

Momentum and default risk. Some results using the jump component

Abstract:

In this paper we separate the total stock return into its continuous and jump component to test whether stock return predictability should be attributed to omitted risk factors or behavioral finance theories. We extend results from the US market to the Spanish stock market, which, despite being a developed market, presents several differences in terms of stock characteristics, financial system, investor typology and cultural dimensions. The results show that the jump component has significant explanatory power for the premium of three characteristics (size, book-to-market and illiquidity), which is at odds with risk-based explanations. Using the same testing strategy, we try to shed some light on an important controversy concerning the relationship between default risk and momentum. The results suggest that default risk is not the source of momentum returns.

Keywords: Jumps, Momentum, Default Risk, behavioral finance

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1. Introduction

Stock return predictability has been related to various stock characteristics, such as size, btm, liquidity, and momentum, among others. These relationships have been explained from risk-based and behavioral perspectives. On the one hand, Fama and French [1992, 1996] claim that size and value premiums are risk factors omitted from models such as the CAPM, a view supported by other authors, such as Jagannathan and Wang (1996) and Zhang (2005). Meanwhile, from the behavioral finance point of view, characteristics such as small size, extreme book-to-market or low liquidity can be interpreted as proxies for stocks with high information uncertainty (Jiang et al., 2005), firms that are hard to value or to arbitrage (Baker and Wurgler, 2006), or stocks attracting limited attention (Abody et al., 2010).

Jiang and Yao (2013) offer a new way to distinguish between these two competing explanations by separating total stock return into its continuous and jump components. These authors assert that, if investors form unbiased rational expectations, the unexpected component of stock return should not be correlated with ex ante firm characteristics. However, if they form biased expectations and this bias is related to stock characteristics, this component will be associated with lagged characteristics, due to price reversion to equilibrium. In this vein, it is widely accepted in financial literature that large discontinuous price changes (price jumps), due to news or liquidity shocks, are rare events that can proxy for significant information shocks. Hence, if the predictable component of stock returns is realized in the form of jumps, the predictability is unlikely to be driven by the risk premium effect. The results obtained by Jiang and Yao (2013) for the US market indicate that size and illiquidity effects, and a significant part of the value premium, are realized in the form of jumps, thus bringing into question risk premium-based explanations for cross-sectional stock return predictability. Furthermore, neither jump risk nor the “martingale restriction” on jumps can explain their results.

In this context, it may be worth analyzing whether these results are stock market-dependent, since firm characteristics, the type of financial system, investor typology and cultural features can affect stock market returns and, probably, their components. In particular, stock characteristics have the potential to change or accentuate investors’

behavioral biases. Some behavioral finance models (see, among others, Daniel, Hirshleifer and Subrahmanyam, 1998 and 2001 or Hirshleifer, 2001) have shown that investors' behavioral biases are stronger among relatively hard-to-value stocks operating in informationally-sparse environments. The type of financial system can also affect stock price behavior due to the potential effect of the degree of shareholder dispersion and separation between ownership and control. Furthermore, in Continental Europe, the majority of institutional investors are banks, whereas, in the Anglo-Saxon system, they are mainly mutual funds or pension funds (MF&PP) and, although institutional investors are sophisticated traders, and their presence contributes to efficient asset pricing due to their superior capacity to acquire and process information (see, among others, Bartov, Radhakrishnan, and Krinsky, 2000, Jiambalvo, Rajgopal, and Venkatachalam, 2002 or Collins, Gong, and Hribar, 2003) they are not a homogeneous group. In fact, MF&PP can be defined as "transient" institutions because they may overweight short-term earnings potential and underweight long-term earnings potential due to their incentives and may pressure managers into a short-term focus (see Bushee, 2001), whereas banks generally have a long-term, stable relationship with firms. Finally, cultural dimensions have been found to play a major role in explaining the impact of investor behavior on market prices (see Schmeling, 2009 or Corredor et al., 2013). For this purpose, we perform the analysis for the Spanish stock market because, despite being a developed financial market, it presents marked differences in all these respects.

In addition, using the same testing strategy, we aim to shed light on other key controversy. In particular, we study the origin of momentum returns and its relation with default risk, which is the most innovative aspect of this paper. While Avramov et al. (2007) and Agarwal and Taffler (2008), using different default risk proxies, conclude that default risk is the key variable to explain the momentum effect, Abinzano et al. (2013) find no empirical support for this claim. They identify default risk as simply one more characteristic of the loser portfolio, which lacks sufficient explanatory power, on its own, to account for total return. Following the logic applied by Jiang and Yao (2013), if default risk is a key factor in the momentum effect, both these characteristics will necessarily show significant premiums on the same (jump or continuous) return component. Otherwise, it can hardly be argued that momentum and default risk are directly related or that one is the direct cause of the other.

Thus, this paper makes two main contributions to the literature. First, it analyzes a market with significantly different firm characteristics, financial system, investor

typology and cultural dimensions for those of the US market in order to determine whether the results obtained by Jiang and Yao (2013) are generalizable to other markets. Second, it breaks down total stock return into its continuous and jump components, to test whether default risk is a potential explanation for the momentum effect, and thereby settle the conflict between the findings of Avramov et al. (2007) or Agarwal and Taffler (2008) and those of Abinzano et al.(2013).

The remainder of the paper is organized as follows: Section 2 describes the statistical procedures used to identify jumps and break down stock returns into their continuous and jump components. Section 3 presents the database and preliminary data analysis. Section 4 summarizes the empirical findings from the analysis of stock characteristics and return predictability, and reports on various robustness checks based on a re-estimation controlling for liquidity shocks, jump risk and the “martingale restriction” on jumps. Section 5 analyzes the continuous and jump components of total stock returns to explore the relationship between the momentum effect and default risk. Finally, section 6 presents the paper’s main conclusions.

