# Firm-specific uncertainty around earnings announcements and the cross-section of stock returns

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*Abstract*

We examine whether the firm-specific component of ex-ante earnings-related uncertainty is a priced characteristic for stocks. We use option-implied expected earnings announcement day jump variance as the measure for uncertainty and extract the firm-specific component by isolating the portion, correlated with the squared market risk sensitivity. Time series asset pricing tests, applied to the portfolios sorted on firm-specific earnings-related uncertainty, yield that this measure has explanatory power for stock returns: We find economically and statistically significant returns in excess of both the Carhart (1997) model and Fama-French (2015) model predictions for a portfolio which loads on firm-specific earnings-related uncertainty. We show that this result is driven by large cap stocks and is independent of operating profitability.

Keywords: fundamental uncertainty, option-implied jumps, asset pricing

JEL Codes: G12, G13, G30

## I. Introduction

Fundamental uncertainty is believed to be the main driver of asset returns. The asset pricing literature primarily focuses on uncertainty with respect to changes in common risk factors. It is widely accepted that assets sensitivities to common risk factors, such as stock market return or returns of factor-mimicking portfolios (size, value, momentum, etc.), explain the cross-section of asset returns. In this paper we show that uncertainty with respect to firm-specific information, contained in quarterly earnings announcements, provides an additional explanation of cross-sectional variation of stock returns, on top of the classical risk factors.

We build upon the literature, showing that the days around earnings announcements are more important to investors than other trading days: (1) there is a surge in fundamental uncertainty, reflected in option prices, prior to the earnings announcement day, which is resolved on the earnings announcement day (Pattel and Wolfson 1979, 1981; Donders and Vorst 1996, Isakov and Perignon 2001, Dubinsky and Johannes 2006); (2) investor trading increases prior to earnings announcements and stays high on the earnings announcement days (3) there is some evidence of a risk premium for holding the stock through the earnings announcement (Ball and Kothari 1991, Cohen et al. 2007). Thus, investors are likely to pay closer attention to stocks prior to earnings announcements, as these periods are riskier, and a substantial group of investors prefers to trade before or right after the earnings announcement.

We argue that the uncertainty connected to earnings announcement is therefore likely to be a major characteristic of a stock from the investor perspective and strongly influences its returns in the long term. Savor and Wilson (2014) and Lucca and Moench (2015) show that stock returns behave differently on the days of macroeconomic and earnings announcements, allowing for a better alignment with the theoretical asset pricing models, in particular CAPM. Furthermore, Savor and Wilson (2014) show that announcement day return realized variance is a better predictor of a quarterly return variance than non-announcement day return realized variance, hence being a superior measure of risk.

This paper uses an ex-ante measure of earnings announcement caused jump variance, extracted from option prices, as the measure of risk.[1] Since Patton and Verrardo (2012) and Savor and Wilson (2014) suggest a substantial proportion of systematic risk on the announcement days, we isolate the firm-specific risk by subtracting the part of the jump variance correlated with the squared CAPM beta. Finally, we show that the extent of our risk measure - idiosyncratic implied earnings announcement day jump variance - is a priced characteristic, using monthly returns of correspondingly sorted portfolios (constructed from 1740 US stocks) over 18 years (1997-2014). In fact, buying stocks with high firm-specific uncertainty and short-selling stock with low firm-specific uncertainty connected to earnings announcements yields 6.1% annual average return in excess of the Carhart (1997) four-factor model and 5.3% annually in excess of Fama-French (2015) five-factor model. Furthermore, we show that the result is driven by the large capitalization stocks and is independent of operating profitability of the firms.

Our paper differs from the literature (Savor and Wilson 2014, Atilgan 2014, Diavatopoulos et al. 2012) as it measures impact of uncertainty on returns in subsequent years, not in a window of several days around the announcement. Furthermore, our measure of uncertainty is based on the implied jump variance measure (used in Dubinsky and Johannes 2006 and Barth and So 2014 in a different context), which is explicitly linked to the information content of the earnings announcement, opposed to volatility spreads in Atilgan (2014) and changes in implied skewness in Diavatopoulos et al. (2012), which may be at best indirectly related to the uncertainty, inherent in the earnings announcement.

The rest of the paper is structured as follows. Section 2 presents the methodology of the empirical study. Section 3 describes the data. Results are provided and discussed in Section 4 and Section 5 concludes.

[1] Diavatopoulos et al. (2008) provides some evidence that option-implied volatility has generally a stronger influence on stock returns than the realized variance.

## II. Methodology

To capture firm-specific fundamental uncertainty we first calculate fundamental uncertainty, associated with the earnings announcement, i.e. the implied variance of the jump on the earnings announcement day (EAD). We follow Dubinsky and Johannes (2006) and Barth and So (2014) to obtain the implied EAD jump variance $\sigma_j^2$ as:

$$\sigma_j^2 = \frac{IV_{T_1}^2 - IV_{T_2}^2}{T_1^{-1} - T_2^{-1}}, \tag{1}$$

where $IV_{T_i}$ denotes implied volatility of an option with time-to-maturity $T_i$, where $IV_{T_2}$ is an implied volatility of a longer option, $T_2 > T_1$, and the earnings announcement day falls into the period prior to expiration of both options.[2] As in Barth and So (2014) we calculate the implied EAD jump variance for days -6 to -2 with respect to EAD (EAD being day 0) and average the five daily estimates for each stock and quarter. To filter out possible noise we furthermore average all available quarterly estimates for a stock for a given calendar year, thus obtaining stock-year implied EAD jump variance estimates.

As we focus on firm-specific uncertainty, it is necessary to filter out the systematic part of the expected jump. The literature suggests that there probably is a considerable portion of systematic, market-wide information in an individual firm's earnings announcement: Ball et al. (2009) show that the earnings process has a systematic component, which explains a substantial part of individual firm's earnings; Patton and Verrardo (2012) report increasing stock return sensitivity to the market risk on earnings announcement days.

To isolate the idiosyncratic risk we follow the idea that the variance of stock returns depends on the variance of the stock market returns in a manner prescribed by the market model:

$$\operatorname{var}[R_i] = \beta_i^2 \operatorname{var}[R_m] + \operatorname{var}[e_i], \tag{2}$$

[2] Since we use fixed time-to-maturity implied volatilities with $T_1$=30 days and $T_2$=60 days the expression in eq. 1 can be simplified to $\sigma_j^2 = \frac{IV_{30}^2 - IV_{60}^2}{252/60}$.

where $\beta$ denotes the slope of the market model, $\mathrm{var}\left[R_m\right]$ denotes variance of stock market index returns and $\mathrm{var}\left[e_i\right]$ denotes idiosyncratic variance of returns of stock *i*. Even though the literature does not allow concluding that this relationship holds one-to-one for the jump on the earnings announcement day, the results of Patton and Verrardo (2012) strongly suggest some relationship to the market beta. In the spirit of equation (2) we extract the systematic part of the jump variance by running the cross-sectional regression for each year of implied EAD jump variances on squared betas:

$$\sigma_{j,i}^2 = \delta_o + \delta_1 \beta_i^2 + u_i \quad (3)$$

whereby betas are pre-estimated using daily stock and index returns on a two-year window, including the year of implied EAD jump variance estimation and the preceding one, but dropping the daily observations for the announcement date and the subsequent day.[3] Equation (3) allows us to decompose the implied jump variance into the systematic part $\hat{\delta}_1 \beta_i^2$ and the firm-specific part, $\sigma_{j,i}^{2,FS} = \hat{\delta}_0 + \hat{u}_i$ which we will further call idiosyncratic implied EAD jump variance.[4]

We sort the stocks at the beginning of each year using one-way, two-way and three-way sorting. Thereby one-way sorting is our primary approach, and higher dimensional sorting approaches are applied to obtain further details.

