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Pricing of foreign exchange rate and interest rate risks using short to long horizon returns

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ABSTRACT

In this paper, we test whether foreign exchange (FX) rate and interest rate (IR) risks are priced at short to long return horizons. We also test whether the associated risk premia relate to certain stock characteristics. Our new evidence indicates that risk premia increase with the length of the return horizon and that the risk premium signs depend on the sign of the corresponding exposure beta. Thus, for our longest return horizon of 950 days, positive (negative) FX rate premia increase in absolute value to 2.642% (–2.050%), whereas positive (negative) IR premia increase to 1.039% (–1.151%). Zero exposure betas have zero risk premia. We find that, depending on the level of profitability, Size, book-to-market-ratio (B/M) and sales-to-stock price ratio (S/P) explain most of the variation in exposure betas and risk premia. Our results imply that investors view exposure betas and risk premia as important factors affecting portfolio returns.

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1. Introduction

Rational asset pricing models predict that the cross-section of expected returns is associated with the dispersion in the sensitivities of a set of common risk factors. Almost all theories of asset pricing predict a linear relationship between expected returns and risk factors, including foreign exchange (FX) and interest rate (IR) risk.¹ However, existing evidence provides mixed and sometimes perverse support for the relationship between exposure betas and the associated risk premia of non-financial stocks.² Indeed, using one-period exposure betas, Kolari, Moorman, and Sorescu (2008, 1094) report, ‘... our finding of a negative foreign exchange risk premium is not directly comparable with the predictions of any known theoretical foreign exchange model,’ and that ‘[t]he striking difference between the inverse *U*-shape relation documented in our study and the linear relation predicted by standard asset-pricing models is quite puzzling.’ Stock characteristics do not appear to fully explain the signs and magnitude of exposure betas, either (see He and Ng 1998; Bodnar and Wong 2003; Doidge, Griffin, and Williamson 2006). Even if prior studies suggest a link between exposure betas and stock characteristics, the link between risk premia and stock characteristics remains unexplored.

Our study therefore explores the relationship between the exposure betas and risk premia in unconditional pricing models, and the extent to which they can be explained by stock characteristics. Most studies of risk premia that use one-period individual stock returns in the unconditional capital asset pricing model (CAPM) provide weak evidence of FX rate and IR risk premia (Sweeney and Warga 1986; Ehrhardt 1991; Jorion 1991; Prasad and Rajan 1995). Using industry portfolios in an unconditional model, Choi, Hiraki, and Takezawa (1998) find FX rate risk premia during both weak and strong bilateral yen/dollar periods. However, the coefficient signs of FX rate risk premia change across sub-periods and their results for IR risk premia are weak. However, using the conditional CAPM, they report stronger results for changes in both the bilateral yen/dollar

and the FX rate index – an approach that tends to provide superior results. Azeez and Yonezawa (2006) use Japanese aggregate industry portfolio returns in an unconditional model and report negative FX rate risk premia for their sub-periods, contrary to the mixed premium signs in the Choi, Hiraki, and Takezawa (1998) study. Similar to Choi, Hiraki, and Takezawa (1998), IR risk premia are negative but not always significant.

Prior studies indicate that the conditional CAPM outperforms the unconditional model (Choi, Hiraki, and Takezawa 1998). This result also holds for the conditional international CAPM (ICAPM) compared to the unconditional ICAPM (Dumas and Solnik 1995). While De Santis and Gérard (1998) make a similar claim in favour of their conditional ICAPM, two important points are worth noting regarding their study. First, they report that, during the 1980 to 1985 period, the negative FX rate premium is large enough to cause total world risk premia to be negative for all stocks. They further argue that, since positive FX premium is a small fraction of total risk premium, i.e. the sum of FX and market risk premium, the unconditional ICAPM does not capture the dynamics in FX rate risk premia. Both factors are argued to contribute to the weak FX rate risk premia in unconditional models. Second, their explanation for the positive FX rate premia in some sub-periods is inconsistent with Adler and Dumas (1983) theoretical prediction of negative risk premia during periods of high risk aversion. Conditional models tend to rely on aggregate stock returns as opposed to disaggregate returns in the unconditional case. While conditional models tend to outperform unconditional models, they also tend to generate strong variation in the signs of risk premia. Variation in the signs of the risk premia is often explained in terms of market conditions rather than investors' preferences for particular sets of stocks (De Santis and Gérard 1998; Azeez and Yonezawa 2006).³ Stock characteristics influence expected stock returns (Fama and French 1992, 1993, 1995), which may in turn influence risk premia. As such, it is important to re-examine the risk premia in the context of the underlying exposure betas of individual stocks in unconditional models and relate the associated risk premia to stock characteristics.

Based on the above discussion, three important weaknesses of prior studies are worth noting, when using individual stock returns in unconditional models. First, tests of FX rate and IR rate risk premia are performed against the backdrop of very weak support for significant one-period exposure betas (see, Jorion 1991; Prasad and Rajan 1995; Doukas, Hall, and Lang 2003).⁴ Given the weak evidence for significant exposure betas, it is questionable whether the estimated risk premia are reliable since they are estimated against first-stage exposure betas that are largely insignificant.⁵

Second, the tendency for prior studies to use one-period returns to test for risk premia, ignores existing evidence that the magnitude of FX and IR exposure betas increases with the length of the return horizon and that more stocks have exposure betas at longer return horizons (Chow, Lee, and Solt 1997a, 1997b; Bodnar and Wong 2003; Joseph, Lambertides, and Savva 2015). This evidence thus provides an interesting setting to test for risk premia. Both features provide conditions for more reliable tests of risk premia in unconditional models. Using short to long horizon returns also allows us to avoid the assumption that exposure betas and risk premia are constant at all return horizons.

Finally, several sources exist through which FX rate and IR sensitivity can affect a firm's cash flows and in turn its value (Adler and Dumas 1984). If stock characteristics are an important consideration for investors, when allocating stocks to their portfolios (Barberis and Shleifer 2003), then stock characteristics may relate to exposure betas and in turn risk premia. However, using a double sort of firm size on one-period FX rate exposure betas, Doidge, Griffin, and Williamson (2006, 568) state: '... the effects of exposure on stock returns are present in large stocks ... but not in the small stock group ... Even though these results seem to indicate that there is less exposure in small stocks ... we are hesitant to conclude too much from these results.'⁶ The relation between exposure betas and stock characteristics also generates inconsistent results in short to long horizon studies (Chow, Lee, and Solt 1997a; 1997b; Bodnar and Wong 2003; Dominguez and Tesar 2006). Kolari, Moorman, and Sorescu (2008) argue that FX rate exposure betas tend to relate to stocks whose cash flows are more exposed to FX rate changes. These stocks are more likely to experience financial distress, such that investors would require compensation for the risk. The availability of cash flows to meet financial obligations is a fundamental condition for avoiding financial distress, as well as a primary driver of corporate hedging decisions (Froot, Scharfstein, and Stein 1993; Joseph and Hewins 1997).⁷ However, using cash flow exposure betas, Bodnar and Wong (2003) report that the largest firms exhibit negative FX exposure betas, whereas the smallest firms with no exposure have positive exposure betas.

In this paper, we employ a research design that accommodates many of the above concerns. Similar to Kolari, Moorman, and Sorescu (2008), we augment FX rate changes in the unconditional Carhart (1997) four-factor CAPM, but, in addition, we include IR changes since short-term IRs predict excess returns (Ang and Bekaert 2007).⁸ Furthermore, IR changes are an important component of the model, since IR increases cause firms to reduce investment and borrowing plans (Gertler and Gilchrist 1994; Benito and Young 2007). We follow prior short to long horizon studies and estimate the FX and IR exposure betas (Chow, Lee, and Solt 1997a; 1997b; Joseph, Lambertides, and Savva 2015).⁹ However, we then sort the exposure betas according to their signs when significant, and estimate the risk premia in line with the Fama–MacBeth approach. Thus, we move away from the usual approach of aggregating all exposure betas in tests of risk premia, since aggregation can conceal important information that can adversely affect risk premium estimates (see also Shanken 1982).

Some stocks will switch between positive and negative exposure betas as the return horizon increases. However, while stock returns and systematic risk should be independent of the interval at which they are measured, systematic risk could exhibit significant shifts because of the intertemporal relation between stock returns and market-wide movements or other systematic risk factors (Hawawini 1980). The use of long horizon returns allows continuous compounding of returns over the investment horizon. We use robust standard errors to correct for the potential serial correlation and heteroscedasticity in the estimated standard errors. We follow prior studies and use overlapping returns to estimate exposure betas in long horizon studies (Chow, Lee, and Solt 1997a; 1997b; Bodnar and Wong 2003). Chow, Lee, and Solt (1997a) and Bodnar and Wong (2003) argue that exposure betas are more detectable over longer return horizons due to the complexities of factors affecting exposure estimates, which can include corporate hedging. Finally, we construct 3×3 portfolios by centring return on equity (ROE) portfolios, on Size, B/M, and total sales to stock price (S/P) ratio portfolios, to explain the variation in exposure betas and the associated risk premia.

We summarise our main results as follows. Using our six-factor unconditional CAPM, a key result is that FX rate and IR risk premia monotonically increase or decrease as the return horizon increases, depending on the exposure beta sign.¹⁰ Positive (negative) exposure betas are associated with positive (negative) risk premia. Unsurprisingly, insignificant exposure betas have insignificant risk premia. Aggregating the positive and negative significant exposure betas at each return horizon still generates significant risk premia. Thus, while we attribute our results to the elimination of the insignificant exposure betas before estimating risk premia, the main strength of our results lies in our use of short to long horizon exposure betas. Specifically, the positive and negative FX rate risk premia have values of 0.249% (p -value ≤ 0.01) and -0.151% (p -value ≤ 0.05), respectively, at $h_{D,1}$ (i.e. for one-day return horizon). Their values increase (in absolute terms) to 2.642% (-2.050%) for positive (negative) risk premia at $h_{D,950}$ or 950 days (p -value ≤ 0.01), the end of our daily return horizon. While the positive (negative) IR risk premia are not significant until $h_{D,100}$ ($h_{D,20}$), at $h_{D,950}$, the positive (negative) IR risk premia increase (in absolute terms) to 1.039% (-1.151%). Negative IR premia dominate positive IR premia in line with the general tendency for prior studies to report negative IR premia in one-period returns, when significant (Azeez and Yonezawa 2006). We find related results for weekly risk premia and alternative return horizons.

Finally, we find that the levels of ROE, Size, B/M, and S/P ratio explain most of the cross-section of the associated risk premia. For example, high ROE–large Size portfolios contain most of the stocks with positive and negative FX rate risk premia, for high ROE on Size portfolios. As the value of ROE decreases, a larger number of small stocks have FX rate risk premia, such that low ROE–small Size portfolios contain almost all of the stocks with positive and negative FX rate risk premia, for low ROE on Size portfolios. Thus, contrary to the mixed results in prior work (He and Ng 1998; Bodnar and Wong 2003; Doidge, Griffin, and Williamson 2006), both small and large stocks have a high attraction for exposure betas, depending on the level of profitability, and disproportionately more small stocks have exposure betas. As such, the premium required for low profitability–small stocks will be higher compared to that for high profitability–large stocks to compensate for the higher risk, although we do not specifically conduct such a test. We also find the interesting result that, for certain portfolios, such as high ROE–small Size and low ROE–large Size portfolios, the number of stocks with FX rate risk premia is constant over the length of the return horizon. Very few stocks are contained in these portfolios, even if they have significant risk premia. The results for ROE on B/M portfolios are generally opposite to those of ROE on Size portfolios, while the results for ROE on S/P portfolios are in line with those for ROE on Size portfolios.

As a general interpretation, we suggest that the increase in risk premia relates to the tendency for firms to leave longer-term exposures unhedged (Bodnar, Hayt, and Marston 1998), thereby causing exposures to be priced. A more specific interpretation relates to the risks associated with investment opportunities including financial distress, which carry higher risk premia at longer return horizons. Our findings suggest that investors view stock characteristics as important sources of risk premia. Our results hold up well across our model specifications and the length of the return horizons. We find related results for IR risk premia.

Our paper extends and contributes to prior studies by providing evidence in four key areas. First, we show that the unexpected shifts in the proportion of stocks with positive and negative exposure betas also appear in our risk premium estimates. The shifts are more dramatic at short return horizons when exposure betas are more difficult to detect – becoming more stable at medium to long return horizons, when risk premia also become more pronounced. Using monthly returns, Bodnar and Wong (2003) suggest that the shifts in exposure betas are far too widespread and sudden to be explained by changes in cash flows or firms' competitive position. Chow, Lee, and Solt (1997b) put forward a business cycle interpretation for those shifts, by relying on business cycle patterns in stocks and bonds (see Fama and French 1989). While we do not dispute these interpretations, we show that stock characteristics have a direct influence on exposure betas and this influence also affects risk premia. Regardless of the particular interpretation, our results indicate that the variation in stock characteristics and risk premia stabilises at long horizons, and that risk premia are constant for certain stock portfolios.

For our second contribution, we show that risk premia are conditional on both the exposure beta sign and the length of the return horizons. Prior studies suggest that risk premia change sign, conditional on market conditions, and the conditional pricing models are more effective in capturing risk premia (Choi, Hiraki, and Takezawa 1998; De Santis and Gérard 1998; Doukas, Hall, and Lang 1999).¹¹ Using rolling regressions, Bartram and Bodnar (2012) also suggest that FX rate premia depend on currency appreciations/depreciations. To the best of our knowledge, all prior risk premium studies in our setting use one-period returns and estimate risk premia using one-period exposure betas. We improve on the research design by capturing the exposure betas at short to long return horizons, since risk premia are unlikely to be constant at all return horizons and investors' assessment of the required risk premium or discount rate would depend on the length of the return horizon. We show that risk premia monotonically increase in absolute value, in line with the magnitude of the exposure betas, while also maintaining the same sign as the exposure betas. Our results help clarify the changing risk premium signs in one-period studies (Azeez and Yonezawa 2006). Our exposure model is consistent with theoretical and empirical studies that treat the relationship between stock returns and FX and IR changes as exogenous. However, we note the growing body of work that considers the relationship to be endogenous (Lustig, Roussanov, and Verdelhan 2011; Du 2018).¹²

Third, we provide evidence on the relationship between risk premia and characteristic-based stock portfolios. Since investors generally categorise assets into broad characteristics or classes when allocating them to portfolios (Barberis and Shleifer 2003; Doidge, Griffin, and Williamson 2006), the particular characteristics that a set of stocks have influence portfolio returns (Cenedese et al. 2016). Thus, using 3×3 portfolios, we demonstrate why one-period studies provide contradictory results for the relation between exposure betas and stock characteristics (He and Ng 1998; Bodnar and Wong 2003; Doidge, Griffin, and Williamson 2006). For example, depending on the level of profitability (ROE), both large and small Size portfolios and high and low B/M portfolios capture most of the stocks with exposure betas. We extend the analysis to the case of short to long horizon risk premia.

Finally, as per Adler and Dumas (1983), an asset's expected return depends on its nominal expected value, which relates to expected inflation risk and the covariance of the nominal return with expected inflation risk. Risk aversion influences the amount of compensation an investor requires for carrying a given level of risks. We show that the risk premia associated with FX rate and IR factors depend on the length of the return horizons – increasing as the return horizon increases. The related literature (see Fama and French 1992, 1993) shows that stock characteristics influence stock returns.