2. Jump Measure

From all the statistical jump detection ¹ options proposed in literature, we select the one developed by Jiang and Oomen (2008). Our reasons for this choice are basically threefold. Firstly, it is a powerful method for identifying large, infrequent jumps in returns and provides reliable estimates of jump returns. Secondly, it is more sensitive to jumps than other tests because it uses both second and higher-order moments. Jiang and Oomen (2008) provide simulations which show their statistic to perform comparatively well. Thirdly, the approach is model free, as it does not impose functional specifications on the drift, diffusion or jump dynamics. Moreover, its implementation requires only asset prices. Hence, its implementation on a large cross-section of stocks over a long time period is straightforward.

This test is inspired by the variance swap, a contract whose payoff depends on the realized variance. Intuitively, it reflects the cumulative gain of a variance swap

¹ For instance, Barndorff-Nielsen and Shephard (2006) develop a test based on bipower variation. A modified version of this test is used by Huang and Tauchen (2005) and Andersen, Bollerslev and Diebold (2007). Lee and Mykland (2008) also use bipower variation but in a different way, developing a nonparametric statistical test of jumps. Aït-Sahalia and Jacod (2009) and Tauchen and Zhou (2011) propose nonparametric tests for presence of jump.

replication strategy, which is minimal (substantial) in the absence (presence) of jumps. Specifically, when there is no jump, the difference between simple returns and log returns equals one half of the instantaneous return variance. Based on this result, the variance swap replication strategy is perfect. However, when jumps occur, the difference is also a function of realized jumps and the aforementioned replication strategy fails. The method is based on precisely this insight.

Let S_t be the price of a stock at day t , where $R_t = (S_t - S_{t-1})/S_{t-1}$ is the simple return and $r_t = \ln(S_t/S_{t-1})$ denotes the continuously compounded or log return. The variance swap measure is computed as

$$SV_T = 2 \sum_{t=1}^T (R_t - r_t) \quad (1)$$

where T denotes the sample size, whereas the realized variance is defined as

$$RV_T = \sum_{t=1}^T r_t^2 \quad (2)$$

which is known to converge to the total variation of the process. Thus, by construction, the difference between the SV_T and RV_T values can be used to detect the presence of jumps. When jumps are absent, their ratio will be indistinguishable from one, but when they are present it will reflect the replication error of the variance swap. Under the null hypothesis of no jumps over the period $[0, T]$, Jiang and Oomen (2008) proposed the following ratio test:

$$JT = N \frac{V_{(0,T)}}{\sqrt{\Omega_{SV}}} \left(1 - \frac{RV_T}{SV_T}\right) \xrightarrow{d} N(0,1) \quad (3)$$

where $V_{(0,T)} = \int_0^T V_t dt$ where V_t is the diffusive variance when there is no random jump, and $\Omega_{SV} = \frac{1}{9} \mu_6 \int_0^T V_t^3 dt$ with $\mu_p = 2^{p/2} \Gamma((p+1)/2) / \sqrt{\pi}$ for $p > 0$ where $\Gamma(\cdot)$ denotes the gamma function. Consistent estimates of $V_{(0,T)}$ and Ω_{SV} are given by bi-power variation

$$\hat{V}_{(0,T)} = BPV_T = \frac{1}{\mu_1^2} \frac{T}{T-1} \sum_{t=1}^{T-1} |r_t r_{t+1}| \quad (4)$$

and multi-power variation

$$\hat{\Omega}_{SV}^{(p)} = \frac{\mu_6}{9} \frac{T^3 \mu_6^{-p}}{T-p+1} \sum_{t=0}^{T-p} \prod_{k=1}^p |r_{t+k}|^{6/p} \quad (5)$$

respectively, where p is equal to six².

After identifying jump days³, jump and continuous return components are disentangled from total stock returns each year. Let TR be the total annual stock return and $\{r_k^J\}_{k=1}^K$ the log of identified jump returns during the year. The jump (JR) and continuous (CR) returns are computed as

$$JR = \exp\left(\sum_{k=1}^K r_k^J\right) - 1; \quad CR = TR - JR \quad (6)$$

Following Jiang and Yao (2013), we also construct a so-called liquidity-adjusted jump return, LJR , where each jump day's return is now calculated by aggregating returns from k to $k+4$. This measure should mitigate the effect of liquidity shocks, taking into account that this kind of jumps will revert over subsequent trading days. Likewise, the liquidity-adjusted continuous return is computed as

$$LCR = TR - LJR \quad (7)$$

Finally, the total jump risk of stock returns is constructed annually by

$$JRisk = RV - BPV \quad (8)$$

a measure that captures jump return variance (Barndorff-Nielsen and Shephard, 2004).

3. Data and Preliminary Analysis

Given that behavioral finance theories have emphasized the role of variables such as type of financial system, investor typology, stock characteristics, and cultural dimensions on stock prices, the key question is whether the results of Jiang and Yao (2013) for US data are market-dependent or can be generalized to other markets. To explore this issue, we have chosen the Spanish stock market because, although it is a developed financial market, it displays major differences in all of the above variables. In relation to stock characteristics, in particular, the spreads are lower in the Spanish market than in the

² p must be 4 or 6 for the robust estimation of Ω_{SV} (Jiang and Oomen, 2008). We perform the analysis for both values and the results are consistent. Therefore, we show only those corresponding to p equal to six (the rest are available upon request).

³ A sequential approach is carried out in order to identify days that experience stock price jumps (see Jiang and Yao, 2013 for more details about the procedure).

US market, probably reducing their premiums. Moreover, as average firm size in the Spanish market is bigger⁴, we expect jumps to be less frequent and smaller on average.

