Asymmetry and Time-Variation in Exchange Rate Exposure – An Investigation of Australian Stocks Returns

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Abstract

This study provides some insights into the exchange rate exposure of Australian stock returns. Specifically, using a dynamic econometric approach that allows for both asymmetry and time-varying risk exposures in both the exchange rate variable and the market variable, we test a large sample of Australian firms over the period January 2001 and December 2005. We analyse the data using three different classification methods, forming portfolios according to industry sector, size deciles and censoring deciles. Although the evidence of exchange rate exposure is limited across our sample of industries, we find (i) a time-varying asymmetric effect primarily in the utilities sector; (ii) time-varying exposure in the materials and energy sectors; and (iii) an asymmetric effect in the technology sector. Further, we find some time-varying asymmetric exchange rate exposure across most size and censoring deciles. Finally, we find substantial evidence of a positive asymmetric effect in the market beta across all three classification methods.

Keywords: Time-varying Exchange Rate Risk Exposure; GARCH; Asymmetry; Australian Stock Market

JEL Classification: G12

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1. Introduction

The relationship between a firm's value and fluctuations in the exchange rate has been an important empirical issue for some time. Interestingly, while the relationship is apparent in practice, the empirical evidence in this area of research has been relatively weak. While many studies have investigated the foreign exchange (FX) exposure of shareholder returns in different stock markets around the world using various empirical approaches and addressing a number of relevant research design issues, the question of how unanticipated changes in the exchange rate actually impact on the wealth of shareholders remains a puzzle.

The primary objective of this paper is to investigate two of the research design issues identified in the recent literature as being potentially important in explaining the weak findings of many FX investigations. Specifically, we model the time-variation and asymmetric nature of FX exposure of Australian stock returns. The relative importance of these two features has emerged in a number of studies. First, the possibility that weak findings in early investigations could be explained by the asymmetric nature of FX exposure was initially suggested by Bartov and Bodnar (1994). Against a backdrop of literature that reports overwhelming insensitivity of stock returns to exchange rate changes [e.g., Jorion (1990, 1991), Bodnar and Gentry (1993), and Amihud (1994)], Bartov and Bodnar (1994) suggest that it may be the non-linear (or asymmetric) nature of the relationship between the firm's value and exchange rate fluctuations that prevents the sensitivity from being detected.

A number of theoretical papers suggest possible reasons for the asymmetric response of stock returns to exchange rate movements and much of this literature revolves around the behaviour of the firm, for example pricing-to-market strategies and resulting pass-through effects [Mann (1986), Giovannini (1988), Froot and Klemperer (1989), Marston (1990), Knetter (1994)]; hysteretic behaviour [(Baldwin, (1988); Baldwin and Krugman (1989); Dixit (1989); Christophe (1997)]; or hedging activities. More recently, empirical evidence of an asymmetric response is reported in a number of studies. These include Choi and Prasad (1995); Di Iorio and Faff (2000), Bodnar and Wong (2003); Koutmos and Martin (2003a,b, 2006), Tai (2005), Doidge et al. (2006) and Muller and Verschoor (2006).

Specifically, Koutmos and Martin (2003a) investigate nine sector indices across four countries over appreciation-depreciation cycles and find asymmetric exposure in several instances. Their more recent investigation of US stocks [Koutmos and Martin (2006)], also reveals an asymmetric response in stock returns. Following Bodnar and Wong (2003) who suggest the use of returns to market-capitalisation-based portfolios controls for macroeconomic variables when using firm-level data, Koutmos and Martin (2006) examine decile and industry sector portfolios and find asymmetric exposure to be pervasive across the decile portfolios as well as the financial and industrial sectors.