The next section briefly reviews the relevant literature and develops our hypotheses. Section 3 presents our dataset and empirical exposure model. The empirical results are presented in Sections 4 and 5, while Section 6 reports our robustness checks. The final section concludes the paper.

2. Related literature and hypotheses

If FX rate and IR changes are important sources of non-diversifiable risk, we should expect these risks to be priced, since investors would require compensation for holding such stocks. One-period returns provide weak support for exposure betas using unconditional pricing models (Jorion 1990; Ehrhardt 1991; Bartram 2002, 2007). The evidence is still weak for industry sector studies (Prasad and Rajan 1995; Olugbode, El-Masry, and Pointon 2014).

Given the above results, the evidence for pricing in the APT sense is unsurprisingly mixed. Hamao (1988) finds no evidence for pricing in Japanese stocks. Jorion (1990) and Du and Hu (2012) find no support for FX rate pricing in U.S. stocks, which contradicts Kolari, Moorman, and Sorescu's (2008) results. Using the unconditional ICAPM, Carrieri and Majerbi (2006) find support for FX rate pricing in emerging markets in line with Choi, Hiraki, and Takezawa's (1998) results for developed markets. Priestley (1996, 886) finds a significant FX rate premium of 0.748% in the U.K. setting, whereas Clare and Thomas (1994, p. 323) find insignificant risk premia for the British pound and U.K. debenture yields. Theoretically, a specific risk premium sign is unrealistic in a world where state variables are expected to vary and parity conditions do not hold (Backus and Gregory 1993). Driessen et al. (2019) show that low volatility (high volatility) portfolios experience negative (positive) IR exposure with time-varying IR premia. Bartram and Bodnar (2012) find significant FX rate premia that correspond to currency appreciations and depreciations.

Conditional pricing models tend to outperform the conditional ICAPM, especially when aggregate returns are used. Thus, under the ICAPM, the covariance of stock returns and risk factors such as FX rate and IR changes are priced when parity conditions are violated (Solnik 1974; Adler and Dumas 1983). Conditional pricing models provide strong support for pricing, but the risk premium signs change over time (Dumas and Solnik 1995; De Santis and Gérard 1998). According to the home bias puzzle, investors tend to incorporate mostly domestic stocks in their portfolios. This factor strengthens our case for testing risk premia in the *home* setting.

Tests for risk premia are economically important, since evidence of risk premia may indicate whether risk management is an appropriate strategy for firms (see Jorion 1991).¹³ Long horizon studies report significant exposure betas for up to 89% of stocks (Chow, Lee, and Solt 1997a). The magnitude of the exposure betas increases with the length of the return horizons (Chow, Lee, and Solt 1997b; Bodnar and Wong 2003; Dominguez and Tesar 2006; Muller and Verschoor 2006). Both conditions are likely to enhance tests of risk premia. Thus, we test the following hypotheses:

Hypothesis 1: Stocks with positive (negative) and significant FX rate betas are more likely to have positive (negative) and significant FX rate risk premia that increase with the length of return horizon.

Hypothesis 2: Stocks with positive (negative) and significant IR betas are more likely to have positive (negative) and significant IR risk premia that increase with the length of return horizon.

Finance theories predict that corporate risk management increases firm value by reducing the expected cost of bankruptcy and financial distress (Smith and Stulz 1985) and investment distortion costs (Froot, Scharfstein, and Stein 1993), amongst others. Firms use financial derivatives to manage and hedge their FX rate and IR exposures (Joseph and Hewins 1997; Panaretou 2014).¹⁴ While some studies show that risk management favourably impacts leverage, market risk, liquidity, and book-to-market (B/M) by enhancing firm value (Cornaggia 2013; Pérez-González and Yun 2013), the link between derivatives usage and the level of exposure is not well-established in empirical work (Bali, Hume, and Martell 2007; Bae, Kwon, and Park 2018; Sikarwar and Gupta 2019). Depending on the type of managerial incentive and the presence of investment distortion costs, some firms may not use derivatives (Tufano 1998; Francis et al. 2017), while others may use derivatives to increase leverage or alter their capital structure (Graham and Rogers 2002; Borokhovich et al. 2004).¹⁵ Irrespective of the particular perspective taken by firms, both theoretical and empirical studies support the view that risk management has positive effects. Despite theoretical and empirical results, the relation between exposure betas and stock characteristics is inconclusive.

In general, stock characteristics play an important role in asset allocation and in influencing investors' perception of exposure to risk factors (Doidge, Griffin, and Williamson 2006). Related empirical work shows that B/M, size and profitability have significant effects on the stock return predictability (see Fama and French 1993,

1995; Novy-Marx 2013). Krapl (2017) reports a positive relationship between FX rate exposure asymmetries and B/M values, and between FX rate exposure asymmetries and liquidity. Stock characteristics may influence the level of risk premia if, for certain stocks, exposure to risk factors relates to stock characteristics. Furthermore, the particular sign of the risk premia would depend on a firm's investment opportunities and, in turn, their effects on expected stock returns (Maio and Santa-Clara 2012). Thus, we test:

Hypothesis 3: Stock characteristics explain both FX rate and IR risk premia and become more economically important as the length of the return horizon increases.

Testing **Hypothesis 3** is important for several reasons. Stock characteristics are known to predict stock returns (Banz 1981; Fama and French 1995). Both stock portfolio performance and hedging decisions depend on the correlation among equity returns and FX rate and IR changes. Demand pressure on equities increases the correlation amongst stock returns, and FX rates and IRs (Chabot, Ghysels, and Jagannathan 2014). Barsky (1989) argues that increases in risk can explain the relation between low stock values and low real IR, such that a fall in IR is a consequence of higher risk, as investors move away from riskier stocks. Using these arguments, we examine the relation between risk premia and stock characteristics.

3. Data and methodology

We calculate the daily and weekly excess stock returns (inclusive of dividends) for stocks listed on the London Stock Exchange (LSE). All financial stocks with the two-digit Industry Classification Benchmark (ICB) codes of 30 and 35 are excluded, as most of them are also market-makers in FX rate and IR derivatives and/or financial stocks (see, Zhou and Wang 2013). Stocks with fewer than 500 non-trading days are excluded to avoid the thin-trading problem. Our final sample consists of between 405 and 407 non-financial U.K. stocks, depending on the sample period of the particular stock. The sample period spans January 1st, 1994 to December 29th, 2017. The final sample includes 44 dead stocks in an attempt to reduce survivorship bias. Our final sample is comprised of the largest non-financial stocks, since large firms are more likely to use derivatives and operate in global markets. Using the largest stocks means that they are less likely to be affected by investor psychological biases and slow information diffusion (Hong and Stein 1999; Hong, Lim, and Stein 2000).

We follow prior studies and augment an unconditional version of CAPM with FX rate and IR changes to estimate our exposures. Our six-factor CAPM is therefore the Carhart (1997) four-factor model, augmented with FX rate and IR changes. Kolari, Moorman, and Sorescu (2008) estimate a similar model, but with the exclusion of IR changes. Thus, our six-factor CAPM is represented by:¹⁶

$$Z_{i,t} = \alpha_{1,t} + \beta_{1,m,i}Z_{m,t} + \delta_{1,fx,i}r_{fx,t} + \eta_{1,f,i}r_{f,t} + \lambda_{1,i}SMB_t + \lambda_{2,i}HML_t + \lambda_{3,i}MOM_t + \varphi_{1,i}d_t + \varepsilon_{1,i,t} \quad (1)$$

where $Z_{i,t} = R_{i,t} - R_{f,t}$ represents the excess return for stock i , derived from the difference between raw stock return ($R_{i,t}$) and the risk-free rate ($R_{f,t}$), which is the three-month U.K. Treasury bill (TB) rate, de-annualized for one day or one week as required. $Z_{m,t} = R_{m,t} - R_{f,t}$ represents the excess market return, derived from the return on the FTSE All-Share Index ($R_{m,t}$) and the risk-free rate. $r_{fx,t}$ represents the change in the Bank of England trade-weighted British pound FX rate index, based on the trade-weighted value of sterling relative to foreign currencies (see, Agyei-Ampomah, Mazouz, and Yin 2012). We use a trade-weighted index as is common in prior studies, even if: (i) Choi, Hiraki, and Takezawa (1998) report that the FX rate premium is insignificant in a joint FX rate and IR unconditional pricing model (for Japanese stocks); and (ii) Du (2018) suggests that changes in the U.S. trade-weighted exchange rate index is not priced, using its slope as a carrying factor. We find significant results, using our trade-weighted FX exchange index. $r_{f,t}$ represents the change in the yield of the three-month U.K. Treasury bill (TB) rate. The TB rate can be viewed as a market-wide IR indicator (see, Perez-Quiros and Timmermann 2000). IR changes are important in a U.K. context, since U.K. bankruptcy codes favour creditors over investors, unlike their U.S. counterparts (Franks and Torous 1993). IR changes also impact on business cycles and have implications for firms' cost of capital. $\delta_{1,fx,i}$ and $\eta_{1,f,i}$ are FX rate and IR exposure betas, respectively. A positive (negative) $\delta_{1,fx,i}$ coefficient indicates that the excess stock return increases (decreases) following a depreciation (appreciation) of the British pound. A positive (negative) $\eta_{1,f,i}$ coefficient indicates

that the excess stock return increases (decreases) when IR increases (decreases). SMB_t , and HML_t are the zero-investment factor-mimicking portfolios as in Fama and French (1993). MOM_t captures momentum in portfolio returns as in Carhart (1997). d_t is a dummy variable which has a value of one from August 9, 2007 to June 30, 2009; zero, otherwise, to capture the Global Financial Crisis.¹⁷ Finally, $\alpha_{1,t}$ and $\varepsilon_{1,i,t}$ represent the intercept term (constant) of the regression and the error term, respectively. We follow Dominguez and Tesar (2006) and estimate Eq. (1) using the generalised method of moments (GMM), with HAC robust standard adjustment. We jointly estimate FX rate and IR risk premia since exposure to FX rate changes is not fully offset by IR changes (see Lustig, Roussanov, and Verdelhan 2011). This dataset is from DataStream.

Our initial estimates for Eq. (1) are based on daily returns, i.e. $h_{D,N} = 1$, where N denotes the length of the return horizons for day(s) D . We then use a fixed window of overlapping observations to estimate the exposure betas at other return horizons. As such, our next set of exposure betas are based on the sum of a fixed window of overlapping five-day observations, i.e. $h_{D,N} = 5$, then fixed 10-day intervals, $h_{D,N} = 10$, and so on. Thus, for daily price changes of the entire sample period, we generate return horizons of $h_{D,N} = 1, 5, 10, 15, 20, \dots, 950$ days. Similarly, for weekly price changes, we use a fixed window of overlapping observations of $h_{W,N} = 1, 2, 3, 4, \dots, 190$ weeks. The intervals are arbitrary and the empirical literature provides no guidance (see, Dominguez and Tesar 2006). However, we also use an alternative fixed window of $h_{D,N} = 1, 7, 14, 21, 28, 35, \dots, 952$ days as a sensitivity test.

To test if the exposure betas are priced, we estimate a number of second pass regressions at each return horizon based on the sign of the exposure betas. This model takes the general form:¹⁸

$$E(\bar{Z}_i) = K_0 + K_1\beta_{1,m,i} + K_2\delta_{1,fx,i} + K_3\eta_{1,f,i} + K_4\lambda_{1,i} + K_5\lambda_{2,i} + K_6\lambda_{3,i} \quad (2)$$

where $E(\bar{Z}_i)$ is the average expected excess stock return over the entire sample period for the particular return horizon. K_0 is the intercept term, i.e. the average return on a zero-beta portfolio in excess of the risk-free rate and assumed to be zero; K_1 to K_6 are risk premia on the respective variables. We use GMM with HAC standard errors for the estimation.

To allocate the stocks to portfolios, we use 3×3 portfolios and centre ROE on Size, B/M, and S/P in the previous June. We then construct 3×3 ROE on Size portfolios, 3×3 ROE on B/M portfolios, and 3×3 ROE on S/P portfolios. These financial variables are obtained from the London Share Price Database (LSPD).

4. Descriptive statistics, exposure betas and risk premia

This section presents the descriptive statistics for the explanatory variables used in the model as well as the exposure betas and risk premium estimates. Our results support hypotheses 1 and 2.

4.1. Descriptive statistics and correlations

Table 1 shows the descriptive statistics for the explanatory variables used in the regressions. Only momentum (MOM) has a non-zero mean (p -value ≤ 0.01). We find this result for both daily and weekly observations. All the variables have significant skewness and kurtosis, indicating that the observations are non-normally distributed. Using the Q -statistic, the observations have significant autocorrelations at several lags, based on their square values (p -value ≤ 0.01). The presence of autocorrelation indicates strong persistence in the data. The autocorrelation is stronger for excess returns, SMB, HML, and MOM, especially using daily data. Non-normality and autocorrelation create estimation problems for linear models since their presence represents a violation of assumptions. Thus, our GMM is estimated using HAC robust standard errors to mitigate this problem.

We perform correlation tests on the variables in Table 1. The untabulated results for the bivariate Spearman rank correlation r_s and the Pearson correlation r_p coefficients are within reasonable ranges. We have no concerns regarding multicollinearity. The largest correlation value (in absolute terms) is between excess market return and SMB for daily data. This correlation value is -0.529 for r_s and -0.539 for r_p (p -value ≤ 0.01). Daily FX rate changes are positively correlated with IR changes ($r_s = 0.053$; p -value ≤ 0.01) and SMB ($r_s = 0.073$; p -value ≤ 0.01), but are negatively correlated with excess market return ($r_s = -0.040$; p -value ≤ 0.01). Weekly

Table 1. Descriptive statistics for main explanatory variables

	N	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Auto (1)	Auto (5)	Auto (10)	Auto (15)	Auto (20)
Panel A: Daily data												
Exchange rate changes	6,061	-0.00002	0.024	-0.068	0.004	-0.880 ^a	15.567 ^a	0.155 ^a	0.075 ^a	0.075 ^a	0.068 ^a	0.050 ^a
Interest rate changes	6,061	-0.00022	0.403	-0.263	0.019	1.884 ^a	81.593 ^a	0.129 ^a	0.064 ^a	0.049 ^a	0.049 ^a	0.054 ^a
Excess market return	6,061	0.00021	0.092	-0.084	0.011	-0.096 ^a	9.387 ^a	0.225 ^a	0.325 ^a	0.269 ^a	0.231 ^a	0.121 ^a
SMB	6,061	0.00001	0.036	-0.063	0.007	-0.573 ^a	8.353 ^a	0.313 ^a	0.247 ^a	0.171 ^a	0.136 ^a	0.111 ^a
HML	6,061	0.00006	0.058	-0.042	0.006	0.274 ^a	9.577 ^a	0.235 ^a	0.247 ^a	0.175 ^a	0.196 ^a	0.173 ^a
MOM	6,061	-0.00038 ^a	0.060	-0.081	0.008	-0.578 ^a	11.492 ^a	0.259 ^a	0.230 ^a	0.180 ^a	0.195 ^a	0.144 ^a
Panel B: Weekly data												
Exchange rate changes	1,252	-0.00004	0.065	-0.070	0.010	-0.370 ^a	7.948 ^a	0.277 ^a	0.151 ^a	0.077 ^a	0.129 ^a	0.083 ^a
Interest rate changes	1,252	-0.00155	0.309	-0.301	0.034	-0.907 ^a	31.246 ^a	0.252 ^a	0.140 ^a	0.130 ^a	0.041 ^a	0.052 ^a
Excess market return	1,252	0.00099	0.134	-0.116	0.022	-0.252 ^a	6.298 ^a	0.306 ^a	0.127 ^a	0.066 ^a	0.108 ^a	0.039 ^a
SMB	1,252	0.00004	0.063	-0.131	0.016	-0.826 ^a	10.042 ^a	0.225 ^a	0.030 ^a	0.069 ^a	0.072 ^a	0.039 ^a
HML	1,252	0.00028	0.098	-0.078	0.016	0.304 ^a	8.294 ^a	0.250 ^a	0.212 ^a	0.254 ^a	0.230 ^a	0.145 ^a
MOM	1,252	-0.00185 ^a	0.138	-0.162	0.019	-0.611 ^a	12.627 ^a	0.318 ^a	0.076 ^a	0.132 ^a	0.058 ^a	0.067 ^a

The foreign exchange (FX) and interest rate (IR) variables are in price changes. The excess market return is the overall market return using the FTSE All-Share Index less the three month U.K. treasury bill rate. SMB, HML are constructed according to Fama and French (1993). MOM is as defined in Carhart (1997). Auto denotes the autocorrelation coefficient at various lags based on the square of the observations of the associated variables. The significance of the autocorrelation is based on the *Q*-statistic. ^a, ^b and ^c indicate statistical significance at 1%, 5% and 10% respectively.

data also display similar patterns in the correlations. The positive correlation between FX rate and IR changes is in line with the interest rate parity condition, meaning that FX rate depreciation is associated with increases in IRs. Causality is not implied for any of the correlation tests. Excess market returns are positively correlated with HML but negatively correlated with SMB and MOM (p -value ≤ 0.01). Fama and French (1995) find that SMB and HML capture cross-sectional variation in stock returns not captured by market beta. Incorporating these pricing factors into our exposure model improves our estimation.

