Q4 Investment Spikes and Stock Returns

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Abstract

Constructing portfolios based on abnormal fourth quarter capital expenditures, we find that firms with higher Q4 investment spikes (qspikes) subsequently have lower returns in the stock market. This effect is largely driven by the period of the late 1990s/early 2000s. While qspikes are by construction linked to the investment growth factor, we find that the portfolio overlap and the cross-sectional return correlation are surprisingly low. Nevertheless, abnormal returns of both strategies highly cluster in time. We interpret our findings as further evidence for managerial agency conflicts in the investment decision process: the qspike effect is stronger for firms with high cash flows and for firms that introduce dividends.

Keywords: investment-based asset pricing, capital expenditures, investment anomaly, agency costs

JEL Classification: G11, G12, G14

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1 Introduction

A recent development in the asset pricing literature led to the emergence of new empirical models that contain a profitability and an investment factor (Hou et al., 2014; Fama and French, 2015). Based on predictions from the neoclassical q-theory, Hou et al. (2014) suggest that firms' capital investments are inversely correlated with firms' expected stock returns. This is the case because, after holding a firm's expected profitability fixed, high discount rates imply low valuations, which in return leads to low investment today. This literature also builds a natural link to book-to-market values, as investments are positively related to the discrepancy between the market value of installed capital and its replacement cost (Anderson and Garcia-Feijoo, 2006). As an empirical consequence, Fama and French (2015) show that the value factor HML becomes redundant once the investment factor is added to their three-factor model.

Prior to its natural emergence in investment-based asset pricing, the investment factor has been largely considered an anomaly (Titman et al., 2004; Anderson and Garcia-Feijoo, 2006; Xing, 2007; Polk and Sapienza, 2008). Several explanations have been put forth to explain the existence of an investment effect, from empire building theories (Titman et al., 2004) to behavioral explanations related to mispricing (Baker and Wurgler, 2002). Of particular interest to our study is the work by Titman et al. (2004), as their idea of agency conflicts resounds in how we think about the effect presented here.

Our paper contributes to this literature with a novel approach that is distinct from the standard investment anomaly, which is commonly captured by the impact of an increase in capital investments on stock returns. Instead, we employ an investment measure that is borrowed from the corporate finance literature and calculated as the ratio between fourth quarter capital expenditures and the average of the three prior quarters, which we label a Q4 investment spike or shortly qspike. The qspike captures the abnormal increase/decrease in capital expenditures of companies in the fourth quarter of their fiscal year. While such an effect is not considered in neoclassic theories of efficient investment, prior research in corporate finance connects it with managerial agency problems and active tax management (Shin and Kim, 2002; Xu and Zwick, 2020).

In our main analysis we sort U.S.-listed stocks by qspike values and assign them into three portfolios based on 30-40-30 cut-offs in the qspike distribution. We find that firms with higher Q4 investment spikes have relatively lower returns in the stock market. Specifically, a zero-investment portfolio long firms with low qspike values and short firms with high qspike values delivers on average 0.32% per month for the 34 years in our sample. Further tests, such as factor model regressions and Fama-Macbeth regressions, confirm our baseline findings.

To verify that our findings are not fully subsumed by the investment anomaly, we extend our univariate analysis. We first provide a comparison of the two underlying sorting variables. As its construction is most similar to our qspike variable, we base our comparison on Titman et al. (2004)'s definition of abnormal capital investments (ci), which is calculated as the fraction of annual capital expenditures divided by the average over three prior years. Looking at the time-series averages of both variables, we find that they are highly correlated, with an indication that qspikes are able to pick up large swings earlier. In the cross-section, however, the correlation is not so high. When comparing the overlap of portfolio assignments, for instance, we can see that 35.8% of firms assigned to the low value qspike portfolio would also end up in the low value portfolio if stocks were sorted by ci values instead. This number needs to be compared to 30%, which would indicate the expected overlap by chance.

Next, we investigate the importance of this correlation for the cross-section of stock returns. Therefore, we construct double-sorted portfolios based on both factors. To investigate whether qspikes are redundant once taking account for the investment factor in the analysis, we conduct a sequential double sort. We first sort stocks into three groups based on ci values, which maximizes the absorption of its mechanism. Then, within each group, we sort stocks into 3 portfolios according to qspike values. When looking at the resulting zero-investment portfolios, we still find evidence for a qspike effect, which holds true for stocks with low abnormal capital investments as well as for stocks with high values.

Looking at the time-series pattern of abnormal returns, we find that the qspike effect is predominantly driven by the years 1998-2004, and that it is weaker in subsequent years. Interestingly, this is precisely the period when the investment factor is also performing strongly. Thus, despite the low correlation previously documented in the cross-section, abnormal returns of both factors are again highly clustered in time.

The time-series result leaves the question why Q4 investment spikes are driving stock returns between 1998 and 2004. We propose managerial agency conflicts as one plausible mechanism that is able to reconcile such a finding, something that has already been introduced by Titman et al. (2004) with respect to the investment anomaly before that results has been rationalized in return with the help of the investment CAPM. We argue that these years are characterized as a period of enormous capital investments and, at the same time, relatively weak managerial oversight.

To provide suggestive evidence in support of the agency hypothesis, we first separate our sample into firms with above-median cash flows and firms with below-median cash flows. In line with Jensen (1986)'s free cash flow problem, we find that the qspike effect is larger for firms with above-median cash flows and that the difference materializes precisely during the years 1998-2004.

Based on similar arguments, we also investigate firms' dividend policies. Firms that are just about to introduce dividends are likely the ones generating excess cash flows, which could end up being reinvested excessively in the business under agency conflicts. If we separate firms introducing dividends in our analysis, we again find that their qspike effect is relatively larger. Thus, after a period during which managers overinvest during the late 1990s/early 2000s, the qspike effect gradually disappears when overall investment levels come down after the burst of the dot.com bubble and investors demand higher dividend payouts.

Our paper adds evidence to the effect of Q4 investment spikes in capital expenditures, a variable which has been subject to research in corporate finance. Shin and Kim (2002) document that Q4 capital expenditures exceed prior fiscal quarters and find that these year-end investments exhibit a weaker correlation with Tobin's Q. Sensitivities of large, cash-rich, and diversified firms are particularly low, which they interpret as evidence for agency costs. More recently, Xu and Zwick (2020) take a different perspective by arguing that tax-minimizing incentives also lead to Q4 spikes as year-end investments still enable a partial generation of depreciation tax shields. Our paper introduces Q4 investment spikes to the asset pricing literature by investigating its link with stock returns.

Building portfolios with capital expenditures naturally ties our analysis to investment-based asset pricing. There are several influential papers associated with an investment anomaly in stock returns (Titman et al., 2004; Anderson and Garcia-Feijoo, 2006; Xing, 2007; Polk and Sapienza, 2008).[1]While these studies largely capture abnormal investments through increases in capital expenditures from one year to the other, our approach differs by capturing abnormal year-end investment within a fiscal year. Out-of-sample evidence for the investment factor is also weaker, in particular for developing countries (Titman et al., 2010) and U.S. stock returns between 1940 and 1963 (Wahal, 2019), which justifies more research on the topic.

[1]In attempts to reduce the number of asset pricing factors, even a wider set of pricing puzzles has been shown to be related to the investment anomaly. We restrict our discussion to the ones that most closely relate to Q4 investment spikes in terms of data origination to construct the factors.

Ultimately, our findings contribute to the discussion of an investment factor in recent asset pricing models. Fama and French (2015) and particularly Hou et al. (2014)'s investment CAPM provide arguments why capital investments should be expected to be a priced factor in the cross-section of stock returns. The evidence in this paper highlights the multi-dimensionality of investment decisions. While these models suggest that the standard investment factor arises in line with perfectly efficient markets, we interpret the qspike effect as likely to be driven by agency costs.

2 Data and Portfolio Construction

Our sample is based on the intersection of CRSP/Compustat Merged (CCM) and Compustat's quarterly data. The quarterly data does not go back to the 1960s, which restricts our sample to the period from January 1985 to December 2019. As we attempt to predict stock returns with Q4 spikes in capital expenditures, our return data starts in 1986. Our sample only contains US-listed common shares (based on CRSP shrcd 10 and 11), i.e. American Depositary Receipts, closed-end funds, REITs, and units are excluded. In our main analysis we keep financial and utilities companies, yet we verify that results are not driven by these types of companies.

2.1 Quarterly spikes in capital expenditures

Our main variable of interest are abnormal capital investments during the last quarter of a firm's fiscal year. For a corporate finance motivation for this variable we refer to Shin and Kim (2002) and Xu and Zwick (2020). We follow their definition by constructing Q4-spikes in capital expenditures (qspike) in the following way:

$$qspike_{it} = \frac{CAPEX_{it,Q4}}{avg(CAPEX_{it,Q1-Q3})}$$

We calculate qspike values for firms with at least 10$ million of assets. We drop observations with missing capital expenditures in the annual data and negative values for quarterly capital expenditures. We also drop observations with annual capital expenditures below $100,000, and observations where the sum of all quarterly expenditures exceeds 110% of the value declared in the annual data. 20% of quarterly observations have zero or no capital expenditures, leading to a missing value in the qspike. Finally, we assign a cap to the qspike equal to the 99% percentile value. Figure 1 plots the time-series of average quarterly capital expenditures standardized by each firm's yearly average. Spikes in the fourth quarter are clearly visible for all years in our sample. For most years Q4 capital expenditures exceed their annual average by 10-20%. In more recent years this number has been slightly smaller.