In financial system terms, the US market is Anglo-Saxon, that is, it is characterized by shareholder dispersion and a wider separation between ownership and control. Spain, on the other hand, has a continental system, characterized by a highly concentrated ownership structure. Blockholder ownership is also greater in the Spanish than in the US market. This reduces the short-term pressure of these investors and thereby their impact on prices. Although the higher ownership concentration of the Spanish stock market can reduce stock liquidity, thereby increasing the probability of jumps, the effect of blockholder ownership and the importance of banks as reference institutional investors may offset this effect, reducing both the likelihood and average size of jumps.

The US and Spain also display contrasting cultural profiles based on the dimensions coined by Hofstede (2001). The US/Spanish scores on the five dimensions are Power Distance (40/57), Individualism (91/51), Masculinity (62/42), Uncertainty avoidance (46/86) and Long-term orientation (29/19).

The study data were obtained from the Thomson Financial⁵ database, where from all the stocks listed on the Spanish continuous market (SIBE), we were able to collect daily return data for 208 stocks listed on the Spanish stock exchange between January 1990 and July 2011. Using a critical value of 1%⁶, we performed the above econometric jump test on daily stock returns over each calendar quarter⁷. This requires a minimum of 44 daily return observations during the quarter, thus, 176 observations to calculate the total jump risk given by (8). If the test is unfeasible, a zero jump return is recorded. To avoid the misinterpretation of no trading activity, any observations for which the previous three days' return data are not available are not classed as jumps.

⁴ According to Datastream data for 2011 the New York stock exchange lists both very small and very large firms. However, the average size of the firms listed in the Spanish stock market is approximately three times that of those listed in the NYSE.

⁵ Various filters suggested by Ince and Porter (2006) were applied to avoid bias from the naive use of the Thomson Datastream database.

⁶ Results (available upon request) are robust if we focus mainly on the large jumps by changing the critical value of the jump test to 3 or 4 (e.g. Andersen et al., 2007 and Huang and Tauchen, 2005).

⁷ Although the literature seems to focus on very high frequency data in calculating statistical measures of jumps, following Jiang and Yao (2013) we focus on daily data for several reasons. Availability of intra-day data is limited. Besides, daily frequency helps mitigate market microstructure noise and avoids the need for the corresponding modified JO test for high frequency data. In fact, Christensen, Oomen and Podolskij (2011) show that many intra-day jumps often quickly revert, since they are caused by market microstructure noise or liquidity. Daily data is also useful for picking out infrequent and large jumps over a holding period of one year. Daily frequency seems indeed acceptable since the majority of investors do not rebalance continually, or even daily. Finally, the jump test is performed quarterly to take into account time-varying volatility of stock returns (see Jiang and Yao, 2013, for more details).

A brief summary statistics of jumps is shown in Table 1. The jump frequency for each stock is computed in annual terms (from July of year t to June of year $t + 1$) as the ratio of the total number of jumps to the number of years the stock is in the sample. Jump size is the average in absolute value of all realized jumps. We also compute the jump size for positive and negative jumps. The mean and median jump frequencies are 1.11 and 1.00, which is clearly lower than those obtained by Jiang and Yao (2013) for the US market (2.02 and 2.00, respectively for the most recent sample period 1962-2009). The mean and the median of the absolute jump sizes are 9.87% and 8.82%, respectively. Once again, these figures are lower than those obtained for the US market (14.24% and 11.84%). The jumps estimated at 5th and 95th percentiles in the Spanish stock market (4.55% and 19.32%) are both clearly lower than in the US market (5.49% and 30.76%).

The statistics for positive and negative jumps reveal that the positive jumps are notably more frequent (0.84) than the negative ones (0.26), which is in line with the findings reported by Jiang and Yao (2013) and consistent with the average positive skewness in daily stock returns documented in the literature (see Campbell, Lo and MacKinlay, 1997). However, it is important to note that the average size of negative jumps (-11.21%) is greater than that of positive ones (9.52%)⁸.

These results show that the differences between the two markets have a not negligible impact on the jump distribution and intensity. In particular, the lower frequency and smaller size of jumps in the Spanish stock market could be due to various reasons. These include differences in firm size, because the smallest firms in the Spanish stock market are not listed; differences in ownership concentration, because in Spain ownership is clearly more highly concentrated; and differences in investor typology, because, in contrast to the US market, where they are mutual funds or pension plans, the main institutional investors in Spain are banks, which have more a stable relationship with firms. The major differences observed in the jump distribution further fuel our aforementioned interest in testing whether they might significantly influence our conclusions as to whether or not jumps, as a proxy for the unexpected return component, are correlated with ex-ante firm characteristics and whether this might alter the explanatory power of risk-based and behavioral explanations of stock return predictability.

⁸ As a robustness check, we define as a jump any return which is smaller (bigger) than the mean minus (plus) k standard deviations and this pattern holds: positive jumps are more frequent but smaller than the negative ones. This result holds for $k = 1.5, 2, 2.5$ and 3 . Furthermore, both patterns become clearer with increases in the value of k .

The size and btm variables are based on monthly data drawn from the Thomson Financial database. Size is computed as the Ln of market capitalization and btm is the ratio between the book value and the market value. Liquidity is proxied by the illiquidity measure developed by Amihud (2002), which is the average ratio of the absolute daily return to the (monetary unit) trading volume on that day:

$$IL_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_{i,t}|}{V_{i,t}} \quad (9)$$

where $D_{i,t}$ is the number of days for which data are available for stock i in month t , and $R_{i,t}$ and $V_{i,t}$ denote the daily return and daily trading volume (in euros), respectively, at day t .

Table 2 reports the descriptive statistics of jumps in portfolios sorted by size, btm, illiquidity ratio and momentum. Most of the jumps found in the size-sorted portfolios are in the smallest firm quintile and the data show a decreasing monotonic pattern overall, except in the second quintile. Average jump size is significantly greater for small firms than for big ones, although the difference is not significant in the case of negative jumps.