In addition, Tai (2005) reports significant asymmetric currency exposure in 80% of his sample of US bank stocks for the period 1978 to 2001, while Muller and Vershoor (2006) note an increase in the precision and the significance of exposure estimates when they introduce nonlinearity in foreign currency risk exposure. They further note that asymmetries are more pronounced towards large and small currency fluctuations that over appreciation and depreciation cycles. On the other hand, Doidge et al. (2006) find that during periods of large currency depreciations (appreciations), firms with high international sales outperform (underperform) those with no international sales in 14 of 18 (16 of 18) countries in their sample. Finally, Di Iorio and Faff (2000) investigate stock return responses in the Australian stock market and find some evidence of asymmetry to exchange rate changes of different sign and magnitude.

Associated with the argument that FX exposure is indeed non-linear is the issue that this type of exposure varies across time. Traditionally the implicit assumption made in many of the earlier empirical studies in this area of research is that FX exposure is stable, or constant. It has been suggested that a possible reason for the statistical insignificance of FX exposure coefficients may be that the econometric approaches implemented in these studies fail to model the temporal instability of this type of exposure [Levi (1994)]. Since these early investigations, the time-varying FX exposure has been documented in a number of papers, including Brunner et al (2000); Tai (1999, 2000); Allayannis and Ihrig (2001); Williamson (2001); Di Iorio and Faff (2001); Patro, Wald and Yangru (2002); De Santis, Gerard and Hillion (2003); Bodnar and Wong (2003); Ihrig and Prior (2005); and Koutmos and Martin (2006).

Specifically, Tai (2000) applies three different econometric techniques to determine whether exchange rate risk is priced in the US market and reports that of the three, the multivariate GARCH in mean (MGARCH-M) approach produced "strong evidence of time-varying interest rate risk and exchange rate risk." [Tai (2000, p. 397)]. A GARCH approach is also employed by Patro et al. (2002) who find significant currency risk exposures in the equity index returns of 16 OECD countries. Moreover, in their analysis of the relevance of currency risk in the EMU, De Santis et al. (2003) implement a conditional version of the ICAPM and conclude that currency risk and its impact on returns varies over time as a function of changes in economic conditions and the institutional environment. Implementing a dynamic econometric approach to model time-varying parameters of the exchange rate risk factor, Koutmos and Martin (2006) report the time-varying FX exposure of US stock returns. In particular they note that the variability in time-varying exposure is smaller (larger) for the largest (smallest) firms and for industrial (technology) firms.

The temporal instability of FX exposure has also been empirically tested using sub-period analysis. For example, Williamson (2001) examines the time varying nature in exchange rate exposure in the automotive industry by using a 7-year subperiod analysis and for each separate subperiod the exchange rate exposure is related to the prevailing competitive environment of the sector. However, the findings of this study provide only weak evidence of exposure. Similarly, Di Iorio and Faff (2001) partition a ten-year dataset into one-year subperiods and find some evidence of changing exchange rate exposure in Australian stock market returns.

The current paper contributes to the existing literature in a number of ways. First, it provides evidence of the asymmetric and time-variation nature of FX exposure in the Australian stock market, a market that has not been extensively investigated with regard to this type of exposure.[1] Second, while other investigations of the FX exposure in the Australian market have concentrated on industry portfolio indices [e.g., Di Iorio and Faff (2000, 2001)], the current analysis is performed at a firm-level using an extensive dataset of 476 firms.[2] Third, we implement a dynamic

[1] Much of the empirical research in the area of exchange rate exposure has concentrated on the US financial markets [see, for example, Jorion (1990, 1991), Bodnar and Gentry (1993); Amihud (1994); Choi and Prasad (1995); and Chow et al. (1997a,b)]. Analysis of other markets has been limited but has included other developed countries such as Japan [see He and Ng (1998); Chamberlain et al (1997); and Chow and Chen (1998)] as well some emerging markets, for instance Kiyamaz (2003) investigates the Turkish stock market. Notably, studies of the Australian market have been relatively scarce [see Loudon (1993a, b); Khoo (1994); and Di Iorio and Faff (2000, 2001)].