2.2 Description of portfolio construction

The main portfolio sort of this study is based on the qspike variable just introduced. At the end of each month we sort all US-listed stocks into three portfolios using the 30th and the 70th percentile of firms' most recent qspike values (Low, Middle, and High). We employ a 6-month lag of the qspike data to make sure that the information has been disclosed and is publicly disseminated. All firms with invalid qspike values for a given month are subsumed in a residual portfolio for comparability.

Since each firm's qspike value only changes once per year, the strategy of monthly rebalancing does not create excessive turnover. The largest reshuffling will be at the end of June when all firm's with fiscal year ends in December get new qspike values assigned. As an alternative, we also construct portfolios that only get rebalanced once a year at the end of June. The results are reported in the appendix. Since the effect we will document is not as persistent, which we will discuss in the next section, it is beneficial to make use of information more rapidly when it becomes available.

3 Portfolio analysis

3.1 Univariate portfolio analysis

In this section we test if qspike values predict stock returns. Table 1 reports our univariate analysis of monthly portfolio returns sorted by qspike values, as just described. We consider returns in excess of the one-month Treasury Bill rate (exret), industry-adjusted returns calculated as the difference between individual stock returns and its relevant Fama and French 48 industry return (indadj), as well as alphas from time-series regressions of various asset pricing models: the Fama-French three factor model ($FF3$), the Fama-French five factor model ($FF5$), the q-factor model (q), and the extended q-factor model (q^5).

The first thing to notice in Table 1 is that excess returns and alphas monotonically decrease in portfolios with higher qspike values. Looking at a zero-investment portfolio that shorts firms with high qspike values and invests in firms with low values, we find that the average monthly return of the value-weighted hedge portfolio is 0.32%, which is of economic and statistical significance. The corresponding alphas we are estimating in various asset pricing models are of similar magnitude ranging from 0.24% to 0.32% per month. Only the specification with industry-adjusted returns indicates a lower figure of 0.11% suggesting that industry characteristics are of particular importance. For equally-weighted portfolios we find that results are of larger economic magnitude with stronger statistical significance.

Since we do not observe qspike values for all firm-year observations, we also construct a portfolio of firms without valid qspike data. The stock performance of these firms is similar to stocks with high qspike values, sometimes slightly better and sometimes even slightly worse depending on the specification. For equally-weighted portfolios the underperformance of stocks with missing data is less dramatic. According to our definition of qspike values, firms with zero capital expenditures end up in this group, which is apparently a particularly bad signal for large firms.

In a next step we examine how the returns of the hedge portfolio are spread over time. Figure 3 plots cumulative returns from January 1986 to December 2019. Most notable is the strong performance of our investment strategy between 1999 and 2005. In particular value-weighted portfolios realize the major part of their abnormal returns during these years. This holds for cumulative raw returns as well as alphas. Equal-weighted returns tend to outperform already at a smaller pace pre-1999, leading to a larger effect overall. As suggested from our regression result, cumulative returns of industry-adjusted returns are by far the lowest, suggesting that the qspike effect is to some extent related to industry characteristics not picked up by any of the commonly employed risk factors. Yet, there is still a sizable qspike effect for industry-adjusted returns around 2000. Since 2005 neither value-weighted nor equal-weighted portfolios show any signs of continuing outperformance.

Figure 4 shows a similar time-series graph, where we plot the cumulative excess return of the value-weighted hedge portfolio from our qspike sorting against the investment factor (cma) and the value factor (hml) downloaded from Kenneth's French website. The crucial period in our sample are the years 1998 to 2005, during which all of these zero-investment portfolios deliver a stellar performance, accumulating most of their cumulative return. Outside that period the return correlation seems lower. In particular the hml factor perforemed poorly since 2005, which is why these risk factors don't capture the entire alpha in time-series portfolio regressions.

3.2 Comparing portfolio formation

The overlap in cumulative returns of the qspike hedge portfolio with other risk factors, in particular the investment factor, raises the question whether our sorting simply picks up the same ranking underlying the investment factor. The literature has proposed several ways how to derive an investment factor, all based on changes in capital expenditures or total assets. Fama and French (2015) and Hou et al. (2014) use asset changes when creating their factor models. We follow in this section Titman et al. (2004)'s calculation because they apply a formula most similar to ours that also uses capital expenditures. They define abnormal capital investments (ci) as last year's capital expenditures over total sales divided by the average over the three prior fiscal years. Thus, it is exactly the same formula applied to annual instead of quarterly capital expenditures.

Figure 2 plots yearly averages of qspike values against ci values. We can see that qspike values are above one for basically every year in our sample. Crisis periods are clearly visible as there are lower values observed for the years 1990, 2001, and 2008. Ignoring these negative outliers, the time-series reveals a downward sloping trend: prior to 2000 most values are above 1.2, while observations towards the end of our sample are more in the range of 1.1. Turning to a comparison between the two graphs, we can see that both time-series are highly correlated. Yet, it appears that in many cases movements are first captured in an adjustment of qspike values before they are picked up by ci values, i.e. the qspike series seems to lead the ci series.

To draw a cross-sectional comparison between the two variables, our first approach attempts to track qspike and ci values for five years before and after portfolio formation. We first compute average values for each portfolio (Small, Middle, High), formation year, and event time. Then, in a second step, we further collapse the year dimension of portfolio formation. The resulting event graph is plotted in Figure 5.[2]

Panel A presents the evidence for Low and High portfolios sorted by qspike values. Evident are the extreme spikes in the formation year that exist by construction, positive for the High portfolio and negative for the Low portfolio. In both cases these spikes have no persistence. Apart from a relatively small permanent difference between High and Low portfolios, there is no further variation over the five years prior or post portfolio formation. Looking at average ci values of qspike-sorted portfolios, we find a positive correlation. Stocks with high qspike values are also associated with higher abnormal capital investments, and vice versa. However, the cross-sectional dispersion is much smaller. The sorting also reveals that there is more persistence in ci values as their curve is still visible 1-2 years after portfolio formation, despite portfolios are sorted by qspike values.

Panel B displays the same analysis for ci-sorted portfolios. Again, the extreme spikes in ci values during the formation year are by construction. The average ci value of the High portfolio peaks at a level twice regular investments, which compares in economic terms to a 15% increase we found for qspike-sorted portfolio. Thus, there is a positive correlation between the two variables in the cross-section, yet the correlation is not necessarily as high as we expected. Similar relative magnitudes are obtained when comparing qspike values across panels. The event graph further confirms that the lead of the qspike variable over the ci variable, already observed in the time-series of Figure 5, also holds in the cross-section. Finally, in line with the existing literature, we also find more persistence in ci-sorted portfolios. This holds for ci values, as well as for qspike values.

In a next step, we attempt to construct a direct measure of correlation between the two portfolio sorts. After dividing stocks into Low, Middle, and High portfolios according to qspike values, we calculate which percentage would be assigned into the same group if

[2]See Fama and French (1995) and Anderson and Garcia-Feijoo (2006) for the construction of similar graphs.

we would sort stocks according to ci values instead. The correlation matrix is reported in Table 2. If the two dimensions were perfectly uncorrelated, we would expect each row to take the values 30-40-30. The sample indicates a positive correlation as there is more probability mass on the diagonal. Instead of obtaining a value of 30%, the tail portfolios have an overlap of 35% and 34%, respectively. Since the variables' predictive power for stock returns concentrates over a limited time frame in our sample, we verify that the correlation does not differ during that period. Recalculating the same correlation matrix for the years 1998-2004 yields almost the same numbers. Given that we calculate both measures in very similar ways using capital expenditure data at different frequencies, we interpret that correlation as relatively low. We further evaluate the importance of that correlation for stock returns in the next section.

3.3 Double-sorted portfolios

Our prior analysis indicates that excess returns of the qspike-based hedge portfolio concentrate in a period during which the standard investment factor also performs well. One possibility is that, despite a relatively small overlap between the portfolio assignments, some companies end up in the same tails, and these companies simultaneously drive the returns of both portfolio sorts. Alternatively, the results are driven by differing sets of stocks, which are coincidentally or through a joint omitted variable clustered in time. In this section we attempt to test whether controlling for the investment anomaly absorbs the abnormal returns reported for qspike-sorted portfolios.

We start with a discussion of double-sorted portfolios based on qspike values and ci values. To capture the idea of controlling for the investment factor, we first allocate stocks into three groups based on the 30th and 70th percentile of the ci-distribution. Within each group, we subsequently divide stocks based on the corresponding 30th and 70th percentiles of qspike values. After ignoring stocks assigned to the Middle, this yields two qspike-based hedge portfolios: one with low ci values (LL-LH) and one with high ci values (HL-HH). The results are reported in the top panel of Table 3. For comparability, we also employ the reverse order, which is reported in the bottom panel of the same table.