In the btm-sorted portfolios, the number of jumps follows a u-shaped curve and average jump size an inverted u-shaped curve. However, there are no differences between the extreme quintiles either in the number or the average size of jumps. The only significant difference is the larger number of negative jumps in the low btm ratio quintile.

With the exception of quintile 4, the illiquidity ratio quintiles show an increasing monotonic pattern both in the number and average size of jumps, with the highest values appearing in the more illiquid stocks. The difference between the extreme quintiles is significant at conventional levels except in the case of negative jumps.

While there is no clear pattern in the number of jumps in the momentum portfolio⁹, the average size follows a u-shaped curve. However, neither in the number nor in the average size of jumps is there a significant difference between the two extreme quintiles, winners minus losers. These results suggest that the variables most strongly related to jumps are size and liquidity. They also clearly illustrate that, irrespective of the portfolio-sorting variable, positive jumps are more frequent but smaller in average absolute value than negative ones.

⁹ As mentioned later, this paper uses a 6X6 momentum strategy, whereby momentum is calculated from the past 6 months' cumulative return.

Finally, following Vassalou and Xing (2004) and Abinzano et al. (2013), we use the Black-Scholes-Merton (BSM) measure as a proxy for default risk. We use this measure instead of the credit rating because there is no available credit rating for several stocks in the Spanish stock market and a firm's credit worthiness can vary substantially before its credit rating is readjusted. We use a market-based measure because accounting-based measures have certain disadvantages, particularly stemming from the failure to consider asset volatility, as a result of which firms with the same ratios are attributed with exactly the same likelihood of going bankrupt. This measure of default risk is given by the following expression:

$$P_{def,t} = N \left(- \frac{\ln \frac{V_{A,t}}{D_t} + \left(\mu_t - \frac{\sigma_{A,t}^2}{2} \right) (T-t)}{\sigma_{A,t} \sqrt{T-t}} \right) \quad (10)$$

where $V_{A,t}$ is the value of firm assets at time t , μ_t is the expected immediate rate of return on $V_{A,t}$, $\sigma_{A,t}$ is asset return volatility, D_t is the debt face value, T is the maturity period and $N(\cdot)$ is the cumulative probability of the normal distribution. To find the values of $V_{A,t}$ and $\sigma_{A,t}$, we use an iterative process starting from the market price of the firm's shares (see Vassalou and Xing, 2004). We use debt data for the last three quarters of the current year and the first quarter of the past year and calculate the book value of debt as the sum of short-term debt and 50% of long-term debt.

Shares in banks and finance and insurance companies were excluded from the construction of the default measure, because the difference in their capital structure could skew the resulting default risk estimates. This reduced the sample to 124 shares for this part of the analysis, causing a degree of sample bias. This has little consequence, in the case in hand, however, because, as shown by Muga and Santamaría (2007), the estimates of momentum returns from finance sector stocks in this market are not statistically significant.

4. Empirical results

4.1. Cross-sectional return predictability

In this section, we analyze return predictability based on the four characteristics named above (size, btm, momentum, and illiquidity ratio). In June of year t stocks are sorted by a specific characteristic and the return for the holding period from July of year t to June of year $t + 1$ is then computed. Then returns are aggregated in equal-weighted quintile portfolios. In the case of the momentum portfolios, both the formation period (from January to June of year t) and the holding period (from July to December of year t) are 6 months long¹⁰.

Table 3 shows the return of the four characteristic-based portfolio quintiles and the return spread between their top and bottom quintiles. All of these spreads show the expected sign but, in contrast to the results obtained by Jiang and Yao (2013) for the US stock market, this spread is significant at conventional levels only for the btm and momentum portfolios. The lack of significance of the premium for the size and illiquidity ratio is not exceptional in the market analyzed, due to the high average firm size of SIBE listed companies, as small and medium firms are not listed in this market.

However, the lack of significant premiums associated with size and illiquidity does not rule out the possibility of the jump component having a significant premium offset by the continuous return component (or vice versa), thus resulting in the lack of significance found for the total returns. We clarify this issue with the data displayed in Table 4, which shows the premiums obtained for the 4 characteristics of interest after separating the continuous component (CR) from the jump component (JR) in total returns. This enables us to find significant jump premiums in the size-sorted portfolio returns (6.67% per year) and the illiquidity-sorted portfolio returns (9.92% per year). The fact that these premiums are partially offset by the CR in both these portfolios is the reason for the lack of significance of the premiums observed in Table 3.

The behaviour of the btm premium differs from that of the two variables discussed above, in that both the jump return (3.86% per year) and the continuous return (8.33% per year) are statistically significant.

¹⁰ In their seminal paper, Jegadeesh and Titman (1993) use combinations of formation periods ($J = 3, 6, 9$ and 12 months) and holding periods ($K = 3, 6, 9$ and 12 months) making a possible total of 16 different momentum strategies. Later literature takes as reference the $J = 6, K = 6$ strategy. For examples, see Rouwenhorst (1998) or Griffin, Ji and Martin (2003).

Thus, the results enable us to sustain the claim that the return predictability of stocks with the characteristics of interest in the Spanish stock market cannot be attributed solely to risk-based explanations, given that, if investors form unbiased rational expectations, the unexpected component of stock return should not be correlated with ex ante firm characteristics. These results are consistent with those obtained by Jiang and Yao (2013) for the US stock market.

Finally, the momentum premium behaves differently from the rest of the study variables, in that the continuous return component shows a six-month premium of 10.48%, while the jump return component is negative with a value of -1.87. This separation between JR and CR components is very similar to that in the US stock market.

These results show that, although the literature has repeatedly associated the momentum effect with liquidity, size and btm, momentum returns arise from the CR component, while liquidity and size returns come mainly from the JR component. The btm is the only characteristic to show a significant premium in the CR component (as well as in the JR component) which would suggest that momentum and btm could be related, as claimed by Daniel and Titman (1997).