[2] Indeed, many studies in this area of research are undertaken using industry-level returns. Dominguez and Tesar (2001) suggest, however, that since firms within an industry are not all affected in the same way by exchange rate movements, industry level analysis is subject to an aggregation problem, that is, an aggregation of individual stock returns will average out the individual exposure effects.

multivariate GARCH approach that explicitly allows for asymmetric responses and time variations in asset returns, the Australian-USD exchange rate, and the market return. Interestingly, although previous studies have investigated the time varying asymmetric exchange rate exposure of stock returns [e.g., Koutmos and Martin (2006)], they retain a constant market exposure. We, on the other hand, generalise to a specification that has both time varying and asymmetric market and exchange rate exposures. Finally, we divide our sample into industry sector portfolios and size-based portfolios. Hence, we test the asymmetric and time varying nature of FX exposure across different industries within the Australian market and attempt to capture the relationship between firm size and FX exposure.

The remainder of this paper is structured as follows. Section 2 outlines the empirical framework and data, while the results are presented and discussed in Section 3. The analysis is summarised in Section 4.

2. Empirical Model

Our base model in the analysis is the market model augmented with an exchange rate factor that has been used by a number of studies in analysing exchange rate exposure including Jorion (1990), Di Iorio and Faff (2001), Dominguez and Tesar (2006), Doidge, Griffin and Williamson (2006). Specifically, the model is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{xt} + \varepsilon_{it} \tag{1}$$

where R_{it} is the daily return on individual stock i, R_{mt} is the daily return on the market portfolio (specifically the All Ordinaries Accumulation Index), R_{xt} is the daily return on the Australian-US dollar exchange rate,[3] (α_i, β_i, γ_i) are unknown parameters to be estimated, and ε_{it} is the disturbance term. The γ_i coefficient measures the average exchange rate exposure of firm *i* over the sample period, with a positive (negative) value indicating an appreciation (depreciation) of the exchange rate.

A possible extension to the model is to accommodate for asymmetric responses in individual stock returns to both the market return and the exchange return. The allowance of asymmetries in exchange rate exposure has been done by Di Iorio and Faff (2000) and Koutmos and Martin (2003). Interestingly the studies that allow for asymmetry in exchange rate exposure do not tend to allow for a similar asymmetry in the market exposure along the lines of up and down betas as explored in Bhardwaj and Brooks (1993), Pettengill, Sundaram and Mathur (1995) and Faff (2001). Thus, a model that allows for asymmetry in both the market and exchange rate exposure can be specified as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \beta_i^D D_m R_{mt} + \gamma_i R_{xt} + \gamma_i^D D_x R_{xt} + \varepsilon_{it} \qquad (2)$$

where D_m is a dummy variable that takes the value of unity when the market return is negative, D_x is a dummy variable that takes the value of unity when the exchange rate return is negative, and (β_i^D, γ_i^D) are unknown parameters that measure the asymmetry in the market and exchange rate exposure, respectively.

A further extension is to allow for time varying risk exposures in the model. The challenge is doing this in a way that is tractable for a large number of stocks. In this analysis we follow the approach of Schwert and Seguin (1990) in allowing for time varying exposure coefficients by augmenting the model to also depend on the

[3] The construction of the exchange rate factor AUD/USD is such that a positive exchange rate return is associated with an appreciation of the Australian dollar.

estimated conditional variance of the returns series. In the context of Australian industry portfolios Brooks, Faff and McKenzie (1998) successfully explore the Schwert and Seguin (1990) approach to estimate time varying betas. In the present context the base model could be extended to:

$$R_{it} = \alpha_i + b_{1i}\, R_{mt} + b_{2i}\, R_{mt}/h_{mt} + c_{1i}\, R_{xt} + c_{2i}\, R_{xt}/h_{xt} + \varepsilon_{it} \tag{3}$$

where h_{mt} and h_{xt} are the fitted conditional variances from Bollerslev's (1986) univariate GARCH (1,1) models for the market return and the exchange return respectively.