In the one-way sorting procedure we sort all stocks into five quintile portfolios (Q1,…,Q5) according to the call idiosyncratic implied EAD jump variance, $\sigma_{j,i}^{2,FS}$, measured over the preceding year.

Two-way sorting involves sorting on size and firm specific announcement risk. We divide the stocks under analysis into two size groups: ‘big caps’, stocks with above the median market capitalization in the corresponding year, and ‘small caps’, stocks with below the median market capitalization in

[3] Datastream provides only dates but not the exact timing of the quarterly earnings announcements. Jiang et al. (2012) report that about the half of earnings announcements happen after hours, so that the reaction of the stock market follows only on the subsequent day. Therefore we exclude both days from the market model regression.
[4] We also further use ‘firm-specific announcement jump variance’ and ‘idiosyncratic announcement jump variance’ as synonyms.

the corresponding year. We form ten portfolios combining stocks falling both into a size group and a firm-specific announcement risk quintile Q1B,…, Q5B, Q1S,…,Q5S.[5]

In the three-way sorting procedure we also divide the universe of firms based on their operating profitability, in line with the logic of Fama and French (2015). Operating profitability is defined as operating income minus interest expense, divided by the book value of equity.[6] Thus we sort upon size, operating profitability and idiosyncratic announcement jump variance. To keep the number of portfolios adequate to our sample of stocks, we keep two size categories, three operating profitability categories and introduce three firm-specific announcement risk categories. . In case of operational profitability and firm-specific announcement jump risk the break points are the 30$^{th}$ and the 70$^{th}$ percentiles of the corresponding characteristic in a given year. We call operating profitability categories: Weak, Medium and Robust; and firm-specific risk categories: Low risk, Mid risk and High risk. We obtain 18 portfolios, which we denote with the combination of the first letters of the categories, e.g. BWH is a portfolio of stocks with above median market capitalization in the preceding year ('Big'), which operating profitability was below the 30$^{th}$ percentile in the preceding year ('Weak') and which idiosyncratic EAD jump variance was above the 70$^{th}$ percentile in the preceding year ('High risk').[7]

We calculate value weighted monthly returns of each portfolio by weighting each stock in the portfolio by its relative market capitalization within the portfolio at the end of the previous year. At the end of the procedure we have a time series of monthly returns for 1997 – 2014 for each portfolio, which we regress upon the four Carhart (1997) model factors portfolio returns $R_m$-$R_f$, *SMB*, *HML* and *MOM* as well as upon the five Fama and French (2015) model factors portfolio returns $R_m$-$R_f$, *SMB, HML, RMW* and *CMA.*

Our main test objects are portfolios, which we call difference or long-short portfolios. Such a portfolio combines a long position in the most prone to the firm-specific announcement jump risk stock category with a short position in the least risky in terms of idiosyncratic announcement jump risk stock category. In case of one-way sorting a difference portfolio holds a long position in Q5 and

[5] As this sorting procedure is independent, the number of stocks between the ten portfolios may vary substantially, but even for the least populated portfolio the number of constituents is sufficient for obtaining reliable results.
[6] If interest expense is unavailable, we define operating profitability as operating income divided by book value of equity.
[7] As this sorting procedure is independent, the number of stocks between the 18 portfolios may vary substantially, but even for the least populated portfolio the number of constituents is sufficient for obtaining reliable results.

a short position in Q1, so that the return on such portfolio is $R_{Q5}$-$R_{Q1}$. When we perform the two-way sorting, we create such long-short portfolios for Big and Small stocks separately as well as an 'Aggregate' difference portfolio where we combine the difference portfolios of both size categories with equal weights. Thus, the returns of difference portfolios in these three cases are $R_{Q5B}$-$R_{Q1B}$, $R_{Q5S}$-$R_{Q1S}$ and ($R_{Q5B}$+ $R_{Q5S}$)*0.5-($R_{Q1B}$ + $R_{Q1S}$)*0.5 respectively. The difference portfolios in case of three-way sorting are constructed following the same logic.

If regressions of difference portfolio returns on four and five factor models yield significant and positive alphas, we interpret this evidence as supportive of idiosyncratic EAD jump variance being priced as characteristic, in excess of the included risk factors.

## III. Data and summary statistics

We obtain options data from IvyDB US Optionmetrics. We use implied volatilities for fixed time-to-maturities (30 and 60 days) from volatility surface files of the database. We restrict the study to the ATM implied volatilities of call options (option's $\delta$=0.5). Fixed time-to-maturity implied volatilities are calculated by Optionmetrics as interpolation of implied volatilities of closest options with respect to time-to-maturity and moneyness. Stock price data, market capitalization and earnings announcement dates are coming from Datastream.[8] Returns on the market, size, value, momentum, operating profitability and investment intensity portfolios are taken from the online data library of Kenneth French, which can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We use all stocks, which were constituents of the Standard & Poors Super Composite 1500 index on January 31, 1996, June 30, 2005 and September 30, 2015. After dropping stocks which do not have corresponding options data or earnings announcement dates in 1996-2013 we are left with 1740 stocks for the analysis.

We calculate our main sorting characteristic, option-implied earnings announcement jump, as in Barth and So (2014) as well as Dubinsky and Johannes (2006) as the difference between implied

[8] We match the data using stock tickers. When more than one Datastream mnemonic or Datastream Code correspond to one security ID in the IvyDB US Database we choose the one where the Worldscope ticker corresponds to the IvyDB ticker. If both do, we choose upon IBES ticker correspondence.

volatilities of the shorter and the longer option, divided by the difference of the inverses of time to maturity: $\sigma_j^2 = \frac{IV_{30} - IV_{60}}{252/60}$. This value is calculated for each day, starting from six days up to two days preceding the quarterly earnings announcement, and then averaged over this window. Obtained quarterly estimates are then averaged for each stock and year (to filter out noise) to obtain annual earnings announcement implied jump estimates for each company. Subsequently we run cross-sectional regressions as in Equation (3) to obtain idiosyncratic EAD jump variances $\sigma_{j,i}^{2,FS}$, as explained in the previous section.

Table 1 presents descriptive statistics for these two measures. The average jump variance is about half of a percentage squared, which approximately correspond to a jump standard deviation of slightly above 7%. However, the distribution of expected jumps is strongly right-skewed, so that half of expected jump variances are below a quarter of percentage squared, thus with jump volatilities below 5%. The idiosyncratic part of the implied EAD jump variance is 0.3 percent squared, and is also right-skewed.

In spite of our attempt to balance the sample by including index constituent as of January 1996 and June 2005, the number of observations grows with time,[9] possibly due to increasing with time issuance of options for new underlying stocks. Expected jump variance (both total and idiosyncratic) also grows in the second sub-sample. It could be due to the sub-prime crisis, falling into the second sub-sample, and/or due to a larger number of companies with option data available for them.

Panel B presents the quintiles of the distribution of the expected (total and idiosyncratic) EAD jump variances. One can notice the exponential growth of the total implied jump variances from quintile to quintile, thus for the full sample the difference between the 40$^{th}$ and 20$^{th}$ percentiles are 0.12 squared percentage points, whereas between the 80$^{th}$ and 60$^{th}$ 0.40 percentage points. The same picture can be observed for both subsamples. All quintiles grow substantially in the second subsample.

[9] Detailed table with numbers of observations per year is provided in Appendix, Table A1.