A final point worth noting is that these results show that jump frequency and average jump size are both lower in the Spanish market, probably because of characteristic differences with other markets (specifically, larger average firm size, higher ownership concentration, and a stronger presence of institutional investors from the banking sector whose relationships with the business world are more stable), the main conclusions largely coincide with those of Jiang and Yao (2013) for the US stock market, thereby strengthening the robustness and generalizability of their findings.

4.2. Robustness checks

This section describes the various robustness checks performed in this study. First, returns are calculated for firms with jumps and firms without jumps. For every year t , the “firms with jumps” sample includes all firms presenting at least one jump over the formation period July $t - 1$ to June t . The returns are then calculated for the holding period from July t to June $t+1$ ¹¹. The remaining firms make up the “firms without

¹¹ As in the previous section, six-month formation and holding periods are used for the momentum portfolios.

jumps” sample. The results are in line with those obtained in the previous section (see Table 5). In particular, the yearly size premium of -12.46% and the yearly liquidity premium of 13.25% are significant only in the “firms with jumps” sample, while the six-month momentum premium of 7.61% is significant only in the “firms without jumps” sample. In both samples, the yearly book-to-market premium is significantly positive: 13.76% in the “with jumps” sample and 10.61% in the “without jumps” sample.

Next, we adjust for liquidity shocks in asset prices by constructing the “liquidity-adjusted” jump return LJR and the corresponding “liquidity-adjusted” continuous return LCR described in Section 2. LJR is the originally identified jump return compounded with the stock returns over the subsequent four trading days to overcome potential stock price reversion, and LCR is the difference between total return and LJR. This enables us to mitigate the effect of temporary liquidity shocks on our empirical results. The results (see Table 6) remain the same as those reported in Table 4 for the size, liquidity, and momentum premiums. Jumps fully account for the size and liquidity effects, but they do not drive momentum. The difference emerges in the btm variable. After adjusting for liquidity, the jump premium ceases to be significant, and only the continuous component has a significantly positive premium. This result suggests that liquidity jumps do, in fact, account for a significant part of the value premium.

We then repeat the exercise while controlling for jump risk using a double-sorting procedure. Stocks are first sorted into tertiles based on the jump risk measure *JRisk*. Then, within each tertile, stocks are further sorted into tertiles based on one of the four characteristics (size, btm, momentum, and illiquidity ratio). The new tertile portfolios are obtained by combining all the stocks with the same characteristic tertile rank across three jump risk tertiles, and computing equal-weighted portfolios. This procedure allows each tertile portfolio to capture a different stock characteristic but the same jump risk. The results obtained are very similar to those obtained without controlling for jump risk (see Table 7). In this case, although the total premiums maintain the expected sign, they lack significance for all the variables. Size shows a premium in the continuous component which holds for the momentum effect. The results for the JR follow the same pattern as before with significant premiums for size (-7% per year), BTM (3.43% per year) and liquidity (8.69% per year). The results after controlling for liquidity are basically the same. In summary, after controlling for jump risk, the predictive pattern of size and liquidity premiums realized by jumps remains unaltered.

Finally, we also take into account the implications of the “martingale restriction” on jumps using another double-sorting procedure to control for jumps. First, in June of year t , stocks are sorted into tertiles based on realized jump returns during the holding period from July of year t to June of year $t + 1$. Stocks without jumps are assigned to a separate group. Then, within each of the four jump-sorted groups, stocks are further sorted into tertiles based on each of the four characteristics. The new tertile portfolios are computed by combining into a single equal-weighted portfolio the stocks with the same characteristic ranking across all four different jump groups. Table 8 reports the results. Once again, they are similar to those obtained before controlling for this variable. Size and liquidity, the two characteristics that have been fully realized in the form of jumps in previous results, continue to do so after controlling for jumps. They lack any significant predictive power after controlling for the jump effect.

To sum up, the results obtained have shown that jumps have significant power to explain the premium on three of the four characteristics analyzed (size, btm and illiquidity). More importantly, in the case of size and illiquidity, which the preliminary analysis identified as the variables most strongly related to the presence of jumps (see Table 2), the continuous component prevents significant premiums from developing in total returns. The results obtained for the jump component in the Spanish market are therefore similar to those obtained for the US market, suggesting that the reaction to information captured by the jump component is more homogeneous across different markets than that captured by the continuous component, which may be more strongly tied to market-specific characteristics. While lying beyond the scope of this paper, cross-sectional and time-series analysis of the jump component in overall return patterns across markets might provide useful implications for portfolio management.

5. Jumps, momentum and default risk

The momentum results differ from those of the other characteristics by showing no significant premiums in the jump component while showing a significantly positive premium in the continuous component. Despite this widespread evidence, there is ongoing disagreement as to the source of momentum, with some scholars supporting risk-based explanations and others finding the most satisfactory explanation in behavioral finance theories.

The literature has linked the momentum effect to size (see Hong, Lim and Stein, 2000), due to the greater difficulty of small stocks and those commanding less attention from market analysts to fully incorporate information, and also to the btm ratio, (see Daniel and Titman, 1997) low btm ratios having been linked to asset pricing problems. Other characteristics with which the momentum effect has been related are the firm's industry (see Moskowitz and Grinblatt, 1999) and firm valuation problems (see Muga and Santamaría, 2007). More recently, Avramov et al. (2007) used US stock market data to show that momentum strategies will only achieve significant profits if strategies are constructed from low credit rating stocks, while Agarwal and Taffler (2008), using UK stock market data, concluded that the momentum effect is a direct consequence of market under-reaction to distress risk. However, Abinzano et al. (2013), using a market-based measure of default risk based on the Black-Scholes-Merton option-pricing model in four key European stock markets (France, Germany, Spain and the UK) find that default risk is not necessarily a characteristic of momentum strategies and cannot therefore explain momentum returns.