While the use of GARCH errors in the modelling of exchange rate exposure has been successfully used by Di Iorio and Faff (2001) and Muller and Verschoor (2006), these studies do not make the extension of allowing for GARCH type effects to produce the time varying exposure coefficients of the Schwert and Seguin (1990) approach. The time varying exposure coefficients are then:

$$\beta_{it} = b_{1i} + b_{2i}/h_{mt} \tag{4}$$

$$\gamma_{it} = c_{1i} + c_{2i}/h_{xt} \tag{5}$$

It is also possible to mix together both the asymmetric and time varying exposures. Koutmos and Martin (2006) adopt this approach using a vector GARCH specification in the context of modelling the time varying asymmetric exchange rate exposure for US portfolio data. However, Koutmos and Martin (2006) only allow for the exchange rate exposure to be both asymmetric and time varying. They still retain a constant market exposure. In the context of our approach we generalise to a specification that has both time varying and asymmetric market and exchange rate exposures. Our composite specification is:

$$R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + b_{1i}^{D} D_m R_{mt} + b_{2i}^{D} D_m R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + c_{1i}^{D} D_x R_{xt} + c_{2i}^{D} D_x R_{xt}/h_{xt}\, \varepsilon_{it} \quad (6)$$

3. Data and Results

The data used in our analysis is daily returns data for the period from January 2001 to December 2005 on all of the available stocks in the Datastream database that are members of the Australian All Ordinaries Index. In total this gives data on 476 stocks and 1269 observations. In addition we also collected data on the Australian All Ordinaries Index (also obtained from Datastream). The data on the exchange rate comes from the Reserve Bank of Australia website. All our returns data are calculated assuming continuous compounding.

We analyse the data using three different classification methods. First, we analyse and report on the data according to industry sector. Second, we divide the data into decile portfolios sorted by size where Decile 1 contains the smallest firms and Decile 10 contains the largest. Third, we divide the data into portfolios based on the proportion of daily return observations for companies that are zero. These censoring portfolios are arranged as follows: companies that have (i) less than 10%, (ii) between 10% and 20%, (iii) between 20% and 30%, (iv) between 30% and 40%, (v) between 40% and 60%, and (vi) greater than 60%, of zero daily return observations.

The results of our analysis are reported for the stocks classified by industries in Tables 1 and 2, by size deciles in Tables 3 and 4, and by censoring portfolios in Tables 5 and 6. Within each classification we detail the proportion of significantly positive and significantly negative parameter estimates at a 5% significance level across all of the specifications of the model.

3.1 Industry Results

Tables 1 and 2 report the results of four models. Specifically, Table 1 reports the findings of the base model (Eq. 1), the asymmetric model (Eq. 2) and the time varying model (Eq. 3). Table 2 reports the outcome of the composite model (Eq. 6) that accommodates asymmetric and time varying responses in stock returns simultaneously in the one specification. Since there are a number of results to analyse, a discussion of the market exposure results will be followed by a discussion of the exchange rate exposure findings.

3.1.1 Market Exposure Results

Table 1 reports that generally 75.6% of all Australian stocks exhibit significant market exposure. While this finding is reported for the base model (Eq. 1), market exposure is observed to vary across the different analyses, ranging from 59.6% of stocks (Eq. 3 reported in Table 1) to 34.5% (Eq. 6 reported in Table 2). Further, the degree of market exposure varies considerably when we compare the results for each model across industries. Although there is no discernible pattern, the highest market exposures are observed in utilities stocks in the base model (Eq. 1) and asymmetric model results (recording proportions of 90.9% and 72.7%, respectively) while telecommunication services records the highest proportion of market exposures in the time-varying and composite models (77.8% and 66.7% of all stocks, respectively). In general, the lowest proportion of stocks to record significant market exposures across the four models are in the industry sectors of materials and energy. Interestingly, the greatest variability in the proportion of stocks that exhibit market exposure is observed in utilities (from a high of 90.9% recorded in the base model (Eq. 1) to just over 45% recorded in the time-varying (Eq. 3) and composite models (Eq. 6)).