The analysis indicates that both qspike-based hedge portfolios are not fully accounted for by the standard investment factor. We estimate a monthly excess return of 0.48% for the hedge portfolio with low abnormal investments and 0.27% for the hedge portfolio with high abnormal investments. Marginally smaller alphas are obtained from a three-factor model. After controlling for additional factors this ranking changes. Among companies with large increases in capital expenditures, alphas are in the range of 0.41-0.47% per month, while the ones obtained for companies with low capital expenditure increases become smaller (0.16-0.32%).

When reversing the order of sequential sorting, we find that none of the ci-based hedge portfolios have statistically significant returns after controlling for the qspike. Point estimates of value-weighted portfolios fall in the range of 0.13-0.27% per month. Equal-weighted portfolios remain statistically significant, but they tend to be smaller than the ones obtained from the qspike-based hedge portfolios. Results for a simultaneous double-sorting are reported in the appendix. Loading on both factors shows that monthly excess returns and alphas are 50% larger in comparison to the qspike hedge reported in Table 1.

In an additional attempt to address the return correlation of qspike-sorted portfolio with the investment anomaly, we introduce a modification to our univariate analysis. When sorting stocks according to qspike values, we only consider a sub-sample that does not correlate with a sorting of abnormal capital investments. Starting from Table 2, this implies that we drop all stocks assigned to the same group irrespective of whether stocks are sorted by qspike or ci values (i.e. dropping all stocks on the diagonal of the correlation matrix). With the remaining stocks we construct again three qspike-sorted portfolios (Low, Middle, and High).

The results are reported in Table 4. Excluding stocks that are driving the investment anomaly does not eliminate the qspike effect. We still find that portfolio with high qspike values have smaller returns. The excess return of the value-weighted hedge portfolio is 0.27% per month, which is only marginally smaller than the one reported for the entire sample in Table 1 and statistically significant. The corresponding industry-adjusted returns and the alpha from the three-factor model are insignificant. Alphas from the other models, however, are in the range of 0.26-0.29% per month and statistically significant. Similar conclusions can be drawn from equal-weighted portfolios.

4 Cross-section of stock returns

In the previous section, we use the portfolio sorting and regression analysis to investigate the relevance of the qspike values for the cross-section of stock returns. One can argue that, if the qspike value has little variation over time, problems of autocorrelation might arise. To address this concern, we use a Fama-Macbeth regression that include the qspike and firm characteristics as explanatory variables of the stock returns. We correct the standard errors with the Newey-West (1987) procedure to account for autocorrelation. We estimate five versions of these regression, in which we add one characteristics at the time to determine whether the Q4 spike results hold.

The dependent variable in our regressions is the firm excess stock return. We standardize the explanatory variables to have a mean of 0 and a standard deviation of 1. This procedure allows to interpret the qspike coefficient as the effect on firms stock returns of a one standard deviation change in the variables under consideration. The list of the variables we control for is reported in the table. Details on the variable construction are in the Appendix.

Table 5 shows the estimates for our regressions. First, the table shows that the qspike coefficient stays statistically significant in all our estimations. It has a negative and significant coefficient: one standard deviation increase in the qspike value implies a decrease in the stock returns by 10%, on average. In the FMB regression that includes all the variables (column 6), both the coefficient on investment growth and on capital expenditures turns economically low, while one standard deviation increase in the qspike implies a decrease in the excess stock returns by 20%.

Consistent with past works using the asset growth as a proxy for investments, the investment growth factor and the CAPEX factor become negligible once including firms' asset growth (column (6)), compared to the qspike value. This result suggests that the qspike is capturing some (different) information on firms' investment policy when compared to the investment growth factor, which does not explain itself the under-performance on the stock market of firms that increase their investments. The coefficient of assets growth is statistically significant at 1% level, and it implies a 17% increase in the stock returns after a one standard deviation increase in the firm assets. The largest coefficient refers to the variable REV, which is lagged variable of the returns and it captures the persistence of stock returns across time. Overall, the effect of the Q4 spike ranges between a 20% and a 10% subsequent decrease in the excess stock returns.

5 Discussion

In this section we provide a discussion of possible explanations for why abnormal qspikes matter for the cross-section of stock returns and why the effect is centered between 1998 and 2004. Of course, one could argue that underneath all there is a latent risk factor driving the investment anomaly as well as the qspike effect, which is generally hard to rule out. Our attempt here takes the observed patterns at face value and derives hypotheses able to explain them. Then, we produce suggestive evidence by looking into cross-sectional differences of the qspike effect.

At this point, we consider managerial agency conflicts to be a particularly promising mechanism helping to reconcile such effects. When introducing the investment anomaly, Titman et al. (2004) motivate their results already based on agency conflicts. They argue that the investment anomaly is stronger for firms with greater investment discretion, and during periods of weakened external governance (Pinkowitz et al., 2006). We think that qspikes might be an even better proxy for managerial agency conflicts, as it captures more ad-hoc adjustments in investments. To provide evidence for this agency view, we will test whether firms with more investment discretion, largely based on the idea of Jensen (1986)'s free cash flow problem, also have a stronger qspike effect.

As a first test, we construct the long short strategy by splitting the firms in two categories: firms with high cash flow level (abive the median), and firms with a low cash-flow level (below the median), the latter defined as in Titman et al. (2004) as operating income before depreciation minus interest expenses, taxes, preferred dividends, and common dividends scaled by total assets. We report the results in figure 6. In line with the agency conflicts arising from excess cash availability, firms with high level of cash flow are the one that underperfom when associated with an abnormal increase in the capital investments in the fourth quarter of the year.

We further investigate firms' dividend policies. Fama and French (2001) show that the percentage of dividend-paying firms decreased from 66.5% in 1978 to 20.8% in 1999. They explain this trend with a wave of new IPOs composed by small firms with low profitability and strong growth opportunities (Fama and French, 2001; Myers and Majluf, 1984).[3] This trend dramatically reverts in 2000, after the dot.com bubble. By the end of the first quarter

[3] An alternative theory posits that dividends act as a good signal for the investors about the quality of the future earnings (Gill et al 2010), Ajanthan (2013) Chen et al (2018)).

of 2004 over 40% of U.S. industrials were paying dividends again (Julio and Ikenberry, 2004). One of the reasons related to this change is the lack of trust of investors following the internet bubble, where a number of large and highly rated firms suddenly filed for bankruptcy. Baker and Wurgler (2004) mention in their work a July 16, 2002 Wall Street Journal article titled "Where should you invest now?", reporting that "prices for dividend-paying stocks in the S&P 500 stock index had fallen 8.04% vs. a loss of 28.18% for stocks in the index without dividends."

As an increase in dividends might be one tool to discipline managers (Jensen, 1986), we investigate whether dividend policies affect the cross-section of stock returns of firms with abnormal qspike values. We hypothesize that managers introducing dividends have excess cash-flows, which may also result in overinvestment. We would expect that the detrimental effect of such inefficient investments only slowly disappears when investors increasingly demand higher payouts. First, we identify in CRSP dividend-paying firms, and we merge this sample with firms having non-missing qspike values in our sample. As shown in Figure 7, the percentage of dividend-paying firms in our sample decreases between 1990 and 2000, from 41% to 35%, consistent with the findings of past research (Fama and French, 2001). This downward trend is reversed around 2000, reaching a peak of 45% in 2004-2005.

In a second step, we construct long/short portfolios as before (long 30th percentile of qspike values, short 70th percentile of qspike values), and we split the sample into two parts: firms that start to pay dividends in a given year, and firms that do not change their dividend policy along the sample. We report the cumulative abnormal returns for these two samples in Figure 8. The figure shows that results are much stronger for firms that start to pay dividends in the years following the 2000s. The zero-investment portfolio quadruples its value in terms of the position taken. This compares to a twofold increase for firms that do not change their dividend policy (either not paying or not increasing dividend payout).

Again, in both cases most of the value is generated between 1999 and 2004.

Another factor that we take into account relates to the credit availability between 1990 and 2004. Because the US market keep growing until 2000, and because of the Asian financial crisis of 1998, investors reallocated their portfolios into US government bonds and US stock market. Ventura and Kraay (2005) show that the 1990s was also an era of increasing credit, followed by a sharp decline of firms leverage when the bubble hit the stock market. Titman et al. (2004) finds that the negative relation between abnormal capital investment and stock returns is stronger for firms that have lower debt ratios. We therefore investigate whether debt availability has an effect on the qspike relevance in explaining the cross-section of stock returns. Figure 9 report the cumulative abnormal returns of our long/short portfolios on qspikes for firms with high (above the median) and low (below the median) leverage in our sample. The figure shows that both firms with high and low debt values unperformed when having high qspikes between 2000 and 2005.

Other factors that we do not consider in this study might affect the qspike importance for the stock returns. For example, Brown et al. (2007) find support for a move back from repurchases to dividends in response to a change in tax rates in 2003, which can also have affected the preference for firms investments. Other theories relates to the composition of the sample, which changes between 1994 and 1999 towards IPO firms using the proceeds to finance day-to-day operations, rather than investment plans or debt restructuring (Ljungqvist and Wilhelm, 2003). All these factors can contribute in explaining the underperformance on the stock market of overinvesting firms between 1999 and 2005.