4.2. Testing for FX rate and IR exposures

4.2.1. FX rate exposures

Table 2 shows a cross-section of the stocks with significant FX rate and IR exposure coefficients or betas. We follow prior studies (see, Bodnar and Wong 2003) and present the number of stocks with significant exposure coefficients and the average exposure betas, based on betas with the same sign.¹⁹

Table 2 shows that the average positive and negative $\delta_{1,fx,i}$ exposure coefficients are highly significant at all return horizons (p -value ≤ 0.01). They increase with the length of the return horizons, in line with prior studies (Chow, Lee, and Solt 1997b; Bodnar and Wong 2003; Muller and Verschoor 2006). Using daily observations, 31% ($74 + 52 = 126$ out of 405) of the stocks have positive and negative $\delta_{1,fx,i}$ FX rate exposure coefficients at $h_{D,1}$. For weekly returns, 20.74% (84 out of 405) of the stocks have positive and negative $\delta_{1,fx,i}$ exposure coefficients at $h_{W,1}$ (p -value ≤ 0.01). Taking $h_{D,20}$ as roughly equivalent to one month's return, 34.32% ($69 + 70 = 139$ out of 405) of the stocks have positive and negative $\delta_{1,fx,i}$ exposure coefficients, in line with previous studies that use one-period monthly data (see Jorion 1990; Hutson and Stevenson 2010). In addition, Table 2 shows several shifts in the proportion of stocks with positive and negative $\delta_{1,fx,i}$ exposure coefficients. For example, at $h_{D,1}$, 58.73% (74 out of 126) of the stocks have positive and significant $\delta_{1,fx,i}$ exposure coefficients, whereas 41.27% (52 out of 126) have negative and significant exposure coefficients (see Panel A). By $h_{D,25}$, negative $\delta_{1,fx,i}$ coefficients dominate. Positive $\delta_{1,fx,i}$ coefficients dominate again at $h_{D,30}$ until $h_{D,100}$. By $h_{D,950}$, 63.80% (207 out of 324) of all stocks with significant $\delta_{1,fx,i}$ coefficients have negative $\delta_{1,fx,i}$ coefficients. We find related results for weekly returns although the shifts are less frequent.

Figure 1 shows the shifts in the number of stocks with positive and negative $\delta_{1,fx,i}$ coefficients. Most of the shifts occur at short to medium return horizons. As before, the shifts stabilise at longer return horizons, by which time, negative $\delta_{1,fx,i}$ coefficients dominate (although not entirely). In the medium term, i.e. around $h_{D,525}$ to $h_{D,595}$, almost equal proportions of stocks have positive and negative $\delta_{1,fx,i}$ coefficients. This feature holds for weekly exposure betas around $h_{W,89}$ to $h_{W,153}$. Since daily price changes have more variability than weekly or monthly price changes, this condition may partly explain the higher number of shifts in daily observations. If more firms hedge at short return horizons compared to longer return horizons, this can lead to a smaller number of stocks with significant exposure betas at short return horizons, as well as larger variation in the number of stocks with exposure betas at these horizons. At $h_{D,950}$, 79.61% (324 out of 407) of the stocks have significant $\delta_{1,fx,i}$ coefficients, compared to 66.60% (267 out of 407) at $h_{W,190}$. This evidence is in line with previous studies that report increases in the number of stocks with exposure betas as the return horizon increases (see Dominguez and Tesar 2006; Muller and Verschoor 2006). Also at $h_{D,950}$, positive (negative) $\delta_{1,fx,i}$ coefficients are larger in magnitude compared to those of earlier return horizons, reaching 1.749 (−2.287) at $h_{D,950}$, compared to 0.394 (−0.448) at $h_{D,1}$. The increase in the number of stocks and large exposure coefficients are likely to enhance the estimation of risk premia.

4.2.2. IR exposures

Panel A of Table 2 shows that 13.83% ($22 + 34 = 56$ out of 405) of stocks have positive and negative IR exposure coefficients, $\eta_{1,fi}$ at $h_{D,1}$, compared to 11.36% ($24 + 22 = 46$ out of 405) with positive and negative weekly $\eta_{1,fi}$ coefficients at $h_{W,1}$ (see Panel B). Thus, daily data generate more stocks with significant IR coefficients. At $h_{D,1}$, fewer stocks have significant $\eta_{1,fi}$ coefficients compared to $\delta_{1,fx,i}$ coefficients. The tendency to find stronger support for FX rate exposure compared to IR exposure is in line with prior studies (Sweeney and Warga 1986). Table 1 shows that IR rate changes are more volatile than FX rate changes. This may influence the detection of FX rate and IR effects in our model.

Table 2. Stocks with significant FX rate and IR exposures using daily and weekly price changes under the six-factor CAPM

	Positive (+) and Sig.		Negative (-) and Sig.		Positive (+) and Sig.		Negative (-) and Sig.	
	No.	Coeff. (%)	No.	Coeff. (%)	No.	Coeff. (%)	No.	Coeff. (%)
Panel A: Daily price changes								
$h_{D,N}$	FX rate				IR			
1	74	0.394 ^a	52	-0.448 ^a	22	0.157 ^a	34	-0.085 ^a
5	72	0.367 ^a	48	-0.343 ^a	38	0.116 ^a	33	-0.101 ^a
10	66	0.468 ^a	50	-0.443 ^a	47	0.141 ^a	43	-0.116 ^a
15	72	0.515 ^a	56	-0.523 ^a	57	0.146 ^a	63	-0.123 ^a
20	69	0.555 ^a	70	-0.543 ^a	69	0.152 ^a	73	-0.134 ^a
25	71	0.559 ^a	81	-0.549 ^a	75	0.163 ^a	77	-0.144 ^a
30	79	0.599 ^a	76	-0.593 ^a	75	0.176 ^a	79	-0.155 ^a
35	84	0.626 ^a	76	-0.619 ^a	78	0.185 ^a	84	-0.164 ^a
40	81	0.675 ^a	76	-0.657 ^a	81	0.179 ^a	89	-0.167 ^a
45	89	0.693 ^a	85	-0.643 ^a	79	0.181 ^a	94	-0.173 ^a
50	95	0.729 ^a	84	-0.668 ^a	87	0.174 ^a	100	-0.171 ^a
100	114	0.857 ^a	105	-0.829 ^a	111	0.197 ^a	142	-0.194 ^a
200	120	0.974 ^a	154	-1.094 ^a	116	0.202 ^a	170	-0.229 ^a
400	143	1.269 ^a	166	-1.607 ^a	141	0.309 ^a	181	-0.296 ^a
600	159	1.811 ^a	173	-1.839 ^a	123	0.322 ^a	219	-0.346 ^a
750	143	2.077 ^a	170	-2.464 ^a	121	0.400 ^a	219	-0.432 ^a
850	132	1.808 ^a	197	-2.414 ^a	124	0.415 ^a	226	-0.452 ^a
950	117	1.749 ^a	207	-2.287 ^a	121	0.470 ^a	231	-0.518 ^a
Panel B: Weekly price changes								
$h_{W,N}$	FX rate				IR			
1	50	0.746 ^a	34	-0.556 ^a	24	0.183 ^a	22	-0.150 ^a
2	57	0.481 ^a	33	-0.414 ^a	25	0.123 ^a	26	-0.113 ^a
3	61	0.530 ^a	33	-0.519 ^a	32	0.151 ^a	32	-0.124 ^a
4	51	0.598 ^a	45	-0.566 ^a	36	0.185 ^a	40	-0.141 ^a
5	44	0.636 ^a	55	-0.632 ^a	40	0.200 ^a	43	-0.153 ^a
6	37	0.639 ^a	57	-0.671 ^a	39	0.204 ^a	43	-0.171 ^a
7	34	0.691 ^a	56	-0.702 ^a	37	0.227 ^a	49	-0.178 ^a
8	34	0.715 ^a	57	-0.738 ^a	33	0.238 ^a	48	-0.184 ^a
9	34	0.765 ^a	60	-0.749 ^a	31	0.248 ^a	54	-0.188 ^a
10	39	0.767 ^a	56	-0.786 ^a	33	0.261 ^a	57	-0.201 ^a
20	53	0.993 ^a	62	-0.906 ^a	69	0.217 ^a	97	-0.230 ^a
40	90	1.083 ^a	105	-1.178 ^a	85	0.213 ^a	133	-0.287 ^a
80	129	1.309 ^a	149	-1.616 ^a	102	0.381 ^a	154	-0.345 ^a
120	145	1.987 ^a	136	-1.955 ^a	103	0.392 ^a	182	-0.420 ^a
150	138	2.430 ^a	148	-2.446 ^a	110	0.488 ^a	182	-0.525 ^a
170	114	2.169 ^a	162	-2.350 ^a	109	0.597 ^a	178	-0.575 ^a
190	101	2.128 ^a	166	-2.265 ^a	110	0.624 ^a	186	-0.571 ^a

Panel A (B) shows the number of stocks with positive and negative FX rate and IR exposure betas using daily (weekly) price changes, when significant. The estimates are based on between 405 and 407 stocks including 44 dead stocks. Our six-factor CAPM is defined as: $Z_{i,t} = \alpha_{1,t} + \beta_{1,m,i}Z_{m,t} + \delta_{1,fx,i}r_{fx,t} + \eta_{1,f,i}r_{f,t} + \lambda_{1,i}SMB_t + \lambda_{2,i}HML_t + \lambda_{3,i}MOM_t + \varphi_{1,i}d_t + \varepsilon_{1,i,t}$. $Z_{i,t}$ is the excess return for stock i . $r_{fx,t}$ is the change in the Bank of England trade-weighted British pound FX rate index; $r_{f,t}$ is the change in the yield of the three-month U.K. Treasury bill rate. SMB_t and HML_t are constructed for U.K. stocks using the Fama and French (1993) approach. MOM_t is defined as in Carhart (1997). d_t is a dummy variable for the Global Financial Crisis of 2007–2008. Sig. denotes that the coefficients are significant. The six-factor CAPM is estimated with overlapping fixed return horizons from January 1994 to December 2017, using the GMM with the HAC standard errors. Specifically, the daily price changes are used to generate fixed window overlapping observations at $h_{D,N} = 1, 5, 10, 15, 20, \dots, 950$ days. Similarly, the weekly price changes are used to generate fixed window overlapping observations at $h_{W,N} = 1, 2, 3, 4, \dots, 190$ weeks. N denotes the length of the return horizon and is estimated over 191 return horizons for daily data and 190 return horizons for weekly data. We show a cross section of the exposure betas. The exposure model is estimated over each return horizon for each stock. ^a denotes statistical significance at the 1% level.

Table 2 and Figure 1 also show the presence of shifts in the proportion of stocks with positive and negative IR $\eta_{1,fx,i}$ coefficients. Negative IR $\eta_{1,fx,i}$ coefficients dominate positive IR $\eta_{1,fx,i}$ coefficients at $h_{D,1}$. Positive IR $\eta_{1,fx,i}$ coefficients dominate negative IR $\eta_{1,fx,i}$ coefficients at $h_{D,5}$ and $h_{D,10}$. Afterwards, negative IR $\eta_{1,fx,i}$ coefficients dominate such that, at $h_{D,950}$, 56.7% (231 out of 407) of the stocks have negative IR $\eta_{1,fx,i}$ coefficients compared to 29.7% (121 out of 407) with positive IR $\eta_{1,fx,i}$ coefficients. At $h_{D,950}$, 86.4% (121 + 231 out of 407) of the stocks have significant IR $\eta_{1,fx,i}$ coefficients. For weekly observations, 72% (110 + 186 out of 407) of the stocks have significant $\eta_{1,fx,i}$ coefficients, of which 62.84% have negative IR $\eta_{1,fx,i}$ coefficients. The magnitude of the IR $\eta_{1,fx,i}$

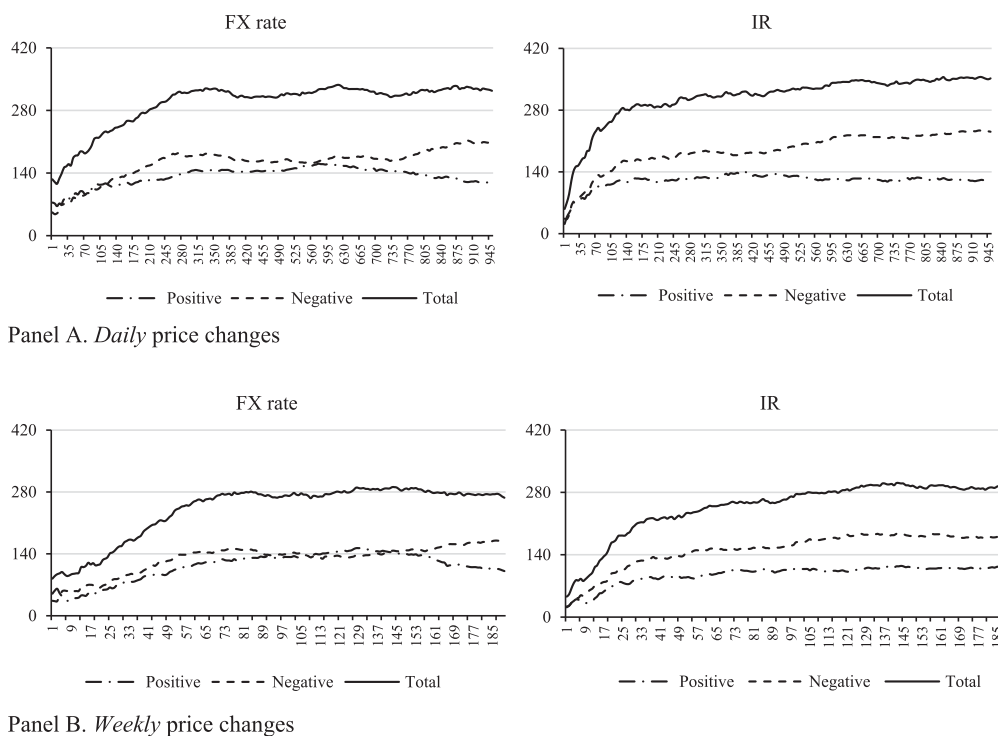


Figure 1. The number of stocks with significant FX rate and IR exposure coefficients under the six-factor CAPM.

coefficients increases with the length of the return horizon, indicating more exposure to IR risk. Weekly betas have a similar pattern.