In this context, analysis of the components of total returns (JR and CR) can be very useful to test whether default risk is the source of the momentum effect, and thereby shed some light on this controversy.

In order to compute the JR and CR components based on the default risk characteristic, in June of every year t , we sort the stocks using the BSM measure given by (10) and then compute the return for the holding period from July of year t to June of year $t + 1$. The stocks are then grouped into equal-weighted quintile portfolios. As a robustness check, we also compute LJR and LCR, and JR and CR controlling for jump risk and for realized jumps returns.

Tables 9 and 10 report the results. Although we find a default-risk premium of 6.54% per year, it is largely attributable to the JR component, which accounts for 6.17%, the contribution of the CR component being virtually null (0.37%) and non-significant. These results differ completely from those reported for the momentum premium, where the JR component was negative and non-significant (-1.86%) and the CR component positive and significant (10.47%). Thus, the default risk and momentum premiums arise from different origins, the continuous return component in the case of momentum and the jump component in that of default risk. These results appear to corroborate the conclusions reached by Abinzano et al. (2013) rather than those of Avramov et al. (2007)

or Agarwal and Taffler (2008) and enable us to assert that default risk is not the source of momentum effect.

It is worth noting that, apart from momentum, the only characteristic of those analyzed in this paper that consistently displays a CR-related premium is btm, thereby corroborating the arguments put forward by Daniel and Titman (1997). Thus, insofar as btm is related with size, illiquidity and default risk, we can observe that momentum returns are also related to these three variables, but that the source of the returns is different. Nevertheless, when total returns are broken down into their components (JR and CR), only btm appears to share the same origin as the momentum effect. These results are highly revealing and suggest that the search for the origin of the momentum effect should be oriented towards btm-related variables, enabling us to cast aside numerous other explanations based on size, illiquidity or default risk.

In addition, the results obtained using the liquidity-adjusted measures (see Table 9) are similar to those provided by the unadjusted measures, notably in that the default risk premium is shown to be almost entirely due to the jump component. Furthermore, the analysis controlling for jump risk and for realized jump returns (see Table 10) again reveals no significant positive premium attached to the CR component, in contrast to the findings for the momentum strategies. Thus, there is no difference between these and the results reported above.

6. Conclusions

The relationship between stock return predictability and various stock characteristics has been widely treated in the literature, which has offered risk-based as well as behavioral finance explanations. Jiang and Yao (2013) present a new way to unravel this controversy by separating the total stock return into its continuous and jump components. Their results for the US market indicate that stock return predictability is unlikely to be driven by a risk-based explanation.

In this paper, we analyze the Spanish stock market in order to test whether Jiang and Yao's (2013) findings are stock market-dependent. The Spanish stock market presents key differences in aspects such as the financial system, investor typology, stock characteristics and cultural dimensions. Our results show that these differences have major repercussions on the frequency and intensity of jumps, both of which are lower in

the Spanish stock market. This finding is probably due to factors such as the larger average size of Spanish listed companies, their higher ownership concentration, and the stronger presence of institutional investors from the banking sector who have more stable relationships with firms. In spite of these differences, however, the main conclusions hold. Thus, our findings strengthen the robustness and generalizability of those of Jiang and Yao (2013), ours having been obtained in a setting that contrasts markedly with theirs in certain key market characteristics. Particularly, the jump component displays significant premiums in 3 of the 4 characteristics (size, btm and the illiquidity ratio), showing that the unexpected component of stock returns is related to lagged stock characteristics and is therefore difficult to reconcile with risk-based explanations.

In addition, analysis of the JR and CR components of total return has proven very useful for testing the default risk explanation for momentum, and thereby shedding some light on this controversy. Our results have shown that default risk premium is basically attributable to the jump component and the premium for the continuous component is virtually null. In the momentum premium, meanwhile, the role attributable to the jump component is non-significant, while that of the continuous component is positive and significant. This confirms the conclusions reached by Abinzano et al. (2013) and enables us to assert, in contradiction to the claims put forward by Avramov et al. (2007) and Agarwal and Taffler (2008), that default risk is not the source of momentum returns. In fact, the only other characteristic of those considered in this study which, like momentum, shows a significant premium attached to the continuous component is the btm ratio.

These very revealing findings suggest that we should direct the search for the source of momentum profits towards btm-related variables, in line with arguments presented by Daniel and Titman (1997), thereby ruling out numerous explanations based on size, illiquidity, or default risk.

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Table 1 Descriptive Statistics of stock price jumps

	5%	25%	mean	median	75%	95%	st. dev.
J / year	0.00	0.57	1.11	1.00	1.44	2.31	0.98
(+) J /year	0.00	0.41	0.84	0.75	1.09	1.77	0.81
(-) J / year	0.00	0.05	0.26	0.19	0.37	0.80	0.30
J size %	4.55	6.90	9.87	8.82	11.64	19.32	4.65
(+) J size %	4.55	6.88	9.52	8.62	11.60	18.62	4.44
(-) J size %	-31.55	-12.85	-11.21	-9.45	-7.03	-4.84	7.70

This table reports the descriptive statistics (5th percentile, 1st quartile, mean, median, 3rd quartile, 95th percentile, and standard deviation) of jumps of individual stock prices. J / year ; (+) J /year ; (-) J / year is calculated in annual terms (from July of year t to June of year $t + 1$) as the ratio of total number of jumps / positive jumps/ negative jumps to the number of years the stock is in the sample. J size % is the average in absolute value of all realized jumps. (+)J size %/ (-) J size % is the average of all positive /negative jumps.