Our study also provides an analysis of downside market risk exposure. We test for this exposure by firstly using the asymmetric model (Eq. 2) and secondly in our implementation of the composite specification (Eq. 6). Tables 1 and 2 report the proportion of significant stocks for both positive and negative parameters and the interesting features of our results can be summarised as follows. First, in the case of positive (negative) parameters, the results of our simple asymmetric model (Eq. 2) in Table 1 report that 18.3% (1.1%) of all stocks exhibit downside market exposure while this proportion decreases to 17.6% (1.0%) of stocks when the composite model (Eq. 6) is implemented (Table 2). Hence, the results indicate that in general just under one fifth of the firms in our sample exhibit increased sensitivity in their stock returns on days when the market moves downwards. Of the remainder, only a marginal number of firms exhibit decreased sensitivity, while the sensitivity of the returns of the majority of companies exhibit no change.

When we examine the results by industry sector, we find that all stocks except telecommunication services exhibit some downside market risk exposure when we implement the simple asymmetry model (Eq. 2). A strong incidence of exposure (20% of the stocks or more) is reported in five of the ten industries in Table 1. Our composite model (Eq. 6) results in Table 2 confirm that the materials industry exhibits the highest downside market exposure (27.8% of stocks), while telecommunication services and utilities exhibit no such exposure.

In contrast to the positive parameter outcome, the incidence of downside market exposure is significantly lower when we consider the negative parameter results. Table 1 reports that the stocks in only two industries [consumer discretionary (14.5%) and utilities (9.1%)] exhibit some exposure when the asymmetric model (Eq. 2) is implemented. This exposure, however, virtually disappears in our composite model (Eq. 6) analysis (Table 2).

A further aspect of our analysis is the examination of the time varying nature of both the market and FX exposure. This investigation is undertaken using the simple time varying model (Eq. 3) and the composite model (Eq. 6). From a market perspective, the results reported in Table 1 indicate some time variation. Specifically, 5.9% of all stocks record statistically significant positive parameters while 15.3% record significant negative parameters. Of note, 27.2% of utilities stocks report a significant positive parameter, while health care (24.4%), information technology (24%), telecommunication services (22.2%) and financials (21.5) all report over 20% of stocks recording a significant negative parameter. In contrast, four industries do not record any significant positive parameters (consumer staples, industrials, information technology, and telecommunication services) while utilities does not record any significant negative parameters.

These results decrease markedly in Table 2. The overall composite model (Eq. 6) findings are 3.6% (positive parameters) and 5.9% (negative parameters) respectively. Across the industries, utilities again records the highest (positive) time varying market exposure (9.1% of stocks) while consumer staples, health care, industrials, information technology, and telecommunications services record no significant positive parameters. In contrast, 17.1% of Health Care stocks report a significant negative parameter. Stocks in consumer discretionary (8.7%) and financials (8.3%) also exhibit (negative) time-varying market exposure, while no significant negative parameter is found in the industries of energy, telecommunication services and utilities.

Extending our market exposure analysis, we explore the time varying downside market exposure of our sample of firms. Using the composite model (Eq 6), we find that 1.0% (6.3%) of all Australian stocks exhibit positive (negative) time varying downside market exposure (Table 2). The strongest evidence of positive exposure is in utilities stocks (9.1%), while negative exposure is found in the industries of materials (10.1%), energy (8.6%), information technology (8.0%) and industrials (7.7%). Overall, however, the number of industries that have no or very weak evidence of time varying downside risk is relatively high. Six (two) industry classifications report no significant positive (negative) parameters.