**Table 1. Descriptive statistics for option-implied earnings announcement day jump variance (annual averages)**

The table presents various descriptive statistics for option-implied earnings announcement day jump variance measures as $\sigma_j^2 = \frac{IV_{30}^2 - IV_{60}^2}{252/60}$ for each day from -6 to -2 with respect to the earnings announcement day (day 0) and averaged over this period for each stock and quarter. Subsequently four quarterly jump estimates within a calendar year are averaged to obtain annual estimates. Idiosyncratic EAD jump variances $\sigma_{j,i}^{2,FS}$ are $\sigma_{j,i}^{2,FS} = \hat{\delta}_0 + \hat{u}_i$, whereby $\hat{\delta}_0$ and $\hat{u}_i$ are obtained from cross-sectional regressions $\sigma_{j,i}^2 = \delta_o + \delta_1 \beta_i^2 + u_i$ for each year (see Equation (3) and subsequent explanations).

| | Full sample | | 1996-2004 | | 2005-2013 | |
|---|---|---|---|---|---|---|
| | Total | Idiosyncratic | Total | Idiosyncratic | Total | Idiosyncratic |
| *Panel A: Summary statistics* | | | | | | |
| Mean | 0.0052 | 0.0030 | 0.0034 | 0.0016 | 0.0065 | 0.0040 |
| Median | 0.0025 | 0.0009 | 0.0015 | 0.0004 | 0.0033 | 0.0013 |
| Std. Dev. | 0.0133 | 0.0127 | 0.0095 | 0.0091 | 0.0153 | 0.0147 |
| Skewness | 16.57 | 18.21 | 14.07 | 15.59 | 16.08 | 17.48 |
| Number of observations | 21178 | 20817 | 8724 | 8574 | 12454 | 12243 |
| *Panel B: Percentiles* | | | | | | |
| 20th | 0.0005 | -0.0009 | 0.0001 | -0.0011 | 0.0009 | -0.0007 |
| 40th | 0.0017 | 0.0003 | 0.0009 | -0.0001 | 0.0023 | 0.0005 |
| 60th | 0.0035 | 0.0017 | 0.0023 | 0.0011 | 0.0045 | 0.0023 |
| 80th | 0.0075 | 0.0050 | 0.0052 | 0.0035 | 0.0090 | 0.0061 |

## IV. Results and discussion

### *IV.1. One-way sorting*

**Table 2. Summary statistics for returns of portfolios sorted on idiosyncratic implied EAD jump variance.**

At the end of each year we sort stocks based on the idiosyncratic implied EAD jump variance, i.e. based on the residuals of the cross-sectional regression of annual implied EAD jump variances on two-year market model betas, according to eq. (3). Thereby annual implied EAD jump variances are calculated according to eq. 1. Thus, quintile 1 contains stocks with the lowest implied idiosyncratic EAD jump variance and quintile 5 with the highest. We form value-weighted portfolios by weighting each stock in the quintile by its relative market capitalization within the quintile at the end of the year. After portfolio formation, we record the monthly returns for each quintile portfolio for a year period. We repeat this procedure by rolling the implied EAD jump variance estimation window by one year. At the end of the procedure we have a time series of monthly returns as well as a time series of annual (idiosyncratic) implied EAD jump variances for each quintile portfolio. This table reports the average (idiosyncratic) implied EAD jump variances, average excess returns, standard deviations of excess returns and Sharpe ratios.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| implied jump variance | 0.0007 | 0.0015 | 0.0026 | 0.0050 | 0.0132 | |
| Implied idios. jump variance | -0.0023 | -0.0003 | 0.0011 | 0.0031 | 0.0104 | |
| Market cap | 10348 | 13592 | 10944 | 6798 | 3656 | |
| Operating profitability | 0.1860 | 0.3832 | 0.3824 | 0.3414 | 0.2320 | |
| | | | | | | |
| Mean | 0.0050 | 0.0062** | 0.0062* | 0.0072* | 0.0110** | 0.0059*** |
| SD | 0.0593 | 0.0459 | 0.0462 | 0.0504 | 0.0637 | 0.0328 |
| Sharpe ratio | 0.0852 | 0.1358 | 0.1346 | 0.1428 | 0.1723 | 0.1808 |

Table 2 gives an overview of the quintile portfolios implied jump variance and their monthly return properties. The implied EAD jump variance grows non-linearly from quintile to quintile, making the largest step from quintile 4 to quintile 5. The same is valid for the non-systematic part of the jump variance. The average size grows from the first to the second decile and decreases thereafter; thereby an average company in the highest firm-specific risk decile has a market capitalization of less than a third of a market capitalization of an average company in the second decile. Operating profitability exhibits an inversed U-shape pattern, whereby the firm-specific riskiest stocks yield a somewhat higher operational profitability than those with the lowest idiosyncratic risk, but they are considerably less profitable than the firms in the middle quintiles.

The average portfolio excess return is monotonically increasing. Thereby the fifth-quintile-portfolio excess return is more than double of the excess return of the first-quintile portfolio. Correspondingly, the long-short portfolio Q5-Q1 has the monthly excess return of 59 basis points, or 7.1% annualized, which is also significant at the 1% significance level. Standard deviation of portfolio monthly returns is U-shaped, with the first and fifth quintile portfolio returns being mostly volatile with 5.9% and 6.4% standard deviation respectively. The difference portfolio has substantially lower volatility, it reduces almost by half. Sharpe ratio exhibits an upward trend. The long-short portfolio Q5-Q1 has with a Sharpe ratio of 0.18 offers the best return compensation for risk measured by standard deviation.

**Table 3. Regressions of one-way sorted portfolio returns on Fama-French-Carhart four factors**

Table 3 reports the coefficient estimates of the Carhart four factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML* and *MOM*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| α | -0.0004 | 0.0020 | 0.0009 | 0.0020* | 0.0047*** | 0.0051** |
| | (0.0014) | (0.0013) | (0.0009) | (0.0011) | (0.0017) | (0.0021) |
| $\beta_M$ | 1.1560*** | 0.8890*** | 0.9641*** | 0.9789*** | 1.1805*** | 0.0245 |
| | (0.0354) | (0.0312) | (0.0320) | (0.0297) | (0.0417) | (0.0659) |
| $\beta_{SMB}$ | -0.1583*** | -0.1879*** | -0.1405*** | -0.0250 | 0.1384** | 0.2967*** |
| | (0.0470) | (0.0351) | (0.0432) | (0.0422) | (0.0592) | (0.0841) |
| $\beta_{\mathrm{HML}}$ | 0.0141 | 0.0519 | 0.1568*** | 0.1210*** | 0.0351 | 0.0209 |
| | (0.0641) | (0.0678) | (0.0433) | (0.0422) | (0.0599) | (0.0988) |
| $\beta_{\mathrm{Mom}}$ | -0.1732*** | -0.1211*** | -0.0365 | -0.1359*** | -0.1915*** | -0.0183 |
| | (0.0378) | (0.0440) | (0.0266) | (0.0334) | (0.0432) | (0.0671) |
| $R^2$ | 0.90 | 0.86 | 0.90 | 0.89 | 0.89 | 0.11 |

Table 3 reports parameter estimates and explanatory power of the Carhart four-factor model time series regressions. The exposure to market risk appears to be U-shaped: portfolios with the least and the highest announcement risks have a significantly higher sensitivity to the market index as the rest. The exposure to size factor grows substantially, from -0.16 for portfolio Q1 to +0.14 for portfolio Q5, it seems that our measure of idiosyncratic risk is correlated with size. Only portfolios Q3 and Q4 significantly load on the book-to-market factor, and the exposure is positive. All but the returns of Q3 are significantly negatively related to momentum. Whereas alphas of the first 3 quintile portfolios are insignificant, alphas of the fourth and the fifth are positive and significant at the 10% and 1% significance level respectively. More importantly, the alpha of the portfolio long in the stocks with the highest idiosyncratic implied EAD jump variance and short in the stocks with the lowest is positive and significant at the 5% level. After controlling for the four Carhart factors, the difference portfolio yields an excess return of 51 basis points per month, or 6.1% annually. Thus, we find both statistically and economically significant premium for holding stocks with high firm-specific uncertainty around earnings announcement days.