Figure 1 shows the shift in the proportion of stocks with positive and negative IR $\eta_{1,fx,i}$ coefficients. The shifts could be associated with macroeconomic shocks arising from monetary and fiscal policy and expected inflation, which are important sources of changes in TB rates (see, Evans and Marshall 2007). The spread between the positive and negative coefficients is much wider for IR betas compared to FX rate betas. This may be due to a tendency for more U.K. firms to hedge FX rate exposure than IR exposure (Panaretou 2014).

4.3. Do the positive and negative exposure betas come from the same distribution?

Section 4.2 suggests that the observed positive and negative exposure coefficients may have come from different distributions since they exhibit variation in their trends. Therefore, we test whether the betas came from the same distribution to determine whether we can: (i) aggregate the positive and negative exposure betas when testing for risk premia; and (ii) allocate stocks with the same beta sign to the same portfolio.

To perform the test, we estimate the adjusted coefficient of variation (adj. CoV) at each return horizon. The adj. CoV is defined as the standard deviation of the exposure betas at a particular return horizon, divided by the average exposure at that particular return horizon and multiplied by $(1 + 1/4n)$ as a small sample correction.²⁰ A larger adj. CoV implies an increased likelihood of a greater spread (dispersion) for the particular set of positive or negative exposure coefficients, at the particular return horizon. As before, we focus on the stocks with significant exposure coefficients.

Figure 2 shows the plots based on the adj. CoVs for the daily and weekly exposure betas. The plots show that the shifts in the number of stocks with FX rate and IR betas are more frequent at the earliest return horizons. Panel A of Figure 2 shows that stocks with positive FX rate $\delta_{1,fx,i}$ coefficients dominate those with

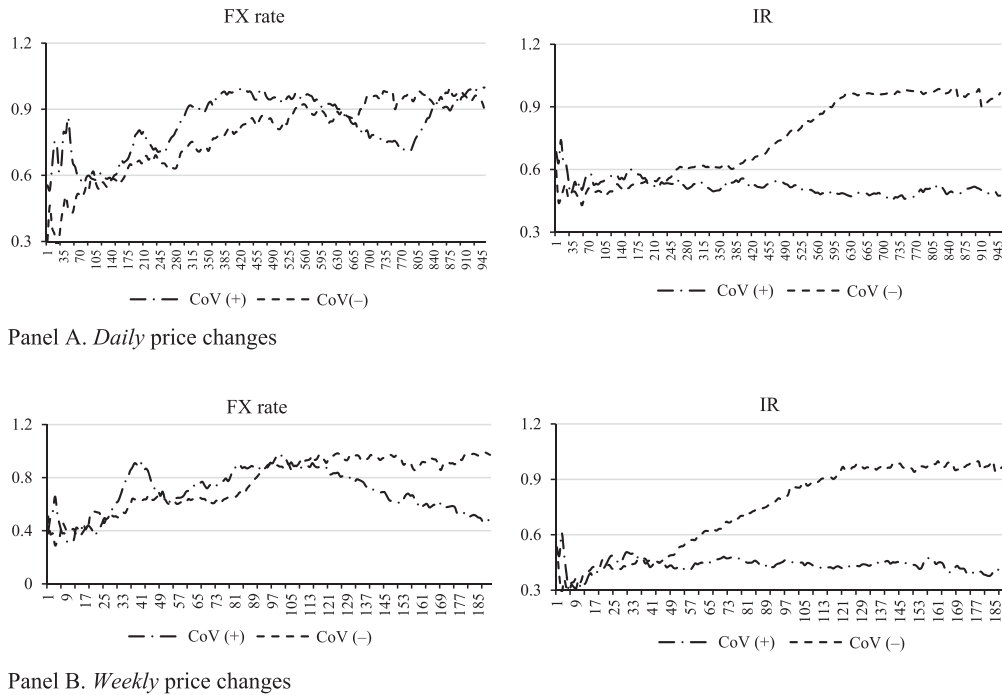


Figure 2. The adjusted coefficient of variations (adj. CoVs) for stocks with significant FX rate and IR exposures under the six-factor CAPM. The adj. CoV is based on the standard deviation of the exposure coefficients at the particulate return horizon for the sample of stocks, divided by the average exposure and then multiplied by $(1 + 1/4n)$ as a small sample correction.

negative FX rate $\delta_{1,fx,i}$ coefficients in terms of higher variability; they do so over the short to medium term, i.e. $h_{D,1}$ to $h_{D,595}$. This result suggests that currency depreciations have more influence on the exposure coefficients than currency appreciation at these return horizons. From $h_{D,665}$ to $h_{D,840}$, negative $\delta_{1,fx,i}$ coefficients dominate. Weekly estimates show related patterns but the shifts are more dramatic at short to medium return horizons.

The IR $\eta_{1,fi}$ coefficients exhibit fewer swings compared to the FX rate $\delta_{1,fx,i}$ coefficients, especially at short to medium return horizons (Figure 2). The betas also have less variability. The negative IR $\eta_{1,fi}$ coefficients have more variability than positive IR $\eta_{1,fi}$ coefficients for up to $h_{W,140}$. After $h_{W,210}$, negative IR $\eta_{1,fi}$ coefficients dominate positive IR $\eta_{1,fi}$ coefficients. Furthermore, at medium to long return horizons, the spreads between the positive and negative IR $\eta_{1,fi}$ plots are much wider compared with those at earlier return horizons. Both features represent substantial variations in the IR plots compared to the FX rate plots. The explanations for these features are not straightforward. One explanation may relate to a greater tendency for firms to hedge FX rate exposures compared to IR exposures, thereby leading to greater variability in the FX rate betas. Another explanation for the higher variability of positive IR $\eta_{1,fi}$ coefficients compared to the negative IR $\eta_{1,fi}$ coefficients may be due to greater economic shocks associated with IR increases, compared to IR decreases. Since most of the shifts occur when fewer stocks have IR exposure, variation in hedging strategies may also contribute to these shifts.²¹

Finally, we apply the van der Waerden W_x statistic to the pairs of positive and negative adj. CoV samples of the return horizons. The W_x statistic is a non-parametric test that uses average normal scores. Untabulated results for the W_x statistic indicate that the null hypothesis that the adj. CoVs based on the positive and negative exposure coefficients (in absolute value) are from the same distribution can be rejected (p -value ≤ 0.01). Since the test confirms that the exposure betas have different distributions, subsequent analyses focus on the exposures with the same beta sign.

4.4. Testing for FX rate and IR risk premia

This section presents the risk premium results using GMM at the second-stage estimation (see Eq. (2)). Our results support hypotheses 1 and 2. Both FX and IR risk premia increase with the length of the return horizons. They carry the same coefficient sign as the exposure betas. Unsurprisingly, insignificant exposure coefficients have insignificant risk premia. The full results are shown below.

4.4.1. FX rate risk premia

The left-hand side of panels A and B of Table 3 shows the daily and weekly FX rate risk premia, respectively, for a cross-section of our results. Panel A shows that the positive and negative FX rate risk premia at $h_{D,1}$ are significant with values of 0.249% (p -value ≤ 0.01) and -0.151% (p -value ≤ 0.05), respectively. The premia increase with the length of the return horizons such that, at $h_{D,950}$, the positive and negative FX rate risk premia increase in absolute value to 2.642% and -2.050% , respectively (p -value ≤ 0.01). The increase in risk premia satisfies Hypothesis 1. The result suggests that investors require more compensation to hold stocks that exhibit more exposure at longer return horizons. Positive risk premia are larger in magnitude compared to negative risk premia, reflecting the tendency for prior one-period studies to often report a positive FX rate risk premium (Priestley 1996; Choi, Hiraki, and Takezawa 1998). Our positive and negative daily FX rate risk premia are largest (in absolute value) at (around) $h_{D,750}$, and $h_{D,850}$, i.e. 3.835% and -2.563% , respectively (p -value ≤ 0.01), just before a decline. The decline suggests that, in the very long term, risk premia are not forever upward or downward sloping. Thus, while the overall trend in risk premia may reflect investors' expectations about investment opportunities – being higher (lower) for particular stocks when the economy is contracting (expanding) – their levels may be flat in the very long term.

In Eq. (2), the intercept term, denoted by K_0 , is the average return on a zero-beta portfolio in excess of the risk-free rate. The intercept provides a simple test of how well the factor loadings capture the cross-section of average returns. Table 3 shows that the intercept terms have significant coefficients, except for the negative FX rate risk premia at $h_{D,1}$ and $h_{D,5}$. Their magnitudes increase with the length of the return horizons (p -value ≤ 0.10). The significant intercept coefficients represent a violation of APT, although this violation may be associated with model misspecification.²²

The weekly FX rate risk premia are highly significant for the corresponding positive and negative exposure betas (p -value ≤ 0.01). The positive and negative FX rate risk premia are 0.385% and -0.272% , respectively, at $h_{W,1}$. The positive and negative premia increase (in absolute value) as the length of the return horizons increases, reaching a maximum (in absolute value) of 6.872% (p -value ≤ 0.01) and -2.918% (p -value ≤ 0.01), respectively, at $h_{W,150}$, before declining at $h_{W,190}$ to 2.729% and -1.857% (p -value ≤ 0.01), respectively, in absolute terms. Except for $h_{W,1}$, average risk premia (intercept coefficients) are significant (p -value ≤ 0.10). Their absolute magnitudes increase with the length of the return horizons.

The W_x statistic rejects the null hypothesis that the positive and negative FX rate risk premia for daily and weekly data came from the same distribution in untabulated results, with positive premia being larger (p -value ≤ 0.01). Combining the pairs of positive and negative FX rate risk premia still leaves an overall positive risk premium.

4.4.2. IR risk premia

The right-hand side of panels A and B of Table 3 shows the daily and weekly IR risk premia, respectively. The daily positive (negative) IR risk premia are not statistically significant until $h_{D,100}$ ($h_{D,20}$), even if the IR exposure betas are significant. As such, investors do not require compensation at earlier return horizons. As before, the positive and negative premia increase (in absolute value) with the length of the return horizons, reaching a maximum (in absolute value) of 1.471% (p -value ≤ 0.01) and -1.645% (p -value ≤ 0.01) at $h_{D,750}$ and $h_{D,850}$ respectively, before a decline. At $h_{D,950}$, the positive and negative daily risk premia are still highly significant, with values of 1.039% (p -value ≤ 0.01) and -1.151% (p -value ≤ 0.01), respectively. One interpretation for the positive and negative IR premia is provided by Barsky (1989). He argues that higher risk may be indicative of a lower level of expected consumption by investors, which in turn increases demand for more assets, and puts further pressure on a decrease in expected returns. This suggests the IR risk premia can be of either sign

Table 3. Stocks with significant and insignificant FX rate and IR risk premia using daily and weekly exposure betas under the six-factor CAPM