Table 2: Descriptive statistics of stock price jumps for portfolios sorted by stock characteristics

	Size	BTM	Illiq	Mom	Size	BTM	Illiq	Mom
	J / year				J size %			
Q1	1.24	1.06	0.76	1.17	0.12	0.10	0.08	0.11
Q2	1.32	1.18	1.12	1.07	0.10	0.08	0.09	0.08
Q3	1.12	1.18	1.28	1.11	0.09	0.09	0.11	0.09
Q4	1.03	1.05	1.43	1.12	0.08	0.09	0.10	0.09
Q5	0.92	1.07	1.28	1.12	0.07	0.11	0.12	0.11
Q5-Q1	-0.32	0.02	0.52	-0.05	-0.05	0.01	0.04	0.00
p-val	0.05	0.93	0.01	0.79	0.00	0.26	0.00	0.73
	(+) J /year				(+) J size %			
Q1	1.04	0.77	0.50	0.94	0.12	0.09	0.07	0.11
Q2	1.03	0.94	0.88	0.85	0.10	0.08	0.08	0.08
Q3	0.92	0.91	0.98	0.82	0.09	0.08	0.10	0.08
Q4	0.77	0.81	1.18	0.90	0.07	0.09	0.11	0.08
Q5	0.68	0.93	1.05	0.87	0.07	0.11	0.12	0.10
Q5-Q1	-0.37	0.15	0.54	-0.07	-0.05	0.02	0.05	-0.01
p-val	0.03	0.38	0.00	0.66	0.00	0.18	0.00	0.34
	(-) J /year				(-) J size %			
Q1	0.21	0.28	0.25	0.23	-0.16	-0.11	-0.09	-0.10
Q2	0.27	0.24	0.25	0.22	-0.09	-0.09	-0.12	-0.10
Q3	0.32	0.27	0.30	0.29	-0.09	-0.09	-0.12	-0.10
Q4	0.24	0.23	0.25	0.22	-0.12	-0.08	-0.10	-0.10
Q5	0.28	0.15	0.24	0.25	-0.08	-0.12	-0.11	-0.11
Q5-Q1	0.06	-0.14	-0.02	0.03	0.08	0.00	-0.01	-0.01
p-val	0.40	0.04	0.81	0.57	0.01	0.88	0.44	0.46

This table reports the descriptive statistics (number of jumps in annual terms and the average jump size) for portfolios sorted on size, btm, illiquidity and momentum. P-val is the p-value associated with the two-sample t-tests for a difference in mean between the extreme quintiles.

Table 3. Descriptive statistics for portfolios sorted on stock characteristics

	SIZE	BTM	ILLIQUIDITY	MOMENTUM
	TR	TR	TR	TR
Q1	0.1649	0.0758	0.0694	0.0885
Q2	0.1207	0.0863	0.1362	0.0869
Q3	0.1067	0.1101	0.0643	0.0713
Q4	0.0882	0.1207	0.1495	0.0838
Q5	0.0912	0.1976	0.1305	0.1746
Q5-Q1	-0.0737	0.1218	0.0611	0.0861
p-val	0.2213	0.0131	0.2751	0.0246

This table reports the average returns across stock characteristic quintiles. In June of each year t , stocks are sorted based on each stock characteristic to form equal-weighted portfolios. These portfolios are held from July t to June $t+1$. The table also shows the spread between the top and bottom quintiles and the p-value associated with the time series t-statistic for the return spreads.

Table 4. Jump returns and continuous returns across stock quintiles

	SIZE		BTM		ILLIQUIDITY		MOMENTUM	
	JR	CR	JR	CR	JR	CR	JR	CR
Q1	0.0931	0.0719	0.0391	0.0366	0.0118	0.0576	0.0793	0.0093
Q2	0.0615	0.0592	0.0509	0.0355	0.0383	0.0979	0.0420	0.0449
Q3	0.0648	0.0419	0.0447	0.0655	0.0637	0.0007	0.0434	0.0280
Q4	0.0226	0.0657	0.0514	0.0694	0.0945	0.0550	0.0396	0.0442
Q5	0.0264	0.0648	0.0777	0.1199	0.1110	0.0196	0.0606	0.1141
Q5-Q1	-0.0667	-0.0071	0.0386	0.0833	0.0992	-0.0380	-0.0187	0.1048
p-val	0.0006	0.8829	0.0079	0.0504	0.0011	0.4504	0.2563	0.0012

This table reports the time series averages of jump returns (JR) and continuous returns (CR) for each characteristic-sorted quintile. Q5-Q1 is the spread between the top and bottom quintiles. P-val is the p-value associated with the time series t-statistic for the return spreads..

Table 5. Jump returns and continuous returns across stock quintiles. Firms with jumps and without jumps

	Total sample		Firms without jumps		Firms with jumps	
	return	p-value	return	p-value	return	p-value
TR Size	-0.0738	0.2213	-0.0423	0.4892	-0.1246	0.0936
TR btm	0.1219	0.0131	0.1061	0.0557	0.1376	0.0150
TR Illiquidity	0.0612	0.2751	-0.0149	0.7567	0.1325	0.1004
TR Momentum	0.0861	0.0246	0.0761	0.0828	0.0505	0.3766

This table reports the average returns across stock characteristics quintiles. In June of each year t , stocks are sorted based on each stock characteristic to form equal-weighted portfolios. These portfolios are held from July t to June $t+1$. The table shows the spread between the top and bottom quintiles and the p-value associated with the time series t-statistic for the total return spreads

Table 6. “liquidity-adjusted” Jump returns and “liquidity-adjusted” continuous returns across stock quintiles