6 Conclusion

In this paper we analyze the pricing of portfolios sorted by abnormal capital investments in the fourth fiscal quarter. We find that stocks of firms with high capital expenditures towards the end of a fiscal year subsequently underperform in comparison to firms with low capital investments. In line with Titman et al. (2004)'s interpretation of the standard investment anomaly, we think that managerial agency conflicts are particularly able to explain the pattern. First, the qspike measure itself may have an agency interpretation when firms realizing windfall profits suddenly increase their investment towards the end of the year. Such short-term adjustments may potentially not lead to the most efficient investment allocation. Second, further investigating the cross-section of results, we find that the qspike effect becomes stronger for firms with large cash flows and for firms that are about to introduce dividends, which may indicate the existence of a free cash flow problem.

The goal of this study is not to argue that qspikes should be included as an additional risk factor to asset pricing models, or that qspikes supersede the investment factor derived from investment-based asset pricing and currently used. We rather want to point towards the potential multi-dimensionality through which investment decisions are intertwined with stock prices. The interest finding of this study is that by sorting stocks by last fiscal quarter abnormal investments instead of abnormal investments across years, we generate portfolios that show relatively low correlation in the cross-section. This holds for the portfolio composition itself as well as for the portfolios' stock returns. At the same time, excess returns of both approaches are highly clustered in time. We also notice that the value factor exhibits a similar time-series cluster. We hypothesize that stock returns during the late 1990s and early 2000s seem to contain a lot of cross-sectional predictability, which could be subject to further research.

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Figure 1: Time-series of quarterly capital expenditures

This figure plots the average quarterly capital expenditures standardized by the average capital expenditures for a given year for our sample period from 1985 to 2019. Source: Compustat quarterly.

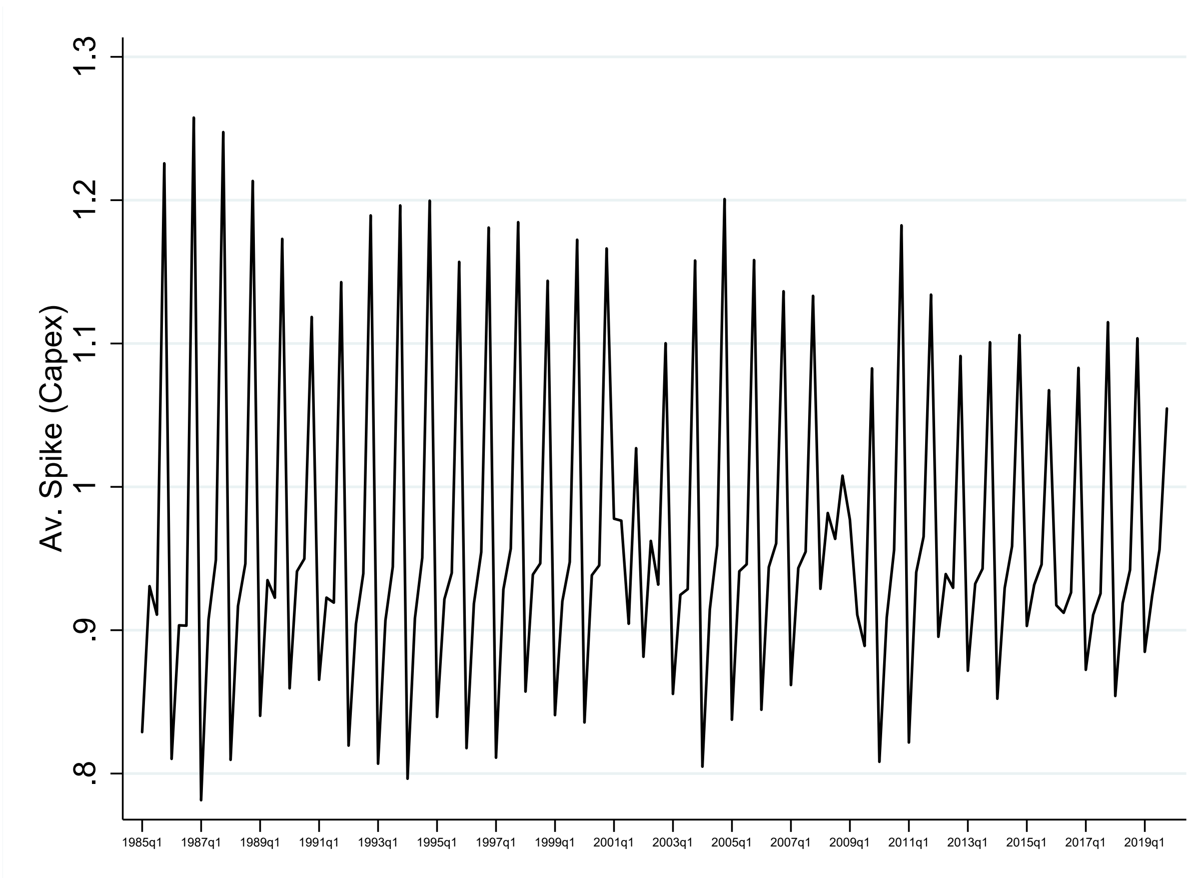


Figure 2: Time-series of Q4 spikes

This figure plots the abnormal capital investments during the last quarter of a firm's fiscal year, the Q4 spikes, together with the investment growth factor, from 1985 to 2019. We follow Shin and Kim (2002) and Xu and Zwick (2020) by constructing Q4-spikes in capital expenditures (qspike) as the ratio between the CAPEX in the fourth quarter and the average CAPEX in the previuos three quarters. The investment growth factor (ci) is defined as last year's capital expenditures over total sales divided by the average over the three prior fiscal years (Titman et al. (2004)). Source: Compustat quarterly.

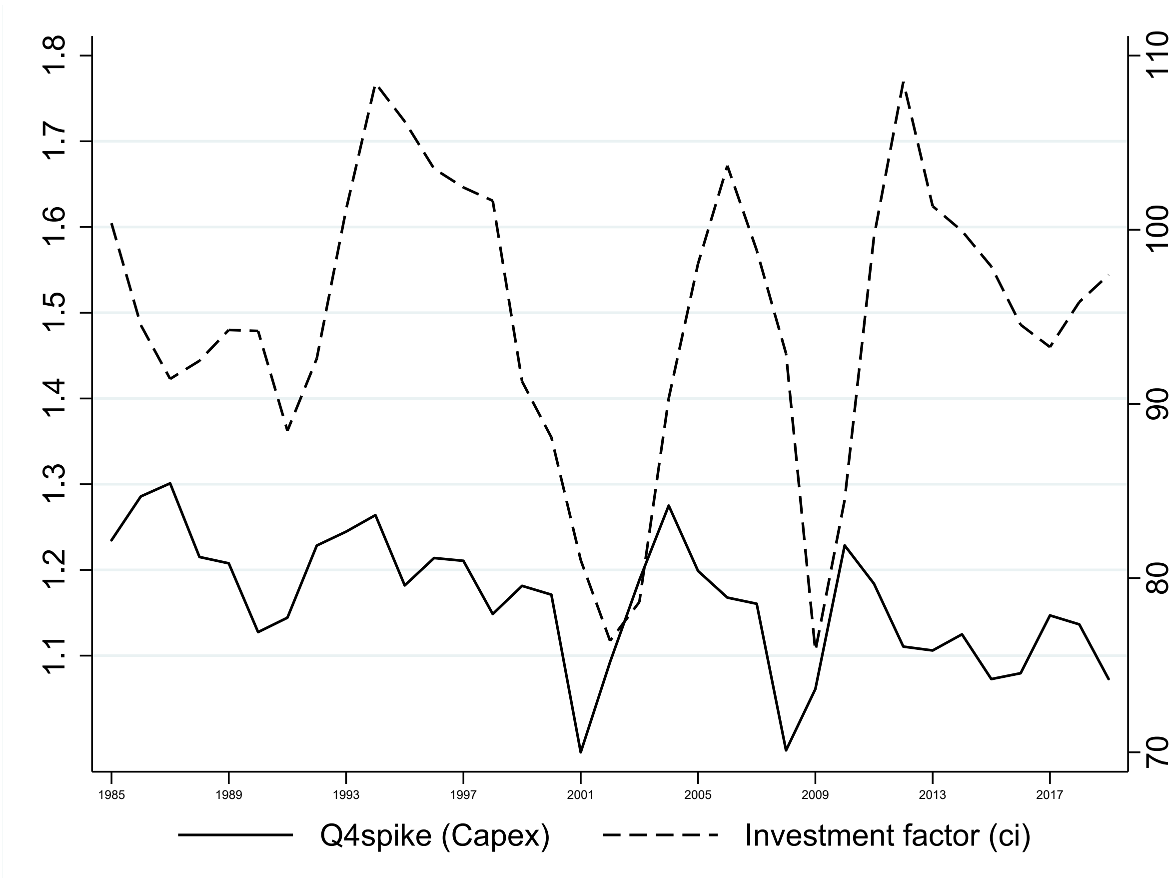


Figure 3: Portfolio returns of long/short strategy

This figure plots cumulative returns of an investment portfolio long firms with low qspike values and short firms with high qspike values. The black solid line refers to the equal-weighted portfolio and the black dashed line to value-weighted portfolios. They gray line shows cumulative alphas from Fama-French 5 factor regressions.