Remarkably, controlling for the Carhart's factors decreases the average return of the difference portfolio only by 1 percentage point. This is due to the fact that the difference portfolio returns are not sensitive to those factors except for the size factor, the size beta being +0.30 and significant at the 1% level.

Firm-specific fundamental uncertainty may be related to the operational profitability of the firm and its investment policy. As Fama and French (2015) show with the help of a five factor model, operational profitability and investment intensity can be viewed as priced factors. To test whether our fundamental uncertainty measure simply reflects these risk factors we estimate the Fama-French (2015) five factor model for the portfolios sorted on firm-specific EAD jump risk. Results are reported in Table 4.

**Table 4. Regressions of one-way sorted portfolio returns on Fama-French (2015) five factors**

Table 4 reports the coefficient estimates of the Fama-French (2015) five factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML*, *RMW* and *CMA*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
| α | -0.0004 | -0.0002 | -0.0006 | 0.0005 | 0.0040** | 0.0044** |
| | (0.0013) | (0.0011) | (0.0013) | (0.0013) | (0.0018) | (0.0022) |
| $\beta_M$ | 1.1772*** | 1.0009*** | 1.0324*** | 1.0584*** | 1.2330*** | 0.0558 |
| | (0.0417) | (0.0346) | (0.0304) | (0.0290) | (0.0536) | (0.0703) |
| $\beta_{SMB}$ | - 0.2294*** | -0.1671*** | -0.0581 | 0.0114 | 0.0746 | 0.3040*** |
| | (0.0694) | (0.0516) | (0.0360) | (0.0558) | (0.0928) | (0.1016) |
| $\beta_{HML}$ | 0.2386*** | -0.0242 | 0.0943 | 0.1425** | 0.1439 | -0.0947 |
| | (0.0771) | (0.0622) | (0.0574) | (0.0673) | (0.1150) | (0.1113) |
| $\beta_{RMW}$ | -0.1490* | 0.1856** | 0.2678*** | 0.1495*** | -0.1122 | 0.0368 |
| | (0.0812) | (0.0881) | (0.0636) | (0.0450) | (0.0979) | (0.1014) |
| $\beta_{CMA}$ | -0.2064 | 0.2168 | 0.0231 | -0.0455 | -0.0652 | 0.1411 |
| | (0.1325) | (0.1398) | (0.0626) | (0.0882) | (0.1774) | (0.1603) |
| $R^2$ | 0.88 | 0.85 | 0.91 | 0.88 | 0.87 | 0.12 |

In Table 4 we follow Fama and French (2015) model specification: the operational profitability factor is denoted by RMW, and is defined as returns on a portfolio with high operational profitability stocks ('robust') minus the return on low profitability stocks ('weak'). Investment intensity factor is captured by returns on a portfolio with low change in total assets ('conservative') minus returns on a portfolio with a high increase in assets ('aggressive'), and is denoted by CMA. Size factor specification for this model is slightly modified by Fama and French (2015) in a way so that it is orthogonal to the new factors.

Table 4 provides for the U-shape in market sensitivity, even though on a somewhat higher level and slightly flatter; for the difference portfolio the exposure to market risk still cancels out. One still observes monotonic increase in exposure to size factor from Q1 to Q5, and the sensitivity of the difference portfolio barely changes compared to the Carhart (1999) model (in Table 3), still being positive and highly significant. Only the first and the fourth quintile portfolios are significantly (and positively) influenced by the value factor, the difference portfolio remains value-neutral. Remarkably, the sensitivity to operational profitability is inverse U-shaped: portfolios Q2-

Q4 are significantly positively exposed, whereby the exposure of Q1 is negative and significant at the 10% level, and that of Q5 negative and significantly lower than of Q4 (but not significantly different from zero). As both extreme portfolios seem to be weak in terms of profitability, the difference portfolio is neutral to that factor. None of the portfolios seem to be sensitive to the investment intensity factor. Out of the five quintile portfolios only the most risky one has a significant alpha, but also a quite pronounced one +40 basis points, or 4.8% annualized. The difference portfolio's alpha is significant at the 5% level. Thus, investing into high firm-specific announcement risk stocks and short selling low announcement risk stocks yields 5.3% p.a.

The above analysis provides for an economically and statistically significant effect of the firm-specific announcement risk on asset pricing. However, the data also suggests that there might be relationship to size. Evidence in Table 4 may raise concerns, that the effect is only relevant for low operational profitability stocks. In what follows with address both issues by (1) a two-way independent sorting on size and firm-specific announcement risk and by (2) three-way sorting on size, firm-specific announcement risk and operational profitability.

### *IV.2. Two-way sorting*

We divide the stocks under analysis into two groups, according to size: 'big caps', stocks with above the median market capitalization in the corresponding year, and 'small caps', stocks with below the median market capitalization in the corresponding year. We form ten portfolios combining stocks falling both into a size group and a firm-specific announcement jump risk quintile. As this sorting procedure is independent, the number of stocks between the ten portfolios may vary substantially, but even for the least populated portfolio the number of constituents is sufficient for obtaining reliable results.

**Table 6. Summary statistics for returns of two-way (on size and idiosyncratic implied EAD jump variance, 2x5) sorted portfolios, big caps.**

At the end of each year we sort stocks based on the idiosyncratic implied EAD jump variance, i.e. based on the residuals of the cross-sectional regression of annual implied EAD jump variances on two-year market model betas, according to eq. (3). Thereby annual implied EAD jump variances are calculated according to eq. 1. Thus, quintile 1 contains stocks with the lowest implied idiosyncratic EAD jump variance and quintile 5 with the highest. We form value-weighted portfolios by weighting each stock in the quintile by its relative market capitalization within the quintile at the end of the year. After portfolio formation, we record the monthly returns for each quintile portfolio for a year period. We repeat this procedure by rolling the implied EAD jump variance estimation window by one year. At the end of the procedure we have a time series of monthly returns as well as a time series of annual (idiosyncratic) implied EAD jump variances for each quintile portfolio. This table reports the average (idiosyncratic) implied EAD jump variances, average excess returns, standard deviations of excess returns and Sharpe ratios.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1B | Q2B | Q3B | Q4B | Q5B | Q5B-Q1B |
| implied jump variance | 0.0008 | 0.0015 | 0.0026 | 0.0050 | 0.0127 | |
| Implied idios. jump variance | -0.0022 | -0.0003 | 0.0011 | 0.0031 | 0.0098 | |
| Market cap | 21098 | 21191 | 17398 | 12336 | 9078 | |
| Operating profitability | 0.1879 | 0.3878 | 0.3901 | 0.3543 | 0.2528 | |
| Mean | 0.0047 | 0.0060* | 0.0061* | 0.0070* | 0.0113** | 0.0066*** |
| SD | 0.0591 | 0.0461 | 0.0463 | 0.0504 | 0.0650 | 0.0355 |
| Sharpe ratio | 0.0787 | 0.1307 | 0.1313 | 0.1391 | 0.1733 | 0.1860 |

The characteristics of big stocks, reported in Table 6, are very similar to the characteristics of one-way sorted portfolios (Table 2), whereby the magnitude of the jump variance is somewhat smaller and also size is less dispersed. One can notice the same monotonic increase in excess returns, with the long-short portfolio yielding 66 basis points per month or 7.9% annually. As in case of one-way sorts, the long-short portfolio pays the highest return per unit of standard deviation, reflected by the highest Sharpe ratio of 0.19.

