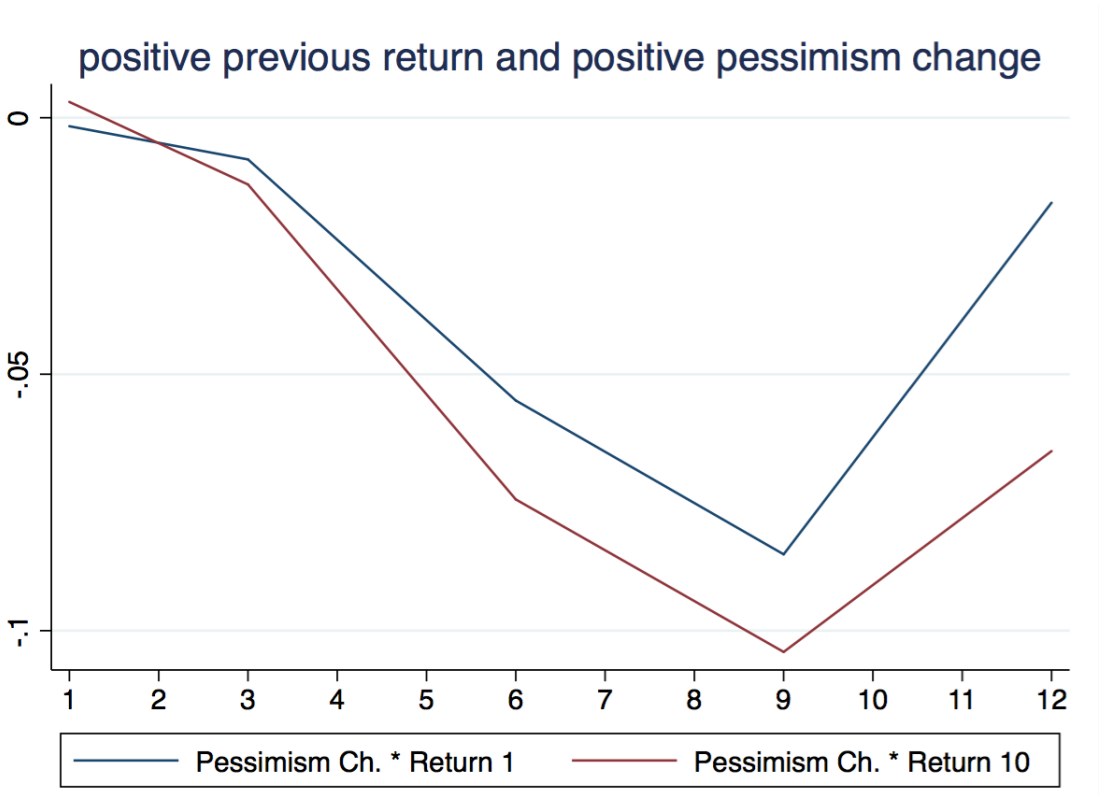

Fig. 10. On every month of every year, 10 portfolios are created, based on the the returns of the period between the previous and the current filing, $Return_{prev}$). Then, I calculate the mean returns for up to twelve (12) months after the submission month. "Momentum 1" corresponds to stocks that performed badly in the previous period, while Momentum 10 corresponds to stocks that performed best in the previous period.

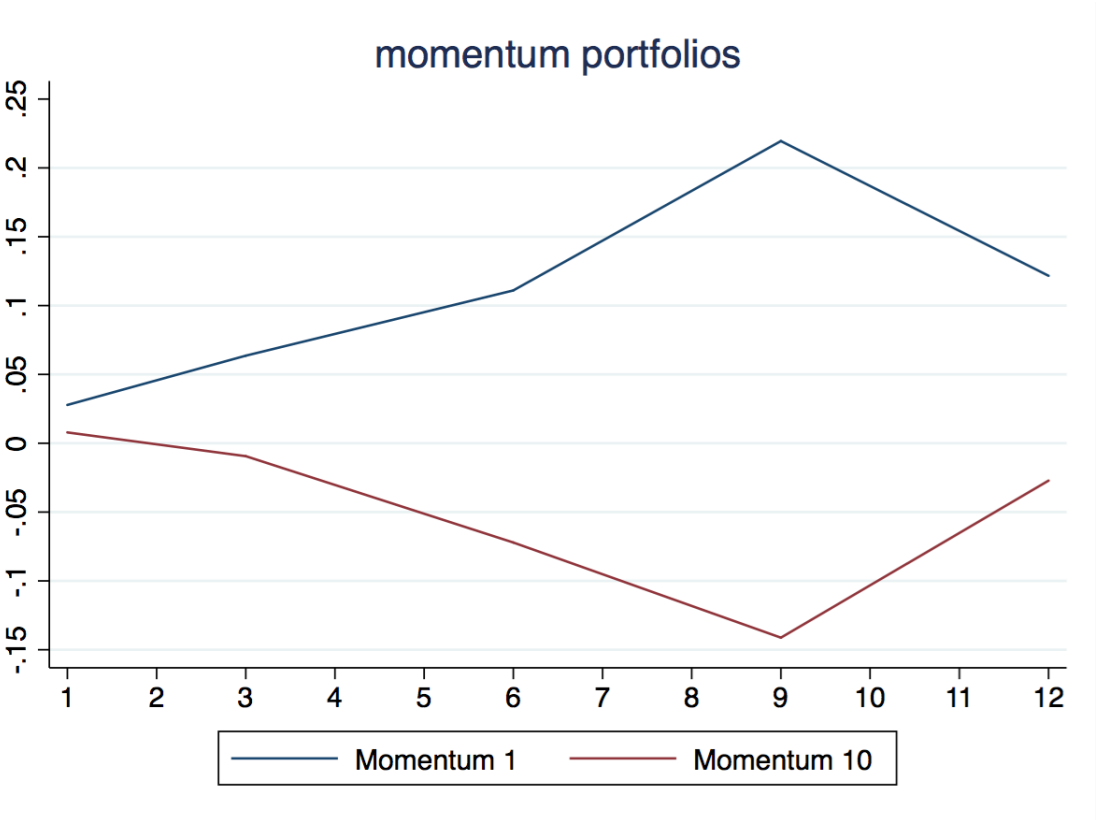

Fig. 11. "Pessimism Ch. * Return 1" corresponds to the portfolios with the lowest values of $\Delta Pessimism_{t,T} \times Return_{prev}$ for every month, taken from Figure 6. "Momentum 1" corresponds to stocks that performed badly in the previous period, while Momentum 10 corresponds to stocks that performed best in the previous period. "Difference" is the difference in returns between the two strategies.