	Positive (+) and Sig.			Negative (-) and Sig.			Statistically insignificant			Positive (+) and Sig.			Negative (-) and Sig.			Statistically insignificant		
	No.	Coeff.	Constant	No.	Coeff.	Constant	No.	Coeff.	Constant	No.	Coeff.	Constant	No.	Coeff.	Constant	No.	Coeff.	Constant
Panel A: Daily risk premia																		
$h_{D,N}$	FX rate									IR								
1	74	0.249 ^a	0.002 ^b	52	-0.151 ^b	-0.004	279	0.004	0.001	22	0.055	0.006 ^b	34	-0.099	-0.013	349	0.002	0.002
5	72	0.266 ^a	0.007 ^b	48	-0.156 ^b	-0.010	287	0.009	0.001	38	0.073	0.012 ^b	33	-0.077	-0.018 ^c	336	0.005	0.003
10	66	0.274 ^a	0.013 ^b	50	-0.175 ^a	-0.020 ^c	291	0.011	0.002	47	0.071	0.019 ^b	43	-0.079	-0.027 ^c	317	0.007	0.003
15	72	0.266 ^a	0.019 ^b	56	-0.194 ^a	-0.027 ^c	279	0.020	0.002	57	0.075	0.025 ^b	63	-0.092	-0.036 ^c	287	0.012	0.004
20	69	0.258 ^a	0.025 ^b	70	-0.196 ^a	-0.031 ^b	268	0.022	0.003	69	0.081	0.032 ^b	73	-0.102 ^c	-0.044 ^c	265	0.015	0.005
25	71	0.259 ^a	0.032 ^a	81	-0.192 ^a	-0.035 ^b	255	0.028	0.003	75	0.089	0.041 ^a	77	-0.102 ^c	-0.053 ^b	255	0.016	0.006
30	79	0.277 ^a	0.038 ^a	76	-0.201 ^a	-0.041 ^b	252	0.031	0.004	75	0.094	0.047 ^a	79	-0.105 ^c	-0.060 ^a	253	0.019	0.006
35	84	0.268 ^a	0.045 ^a	76	-0.204 ^a	-0.048 ^a	247	0.032	0.005	78	0.101	0.056 ^a	84	-0.115 ^c	-0.067 ^a	245	0.020	0.007
40	81	0.279 ^a	0.051 ^a	76	-0.204 ^a	-0.052 ^a	250	0.035	0.007	81	0.099	0.062 ^a	89	-0.110 ^c	-0.074 ^a	237	0.023	0.008
45	89	0.277 ^a	0.057 ^a	85	-0.197 ^a	-0.052 ^a	233	0.036	0.008	79	0.108	0.069 ^a	94	-0.122 ^c	-0.077 ^a	234	0.029	0.008
50	95	0.302 ^a	0.063 ^a	84	-0.202 ^a	-0.058 ^a	228	0.037	0.009	87	0.108	0.117 ^a	100	-0.116 ^c	-0.121 ^a	220	0.031	0.009
100	114	0.382 ^a	0.103 ^a	105	-0.238 ^a	-0.086 ^a	188	0.043	0.010	111	0.161 ^c	0.216 ^a	142	-0.187 ^b	-0.152 ^a	154	0.036	0.011
200	120	0.727 ^a	0.189 ^a	154	-0.608 ^a	-0.134 ^a	133	0.044	0.011	116	0.376 ^b	0.361 ^a	170	-0.262 ^a	-0.311 ^a	121	0.053	0.021
400	143	1.537 ^a	0.347 ^a	166	-1.402 ^a	-0.266 ^a	98	0.052	0.014	141	1.035 ^a	0.419 ^a	181	-0.624 ^a	-0.373 ^a	85	0.067	0.023
600	159	2.188 ^a	0.473 ^a	173	-1.475 ^a	-0.503 ^a	75	0.060	0.016	123	1.019 ^a	0.535 ^a	219	-0.928 ^a	-0.542 ^a	65	0.045	0.024
750	143	3.835 ^a	0.630 ^a	170	-2.132 ^a	-0.632 ^a	94	0.108	0.020	121	1.471 ^a	0.715 ^a	219	-1.564 ^a	-0.699 ^a	67	0.052	0.028
850	132	3.082 ^a	0.601 ^a	197	-2.563 ^a	-0.685 ^a	78	0.090	0.023	124	1.312 ^a	0.794 ^a	226	-1.645 ^a	-0.723 ^a	57	0.044	0.032
950	117	2.642 ^a	0.505 ^a	207	-2.050 ^a	-0.799 ^a	83	0.066	0.026	121	1.039 ^a	0.871 ^a	231	-1.151 ^a	-0.810 ^a	55	0.043	0.035
Panel B: Weekly risk premia																		
$h_{W,N}$	FX rate									IR								
1	50	0.385 ^a	0.003	34	-0.272 ^a	-0.007	321	0.038	0.006	24	0.106	0.016 ^c	22	-0.082	-0.021 ^c	359	0.027	0.004
2	57	0.340 ^a	0.014 ^c	33	-0.280 ^a	-0.017 ^c	317	0.038	0.006	25	0.080	0.020 ^c	26	-0.089	-0.035 ^c	356	0.038	0.006
3	61	0.414 ^a	0.030 ^c	33	-0.314 ^a	-0.033 ^c	313	0.038	0.011	32	0.086	0.032 ^c	32	-0.097	-0.050 ^c	343	0.038	0.008
4	51	0.414 ^a	0.034 ^c	45	-0.343 ^a	-0.054 ^b	311	0.042	0.014	36	0.112	0.039 ^c	40	-0.118 ^c	-0.057 ^b	331	0.038	0.012
5	44	0.424 ^a	0.040 ^c	55	-0.361 ^a	-0.061 ^b	308	0.046	0.017	40	0.127	0.046 ^c	43	-0.119 ^c	-0.065 ^b	324	0.041	0.015
6	37	0.405 ^a	0.052 ^b	57	-0.343 ^a	-0.062 ^b	313	0.053	0.018	39	0.126	0.053 ^c	43	-0.124 ^c	-0.074 ^b	325	0.043	0.018
7	34	0.428 ^a	0.061 ^b	56	-0.365 ^a	-0.076 ^b	317	0.055	0.022	37	0.134 ^c	0.058 ^b	49	-0.131 ^c	-0.093 ^b	321	0.043	0.021
8	34	0.441 ^a	0.066 ^b	57	-0.368 ^a	-0.090 ^b	316	0.060	0.022	33	0.142 ^c	0.059 ^b	48	-0.126 ^c	-0.096 ^b	326	0.044	0.024
9	34	0.442 ^a	0.084 ^b	60	-0.364 ^a	-0.108 ^a	313	0.060	0.022	31	0.150 ^c	0.059 ^b	54	-0.135 ^c	-0.112 ^b	322	0.044	0.025
10	39	0.413 ^a	0.106 ^a	56	-0.376 ^a	-0.126 ^a	312	0.068	0.023	33	0.170 ^b	0.072 ^b	57	-0.157 ^b	-0.117 ^b	317	0.051	0.027
20	53	0.560 ^a	0.188 ^a	62	-0.540 ^a	-0.167 ^a	292	0.067	0.022	69	0.197 ^b	0.232 ^a	97	-0.196 ^b	-0.293 ^a	241	0.043	0.030
40	90	0.866 ^a	0.203 ^a	105	-0.708 ^a	-0.215 ^a	212	0.068	0.023	85	0.474 ^b	0.414 ^a	133	-0.338 ^a	-0.356 ^a	189	0.051	0.035
80	129	1.734 ^a	0.508 ^a	149	-1.142 ^a	-0.324 ^a	129	0.059	0.022	102	1.105 ^a	0.794 ^a	154	-0.669 ^a	-0.704 ^a	151	0.069	0.075
120	145	3.658 ^a	0.880 ^a	136	-1.452 ^a	-0.545 ^a	126	0.084	0.077	103	1.031 ^a	0.765 ^a	182	-0.898 ^a	-0.938 ^a	122	0.062	0.085
150	138	6.872 ^a	1.026 ^a	148	-2.918 ^a	-1.076 ^a	121	0.123	0.065	110	1.494 ^a	1.196 ^a	182	-1.554 ^a	-1.126 ^a	115	0.068	0.104
170	114	3.067 ^a	1.256 ^a	162	-2.169 ^a	-1.506 ^a	131	0.116	0.070	109	1.242 ^a	1.610 ^a	178	-1.198 ^a	-1.420 ^a	120	0.056	0.124
190	101	2.729 ^a	1.150 ^a	168	-1.857 ^a	-1.460 ^a	140	0.093	0.103	110	1.096 ^a	1.761 ^a	186	-0.907 ^a	-1.488 ^a	111	0.040	0.135

The table shows the number of stocks with and without significant risk premia based on Fama–MacBeth two-stage method estimated and GMM with HAC standard errors (see Eq. (2)). The dummy for the Global Financial Crisis is ignored in the estimation. Sig. denotes the coefficients that are significant. ^a, ^b, and ^c denote statistical significance at the 1-, 5- and 10% level, respectively.

for particular stocks. Negative IR risk premia dominate positive IR risk premia, reflecting a tendency for prior studies to report negative IR premia in one-period returns (Choi, Hiraki, and Takezawa 1998). The W_x statistic indicates that the negative and positive risk premia came from different distributions in untabulated results. Combining the positive and negative IR risk premia generates a significant overall negative IR risk premium at medium to long return horizons.

Panel B shows that positive IR risk premia for weekly returns are not significant until $h_{W,7}$ (p -value ≤ 0.10). The negative IR risk premia are significant from $h_{W,4}$ (p -value ≤ 0.10). As before, the positive and negative IR risk premia increase in absolute value, reaching a maximum value of 1.096 (at $h_{W,190}$; p -value ≤ 0.01) and -1.554% (at $h_{W,150}$; p -value ≤ 0.01), respectively. Combining the negative and positive IR risk premia does not generate zero risk premia, except at the earlier return horizons. We find a prevailing disposition towards negative IR risk premia.

5. What stock characteristics explain variation in FX rate and IR risk premia?

The characteristics of a particular stock, e.g. size, are a major consideration for investors when constructing their portfolios (Barberis and Shleifer 2003; Doidge, Griffin, and Williamson 2006). This suggests that investors identify each stock according to its particular characteristic, including its expected FX rate and IR betas (see Cenedese et al. 2016). Given our findings, we ask which stock characteristics predict the patterns in the exposures and risk premia. Since we find that the exposure beta signs correspond to the risk premium signs, the stocks are allocated to portfolios, based on the premium signs at each return horizon.

We justify our use of particular stock characteristics for portfolio construction as follows. If FX rate and IR changes affect earnings through their effects on cash flows, ROE is likely to capture the variability in exposures and risk premia. Novy-Marx (2013) argues that gross profitability provides strong explanatory power for expected stock returns. We therefore scale gross profit by prior year book value of equity. We use gross profit to avoid the effects of discretionary accounting procedures on profitability. ROE is therefore measured as total sales less the cost of goods sold, divided by prior year book value of equity.²³ Fama and French (1993) argue that firm size is useful in capturing variation in the cross-section of returns. We follow prior studies by using firm size, measured as total market capitalization value (see e.g. He and Ng 1998; Doidge, Griffin, and Williamson 2006; Dominguez and Tesar 2006). Size also captures economies of scale in corporate risk management (Géczy, Minton, and Schrand 1997; Bodnar et al. 2013). Total sales also relate to exposure betas. We use total sales rather than foreign sales, since the TB rate in our exposure model (Eq. (1)) influences the market-wide economy (see Perez-Quiros and Timmermann 2000), which in turn is likely to impact total sales more than foreign sales. If sales growth explains how shocks to fundamentals relate to market equity, size, and B/M effects in stock returns (Fama and French 1995), then sales will have a role to play in the characterization of stocks with FX rate and IR premia. Indeed, Barbee, Mukherji, and Raines (1996) argue that S/P explains the cross-section of stock returns better than total sales. Finally, B/M relates to earnings such that relative profitability becomes an important source of common risk for expected returns (Fama and French 1993). We do not rule out other stock characteristics having related effects.

Using these stock characteristics, we generate 3×3 portfolios based on ROE, Size, B/M, and S/P. Centring ROE on Size, B/M, and S/P, we construct 3×3 ROE on Size portfolios, 3×3 ROE on B/M portfolios, and 3×3 ROE on S/P portfolios. We centre our portfolios on profitability, since U.K. firms primarily hedge to reduce operational cash flow variability (Joseph and Hewins 1997). Stocks with significant FX rate and IR exposures are allocated to the portfolios according to their exposure signs. Thus high, medium, and low ROE groups consist of stocks with the highest 30%, middle 40%, and lowest 30% ROE, respectively. The same portfolio structure applies to the highest 30%, middle 40%, and lowest 30% Size, B/M, and S/P groups. In the sub-sections that follow, we present the results for the stocks with significant exposure betas and their associated risk premia at daily intervals. The results for weekly risk premia are generally similar and are available on request. We consider the stocks without significant exposure beta and risk premia in a subsequent section.

5.1. Stock portfolios using daily estimates of FX exposures

A summary of the results is as follows. ROE on Size, ROE on B/M, and ROE on S/P are additional sources of common risks associated with cross-sectional variations in FX rate exposures and risk premia. High ROE–large Size portfolios capture most of the stocks with positive and negative exposure betas, and risk premia (that are significant). High ROE–small Size portfolios contain very few stocks with positive and negative risk premia. The number of stocks with exposures and risk premia increases with the length of the return horizons. Low ROE–small Size portfolios capture most of the stocks that have positive and negative risk premia, for low ROE on Size. To a large extent, ROE on B/M portfolios have opposite results to ROE on Size portfolios. The results for ROE on S/P portfolios are comparable to those for ROE on Size. These results support Hypothesis 3 and are presented in more detail below.

A. ROE on Size portfolios

Prior studies provide mixed results for the relation between Size and FX rate betas (see He and Ng 1998; Bodnar and Wong 2003; Dominguez and Tesar 2006). If FX rate changes affect firms' cash flows and large firms have relatively higher profitability than small firms, then controlling for both Size and profitability could explain the mixed results for Size and FX rate effects and provide additional evidence in support of risk premia.²⁴ At $h_{D,1}$, high ROE–large Size portfolios contain as many stocks as low ROE–small Size portfolios (Panel A, Figure 3). This finding illustrates why prior studies report mixed results.

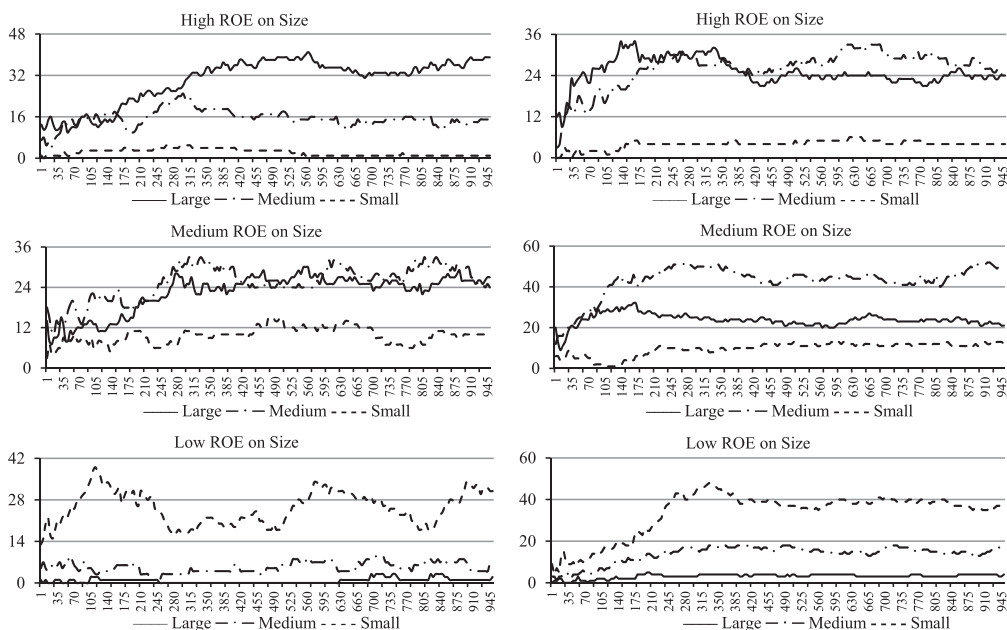
Panel A of Figure 3 shows that high ROE–large Size portfolios contain most of the stocks with positive FX rate risk premia, for high ROE on Size portfolios. This result holds over all return horizons. In contrast, both high ROE–large Size and high ROE–medium Size portfolios capture almost all of the stocks with negative FX rate risk premia (for high ROE on Size portfolios). It is interesting to note that high ROE–small Size portfolios contain the fewest stocks with positive and negative FX rate risk premia, for high ROE on Size portfolios. That is, for high ROE on Size portfolios, large and medium Size portfolios capture almost all of the stocks with risk premia. Thus, the number of stocks with risk premia does not increase with the return horizon, for high ROE–small Size portfolios, irrespective of the risk premium sign. Since the numbers of stocks in high ROE–small Size portfolios are small and their plots are flat, high profitability and small size do not explain much of the risk premia associated with these portfolios. However, a distinguishing feature of high ROE on Size portfolios is that most of the exposure betas and associated risk premia are captured by high ROE on large Size portfolios for positive risk premia and both high ROE–large Size and high ROE–medium Size portfolios for negative FX rate risk premia.

Panel A also shows that medium ROE–medium Size portfolios dominate all other medium ROE on Size portfolios for stocks with positive and negative FX rate risk premia. As the value of ROE decreases, small Size (large Size) portfolios increasingly contain more (fewer) stocks with positive and negative FX rate risk premia (Panel A). Thus, our smallest portfolios, i.e. low ROE–small Size portfolios capture almost all of the stocks with positive and negative FX rate risk premia, for low ROE on Size portfolios. Indeed, low ROE–large Size portfolios have the fewest stocks with positive and negative FX rate risk premia, for low ROE on Size portfolios. The plots for these portfolios are flat at all return horizons, often containing no stock at some return horizons. Low ROE–medium Size portfolios have slightly more stocks than low ROE–large Size portfolios, although the numbers of stocks are still small. Profitability and size matter for the cross-sectional variation in exposure betas and risk premia. Effectively, low ROE–large Size portfolios mirror the performance of high ROE–small Size portfolios in containing the fewest stocks, depending on the level of profitability. Thus, the level of profitability appears to be the main factor distinguishing between the effects of size portfolios on exposure betas and risk premia.