**Table 7. Regressions of two-way sorted portfolio returns on Fama-French-Carhart four factors, big caps**

Table 7 reports the coefficient estimates of the Carhart four factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML* and *MOM*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1B | Q2B | Q3B | Q4B | Q5B | Q5B-Q1B |
| α | -0.0007 | 0.0020 | 0.0008 | 0.0020* | 0.0052*** | 0.0059** |
| | (0.0014) | (0.0013) | (0.0009) | (0.0012) | (0.0020) | (0.0023) |
| $\beta_M$ | 1.1523*** | 0.8858*** | 0.9640*** | 0.9762*** | 1.1993*** | 0.0470 |
| | (0.0359) | (0.0323) | (0.0360) | (0.0315) | (0.0505) | (0.0747) |
| $\beta_{SMB}$ | -0.1910*** | -0.2075*** | -0.1636*** | -0.0667 | 0.0245 | 0.2155** |
| | (0.0470) | (0.0368) | (0.0434) | (0.0407) | (0.0664) | (0.0915) |
| $\beta_{\mathrm{HML}}$ | -0.0026 | 0.0335 | 0.1403*** | 0.0895*** | -0.0295 | -0.0269 |
| | (0.0659) | (0.0698) | (0.0443) | (0.0447) | (0.0699) | (0.1092) |
| $\beta_{\mathrm{Mom}}$ | -0.1664*** | -0.1248*** | -0.0332 | -0.1314*** | -0.1848*** | -0.0184 |
| | (0.0400) | (0.0456) | (0.0270) | (0.0336) | (0.0504) | (0.0744) |
| $R^2$ | 0.89 | 0.85 | 0.90 | 0.88 | 0.86 | 0.06 |

The performance of the Carhart (1999) four factor model, presented in Table 7 is very similar to that of the one-way sorts (Table 3). One observes the same U-shape pattern for market risk loadings, a slightly kinked at Q2B portfolio growth in size sensitivity, whereby the sensitivity mimics the size characteristics (compare Table 6). Thereby the two-way sorting procedure managed to diminish this growth, so that the sensitivity of the difference portfolio to the size risk is with +0.22 lower, than in case of one-way sorts (+0.30, Table 3, col 6), and significant only at the 5% level opposed to 1%. Only the third and the fourth portfolio show exposure to the value factor. All but Q3B are negatively loaded on momentum.

Two riskiest portfolios with regard to the firm-specific announcement risk exhibit significant alphas, the one of the Q5B being significant at the 1% level. The difference portfolio yields an average return in excess of the four factors of 59 basis points or 7.1% p.a., which is significant on the 5% level. Thus the effect is substantially stronger (1 percentage point higher) for the large companies, compared to the overall one-way sorts.

**Table 8. Regressions of two-way sorted portfolio returns on Fama-French (2015) five factors, big caps**

Table 8 reports the coefficient estimates of the Fama-French (2015) five factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML*, *RMW* and *CMA*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1B | Q2B | Q3B | Q4B | Q5B | Q5B-Q1B |
| α | -0.0006 | -0.0003 | -0.0006 | 0.0006 | 0.0048** | 0.0054** |
| | (0.0013) | (0.0011) | (0.0010) | (0.0013) | (0.0021) | (0.0025) |
| $\beta_M$ | 1.1692*** | 0.9984*** | 1.0302*** | 1.0510*** | 1.2405*** | 0.0713 |
| | (0.0417) | (0.0356) | (0.0325) | (0.030) | (0.0609) | (0.0798) |
| $\beta_{SMB}$ | -0.2643*** | -0.1890*** | -0.0852** | -0.0369 | -0.0559 | 0.2085* |
| | (0.0682) | (0.0532) | (0.0373) | (0.0546) | (0.1011) | (0.1122) |
| $\beta_{HML}$ | 0.2281*** | -0.0355 | 0.0808 | 0.1220* | 0.1136 | -0.1144 |
| | (0.0762) | (0.0639) | (0.0608) | (0.0694) | (0.1264) | (0.1273) |
| $\beta_{RMW}$ | -0.1557* | 0.1828** | 0.2603*** | 0.1340*** | -0.1530 | 0.0028 |
| | (0.0831) | (0.0912) | (0.0654) | (0.0480) | (0.1109) | (0.1156) |
| $\beta_{CMA}$ | -0.2082 | 0.2134 | 0.0287 | -0.0458 | -0.0731 | 0.1350 |
| | (0.1322) | (0.1447) | (0.0637) | (0.0901) | (0.1926) | (0.1795) |
| $R^2$ | 0.88 | 0.84 | 0.91 | 0.86 | 0.84 | 0.07 |

The performance of the Fama-French (2015) model for the big cap portfolios is qualitatively similar to one-way sorted portfolios (Table 4): U-shape for market-risk sensitivities, monotonic increase for the size factor exposure and the inverse U-shape for the operational profitability factor; no impact of investment intensity. Thereby the sensitivity of the difference portfolio to size is weaker than in case of one-way sorts (0.21 compared to 0.30), and significant only on the 10% level, in contrast to the 1%. The pattern is slightly different for the value factor, with the first and the fourth portfolio exhibiting significant (at least at the 10% level) positive loadings. Most importantly, alphas of the fifth and the difference portfolios are positive and significant at the 5% level. Thereby the difference portfolio yields 54 basis points or 6.5% per year in excess of the five Fama-French (2015) factors, which is 1.2 percentage point more than in the one-way-sorting case.

**Table 9. Summary statistics for returns of two-way (on size and idiosyncratic implied EAD jump variance, 2x5) sorted portfolios, small caps.**

At the end of each year we sort stocks independently based on the idiosyncratic implied EAD jump variance and size. Below are summary statistics for portfolios of stocks, which market capitalization is below median ('small') and which fall into the corresponding idiosyncratic implied EAD jump variance quintile. Thus, portfolio Q1S contains stocks with the lowest 20% implied idiosyncratic EAD jump variance and are below the median size, and so on. We form value-weighted portfolios by weighting each stock in the portfolio by its relative market capitalization within the portfolio at the end of the year. After portfolio formation, we record the monthly returns for each portfolio for a year period. We repeat this procedure by rolling the implied EAD jump variance estimation window by one year. At the end of the procedure we have a time series of monthly returns as well as a time series of annual (idiosyncratic) implied EAD jump variances for each quintile portfolio. This table reports the weighted average (idiosyncratic) implied EAD jump variances, weighted average operating profitability, average market capitalization, average portfolio excess returns, standard deviations of excess returns and Sharpe ratios.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1S | Q2S | Q3S | Q4S | Q5S | Q5S-Q1S |
| implied jump variance | -0.0010 | 0.0016 | 0.0028 | 0.0051 | 0.0151 | |
| Implied idios. jump variance | -0.0043 | -0.0003 | 0.0011 | 0.0032 | 0.0127 | |
| Market cap | 804 | 1042 | 1062 | 988 | 854 | |
| Operating profitability | 0.1313 | 0.1824 | 0.2163 | 0.1874 | 0.1082 | |
| Mean | 0.0144*** | 0.0121*** | 0.0116*** | 0.0116*** | 0.0120** | -0.0023 |
| SD | 0.0714 | 0.0566 | 0.0542 | 0.0592 | 0.0661 | 0.0225 |
| Sharpe ratio | 0.2014 | 0.2139 | 0.2137 | 0.1962 | 0.1821 | -0.1041 |

Table 9 indicates that small caps differ from big caps in several respects. First, they are far more heterogeneous with respect to implied announcement day jump risk: whereby big cap portfolios span about 0.012 of the overall and firm-specific implied EAD jump variance (see Table 6), small cap portfolio cover a 33% larger range of 0.016 (-0.001 : 0.0151) for the overall and 0.017 (-0.0043 : 0.0127) for idiosyncratic respectively. Second, they are much smaller: average firm in a small cap portfolio has at most ten times smaller market capitalization as in the big portfolio (for the first portfolio the difference is more than 25-fold). Third, in contrast to the big caps, they are homogeneous in size: an average firm in the Q5S portfolio is about as large as in the Q1S portfolio, whereby for the big caps the discrepancy in market capitalization is twofold. Operating profitability is somewhat lower, but exhibit a similar to big caps hump-shaped pattern.