3.1.2 Exchange Rate Exposure Results

Another important feature of the results presented in Tables 1 and 2 are the FX exposure results. First we consider the base model (Eq. 1).

We find that the base model records the highest overall number of stocks (16%) to exhibit significant positive FX exposure. This result, however, halves as we progress through to the results on the asymmetric model (Eq. 2), and halves again when we consider the findings of the time varying model (Eq. 3). Ultimately, only an average of 4.6% of all stocks exhibit positive FX exposure when implementing the composite model (Eq 6). Conversely, a much lower proportion of stocks in our sample exhibit negative FX exposure. The overall results for negative FX exposure does not vary greatly across the four models and ranges from 2.3% in the base model (Eq. 1) to 1.9% in the composite model (Eq. 6). The results of the asymmetry and time varying models are 2.3% and 2.5%, respectively.

The degree of FX exposure varies when we compare the results for each model across industrial sectors. First, when considering the base model, a significant proportion of firms in the sectors of materials, energy and industrials report positive exchange rate exposure. Specifically, we find that stocks in the materials industry exhibit the highest positive FX exposure in all cases. However, as we observed in the overall results, the proportion of stocks that exhibit this type of exposure decreases by more than half (from 44.3% to 21.5%) when the base model is extended to accommodate asymmetric responses, and half again when the base model allows for time varying exposures (from 21.5% to 10.1%). Notably, while industrial stocks report some positive FX exposure in the base model (Eq. 1) and the asymmetry model (Eq. 2), no such exposure is observed when the time varying model (Eq.3) is implemented. Finally, although some of the results of the composite model (Eq. 6) reported in Table 2 reflect those in Table 1 (for instance we do not observe positive FX exposure in health care and telecommunication service), other results are quite surprising. For example, while stocks in the utilities industry report no positive FX exposure in Table 1, these stocks report the highest proportion of significant coefficients of all industries (9.1%) in Table 2.

As discussed above, the stocks examined in this study exhibit relatively low negative exchange rate exposure. Of the industries that exhibit some negative FX exposure, we observe significant negative exposure in 14.3% of consumer staples stocks in the base model results. However, the telecommunication services industry provides the most consistent results with 11.1% of stocks exhibiting significant negative exchange rate exposure across each of the three models outlined in Table 1. This exposure is no longer evident however when the composite model (Eq). 6) is used (Table 2). Of note, just as in the case of positive FX exposure, utilities stocks provide the strongest incidence of negative FX exposure (9.1%) in Table 2.

Our analysis extends to examine the downside FX exposure of Australian stocks. As in our investigation of downside market risk exposure, we test the downside FX exposure using the asymmetric model (Eq. 2) and the composite model (Eq. 6) and we divide our findings into positive and negative parameters. Generally, the results reported in both Table 1 and Table 2 indicate that there is very little evidence of exposure. Specifically, the results in Table 1 indicate that less than 3% of all stocks exhibit downside FX exposure (for both positive and negative parameters). This incidence decreases marginally in the composite model analysis (Table 2). Thus, it would appear from our results that overall the Australian stock returns are not very sensitive to downward movements in the exchange rate.

Notwithstanding this general finding, we note that there is some variation in the degree of downside exchange rate exposure between the various industry portfolios although this variation is not overwhelming. Table 2 indicates that the highest downside exchange rate exposure is observed in (i) the utilities industry with 9.1% of stocks recording significant positive parameters; and (ii) the information technology industry with 8.0% of stocks recording significant negative parameters. These results are reflected in Table 2. Similarly, industries that do not record statistically significantly positive (negative) parameters are also consistent across the two analyses. These results are in complete contrast to those of Koutmos and Martin (2006), who note asymmetric exposure in the financial and industrial sectors.