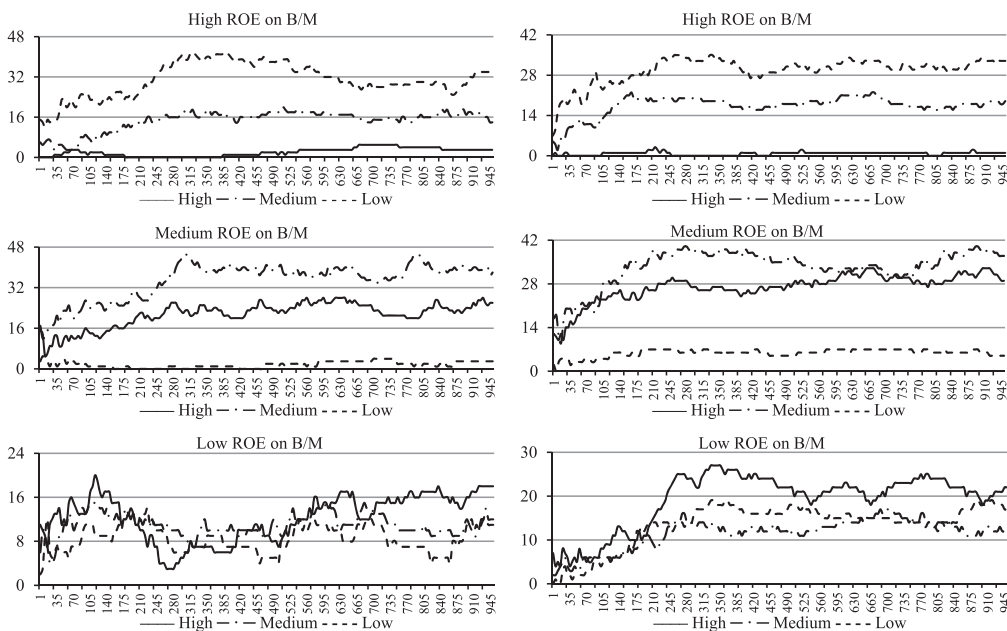
Our plots show a greater tendency for more low ROE–small Size stocks to exhibit risk premia compared to high ROE–large Size stocks, especially for negative FX rate risk premium. We suggest that the risk-premia are larger for low ROE–small size portfolios due to higher risk, although we do not perform a specific test.

Our results appear to explain the mixed results for size and exposure in prior work. Specifically, the results show a gradual reduction in the number of stocks with FX rate beta and risk premia as profitability decreases, such that low ROE–small Size have most of the stocks that have exposure betas and risk premia for low ROE

on Size portfolios. Compared to large firms, small firms are more collaterally constrained, making it difficult for them to access external capital, as well as derivatives to hedge (see Rampini and Viswanathan 2010, 2013).

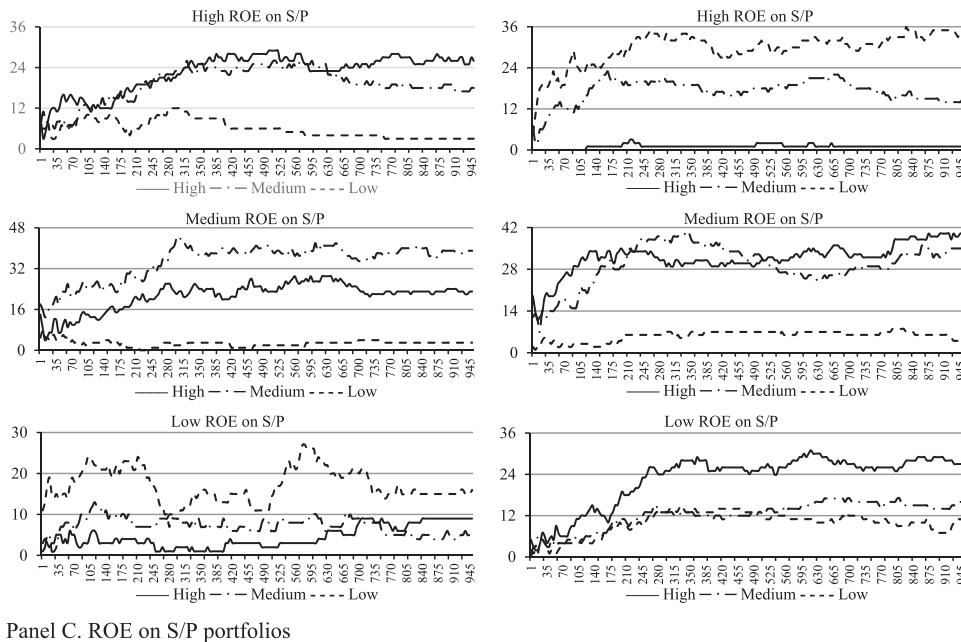


Panel A. ROE on Size portfolios



Panel B. ROE on B/M portfolios

Figure 3. The number of stocks with positive and negative significant FX rate premia in 3×3 portfolios under the six-factor CAPM model, using daily price changes. The plots for stocks with positive FX rate premia are on the left-hand side whereas, the plots for stocks with negative FX rate premia are on the right-hand side.



Panel C. ROE on S/P portfolios

Figure 3. Continued.

Rampini, Sufi, and Viswanathan (2014) argue that, since both financing and the use of financial derivatives require collateral security, financially constrained firms need to establish a trade-off between external finance requirements and derivatives usage. They further argue that financially constrained firms devote more of their net worth to external finance, compared to funding for financial derivatives. This in turn exposes low profitability firms to more FX rate risk, the severity of which increases as profitability and size decrease. Chi and Choi (2017) predict that large firms with high profitability are more likely to experience overinvestment. Since high ROE–large Size firms are likely to have higher available cash flows, they can use hedging substitutes to hedge and in turn avoid external monitoring (Tufano 1998). Accordingly, investors require greater compensation for carrying the FX rate risk of both large and small firms. Given both arguments, it is not too surprising that both high ROE–large Size portfolios and low ROE–small Size portfolios contain most of the stocks that have FX rate risk premia and, correspondingly, the greater proportion of risk premia. In brief, both arguments support the view for increases in risk premia, such that longer horizon portfolios exhibit higher risk premia.

B. ROE on B/M portfolios

The results for ROE on B/M portfolios are largely the opposite of those of ROE on Size. Panel B of Figure 3 shows that high ROE–high B/M portfolios have very few stocks with positive and negative FX rate risk premia, for high ROE on B/M portfolios. Both plots are flat at most return horizons and sometimes contain no stocks. Why do high ROE–high B/M portfolios have so few stocks in the portfolios? High B/M stocks signal poor future earnings and, potentially, financial distress (Fama and French 1992). In this case, they should command a risk premium. However, the number of stocks in these portfolios is small. This may be a characteristic of our sample for these portfolios, since all the stocks have FX rate exposure betas. In contrast, high ROE–low B/M portfolios contain most of the stocks with positive and negative FX rate risk premia, for high ROE on B/M portfolios. Firms with high profitability and low B/M are likely to have high free-cash flows. The availability of high levels of free-cash flows substitutes for using derivatives, and in turn allows firms to avoid external monitoring in capital markets (Tufano 1998; Chi and Choi 2017). This strategy may mean that investors foresee that using free-cash

flow to hedge cannot be pursued indefinitely (Froot, Scharfstein, and Stein 1993), thus requiring compensation for the risk.

Medium ROE–medium B/M portfolios have more stocks with positive and negative FX rate risk premia than other medium ROE on B/M portfolios (Panel B). Panel B shows that the number of stocks in high B/M portfolios increases as the value of ROE decreases. As such, medium ROE–low B/M portfolios have the fewest stocks for medium ROE on B/M portfolios. In contrast, low ROE–high B/M portfolios contain most of the stocks with positive and negative FX rate risk premia, for low ROE on B/M portfolios, although the pattern is not uniform across the return horizons, especially for positive FX risk premia. Thus, from $h_{D,180}$ to $h_{D,490}$, low ROE–high B/M portfolios do not dominate all other low ROE on B/M portfolios, for the case of positive FX risk premia. For negative risk premia, low ROE–high B/M portfolios dominate all other portfolios at almost all return horizons. While high ROE–low B/M stocks have better future prospects than low ROE–high B/M stocks, both sets of stocks carry risk premia, but proportionately more stocks in high ROE–low B/M have risk premia. Correspondingly, more stocks are affected by negative risk premia. High-B/M stocks are likely to be more collaterally constrained than low-B/M stocks (see, Wei and Starks 2013). Rampini, Sufi, and Viswanathan (2014) argue that financially constrained firms hedge less or not at all, implying that they would have higher risk premia in our setting. While both high and low B/M stocks carry risk premia depending on the level of ROE, more stocks with low ROE–high B/M have FX risk premia compared to those with high ROE–high B/M values.

C. ROE on S/P portfolios

Panel C of Figure 3 shows that the rankings of portfolios using ROE on S/P are generally in line with those of ROE on Size portfolios for positive risk premia, suggesting that S/P may be a proxy for size. Both high ROE–high S/P and high ROE–medium S/P portfolios contain most of the stocks with positive FX rate risk premia, for high ROE on S/P portfolios. Note that, although high ROE–low S/P portfolios contain the largest number of stocks with negative FX rate risk premia, high ROE–high S/P portfolios contain almost no stocks for negative risk premia. An explanation for these contrasting results is not straightforward. It can be argued that lower sales do not incentivise risk management, thereby leading to more exposure and more risk premia. The few stocks in high ROE–high S/P portfolios with negative risk premia may also mean that such stocks are not a characteristic of our sample and that only a few such stocks have exposures that are priced. However, for negative risk premia, high ROE–low S/P portfolios dominate all other portfolios with negative risk premia, indicating that a larger proportion of these stocks carry a negative risk premium. Finally, low ROE–low S/P portfolios and low ROE–high S/P portfolios contain most of the stocks that have positive and negative FX rate risk premia, respectively, for low ROE on S/P portfolios. This result indicates a potential asymmetry in the patterns of the risk premia. Krapf (2017) finds evidence that stock returns respond asymmetrically to the sign and magnitude of FX rate shocks.

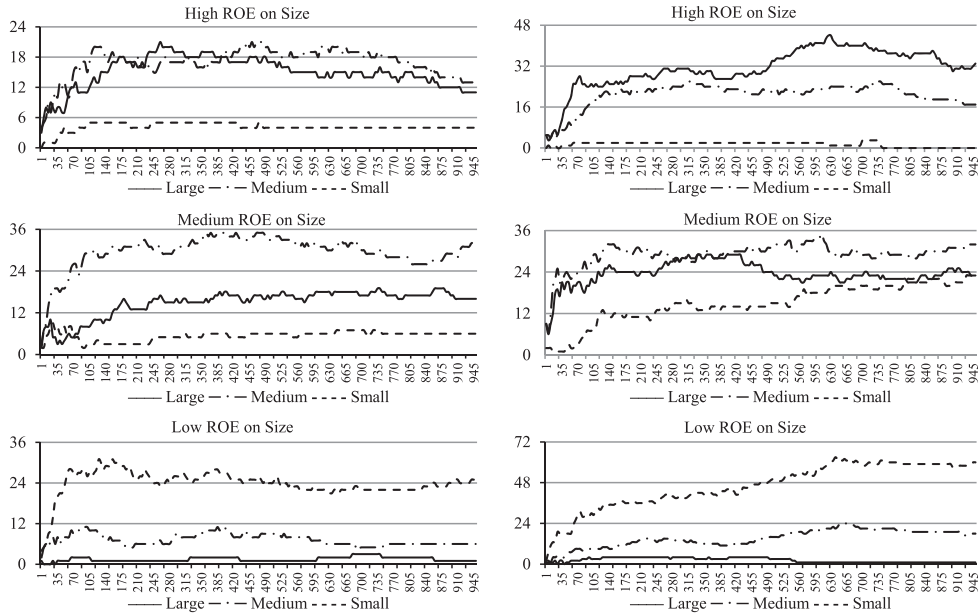
5.2. Stock portfolios using daily estimates of IR exposures

In brief, the results for IR premia and stock characteristics are as follows (Figure 4). High ROE–medium Size (high ROE–large Size) portfolios have more stocks with positive (negative) premia than other high ROE on Size portfolios. Low ROE–small Size portfolios have more stocks with positive and negative exposures compared to other low ROE on Size portfolios. Except for medium ROE on S/P portfolios, the rankings of the portfolios are similar for ROE on B/M and ROE on S/P portfolios, although the plots have different shapes.

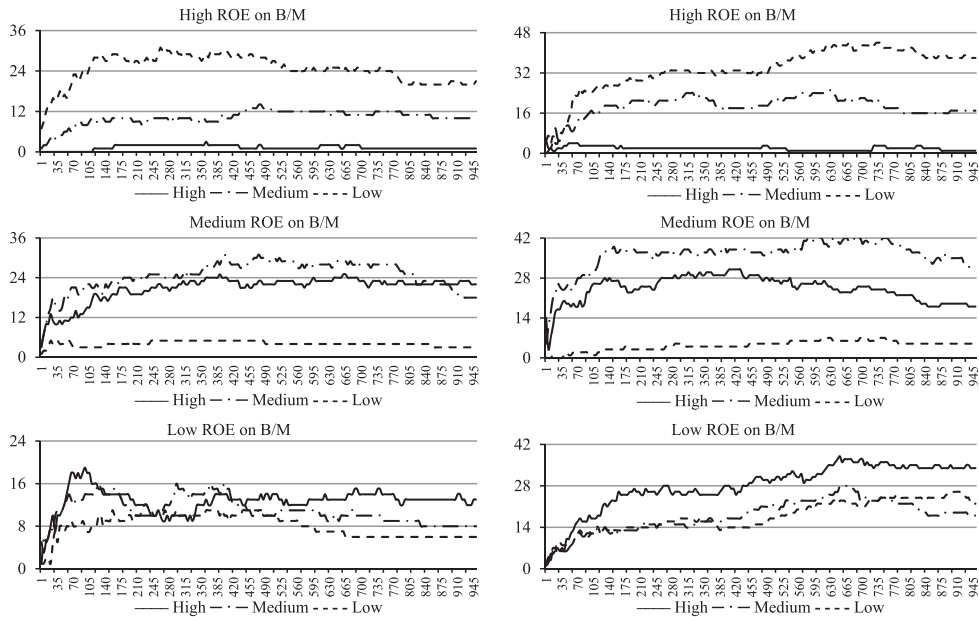
A. ROE on Size portfolios

Perez-Quiros and Timmermann (2000) argue that small firms are more sensitive to variation in business cycle and credit market conditions, causing them to lose collateral and their shareholders to require higher returns. These conditions suggest that IR increases are a greater risk to small firms. Panel A of Figure 4 shows that high ROE–large Size and high ROE–medium Size portfolios have more or less a similar number of stocks with positive IR risk premia, for high ROE on Size portfolios. They contain most of the stocks in high ROE on Size portfolios.