All five small cap portfolios yield a quite high average excess return, between 116 and 144 basis points per month or 14% to 17% per year, which tops an average excess return of any big cap portfolio. Thereby, opposite to our hypothesis, the highest excess return is earned by a portfolio with the lowest announcement day firm-specific risk. Thus, the average excess return on the long-short portfolio is negative, however insignificant at any conventional levels. Overall, mean excess returns of small cap portfolios sorted on implied idiosyncratic EAD jump variance seem to be quite similar, suggesting that sorting on firm-specific implied jump is not informative for expected returns in this case. Even though standard deviation of small cap portfolios is higher than that of the big caps, Sharpe ratios of the small cap portfolios are superior without exception.

**Table 10. Regressions of two-way sorted portfolio returns on Fama-French-Carhart four factors, small caps**

Table 3 reports the coefficient estimates of the Carhart four factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML* and *MOM*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1S | Q2S | Q3S | Q4S | Q5S | Q5S-Q1S |
| *Panel B* | | | | | | |
| α | 0.0063*** | 0.0042*** | 0.0042** | 0.0041*** | 0.0041*** | -0.0022 |
| | (0.0019) | (0.0013) | (0.0017) | (0.0013) | (0.0014) | (0.0016) |
| $\beta_M$ | 1.1965*** | 1.0321*** | 0.9500*** | 1.0001*** | 1.1138*** | -0.0827* |
| | (0.0456) | (0.0451) | (0.0537) | (0.0378) | (0.0286) | (0.0436) |
| $\beta_{SMB}$ | 0.6311*** | 0.4410*** | 0.4048*** | 0.5378*** | 0.6787*** | 0.0476 |
| | (0.1010) | (0.0691) | (0.0999) | (0.0804) | (0.0682) | (0.0556) |
| $\beta_{HML}$ | 0.3733*** | 0.5506*** | 0.6209*** | 0.5687*** | 0.3463*** | -0.0269 |
| | (0.0744) | (0.0759) | (0.0850) | (0.0672) | (0.0559) | (0.0555) |
| $\beta_{Mom}$ | -0.2612*** | -0.0645 | -0.0986** | -0.1933*** | -0.2033*** | 0.0579* |
| | (0.0434) | (0.0476) | (0.0392) | (0.0374) | (0.0334) | (0.0337) |
| $R^2$ | 0.90 | 0.88 | 0.86 | 0.90 | 0.93 | 0.07 |

Small caps substantially differ from the rest also with respect to their Carhart model performance, reported in Table 10. The sensitivity to the market risk for the five small firm-specific risk sorted portfolios does not provide for a symmetric U-shape, rather for a 'smirk' with the riskiest in idiosyncratic sense portfolio having a slightly lower loading on market risk than that of the most certain portfolio. This results into a negative and significant at the 10% level loading on the market risk for the difference portfolio. The sensitivity to the size risk is positive and highly significant for all five quintile portfolios, the coefficients exhibit a quite symmetric U-shape, and the loading for the difference portfolio is statistically indistinguishable from zero. Also all five quintile portfolios load significantly on the value risk factor, the coefficients form and inverse U-shape, so that the effects cancel out for the difference portfolio. Momentum significantly negatively impacts all but the second quintile portfolio, however the difference portfolio loads positively and the coefficient is significant at the 10% level. Most importantly, all quintile portfolio alphas are positive and significant at at least 5% level. However, more than a half of the excess return can be attributed to the risk exposure, as alphas constitute about 40% of the average excess return. If there is any tendency, than alpha seems to decline with increasing idiosyncratic uncertainty. However, the difference portfolio's alpha is insignificant, so one can not conclude that the effect of the firm-specific announcement risk is negative for small caps. We rather find that for small caps this type of risk does not affect returns.

**Table 11. Regressions of two-way sorted portfolio returns on Fama-French (2015) five factors, small caps**

Table 11 reports the coefficient estimates of the Fama-French (2015) five factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML*, *RMW* and *CMA*. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We also report $R^2$ for each time-series regression.

| | Quintile portfolios | | | | | |
|---|---|---|---|---|---|---|
| | Q1S | Q2S | Q3S | Q4S | Q5S | Q5S-Q1S |
| *Panel B* | | | | | | |
| α | 0.0044** | 0.0023* | 0.0013 | 0.0014 | 0.0019 | -0.0025 |
| | (0.0020) | (0.0013) | (0.0014) | (0.0014) | (0.0014) | (0.0017) |
| $\beta_M$ | 1.3072*** | 1.1180*** | 1.0810*** | 1.1368*** | 1.2328*** | -0.0744 |
| | (0.0583) | (0.0407) | (0.0441) | (0.0398) | (0.0429) | (0.0481) |
| $\beta_{SMB}$ | 0.6428*** | 0.5139*** | 0.5907*** | 0.6566*** | 0.7017*** | 0.0589 |
| | (0.1259) | (0.0732) | (0.0754) | (0.0782) | (0.0880) | (0.0694) |
| $\beta_{HML}$ | 0.3733** | 0.3581*** | 0.4260*** | 0.4512*** | 0.2275*** | -0.1458 |
| | (0.1458) | (0.0669) | (0.0854) | (0.0931) | (0.0867) | (0.0928) |
| $\beta_{RMW}$ | 0.0652 | 0.2171** | 0.4999*** | 0.3329*** | 0.1304* | 0.0652 |
| | (0.0984) | (0.0878) | (0.0705) | (0.0736) | (0.0787) | (0.0752) |
| $\beta_{CMA}$ | -0.0922 | 0.1611* | -0.0187 | -0.0433 | 0.0693 | 0.1615 |
| | (0.1941) | (0.0918) | (0.0827) | (0.1088) | (0.1145) | (0.1373) |
| $R^2$ | 0.87 | 0.89 | 0.89 | 0.90 | 0.91 | 0.06 |

Small caps' results for the Fama-French (2015) model presented in Table 11 are somewhat less pronounced, than for the Carhart model, but still quite different from the overall and big caps' results. Market betas appear to build a flat U-shape and the corresponding coefficient for the difference portfolio is not significant. Also, the U-shape for the size sensitivities is barely recognizable, even though all coefficients (but for the difference portfolio) are strongly positive and highly significant. The exposure to the value factor is smaller for the 2nd – 4th value portfolios of small caps compared to the corresponding portfolios of the big caps. On the opposite, the sensitivity to the operational profitability is much stronger pronounced for the middle three portfolios, and even the fifth portfolio coefficient is positive and significant at the 10% level. All but portfolio two loadings on investment intensity are insignificant at conventional levels (second portfolios sensitivity being significant at the 10% level). The huge excess returns (see Table 9) of portfolios Q3S, Q4S and Q5S are absorbed by the loadings on risk factors, so that the corresponding alphas turn insignificant. However, the two 'most certain announcement' portfolios exhibit positive and significant alphas. The alpha of the long-short portfolio is insignificant. Again, it seems that the level of the firm-specific announcement risk does not play a role for expected returns of small caps.