Our discussion now turns to the time variation analysis of our study of Australian industries. Similar to the outcome of our simple asymmetric FX analysis, the evidence is weak. Our findings (Table 1) reveal that only 4.2% of Australian stocks exhibit positive time varying FX exposure while 1.9% of stocks record negative time varying FX exposure. Of the industries examined, materials (8.9%) and energy (8.6%) record the highest incidence of positive parameters, while utilities (9.1%) reports the highest proportion of negative parameters. Further, there is no evidence of time varying FX exposure in consumer staples or telecommunication services stocks.

In our composite analysis (Eq. 6), 11.4% of materials and 9.1% of utilities stocks exhibit positive (negative) time varying FX exposure (Table 2). Of the other industries, consumer discretionary reports that close to 6% of stocks exhibit positive and negative time varying FX exposure, while consumer staples, health care and telecommunication services report no significant parameters.

Finally, using the composite model (Eq. 6) we explore the time varying downside exchange rate exposure of the stocks. Consistent with our time varying downside market exposure results, our findings are generally weak. Specifically, we find evidence of positive (negative) time varying downside exchange rate exposure in 2.5% (2.1%) of all stocks (Table 2). Of the industries examined, utilities (materials) has the highest proportion of positive (negative) time varying downside exchange rate exposure (9.1% and 7.6%, respectively). In contrast, information technology and telecommunication services record no significant parameters.

3.2 Size Decile Results

Tables 3 and 4 also report on the results of the four models discussed in Section 3.2. In this case the results are the outcome for our analysis of size decile portfolios. Once again, the discussion is divided into Market Exposure Results and Exchange Rate results.

3.2.1 Market Exposure Results

Generally the results for market exposure, measured by beta, are consistent across each of the four models. In all cases, Decile 1 (Decile 10) reports the strongest (weakest) evidence of market exposure. The proportions range from 96% (42.3%) in the base model (Eq. 1) results to 78% (3.8%) in the composite model (asymmetric model) results.

In the case of downside market risk exposure, the asymmetric model (Eq. 2) results reported in Table 3 reveal a greater proportion of stocks record significant positive parameters. Four of the 10 portfolios (Deciles 2, 3, 4,and 6) report a proportion of at least 20% while all portfolios report a proportion of over 12%. In contrast, seven of the 10 deciles report no significant negative parameters. The remaining three (Deciles 1, 3 and 6) report considerably less than 10%. These results are reflected in Table 4 where there is very strong evidence of significant positive parameters.

In contrast, the outcome of our time varying investigation of market exposure differs considerably from that of our asymmetric analysis. In this case, the findings indicate a greater proportion of significant negative parameters. First, using the time varying model (Eq. 3), we find that in Deciles 1 and 2 report the greatest proportion of significant positive parameters, while Deciles 1 and 3 report the highest proportion of significant negative parameters (Table 3). However, while the proportion of significant negative parameters does not drop below 11.5% (Decile 10), we find that the proportion of significant positive parameters does not rise above 6% from Deciles 3 to 10. Interestingly, these results are not consistent with those reported in Table 4. When examining the time varying response implementing the composite model (Eq. 6), the evidence becomes generally weaker and the largest impact is observed in the negative parameter results. No decile portfolio reports a proportion of greater than 10%.

Finally, we explore the time varying downside market exposure of stocks. The results reported in Table 4 exhibit very weak evidence of significant positive parameters. Only 4 decile portfolios report some (albeit weak) positive selectivity among stocks (2% for Deciles 4, 5, 7 and 9). In contrast, every decile portfolio reports negative sensitivity (ranging from 12% (Decile 2) to 2% (Decile 9)).

3.2.2 Exchange Rate Results

The findings of our exchange rate analysis using the base model (Eq. 1) supports the results of our investigation using industry portfolios. Specifically, there is strong evidence of positive exposure (Table 3). The proportion of stocks that report significant positive parameters ranges from 24% (Decile 2) to 11.5% (Decile 10). Conversely, Decile 1 reports the highest proportion of significant negative parameters (6%) while Deciles 3, 7 and 10 report no negative sensitivity.