For negative risk premia, high ROE–large Size portfolios clearly dominate, followed by high ROE–medium Size portfolios. High-ROE–small Size portfolios have very few stocks with risk premia, which mirrors our results for FX rate risk premia. Firms’ use of risk management programmes does not explain the differences between the plots for large and small stocks, especially if large firms are more likely to use IR derivatives than small firms

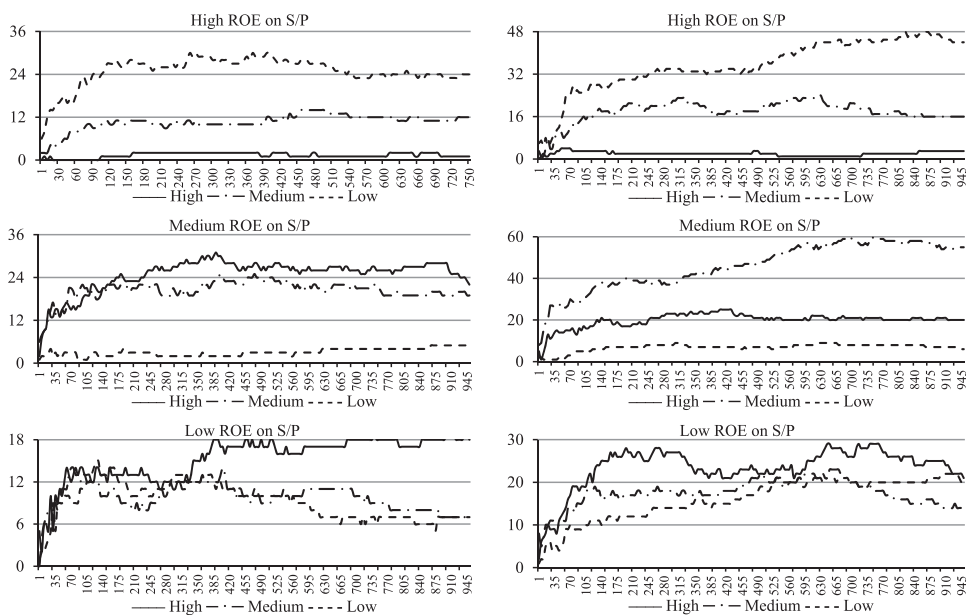


Panel A. ROE on Size portfolios



Panel B. ROE on B/M portfolios

Figure 4. The number of stocks with positive and negative significant IR risk premia in 3×3 portfolios under the six-factor CAPM, using daily price changes. The plots for stocks with positive IR rate premia are on the left-hand side whereas, the plots for stocks with negative IR rate premia are on the right-hand side.



Panel C. ROE on S/P portfolios

Figure 4. Continued.

(Bodnar et al. 2013). If IR derivatives are used to increase leverage and protect expected interest tax shields and capital allowances (Leland 1998; Graham and Rogers 2002), then more high ROE-large stocks will have risk premia, compared high ROE-smaller stocks, as the former have greater leverage capacity. The plots appear to confirm this prediction. An alternative interpretation is that small firms are more effective in their use of risk management programmes such that fewer of them have exposure to risk. This view is not supported by Bodnar et al.'s (2013) findings. However, IR exposure is more critical for small firms since they are more sensitive to variation in business cycles (Perez-Quiros and Timmermann 2000). If small firms rely more on bank finance than on a combination of bank and paper market finance, e.g. commercial paper (Gertler and Gilchrist 1994), they have less flexibility in altering their IR commitments when IRs suddenly increase or fall. In this case, they would appear more risky and the associated risk premia would increase. This may explain the sharp increases in the number of small stocks with positive and negative IR risk premia. Alternatively, IR exposure and risk premia would concentrate in small stocks if risk management is too expensive, even if derivatives usage positively relates to size (Géczy, Minton, and Schrand 1997).

B. ROE on B/M portfolios

An increase in IRs directly reduces firms' cash flows and the value of their collateral assets (see Gertler and Gilchrist 1994). Conversely, a reduction in IRs improves leverage and the value of assets used for collateral. Panel B of Figure 4 shows that high ROE-low B/M portfolios contain most of the stocks with positive and negative IR exposures. These are high profitability stocks. As the value of ROE decreases, more high B/M stocks have IR risk premia, such that low ROE-high B/M portfolios have the highest concentration of stocks with IR risk premia, for low ROE on B/M portfolios. IR increases are more critical for low ROE-high B/M stocks than for high ROE-low B/M stocks. This is because high B/M stocks are likely to be heavily collateralised (Perez-Quiros and Timmermann 2000) and, with low ROE, they face a higher risk of liquidation. Maio and Santa-Clara (2017, 929) show that high B/M (value) stocks have more negative loadings on an IR factor. They suggest that value stocks have more exposure to IR changes due to '... poor financial position and/or expectations of modest growth in future cash flows ... [making them] ... more sensitive to rises in short-term interest rates that further

constrain their access to external finance and the investment[s] ... ' Panel B of Figure 4 suggests that Maio and Santa-Clara's (2017) results are more likely to hold for low ROE–high B/M stocks, especially in the medium to long term. Figure 4 shows that very few high ROE–high B/M stocks are vulnerable to increases or decreases in IRs in the short to long run. For this portfolio, it is high ROE–medium B/M stocks that are more vulnerable to IR changes.

C. ROE on S/P portfolios

Tighter credit conditions affect firms' cash flows through a decline in total sales (Perez-Quiros and Timmermann 2000). Empirical work shows cyclical asymmetries in sales and inventory levels (Gertler and Gilchrist 1994). Sales and inventory levels decline more quickly for small firms compared to large firms, especially during tighter credit conditions (Gertler and Gilchrist 1994; Perez-Quiros and Timmermann 2000).

Panel C of Figure 4 shows the plots for ROE on S/P portfolios. The patterns in the ROE on S/P plots roughly correspond to those of ROE on B/M portfolios (for IR exposures). This observation seems to be in line with the Fama and French (1995) result that sales growth explains how shocks to fundamentals relate to market equity, size, and B/M effects. Panel C also shows that high ROE–low S/P portfolios contain the highest concentration of stocks with positive and negative exposures. Stocks in high ROE–low S/P portfolios are more sensitive to IR changes than those in other high ROE on S/P portfolios. High ROE–high S/P portfolios have the fewest stocks. If high ROE–low S/P portfolios represent stocks with high growth sales, these stocks will also have more investment opportunities and, correspondingly, more of them will have exposure to IR changes. It is useful to emphasize that, as the value of ROE decreases, high S/P stocks dominate almost all the remaining portfolios. This finding emphasizes the close correspondence between low profitability and low sales and the associated risk premia required by investors.

6. Robustness checks

This section presents the results of our robustness checks. We use the same estimation methods. These robustness checks confirm our main findings.

6.1. Portfolios for stocks without significant FX rate risk premia

We first examine the patterns in the stocks with zero exposure betas. Prior work has ignored the patterns in these stocks. Figure 5 shows that the number of stocks with insignificant FX rate betas declines as the return horizon increases. This is the expected pattern if the number of stocks with exposure betas increases with the length of the return horizon (see Panel A of Figure 3). Specifically, Panel A of Figure 5 shows that high ROE–large Size and high ROE–medium Size portfolios decline in tandem. The plot for high ROE–small Size portfolios is flat at all return horizons. This indicates that high ROE–large Size and high ROE–medium Size portfolios contribute almost equally to the number of stocks with significant FX rate betas and risk premia (see also Panel A of Figure 3). That is, almost all the FX rate premia in high ROE on Size portfolios are associated with high ROE–large Size and high ROE–medium Size portfolios (as stated before). Thus, high ROE–small Size portfolios contribute very little to increases in risk premia. In contrast, low ROE–small Size portfolios have the steepest descent in the plots. The decline settles at around $h_{D,350}$. Thus, while low ROE–small Size portfolios contribute the most to the number of stocks with risk premia, in low ROE on Size portfolios, their contribution reaches a maximum fairly early for all return horizons. The plots for high ROE–small Size and low ROE–large Size are flat, indicating a tendency for these portfolios to contribute very little to the observed risk premia. These findings validate previous results in Panel A, Figure 3.

Panels B and C of Figure 5 also show plots that are the opposite of those for ROE on B/M and ROE on S/P portfolios (see panels B and C of Figure 3). The plots have very steep declines as the return horizon increases, especially for high ROE on B/M and medium ROE on B/M. The plots for both high ROE on B/M and medium ROE on B/M portfolios settle relatively quickly, at around $h_{D,350}$. While the plots are not drawn to scale, they explain why high ROE on B/M and low ROE on B/M portfolios capture more stocks with risk premia compared

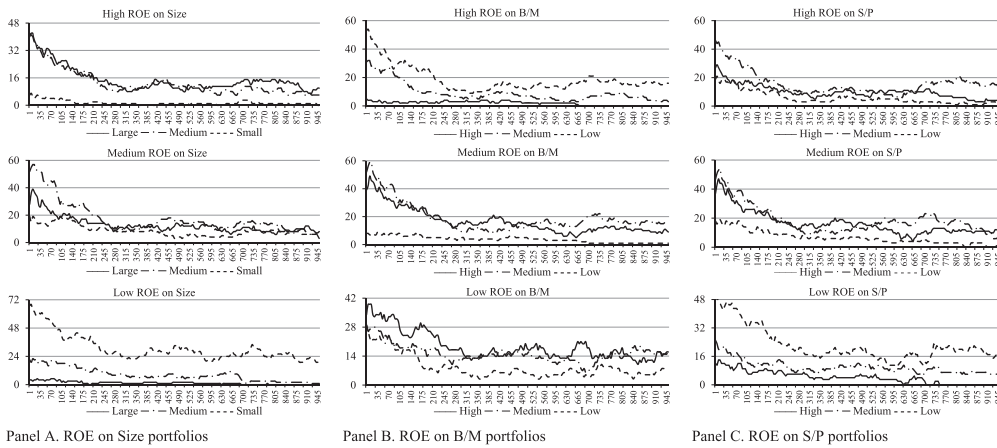


Figure 5. The number of stocks with insignificant FX rate risk premia in 3×3 portfolios under the six-factor CAPM, using daily price changes.

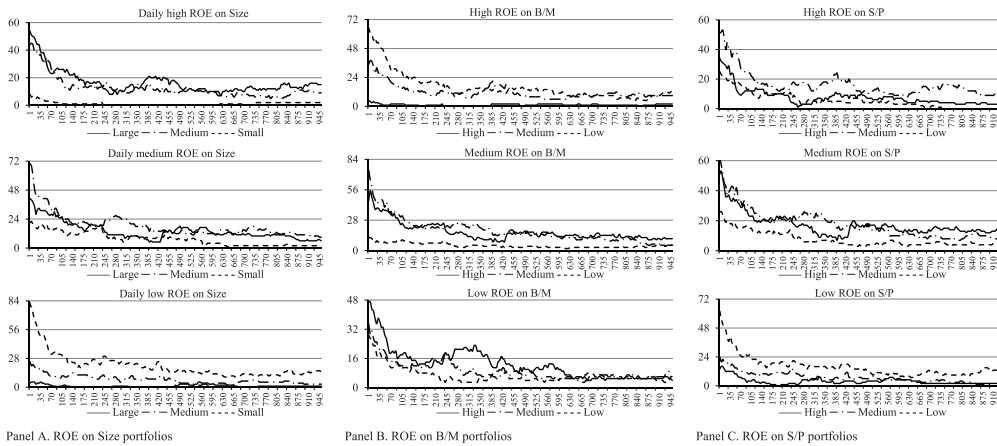


Figure 6. The number of stocks with insignificant IR risk premia in 3×3 portfolios under the six-factor model, using daily price changes.

to high ROE on Size and low ROE on Size portfolios (see Figure 3). It may be that FX rate risk premia have more economic importance for ROE on B/M compared to ROE on Size. However, there is likely to be a financial distress effect through B/M (Fama and French 1992).

6.2. Portfolios for stocks without significant IR risk premia

Figure 6 shows the plots for the insignificant IR risk premia. The plots decline more quickly compared to those for insignificant FX rate premia (see Figure 5). The rapid decline reflects the comparatively early peaks in the number of stocks with significant IR risk premia, compared to those of FX rate risk premia (see Figures 3 and 4). Figure 6 also shows that the plots for most of the portfolios become flat from about $h_{D,450}$. In general, these results confirm our earlier findings that stock characteristics play an important role in influencing the cross-sectional IR risk betas and their associated risk premia.

6.3. Exposure and risk premia using alternative return horizons

To test the sensitivity of our risk premia to a different set of return horizons, we re-estimate the exposure betas and associated risk premia using daily overlapping returns at $h_{D,N} = 1, 7, 14, 21, 28, \dots, 952$ days. We use

Table 4. Stocks with statistically significant FX rate and IR risk premia under the three-factor CAPM