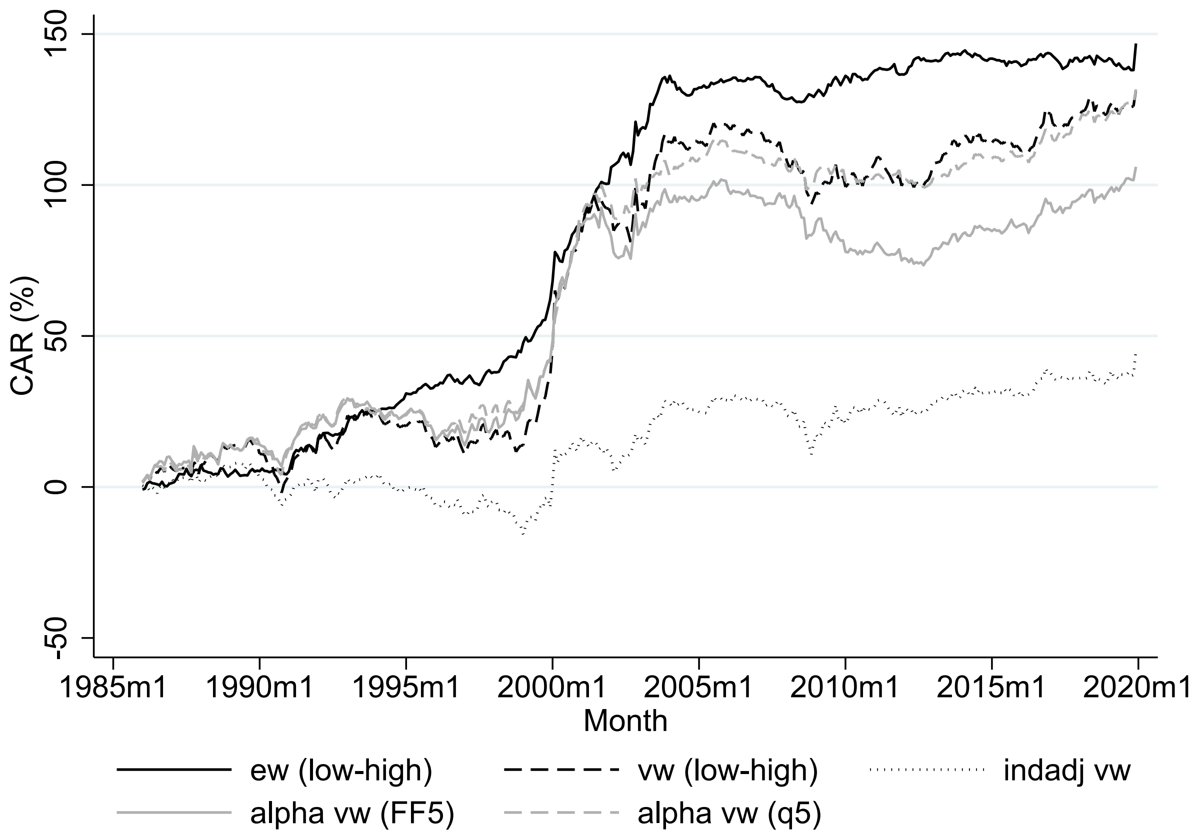


Figure 4: Long/short strategy vs factors

This figure plots the time-series of the cumulative excess return of the value-weighted hedge portfolio from a qspike sort against the investment factor (cma) and the value factor (hml), from 1985 to 2019. The investment and value factor are retrieved from Kenneth's French website, the qspike is constructed as in Shin and Kim (2002) and Xu and Zwick (2020). Source: Compustat Quarterly and CRSP.

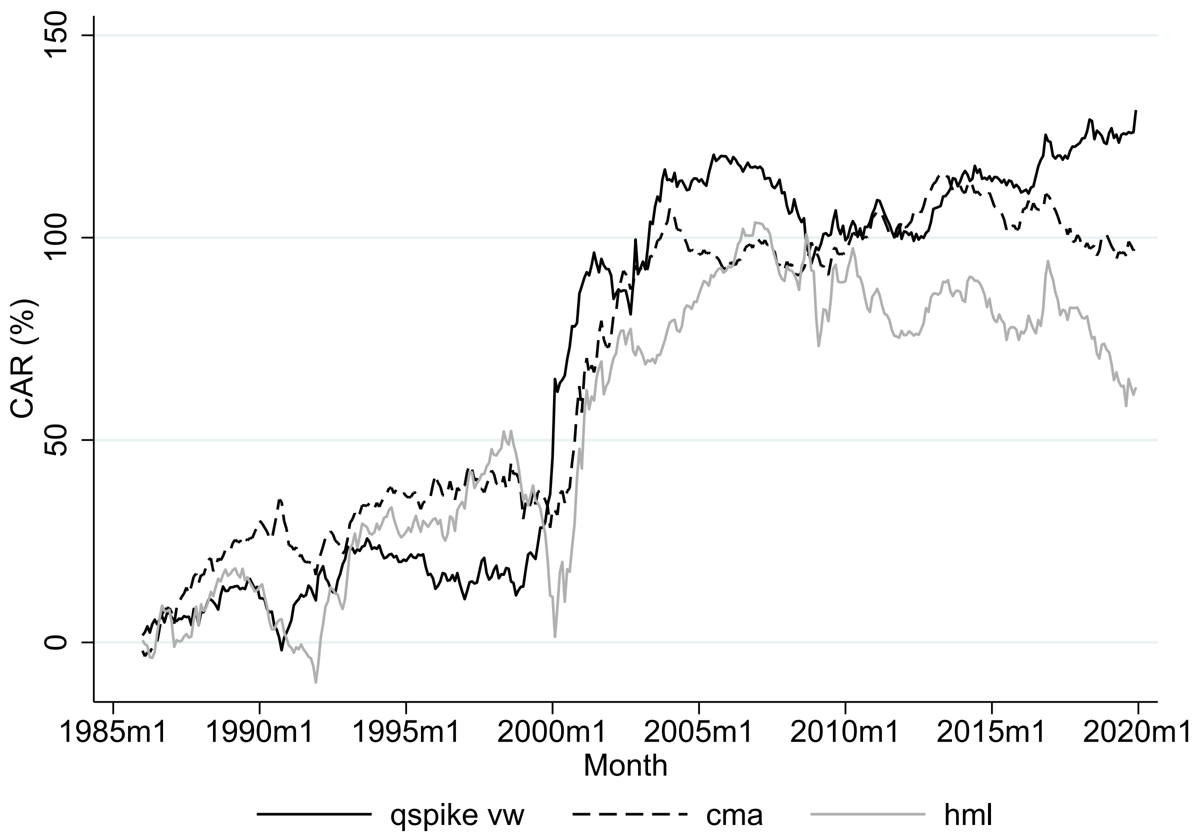
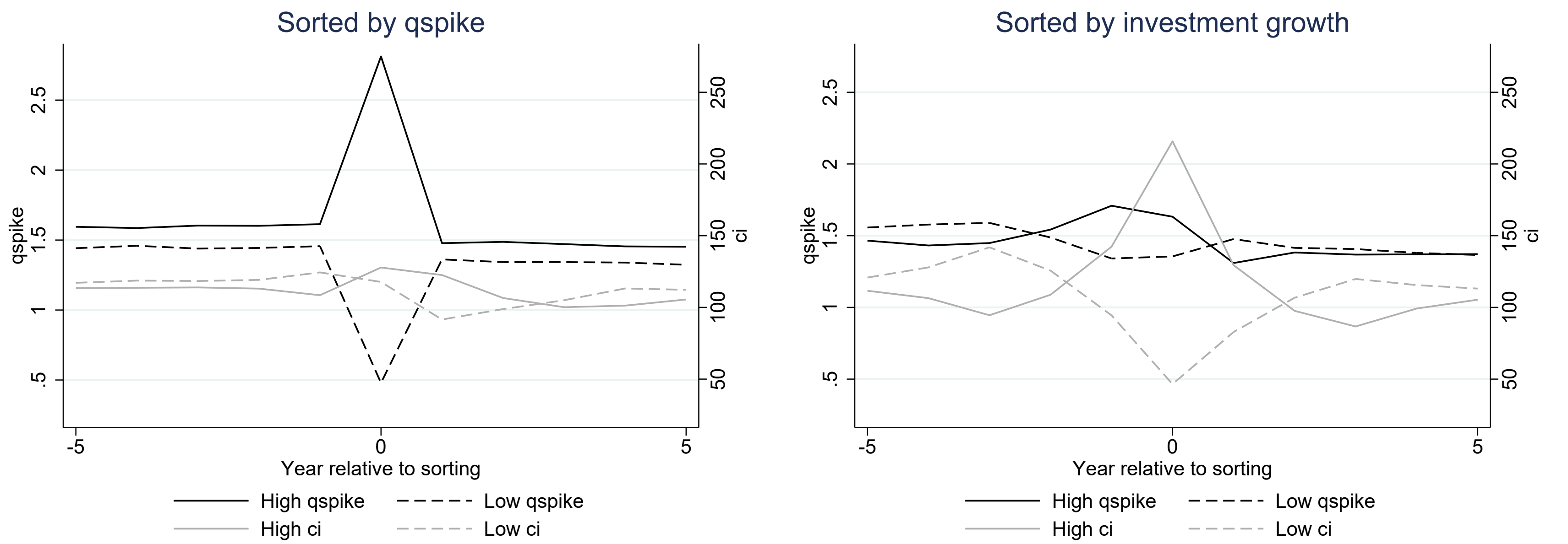


Figure 5: Event study of investment variables around portfolio formation

This figure plots changes in qspike values and Titman et al. (2004)'s abnormal capital investment measure (ci) starting 5 years prior to portfolio formation until 5 years after. We first compute average values for each portfolio, formation year, and event time. Then, we also collapse the year dimension of portfolio formation by taking averages by portfolios and event time. Panel A shows results for qspike-sorted portfolios and Panel B for ci-sorted portfolios.