Analysis of the two-way sorted portfolio establishes that the results for the big caps drive the result of fundamental uncertainty being priced in the one-way sorting case. It does not hold for the small stocks, which however also differ substantially with respect to their size level and diversity, as well as their exposure to systematic risk factors. It could be the case for the small caps that (1) options on small cap stocks are that illiquid that their prices are too noisy to get adequate estimate of the implied EAD jump risk and/or (2) jumps on other occasions or everyday volatility are that high that they dominate the impact of EAD jumps.

### *IV.3. Three-way sorting*

To ensure that fundamental uncertainty is priced not only for unprofitable firms, we perform three-way sorting, where we also divide the universe of firms based on their operational profitability into three groups (listed ascendingly): Weak, Medium and Robust. We keep two sorts on size: Big and Small, and introduce three sorts on firm-specific risk (to keep the number of portfolios reasonable): Low risk, Mid risk and High risk. In case of operational profitability and firm-specific announcement jump risk the break points are the 30th and the 70th percentiles of the corresponding characteristic in a given year.

**Table 12. Summary statistics for three-way (on size, operational profitability and idiosyncratic implied EAD jump variance, 2x3x3) sorted portfolios.**

***,**,* denote significance of the average excess returns (using Newey-West (1987) standard errors) on the 1%, 5% and 10% level respectively.

| | | Big caps | | | Small caps | | |
|---|---|---|---|---|---|---|---|
| | | Low risk | Mid risk | High risk | Low risk | Mid risk | High risk |
| Implied idios. jump variance | | | | | | | |
| | Weak | -0.0021 | 0.0012 | 0.0083 | -0.0033 | 0.0013 | 0.0116 |
| | Medium | -0.0016 | 0.0010 | 0.0072 | -0.0023 | 0.0012 | 0.0090 |
| | Robust | -0.0014 | 0.0009 | 0.0066 | -0.0036 | 0.0013 | 0.0096 |
| Market cap | | | | | | | |
| | Weak | 15694 | 10774 | 7698 | 721 | 872 | 733 |
| | Medium | 20130 | 13549 | 8662 | 992 | 1094 | 964 |
| | Robust | 28538 | 24346 | 13180 | 1045 | 1192 | 1011 |
| Operating profitability | | | | | | | |
| | Weak | -0.1441 | -0.0599 | -0.0736 | -0.0619 | -0.0345 | -0.2110 |
| | Medium | 0.1889 | 0.1871 | 0.1817 | 0.1805 | 0.1791 | 0.1772 |
| | Robust | 0.5421 | 0.5859 | 0.4971 | 0.4519 | 0.5228 | 0.5745 |
| Mean excess returns | | | | | | | |
| | Weak | 0.0017 | 0.0065 | 0.0072 | 0.0154*** | 0.0116** | 0.0121** |
| | Medium | 0.0054 | 0.0061* | 0.0084** | 0.0106** | 0.0108*** | 0.0109*** |
| | Robust | 0.0068** | 0.0069** | 0.0103** | 0.0149*** | 0.0133*** | 0.0114*** |

Table 12 presents summary statistics for the resulting 18 portfolios.

Turning first to the 9 big cap portfolios, one could notice a substantially higher firm-specific announcement jump risk increase from Mid risk to High risk compared to the step-up from Low risk to Mid risk, which is observable for all profitability category, but most strongly pronounced for the ‘weak’ stocks. Dispersion in firm-specific risk is somewhat lower for the ‘robustly’ profitable stocks. Market capitalization decreases in firm-specific risk and grows with operating profitability. Average excess returns strictly grow with firm-specific risk, whereby the growth for ‘weak’ firms is more pronounced from low risk to mid risk, and for the rest from mid risk to high risk. Returns also increase monotonically in operating profitability, except for Mid risk, where the pattern is V-shaped.

Whereby the 9 small cap portfolios share similar features with respect to firm-specific risk distribution, the size pattern with respect to firm-specific risk disappears (however, size still increases with operating profitability). Operating profitability is more diverse for high risk stocks.

Excess returns of the small cap portfolios are V-shaped with respect to profitability and show mixed patterns with respect to firm-specific announcement jump risk: a V-shape for 'weak' stocks, almost no change for 'medium' stocks and monotonic decrease for 'robust' stocks.

**Table 13. Regressions of three-way sorted portfolio returns on Fama-French-Carhart four and Fama-French (2015) five factors**

Table 13 reports the alpha coefficient estimates of the Fama-French-Carhart four factor model and of the Fama-French (2015) five factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML* and *MOM* (for four factor) or $R_m$-$R_f$, *SMB*, *HML, RMW* and *CMA*. ***,**,* denote significance on the 1%, 5% and 10% level respectively (standard errors of the coefficient estimates have been calculated using Newey-West (1987) correction).[10]

| | Big caps | | | Small caps | | |
|---|---|---|---|---|---|---|
| Alpha coefficients, Carhart 4 factor model | | | | | | |
| | Low risk | Mid risk | High risk | Low risk | Mid risk | High risk |
| Weak | -0.0045* | -0.0015 | 0.0008 | 0.0063*** | 0.0032** | 0.0034* |
| Medium | 0.0004 | 0.0004 | 0.0035 | 0.0029* | 0.0038** | 0.0031* |
| Robust | 0.0022* | 0.0028*** | 0.0049** | 0.0074*** | 0.0060*** | 0.0043** |
| Alpha coefficients, Fama French (2015) 5 factor model | | | | | | |
| Weak | -0.0045** | -0.0016 | 0.0022 | 0.0054** | 0.0014 | 0.0023 |
| Medium | 0.0005 | -0.0017 | 0.0022 | 0.0011 | 0.0008 | 0.0002 |
| Robust | 0.0013 | 0.0007 | 0.0034 | 0.0050*** | 0.0029* | 0.0013 |

The pattern of Carhart's model alphas for big caps strongly resembles the pattern for excess returns: monotonically increasing in firm-specific risk and in operating profitability. Thereby Low risk weak stocks have a significantly (at the 10% level) negative alpha of -45 basis points, and high risk robust stocks yield a significant (at the 5% level) positive alpha of 49 basis points. Turning to the Fama-French (2015) 5 factor model, the results appear somewhat weaker for big caps: alphas are still increasing from Low risk to high risk, but not monotonically for Medium and Robust operating profitability. High risk robust portfolio's alpha is not significant at any conventional level, but the low risk 'weak' portfolio's alpha stays the same and becomes significant at the 5% level.

[10] We omit reporting of standard errors as well as the estimates of beta-coefficients for expositional purposes (not to overload the table). Full set of results is available on demand.

For small caps the patterns for alphas are not supportive of our hypothesis. Low risk weak and robust portfolios exhibit alphas positive and significant at at least 5% significance level, which are higher than alphas of the corresponding High risk portfolios, for both models.