	Positive (+) and Sig.			Negative (-) and Sig.			Positive (+) and Sig.			Negative (-) and Sig.		
	No.	Coeff. (%)	Constant	No.	Coeff. (%)	Constant	No.	Coeff. (%)	Constant	No.	Coeff. (%)	Constant
$h_{D,N}$	FX rate risk premia						IR risk premia					
1	123	0.271 ^a	0.004 ^b	29	-0.193 ^b	-0.003	19	0.050	0.005 ^b	45	-0.101	-0.018 ^c
5	94	0.279 ^a	0.010 ^b	35	-0.192 ^b	-0.009	33	0.085	0.012 ^b	39	-0.090	-0.025 ^c
10	82	0.294 ^a	0.017 ^b	47	-0.174 ^b	-0.019 ^c	44	0.082	0.021 ^b	52	-0.100	-0.041 ^c
15	91	0.301 ^a	0.027 ^b	51	-0.184 ^b	-0.023 ^c	43	0.100	0.025 ^b	67	-0.107	-0.045 ^c
20	88	0.288 ^a	0.036 ^b	49	-0.204 ^a	-0.023 ^c	56	0.105	0.034 ^b	86	-0.120 ^c	-0.061 ^b
25	89	0.308 ^a	0.048 ^a	52	-0.227 ^a	-0.027 ^c	60	0.109	0.040 ^b	90	-0.122 ^c	-0.074 ^b
30	93	0.297 ^a	0.048 ^a	59	-0.221 ^a	-0.035 ^b	65	0.115 ^c	0.050 ^a	88	-0.134 ^c	-0.085 ^a
35	102	0.305 ^a	0.062 ^a	64	-0.207 ^a	-0.041 ^b	62	0.128 ^c	0.056 ^a	93	-0.134 ^c	-0.086 ^a
40	105	0.293 ^a	0.069 ^a	65	-0.199 ^a	-0.043 ^b	65	0.127 ^c	0.064 ^a	94	-0.139 ^c	-0.099 ^a
45	117	0.298 ^a	0.081 ^a	65	-0.204 ^a	-0.041 ^b	64	0.133 ^c	0.069 ^a	103	-0.134 ^c	-0.093 ^a
50	121	0.329 ^a	0.087 ^a	65	-0.212 ^a	-0.054 ^b	62	0.153 ^c	0.118 ^a	110	-0.138 ^c	-0.158 ^a
100	165	0.437 ^a	0.171 ^a	86	-0.314 ^a	-0.093 ^a	91	0.219 ^b	0.241 ^a	152	-0.207 ^b	-0.180 ^a
200	146	0.897 ^a	0.284 ^a	120	-0.931 ^a	-0.160 ^a	92	0.448 ^a	0.341 ^a	200	-0.371 ^a	-0.518 ^a
400	153	1.572 ^a	0.380 ^a	156	-1.580 ^a	-0.282 ^a	138	0.768 ^a	0.304 ^a	182	-0.594 ^a	-0.357 ^a
600	159	2.642 ^a	0.571 ^a	169	-1.641 ^a	-0.547 ^a	150	0.789 ^a	0.505 ^a	178	-1.100 ^a	-0.825 ^a
750	146	4.469 ^a	0.750 ^a	181	-2.064 ^a	-0.651 ^a	170	0.940 ^a	0.642 ^a	174	-1.649 ^a	-0.586 ^a
850	143	3.772 ^a	0.797 ^a	184	-2.164 ^a	-0.540 ^a	166	0.882 ^a	0.715 ^a	169	-1.606 ^a	-0.528 ^a
950	157	3.049 ^a	0.782 ^a	174	-1.864 ^a	-0.611 ^a	170	0.578 ^a	0.681 ^a	174	-1.160 ^a	-0.615 ^a
$h_{W,N}$	FX rate risk premia						IR risk premia					
1	82	0.374 ^a	0.005	20	-0.299 ^a	-0.005	20	0.073	0.009	32	-0.092	-0.034 ^c
2	77	0.389 ^a	0.022 ^c	22	-0.284 ^a	-0.011 ^c	26	0.087	0.023 ^c	26	-0.117 ^c	-0.046 ^c
3	74	0.440 ^a	0.039 ^c	33	-0.360 ^a	-0.038 ^c	24	0.105	0.029 ^c	34	-0.115 ^c	-0.063 ^b
4	58	0.409 ^a	0.038 ^c	35	-0.380 ^a	-0.047 ^c	24	0.118 ^c	0.027 ^c	39	-0.124 ^c	-0.058 ^b
5	52	0.451 ^a	0.050 ^c	39	-0.373 ^a	-0.045 ^c	32	0.124 ^c	0.036 ^c	40	-0.135 ^c	-0.069 ^b
6	46	0.424 ^a	0.068 ^b	40	-0.382 ^a	-0.048 ^c	32	0.140 ^c	0.048 ^c	48	-0.135 ^c	-0.090 ^b
7	48	0.378 ^a	0.076 ^b	41	-0.400 ^a	-0.061 ^b	35	0.140 ^c	0.057 ^b	53	-0.134 ^c	-0.103 ^a
8	51	0.408 ^a	0.092 ^b	41	-0.421 ^a	-0.074 ^b	35	0.157 ^c	0.069 ^b	51	-0.145 ^c	-0.117 ^a
9	54	0.422 ^a	0.127 ^a	39	-0.450 ^a	-0.087 ^b	37	0.160 ^c	0.075 ^b	55	-0.168 ^b	-0.142 ^a
10	58	0.410 ^a	0.156 ^a	34	-0.496 ^a	-0.101 ^b	33	0.175 ^b	0.074 ^b	58	-0.185 ^b	-0.140 ^a
20	84	0.593 ^a	0.316 ^a	54	-0.630 ^a	-0.170 ^a	59	0.245 ^b	0.247 ^a	98	-0.243 ^a	-0.367 ^a
40	105	0.890 ^a	0.243 ^a	76	-0.892 ^a	-0.196 ^a	72	0.452 ^a	0.334 ^a	153	-0.364 ^a	-0.441 ^a
80	111	1.645 ^a	0.415 ^a	139	-1.489 ^a	-0.394 ^a	110	0.811 ^a	0.628 ^a	154	-0.793 ^a	-0.834 ^a
120	101	3.255 ^a	0.545 ^a	151	-1.663 ^a	-0.693 ^a	133	0.996 ^a	0.954 ^a	135	-1.058 ^a	-0.820 ^a
150	84	5.738 ^a	0.521 ^a	203	-2.894 ^a	-1.464 ^a	172	1.354 ^a	1.695 ^a	133	-1.671 ^a	-0.885 ^a
170	82	3.608 ^a	1.063 ^a	215	-2.173 ^a	-2.002 ^a	185	1.256 ^a	2.763 ^a	123	-1.154 ^a	-0.945 ^a
190	79	2.398 ^a	0.790 ^a	206	-1.721 ^a	-1.659 ^a	176	1.039 ^a	2.671 ^a	126	-0.961 ^a	-1.068 ^a

The table shows the number of stocks with significant positive and negative FX rate and IR risk premia. We also show risk premia for stocks with insignificant exposure betas. The premium estimates are based on Fama–MacBeth, using GMM with HAC standard errors. The model takes the form of: $E(\bar{Z}_i) = K_0 + K_1\beta_{1,m,i} + K_2\delta_{1,fx,i} + K_3\eta_{1,f,i}$ where $E(\bar{Z}_i)$ is the average expected excess stock return over each return horizon. K_0 is the intercept term (constant). K_1 to K_3 are the premium coefficients for excess market returns, FX rate and IR betas, respectively. Sig. denotes that the coefficients are significant. We use the same intervals and sample period as in Table 3. The risk premia for the stocks with insignificant exposure betas are insignificant and are not shown. ^a, ^b, and ^c denote statistical significance at the 1-, 5- and 10% level, respectively.

the same GMM estimation method. The untabulated results are consistent with those in Tables 2 and 3. The number of stocks with significant exposure betas and the magnitude of the betas increase with the length of the return horizons. The patterns and the estimates of the risk premia show little variation from those in Table 3. Positive (negative) exposure betas are associated with positive (negative) risk premia. Positive FX rate risk premia dominate negative FX rate risk premia. Negative IR risk premia dominate positive IR risk premia, as before. In line with previous results, insignificant exposure betas have insignificant risk premia.

6.4. Exposure and risk premia using the three-factor CAPM

To rule out concerns that our results may depend on the model specification, we replicate our results using the standard CAPM augmented with FX rate and IR changes, hereafter, the three-factor CAPM. Prasad and

Rajan (1995) use a similar model based on one-period raw returns. Under the three-factor CAPM, plots of the number of stocks with negative and positive exposure betas (equivalent to Figure 1) have more dramatic shifts in our untabulated plots. Plots based on the adj. CoV (equivalent to Figure 2) are also more dramatic compared to those under the six-factor CAPM. These plots are not presented. For both sets of plots, the movements are more dramatic in the medium to long term. As such, the six-factor CAPM has greater stabilising effects on both the number of stocks with exposure betas and their beta estimates, compared to the three-factor CAPM. The use of size, value, and momentum captures the link associated with macroeconomic risks (Bergbrant and Kelly 2016). SMB and HML are also able to predict economic growth (Liew and Vassalou 2000). This may explain the superior performance of the six-factor CAPM.

Finally, Table 4 shows that the positive and negative FX rate premia are larger under the three-factor CAPM, compared to the six-factor CAPM, at most horizons. This result holds at most daily and weekly return horizons. Focusing on daily FX rate risk premia, the risk premia under the three-factor CAPM are up to 27% larger than those of the six-factor CAPM (see Tables 3 and 4). Under the three-factor CAPM, the absolute sum of positive and negative IR risk premia, is up to 22% larger in the medium term, compared to the six-factor CAPM (for daily returns). However, the six-factor CAPM generates larger IR risk premia than the three-factor CAPM at the longest return horizons. These features may be due to the ability of the six-factor CAPM to capture broader economic conditions over time. Under the three-factor CAPM, positive FX rate premia and negative IR risk premia are larger by up to 19% and 29%, respectively, compared to the six-factor CAPM, using daily returns. The untabulated plots of the 3×3 portfolios exhibit more dramatic patterns under the three-factor CAPM, compared to the six-factor CAPM.

7. Conclusion

We provide evidence to show that FX and IR exposures are priced in short to long horizon returns, using an unconditional CAPM. Positive and negative risk premia increase in absolute value as the length of the return horizons increases. The risk premia have coefficient signs that correspond to those of the underlying exposure betas. The increases in risk premia are larger at more distant return horizons, when firms are less likely to hedge their exposures. In turn, investors require greater compensation for the risks at longer return horizons. Stocks with insignificant exposure betas have zero risk premia. The strength of our results lies in our research design.

Our 3×3 portfolios show how the risk premia and the underlying exposure relate to stock characteristics. We find that ROE on Size, ROE on B/M, and ROE on S/P are important sources of risk premia. For example, High ROE–large Size portfolios contain most of the stocks with positive and negative FX rate risk premia, for high ROE on Size portfolios. In contrast, low ROE–small size portfolios contain almost all stocks with positive and negative FX rate risk premia, for low ROE on Size portfolios. Small firms are more collaterally constrained than large firms and thus have more difficulties in accessing the derivatives markets to hedge (Rampini and Viswanathan 2010). Large firms with higher profitability have greater cash flows, which in turn enable them to avoid capital markets for hedging. This may increase the associated risk premia. Size also matters for IR risk premia. High ROE–large Size portfolios and low ROE–small Size portfolios have most of the stocks with IR risk premia. We find related results for ROE on B/M portfolios and ROE on S/P portfolios. We show that portfolio characteristics relate to the level of risk premia. Our approach explains some of the contradictory findings regarding the relation between exposure betas and stock characteristics. We extend our results to the case of risk premia.

Notes

1. Shapiro (1975), Marston (2001) and Bodnar, Dumas, and Marston (2002) predict that changes in FX and inflation rates affect the profitability of non-financial stocks and, in turn, their value. In contrast, modern portfolio theory predicts that, if FX rate and IR risks are unsystematic, they can be diversified away in investors' portfolios at no costs and as such are not priced.
2. Stocks and/or firms refer to non-financial stocks or firms. Price changes and returns are used interchangeably in this study. We follow prior studies and argue that the exposure betas represent residual exposure since most firms hedge their exposures using financial derivatives and/or manage their exposures internally (Bartram, Brown, and Minton 2010; Bodnar et al. 2013).
3. De Santis and Gérard (1998) report both positive and negative FX rate risk premia during their sub-periods. Variation in risk premia across sub-periods is often explained in terms of variation in market conditions (De Santis and Gérard 1998; Azeez

and Yonezawa 2006). Kolari, Moorman, and Sorescu (2008, 1075) observe that positive (negative) FX rate premia tend to be associated with the residual (common) component of FX risk premia. This suggests the risk premia can have different signs.

4. Doukas, Hall, and Lang (2003) estimate FX rate risk premia using both the firm- and industry-level returns and both conditional and unconditional CAPMs. They report that the conditional CAPM outperforms the unconditional CAPM in line with prior studies.
5. Karolyi and Stulz (2003, 996) note: ‘... some of the empirical evidence on the pricing of exchange rate risk indicates that one may have to take into account the exposure of stocks to foreign exchange risk. Paradoxically, the evidence on foreign exchange rate exposures of stocks is weak ... making it puzzling that exchange rates would matter so much in the cross-section of returns in some studies’.
6. Bodnar and Wong (2003, 58–62) show that large stock portfolios have negative FX rate exposure coefficients, whereas small stock portfolios have positive coefficients. Dominguez and Tesar (2006) regress the square root of the absolute value of the FX exposure beta on capitalization value. They find that small stocks have more exposure than large stocks. He and Ng (1998) use both the absolute value of FX rate beta and a dummy variable to capture the sign of the FX rate beta. They show that large stocks have more exposure than small stocks.
7. Most theoretical arguments for corporate hedging advocate the preservation of cash flow stability as an important hedging motive (Smith and Stulz 1985; Froot, Scharfstein, and Stein 1993).
8. Using size, value, and momentum in the CAPM also accommodates the link with macroeconomic risks (see Bergbrant and Kelly 2016) which may capture both short and long horizon economic information. Fraser and Pantzalis (2004) use the Fama and French (1993) size and value factors in their exposure model. We are not aware of a prior short to long horizon study that incorporates these pricing factors.
9. Bodnar and Wong (2003, 42) consider the first few overlapping months of their sample period as representing the short horizon and the months after that to represent the long horizon. We adopt a similar approach in terms of daily/weekly returns. We also follow prior studies by including one-period exposure betas in our study. They represent short-horizon exposure betas and provide a benchmark for comparing the exposure betas of prior studies (Bodnar and Wong 2003; Joseph, Lambertides, and Savva 2015).
10. For daily price changes, we use a fixed window of moving overlapping observations of $h_{D,N} = 1, 5, 10, 15, 20, \dots, 950$ days, where N denotes the length of the return horizons for day D . For weekly price changes, we use a fixed window of moving overlapping weekly observations of $h_{W,N} = 1, 2, 3, 4, \dots, 190$ weeks.
11. It can be argued that our beta and risk premium estimates are based on a conditional approach since they depend on the interval of the returns.
12. Some earlier studies acknowledge that FX rates and stock prices may be driven by underlying factors (Jorion 1990, 1991), suggesting that the FX rate and IR effects on stock returns may be endogenous.
13. Firms manage their exposures to FX rate, IR and commodity price changes (Huang et al. 2018). Firms are of the view that risk management and exposure reporting are informative to shareholders and financial analysts (Hecht 2019).
14. Up to 71.79% of U.K. firms hedge FX rate exposure, whereas 68.22% hedge IR exposure (see Panaretou 2014). Slightly higher percentages are observed for U.S. stocks (see Bodnar, Hayt, and Marston 1998).
15. In theory, firms use financial derivatives to reduce: (i) expectations of investment distortion costs (Bessembinder 1991; Froot, Scharfstein, and Stein 1993); (ii) the risk of financial distress and bankruptcy costs (Smith and Stulz 1985; Stulz 1996); and (iii) expected tax liabilities (Smith and Stulz 1985). Huang et al. (2018) show that firm-level governance and monitoring mechanisms influence the risk management strategies of firms.
16. Specifically, we construct the daily and weekly SMB, HML, and MOM factors for U.K. stocks strictly following Fama and French (1993) for SMB and HML, and Carhart (1997) for MOM.
17. We use August 9, 2007 since this is the date BNP Paribas became the first major financial institution to cease trading due to the crisis (<https://www.reuters.com/article/us-bnpparibas-subprime-funds-idUSWEB612920070809>, accessed June 15, 2020). This date is commonly used in many studies (Joseph et al. 2020). June 2009 is based on macroeconomic indicators (<https://reut.rs/3kNRxOk>, accessed June 15, 2020).
18. We exclude the dummy variable, d_t , from Eq. (2) to avoid an unnecessary complication in the interpretation of the results. Our findings are unaffected by its inclusion. These and other results not fully presented are available on request.
19. The average exposure betas are based on the betas for all stocks at each return horizon when significant, according to their beta sign. That is, the sum of the exposure coefficients with the same sign, divided by the number of stocks at the particular return horizon. The significance of the average exposure beta is determined using the standard t -statistic. Since we have a large number of return horizons, we show a cross-section of the results.
20. Since Grant (1977), the CoV has been used to show how market risk premia vary with portfolio switching in investment decisions.
21. The specific effects of derivatives usage on exposure are unclear (Bali, Hume, and Martell 2007; Bae, Kwon, and Park 2018; Sikarwar and Gupta 2019). Most firms partially hedge, using derivatives with maturity of 90 days or less. The use of derivatives by firms declines as the length of the return horizons increases (Bodnar, Hayt, and Marston 1998).
22. Theoretically, the intercept should be zero. The zero-beta rate is assumed to be equivalent to the risk-free rate and is known. A zero-intercept is difficult to achieve in empirical work (Shanken and Zhou 2007).

23. Our ROE measure is closely related to the operating cash flow measure used by Barber and Lyon (1996) based on sales less cost of goods sold, less selling and administrative expenses, plus depreciation, goodwill, and amortization – a relatively clean profitability measure.
24. For the results that follow, the numbers of stocks in our portfolios do not consistently match those in Table 2. This is because DataStream and LSPD do not each have the same number of stocks.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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