(a) (b)

Figure 6: Portfolio returns of long/short strategy: free cash flow

This figure plots cumulative value-weighted returns of an investment portfolio long firms with low qspike values and short firms with high qspike values. The black solid line refers to portfolios of firms with cash-flow (asset adjusted) above the median, while the black dashed line refers to portfolios of firms with cash-flow (asset adjusted) below the median. Cash-flow is defined as in Titman et al. (2004) as operating income before depreciation minus interest expenses, taxes, preferred dividends, and common dividends scaled by total assets.

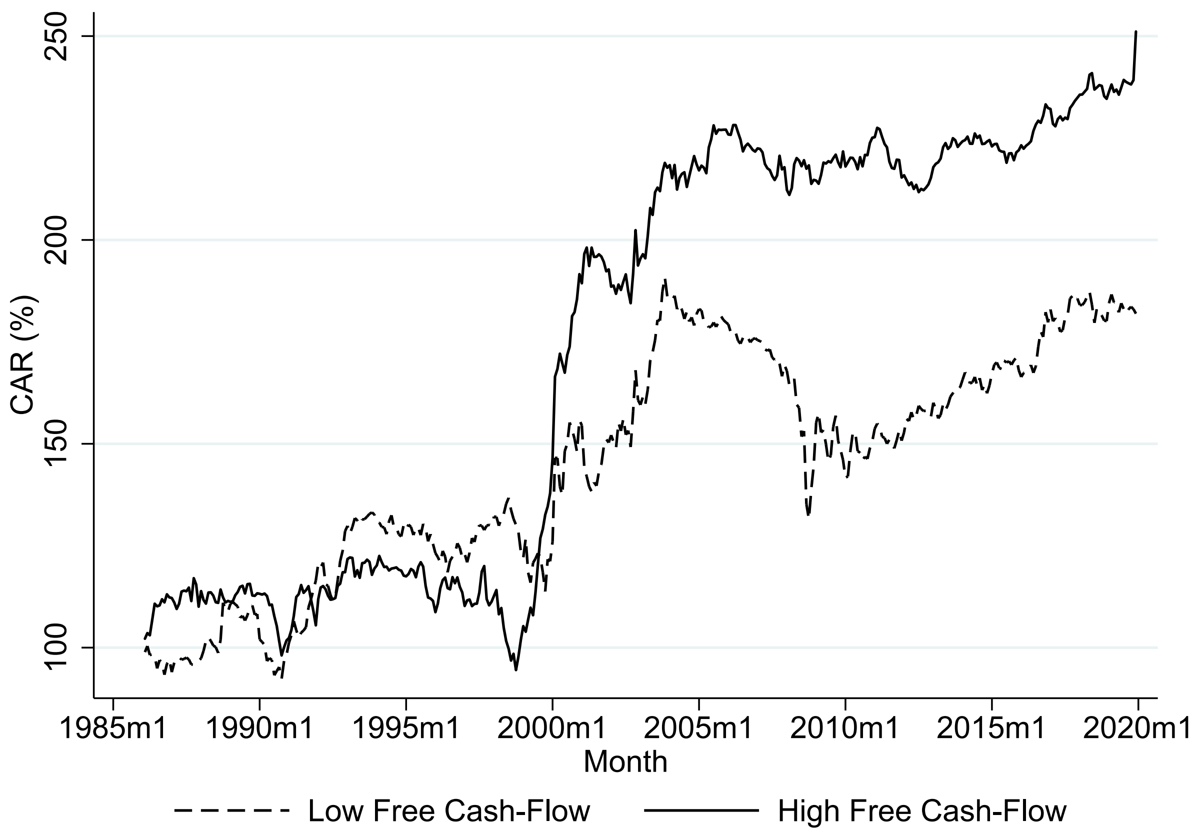


Figure 7: Ratio of Sample Firms Paying Dividends

This figure plots the percentage of firms in our sample that pay dividends, scaled by the total number of firms in the sample, for each year. We report the percentage of dividend paying firms for the entire sample period (left graph) and in years between 1999 and 2005. Data are retrieved from CRSP.

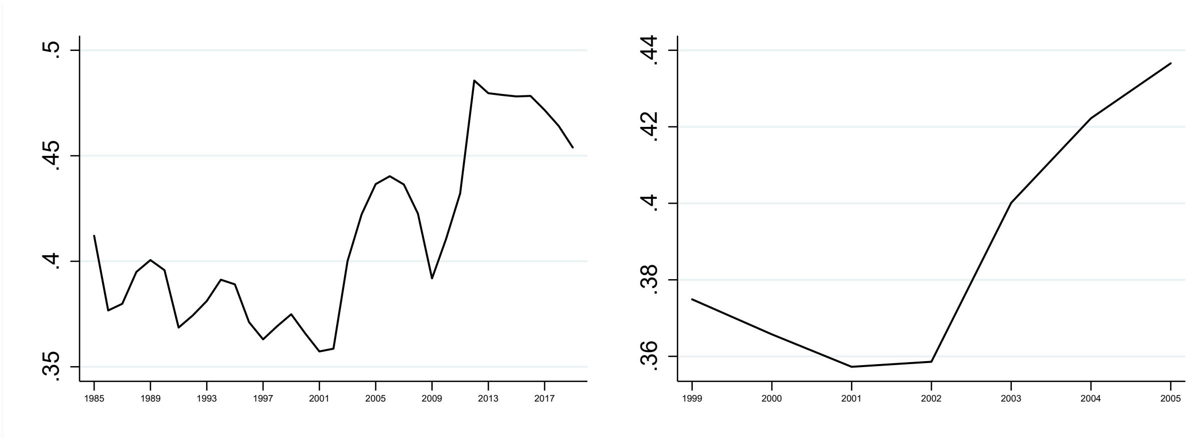


Figure 8: Portfolio returns of long/short strategy: dividends Policy Change

This figure plots cumulative value-weighted returns of an investment portfolio long firms with low qspike values and short firms with high qspike values. The black solid line refers to portfolios of firms that start to pay dividends, defined as firms that increase their dividend payout from zero in the last 2 years to positive in the following two years. In the overall sample, there are 1,354 firms on a total number of firms of 13,298 that start to pay dividends, for a total of 10% and a yearly average of 0.3% . The black dashed line refers to portfolios of firms that did not change their dividend policy.