**Table 14. Summary statistics and regressions of the difference (long-short) portfolio returns on Fama-French-Carhart four and Fama-French (2015) five factors**

Table 14 reports the coefficient estimates of the Fama-French-Carhart four factor model and od the Fama-French (2015) five factor model, obtained by running a time series regression of the portfolio monthly returns on monthly $R_m$-$R_f$, *SMB*, *HML* and *MOM* (for four factor) or $R_m$-$R_f$, *SMB*, *HML, RMW* and *CMA*. The returns on the difference portfolios are defined as follows: Big: $(R_{BWH}+R_{BMH}+R_{BRH})/3 - (R_{BWL}+R_{BML}+R_{BRL})/3$; Small: $(R_{SWH}+R_{SMH}+R_{SRH})/3 - (R_{SWL}+R_{SML}+R_{SRL})/3$; Average: $(R_{BWH}+R_{BMH}+R_{BRH}+ R_{SWH}+R_{SMH}+R_{SRH})/6 - (R_{BWL}+R_{BML}+R_{BRL}+ R_{SWL}+R_{SML}+R_{SRL})/6$. The Newey-West (1987) standard errors of the coefficient estimates are reported in parentheses. ***,**,* denote significance on the 1%, 5% and 10% level respectively. We report $R^2$ for each time-series regression.

| | Big caps | | Small caps | | Aggregate | |
|---|---|---|---|---|---|---|
| | Carhart | FF (2015) | Carhart | FF (2015) | Carhart | FF (2015) |
| *Panel A* | | | | | | |
| Mean | 0.0040** | | -0.0022* | | 0.0009 | |
| SD | 0.0281 | | 0.0171 | | 0.0172 | |
| Sharpe | 0.1420 | | -0.1260 | | 0.0326 | |
| *Panel B* | | | | | | |
| α | 0.0037** | 0.0035* | -0.0019 | -0.0026* | 0.0009 | 0.0005 |
| | (0.0018) | (0.0019) | (0.0012) | (0.0013) | (0.0012) | (0.0012) |
| $\beta_M$ | -0.0246 | -0.0133 | -0.0473 | -0.0094 | -0.0359 | -0.0114 |
| | (0.0561) | (0.0611) | (0.0303) | (0.0328) | (0.0357) | (0.0390) |
| $\beta_{SMB}$ | 0.2612*** | 0.2732***,a | 0.0819** | 0.0853*,a | 0.1716*** | 0.1792***,a |
| | (0.0657) | (0.0816) | (0.0399) | (0.0478) | (0.0377) | (0.0492) |
| $\beta_{HML}$ | -0.0332 | -0.0572 | 0.0209 | -0.0041 | -0.0062 | -0.0307 |
| | (0.0905) | (0.0946) | (0.0386) | (0.0543) | (0.0490) | (0.0555) |
| $\beta_{MOM}$ | -0.0318 | | -0.0555** | | -0.0436 | |
| | (0.0556) | | (0.0275) | | (0.0344) | |
| $\beta_{RMW}$ | | 0.0118 | | 0.0547 | | 0.0332 |
| | | (0.0867) | | (0.0593) | | (0.0577) |
| $\beta_{CMA}$ | | 0.0336 | | 0.0268 | | -0.0034 |
| | | (0.1539) | | (0.0845) | | (0.0841) |
| $R^2$ | 0.11 | 0.12 | 0.05 | 0.02 | 0.12 | 0.11 |

In Table 14 we report the performance of long-short portfolios, formed from three-way sorted portfolios to neutralize the effect of operating profitability. The return of the big caps long-short portfolio is thus the simple average of returns of Big High risk Weak, Big High risk Medium and Big

High risk Robust portfolios minus the simple average of returns of Big Low risk Weak, Big Low risk Medium and Big Low risk Robust portfolios. Analogically we calculate returns for the small caps difference portfolio. The returns of the 'Aggregate' long-short portfolio are defined as simple average of returns of all six High risk portfolios minus simple average of returns of all six Low risk portfolios.

Panel A of Table 14 presents the descriptive statistics of the difference portfolios. Average excess return of taking long positions in the three big caps High risk portfolios and shorting the three big caps Low risk portfolios is 40 basis points (or 4.8% p.a.) and is significant at the 5% significance level. Hence, for big caps firm-specific risk is priced even when we neutralize the exposure to operating profitability.

This is not the case for small caps: the average excess return is negative and significant at the 10% significance level, but about a half in magnitude of the average excess return for big caps. This result is somewhat puzzling and is possibly driven by low liquidity of options on small caps and higher overall volatility of small caps' returns.

In the 'Aggregate' portfolio, in which big cap and small cap long-short portfolios are combined with equal weights, effects cancel out, so that the resulting mean excess return is positive, but not significant at any conventional level.

Panel B of Table 14 provides regression results of long-short portfolios on Fama-French-Carhart four and Fama-French (2015) five factors. We still find support for our original findings for the big caps: the alpha is positive and significant at the 5% level for the Carhart's (1997) model and at the 10% for the Fama-French (2015) five factor model. The economic magnitude is also substantial: 37 and 35 basis points on monthly basis, or 4.4% and 4.2% p.a. can be earned by exposing oneself to the firm-specific quarterly announcement jump risk, adjusted for the four and the five risk factors respectively. In both models long-short portfolio exhibits significant sensitivity only to the size risk. Hence, the lower significance of alpha in case of the five factor model may be caused by a one more redundant risk factor.

For small caps the alpha of the difference portfolio is insignificant for the four factor model and significantly (on the 10% level) negative for the five factor. However, in the Carhart's model both size and momentum factors have significant loadings. Hence, the Fama-French (2015) specification may be lacking a relevant risk factor (as it does not include momentum) and the significant result for the alpha could be due to the omitted variable bias.

For the 'aggregate' difference portfolio alphas are insignificant in both specifications, and the long-short portfolio is neutral to all factors but size.

To summarize, our results for big caps are robust to three-way sorting: loading on firm-specific announcement jump risk yields returns in excess of the popular multifactor models, independently of operating profitability. However, we also find still no evidence of the jump risk premium for small caps. Combining big caps and small caps portfolios with equal weights leads to the deterioration of the premium result, achieved for the big caps.

## V. Conclusion

We examine whether the ex-ante uncertainty about the content of earnings announcements, unrelated to the market risk, is a priced characteristic for stocks. We use option-implied expected earnings announcement day jump variance as the measure for uncertainty and extract the firm-specific part by subtracting the portion, linearly related to the market risk sensitivity squared. After forming value-weighted portfolios, sorted according to our uncertainty measure, we run time series regressions for the Carhart four factor model and the Fama and French (2015) five factor model. We find economically and statistically significant returns in excess of both models' predictions for a portfolio long in the stocks with the highest degree of firm-specific earnings-related uncertainty and short in the stocks with the lowest firm-specific earnings-related uncertainty. We show that this result is driven by stocks of companies with large capitalization and is independent of operating profitability of the firms.

A promising line of future research would be to detect, whether it is solemnly the expected behavior on four days in a year that yields an annual return of 5.3% -6.1% in excess of popular risk factor model predictions, or there are some features of stocks determining both the announcement day jumps and monthly return dynamics, which result in such an impressive premium. Along these lines the future steps could include testing firm-specific announcement risk as a factor, as well as taking into account further risk factors, such as liquidity risk.

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**Appendix**

**Table A1. Number of observations by year**

| Year | # of obs. |
|---|---|
| 1996 | 661 |
| 1997 | 814 |
| 1998 | 923 |
| 1999 | 1003 |
| 2000 | 922 |
| 2001 | 961 |
| 2002 | 1060 |
| 2003 | 1090 |
| 2004 | 1140 |
| 2005 | 1190 |
| 2006 | 1240 |
| 2007 | 1298 |
| 2008 | 1351 |
| 2009 | 1388 |
| 2010 | 1399 |
| 2011 | 1441 |
| 2012 | 1458 |
| 2013 | 1478 |