	SIZE		BTM		ILLIQUIDITY		MOMENTUM	
	LJR	LCR	LJR	LCR	LJR	LCR	LJR	LCR
Q1	0.1069	0.0581	0.0558	0.0200	0.0178	0.0516	0.1101	0.0049
Q2	0.0621	0.0586	0.0556	0.0307	0.0496	0.0866	0.0440	0.0423
Q3	0.0765	0.0302	0.0534	0.0568	0.0688	-0.0045	0.0500	0.0191
Q4	0.0315	0.0567	0.0536	0.0672	0.1009	0.0486	0.0500	0.0348
Q5	0.0349	0.0563	0.0946	0.1030	0.1403	-0.0097	0.0669	0.1066
Q5-Q1	-	-	-	-	-	-	-	-
	0.0720	-0.0018	0.0389	0.0830	0.1225	-0.0613	-0.0209	0.1070
p-val	0.0048	0.9666	0.1248	0.0438	0.0070	0.2251	0.3610	0.0006

This table reports the time series averages of “liquidity-adjusted” jump returns (LJR) and “liquidity-adjusted” continuous returns (LCR) for each characteristic-sorted quintile. LJR is the originally identified jump return compounded with the stock returns over the subsequent four trading days to compensate for the potential reversion of stock prices, and LCR is the difference between total return and LJR. Q5-Q1 is the spread between the top and bottom quintiles. P-val is the p-value associated with the time series t-statistic for the return spreads.

Table 7. Return spreads across stock quintiles: controlling for Jump risk

	Size		btm		ILLIQUIDITY		Mom	
	return	p-value	return	p-value	return	p-value	return	p-value
TR	-0.0066	0.8795	0.0498	0.1761	0.0293	0.4989	0.0389	0.1810
JR	-0.0700	0.0005	0.0343	0.0121	0.0869	0.0000	-0.0105	0.3845
CR	0.0634	0.0876	0.0155	0.5844	-0.0576	0.1265	0.0495	0.0715
LJR	-0.0757	0.0029	0.0359	0.0598	0.0998	0.0009	-0.0095	0.5729
LCR	0.0691	0.0526	0.0139	0.6115	-0.0705	0.0734	0.0485	0.0982

Results controlled for jump risk using a double-sorting procedure. First, stocks are sorted into tertiles based on the jump risk measure *JRisk*. Then, within each tertile, stocks are further sorted into tertiles based on one of the four characteristics (size, btm, illiquidity ratio and momentum.). The new tertile portfolios are obtained by combining all the stocks with the same characteristic tertile ranking across three jump risk tertiles, and computing equal-weighted portfolios. This table shows the spread between the top and bottom quintiles and the p-value associated with the time series t-statistic for the return (TR, JR, CR, LJR and LCR) spreads.

Table 8. Return spreads across stock quintiles: controlling for Jump effects

	Size		btm		ILLIQUIDITY		Mom	
	return	p-value	return	p-value	return	p-value	return	p-value
TR	-0.0597	0.2595	0.1115	0.0109	0.0034	0.9372	0.0534	0.0536
CR	0.0131	0.7643	0.0795	0.0130	-0.0685	0.1174	0.0553	0.0452
LCR	0.0234	0.5517	0.0700	0.0179	-0.0746	0.1067	0.0487	0.0683

Results controlled by jump effect using a double-sorting procedure. In June of year t , stocks are sorted into tertiles based on realized jump returns during the holding period from July of year t to June of year $t + 1$. Stocks without jumps are assigned to a separate group. Then, within each of the four jump-sorted groups, stocks are further sorted into tertiles based on each of the four characteristics. The new tertile portfolios are computed by grouping into a single equal-weighted portfolio the stocks with the same characteristic ranking across the four different jump groups. This table shows the spread between the top and bottom quintiles and the p-value associated with the time series t-statistic for the return (TR, CR and LCR) spreads.

Table 9. Jump returns and continuous returns across default risk quintiles

	TR	JR	CR	LJR	LCR
Q1	0.1313	0.0428	0.0886	0.0630	0.0684
Q2	0.0891	0.0371	0.0520	0.0491	0.0400
Q3	0.1186	0.0587	0.0599	0.0690	0.0496
Q4	0.0908	0.0540	0.0369	0.0553	0.0356
Q5	0.1968	0.1044	0.0923	0.1151	0.0817
Q5-Q1	0.0654	0.0616	0.0037	0.0521	0.0133
p-val	0.4606	0.0234	0.9655	0.0999	0.8816

This table reports the time series averages of Total returns (TR), jump returns (JR), continuous returns (CR), “liquidity-adjusted” jump returns (LJR) and “liquidity-adjusted” continuous returns (LCR) for each quintile sorted on default risk. Q5-Q1 is the spread between the top and bottom quintiles. P-val is the p-value associated with the time series t-statistic for the return spreads.

Table 10. Return spreads across default risk quintiles: controlling for Jump risk and jump effects

	Jump risk		Jump realized	
	return	p-value	return	p-value
TR	0.0291	0.6413	0.0392	0.5848
JR	0.0422	0.0460	-	-
CR	-0.0403	0.4903	-0.0115	0.8628
LJR	0.0455	0.0262	-	-
LCR	-0.0163	0.7919	-0.0081	0.8966

Results controlled for jump risk and jump effects using a double-sorting procedure. First, stocks are sorted into tertiles based on the jump risk measure $JRisk$. Then, within each tertile, stocks are further sorted into tertiles based on default risk. The new tertile portfolios are obtained by combining all the stocks with the same characteristic tertile ranking across three jump risk tertiles, and computing equal-weighted portfolios. Then, in June of year t stocks are sorted into tertiles based on realized jump returns during the holding period from July of year t to June of year $t + 1$. Stocks without jumps are assigned to a separate group. Then, within each of the four jump-sorted groups, stocks are further sorted into tertiles based on default risk. The new tertile portfolios are computed by grouping into a single equal-weighted portfolio the stocks with the same characteristic ranking across the four different jump groups. This table shows the spread between the top and bottom quintiles and the p-value associated with the time series t-statistic for the return (TR, JR, CR, LJR and LCR) spreads.