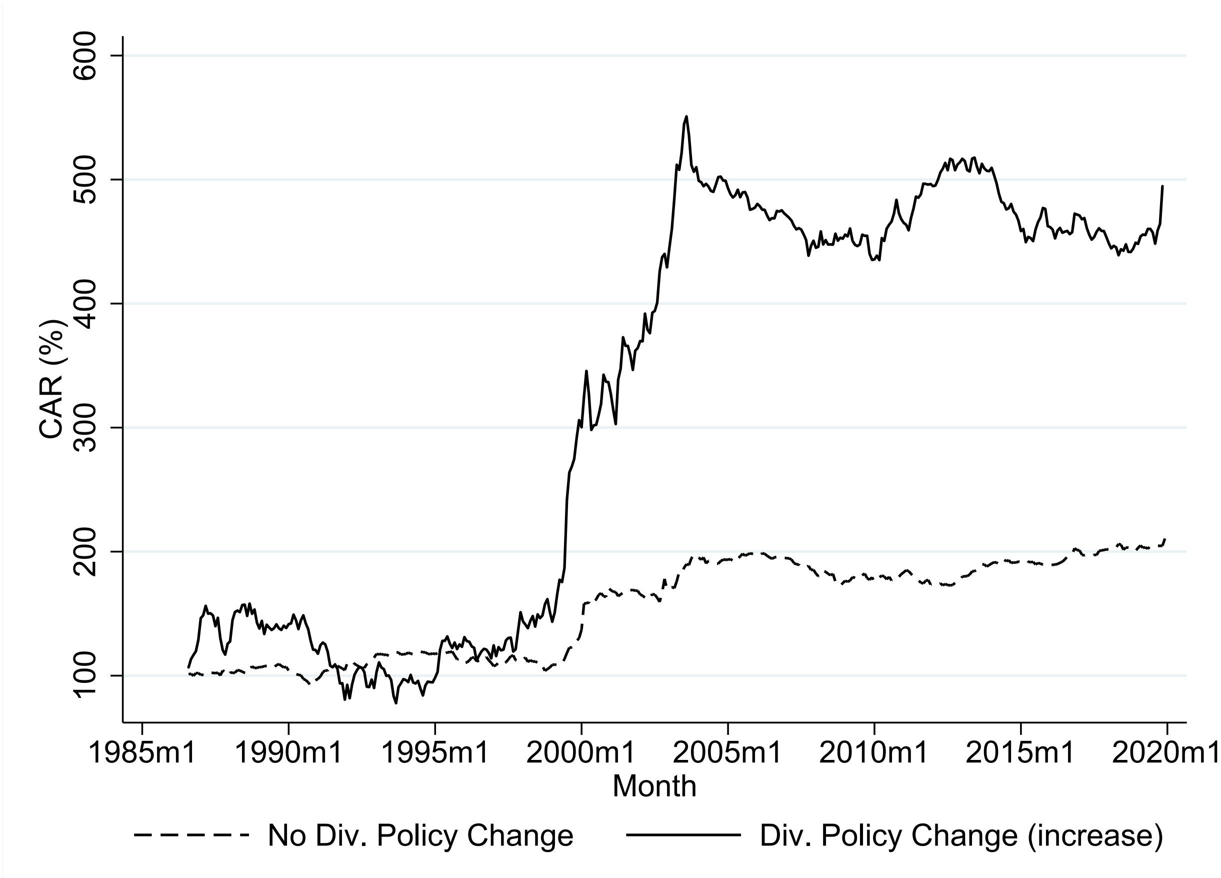


Figure 9: Portfolio returns of long/short strategy: leverage

This figure plots cumulative value-weighted returns of an investment portfolio long firms with low qspike values and short firms with high qspike values. The black solid line refers to portfolios of firms with leverage below the median, and the black dashed line to portfolios of firms that did not change their dividend policy.

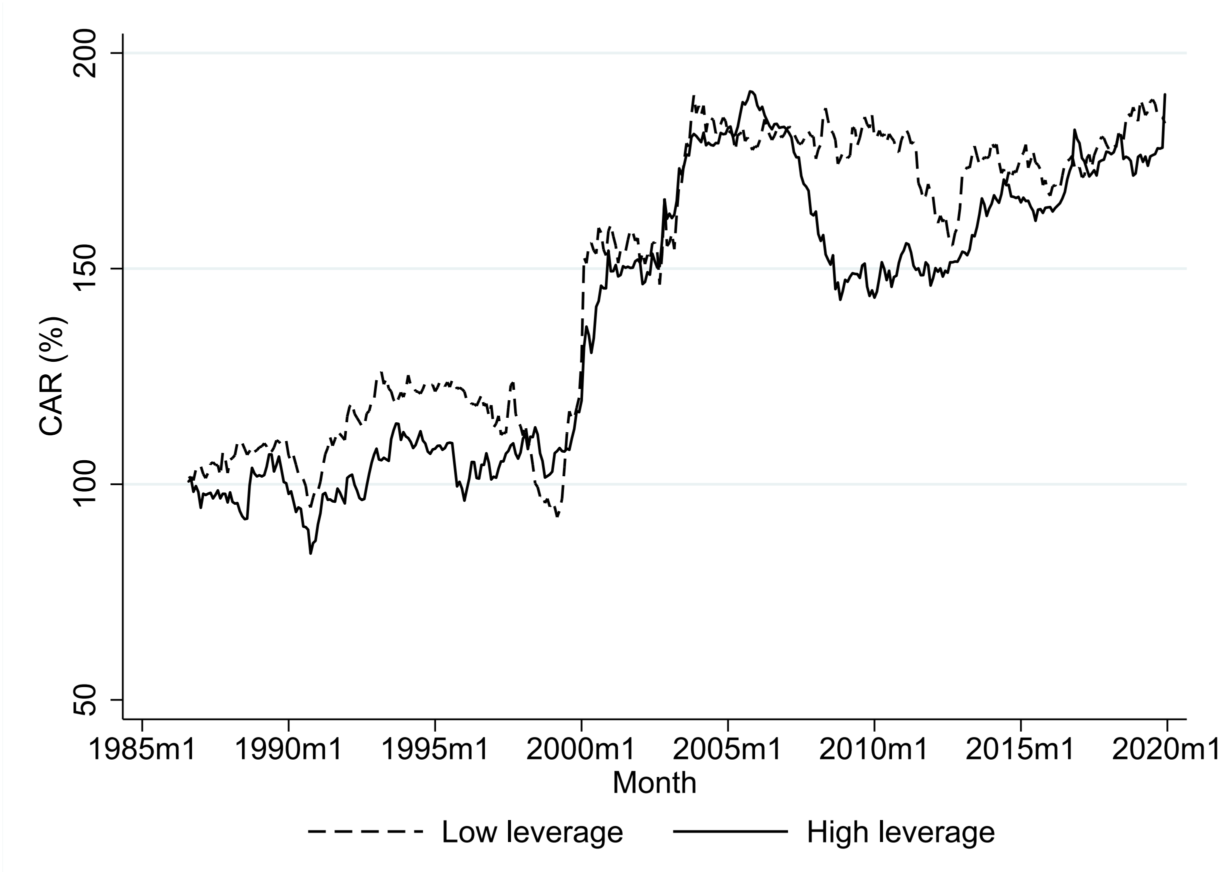


Table 1: Single-sorted Portfolios

This table reports excess returns and alphas of portfolios sorted by qspike values. We construct three portfolios (Low, Middle and High) based on a 30/40/30 division of the qspike distribution, plus a long/short strategy (Low - High). Stocks without valid qspike values are in the No data portfolio. Portfolio returns are equal-weighted and value-weighted: *exret* are returns in excess of 1-Month Treasury Yield and *indadj* are returns adjusted for FF48 industries. The remaining columns represent alphas from various asset pricing models: $FF3$ and $FF5$ refer to the Fama-French 3 and 5 factor models (Fama and French, 1993, 2015), q to the q-factor model introduced in Hou et al. (2014), and q^5 to Hou et al. (2020)'s latest model augmented by an expected growth factor. t-statistics are reported in parentheses.

	Value-weighted Portfolios						Equal-weighted Portfolios					
	exret	*indadj*	$FF3$	$FF5$	q	q^5	*exret*	*indadj*	$FF3$	$FF5$	q	q^5
No data	0.65	-0.01	-0.16	-0.03	-0.24	-0.18	0.77	-0.05	0.08	0.27	0.38	0.46
	(2.65)	(-0.24)	(-1.67)	(-0.35)	(-1.87)	(-1.43)	(2.67)	(-0.76)	(0.57)	(1.62)	(2.13)	(2.43)
Low	0.92	0.08	0.15	0.24	0.24	0.22	1.00	0.21	0.21	0.36	0.53	0.52
	(3.48)	(1.29)	(1.81)	(3.11)	(2.68)	(2.63)	(3.29)	(5.76)	(2.04)	(2.98)	(3.88)	(3.49)
Middle	0.70	-0.01	0.04	-0.01	0.02	-0.01	0.82	0.09	0.03	0.08	0.21	0.25
	(3.27)	(-0.40)	(1.20)	(-0.25)	(0.67)	(-0.16)	(2.99)	(1.62)	(0.37)	(0.85)	(1.76)	(1.88)
High	0.60	-0.03	-0.09	-0.08	-0.06	-0.04	0.64	-0.06	-0.16	0.00	0.13	0.23
	(2.60)	(-0.72)	(-1.64)	(-1.38)	(-1.05)	(-0.57)	(2.18)	(-1.28)	(-1.70)	(0.01)	(0.83)	(1.35)
Long/short	0.32	0.11	0.24	0.32	0.30	0.26	0.36	0.28	0.37	0.36	0.40	0.30
	(2.83)	(1.35)	(2.13)	(2.89)	(2.53)	(2.26)	(4.92)	(4.81)	(5.40)	(5.53)	(5.30)	(4.20)

Table 2: Portfolio overlap with investment increase

This table compares the portfolio allocation between two different sorts. We first assign stocks into three portfolios based on qspike values. Then we compare in which of the portfolio stocks would end up if we would sort stocks according to Titman et al. (2004)'s investment factor instead. Panel A reports the overlap for the entire sample, whereas Panel B only covers the sub-sample starting in 1998 and ending in 2004.

Panel A: 1986-2019		Investment factor (ci)			
		Low	Middle	High	Total
qspike	Low	35.8	34.3	29.9	100.0
qspike	Middle	27.6	45.4	27.0	100.0
qspike	High	27.5	38.4	34.2	100.0
Panel B: 1998-2004		**Investment factor (ci)**			
		Low	Middle	High	Total
qspike	Low	35.1	35.3	29.6	100.0
qspike	Middle	28.0	44.9	27.1	100.0
qspike	High	27.5	38.2	34.3	100.0

Table 3: Double-sorted Portfolios (sequential)

This table reports excess returns and alphas of double-sorted portfolios. The two dimensions are qspike values and ci values. We perform sequential sorts, i.e. we first construct three portfolios (Low, Middle and High) based on a 30/40/30 division of one dimension and then within each group create three other portfolios (Low, Middle and High) according to the other dimension. We construct two long/short strategies for the second dimension that either take low (LL - LH) or high values (HL - HH) according to the first dimension. Panel A first sorts by ci values and then by qspike values, whereas Panel B takes the opposite order. Portfolio returns are equal-weighted and value-weighted: *exret* are returns in excess of 1-Month Treasury Yield. The remaining columns represent alphas from various asset pricing models: $FF3$ and $FF5$ refer to the Fama-French 3 and 5 factor models (Fama and French, 1993, 2015), q to the q-factor model introduced in Hou et al. (2014), and q^5 to Hou et al. (2020)'s latest model augmented by an expected growth factor. t-statistics are reported in parentheses.

Sort1	Sort2	Value-weighted Portfolios					Equal-weighted Portfolios				
ci	qspike	*exret*	$FF3$	$FF5$	q	q^5	*exret*	$FF3$	$FF5$	q	q^5
Low	Low	1.09	0.31	0.39	0.36	0.37	1.06	0.27	0.44	0.36	0.37
		(3.67)	(2.32)	(3.06)	(2.47)	(2.82)	(3.27)	(2.11)	(3.13)	(2.47)	(2.82)
Low	High	0.62	-0.16	0.07	0.06	0.21	0.74	-0.06	0.15	0.06	0.21
		(2.01)	(-1.19)	(0.49)	(0.42)	(1.46)	(2.35)	(-0.55)	(1.04)	(0.42)	(1.46)
LL - LH		0.48	0.46	0.32	0.30	0.16	0.32	0.33	0.29	0.30	0.16
		(2.60)	(2.50)	(1.66)	(1.52)	(0.89)	(3.18)	(3.34)	(2.97)	(1.52)	(0.89)
High	Low	0.81	0.00	0.27	0.30	0.29	0.87	0.08	0.31	0.30	0.29
		(2.58)	(0.03)	(2.01)	(2.07)	(2.01)	(2.80)	(0.68)	(2.10)	(2.07)	(2.01)
High	High	0.54	-0.23	-0.15	-0.17	-0.12	0.39	-0.41	-0.19	-0.17	-0.12
		(1.97)	(-2.17)	(-1.30)	(-1.50)	(-1.01)	(1.29)	(-3.47)	(-1.26)	(-1.50)	(-1.01)
HL - HH		0.27	0.24	0.42	0.47	0.41	0.48	0.49	0.49	0.47	0.41
		(1.55)	(1.33)	(2.24)	(2.43)	(2.15)	(5.50)	(5.83)	(5.23)	(2.43)	(2.15)
Sort1	Sort2	Value-weighted Portfolios					Equal-weighted Portfolios				
qspike	ci	*exret*	$FF3$	$FF5$	q	q^5	*exret*	$FF3$	$FF5$	q	q^5
Low	Low	1.04	0.23	0.40	0.37	0.46	1.13	0.34	0.51	0.37	0.46
		(3.31)	(1.80)	(3.35)	(2.59)	(3.19)	(3.44)	(2.52)	(3.46)	(2.59)	(3.19)
Low	High	0.77	-0.03	0.20	0.26	0.24	0.85	0.07	0.29	0.26	0.24
		(2.44)	(-0.24)	(1.45)	(1.75)	(1.61)	(2.75)	(0.56)	(2.01)	(1.75)	(1.61)
LL - LH		0.27	0.27	0.20	0.11	0.22	0.28	0.27	0.21	0.11	0.22
		(1.59)	(1.50)	(1.12)	(0.60)	(1.21)	(2.54)	(2.61)	(2.15)	(0.60)	(1.21)
High	Low	0.59	-0.18	0.02	0.04	0.19	0.68	-0.11	0.09	0.04	0.19
		(1.96)	(-1.42)	(0.15)	(0.26)	(1.31)	(2.20)	(-0.97)	(0.65)	(0.26)	(1.31)
High	High	0.46	-0.32	-0.19	-0.21	-0.09	0.39	-0.41	-0.16	-0.21	-0.09
		(1.68)	(-2.88)	(-1.68)	(-1.85)	(-0.77)	(1.28)	(-3.38)	(-1.10)	(-1.85)	(-0.77)
HL - HH		0.13	0.14	0.21	0.25	0.28	0.29	0.30	0.26	0.25	0.28
		(0.80)	(0.84)	(1.21)	(1.39)	(1.61)	(3.47)	(3.56)	(3.13)	(1.39)	(1.61)

Table 4: Single-sorted Portfolios (sub-sample uncorrelated with investment anomaly)

This table reports excess returns and alphas of portfolios sorted by qspike values. We construct three portfolios (Low, Middle and High) based on a 30/40/30 division of the qspike distribution, plus a long/short strategy (Low - High). In contrast to Table 1, we only consider a sub-sample of stocks that would have not been assigned to the same group based on a sort of abnormal capital investments (ci). Portfolio returns are equal-weighted and value-weighted: $exret$ are returns in excess of 1-Month Treasury Yield and $indadj$ are returns adjusted for FF48 industries. The remaining columns represent alphas from various asset pricing models: $FF3$ and $FF5$ refer to the Fama-French 3 and 5 factor models (Fama and French, 1993, 2015), q to the q-factor model introduced in Hou et al. (2014), and q^5 to Hou et al. (2020)'s latest model augmented by an expected growth factor. t-statistics are reported in parentheses.

	Value-weighted Portfolios						Equal-weighted Portfolios					
	$exret$	$indadj$	$FF3$	$FF5$	q	q^5	$exret$	$indadj$	$FF3$	$FF5$	q	q^5
Low	0.89	0.05	0.11	0.22	0.23	0.23	0.97	0.18	0.18	0.32	0.49	0.50
	(3.32)	(0.70)	(1.15)	(2.40)	(2.33)	(2.36)	(3.26)	(4.14)	(1.81)	(2.70)	(3.58)	(3.23)
Middle	0.75	-0.04	0.06	0.09	0.10	0.05	0.77	0.04	-0.03	0.07	0.22	0.27
	(3.11)	(-0.69)	(0.82)	(1.21)	(1.32)	(0.67)	(2.66)	(0.71)	(-0.33)	(0.57)	(1.53)	(1.69)
High	0.62	-0.03	-0.04	-0.07	-0.05	-0.03	0.75	0.04	-0.04	0.08	0.19	0.27
	(2.75)	(-0.53)	(-0.77)	(-1.13)	(-0.80)	(-0.42)	(2.62)	(0.81)	(-0.45)	(0.69)	(1.32)	(1.67)
Long/short	0.27	0.08	0.16	0.29	0.28	0.26	0.21	0.13	0.22	0.24	0.30	0.23
	(2.08)	(0.79)	(1.23)	(2.35)	(2.18)	(1.99)	(3.11)	(2.34)	(3.28)	(3.60)	(4.30)	(3.31)

Table 5: Fama Macbeth

This table reports results from a Fama-Macbeth regressions of excess stock returns of U.S. firms on multiple characteristics. The variable Q4 spike is defined as the ratio between the expenditures in the fourth quarter and the average capital expenditures of the previous three quarters. The variable CAPEX is computed the capital expenditures scaled by the lagged total assets, while the investment growth variable is the CAPEX annual growth. We also control for additional control variables in columns 5-7, defined in the appendix. All variables are standardized to mean zero and unit standard deviation so that the magnitude of coefficients represents the effect on stock returns of a one standard deviation move in the explanatory variable. The regression includes industry fixed effects, and we correct the standard errors with the Newey-West (1987) procedure to account for autocorrelation. In all regressions, the firm control variables are lagged by one period . ***,**, and * indicate significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Q4SPIKE	-0.142***	-0.142***	-0.143***	-0.138***	-0.126***	-0.205*	-0.109***
	(0.026)	(0.026)	(0.028)	(0.024)	(0.027)	(0.111)	(0.021)
CAPEX		-0.084*		-0.053	-0.036	0.073	0.015
		(0.050)		(0.058)	(0.027)	(0.080)	(0.061)
INVGROWTH			-0.080***	-0.092**	-0.112**	-0.036**	-0.168*
			(0.026)	(0.043)	(0.052)	(0.018)	(0.096)
Size						-0.017	-0.022
						(0.065)	(0.068)
BM						0.203***	0.230***
						(0.059)	(0.061)
REV						-0.715***	-0.696***
						(0.074)	(0.075)
ROA						0.230***	0.160***
						(0.060)	(0.057)
R&D						0.174**	0.111**
						(0.068)	(0.056)
NETISSUES						-0.016	
						(0.018)	
ASSETGROWTH						-0.179***	
						(0.028)	
Constant	1.061***	1.112***	1.111***	1.111***	0.414	0.941	0.724
	(0.307)	(0.295)	(0.293)	(0.294)	(0.625)	(0.743)	(0.661)
Observations	1,453,241	1,234,636	1,234,636	1,234,636	1,234,636	1,136,565	1,226,235
R-squared	0.001	0.005	0.002	0.006	0.071	0.097	0.092
Number of groups	408	408	408	408	408	407	407
Industry FE	No	No	No	No	Yes	Yes	Yes
Newey-West Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1