These results are reflected in the outcome of the asymmetric model (Eq. 2). Although the proportion of stocks that report significant positive parameters is lower than in the base model (Eq. 1), there is still relatively strong evidence of positive exchange rate exposure. Decile 1 reports the highest proportion (12%) while Deciles

2, 3, and 7 report the lowest (6% each). In contrast, six of the ten decile portfolios report significant negative parameters with the highest being 6% (Deciles 1 and 2).

Also reflecting the industry analysis reported in Section 3.1, evidence of exchange rate exposure diminishes when we test the time varying response of stock returns. While some results remain unchanged (for example Deciles 4 and 5), the overall effect is considerably weaker FX exposure. Finally, when considering the findings in Table 4 of the composite model (Eq. 6), we again find some strengthening in the evidence of positive FX exposure although it is not as strong as we observe in the original base model (Eq. 1).

Using the asymmetric model (Eq. 2), we test the downside FX exposure of the decile portfolios. Again reflecting the industry analysis, our findings in Table 3 indicate that there is very little difference between the proportion of significant positive and negative parameters. Overall, the evidence is weak with only one decile portfolio resulting in a proportion of significant (positive) parameters greater than 10% (Decile 10 – 11.5%). These results are consistent with those reported in Table 4.

Again, in keeping with the industry results, our examination of the time varying nature of exchange rate exposure provides stronger evidence of significant positive parameters. However, generally our findings are weak with no decile portfolio reporting a proportion of greater than 10% of stocks. In fact, six of the 10 deciles reported no significant negative parameters. Hence, notwithstanding some minor differences observed in the results reported in Table 4, evidence of a time variation response to exchange rate movements is weak.

Finally, we examine the time varying downside exchange rate exposure using the composite model (Eq. 6). The results of this investigated presented in Table 4 again provide weak evidence of exposure. The proportion of stocks that report significant positive parameters ranges from 6% (Decile 4) to 2% (Deciles 1, 3 and 6). A similar result is observed in the negative parameter results.

3.3 Censoring Decile Results

Tables 5 and 6 report the results of the four models using censoring deciles. As in the industry and decile portfolio analyses, Table 5 reports the results of the base model (Eq. 1), the asymmetric model (Eq. 2) and the time varying model (Eq. 3). Table 6 reports the outcome of the composite model (Eq. 6).

3.3.1 Market Exposure Results

In general, the results of this analysis indicate that the market risk exposure is most significant for the portfolios in which a relatively small proportion of the daily returns are zero. Specifically, the largest proportion of significant market beta estimates are observed in the censoring decile $0<c<0.1$ across the results of the four models reported in Tables 5 and 6. For example, in Table 5 we observe 96.8% of stocks in this portfolio exhibit significant market exposure in the base model (Eq. 1). Conversely, the lowest market risk exposure is observed in censoring decile portfolios with a higher percentage of zero daily returns.

Table 5 also reports the findings of our asymmetric (Eq. 2) and time-varying analyses (Eq. 3). When considering a potential asymmetric and time-varying effect in the market variable, we find (i) a greater percentage of stocks exhibit a positive response rather than a negative response when considering downside risk, and (ii) a greater percentage of stocks exhibit a negative rather than positive time-varying response. While 23.7% of stocks in the censoring decile portfolio $0.1<c<0.2$ record statistically significant positive estimates in our analysis of downside market risk, 20.7% of stocks in the portfolio c=0 record significant negative time-varying exposure. Again in both analyses, generally the percentage of stocks that demonstrate a statistically significant response is greater (less) for censoring decile portfolios with smaller (larger) proportions of zero daily returns. These results are reflected in Table 6 although it appears that the time-varying effect diminishes somewhat in the composite specification (Eq. 6).

As in the study of industry and size decile portfolios, an additional variable in the composite model (Eq. 6) that is not tested in the individual models reported in Table 5 is time-varying downside market risk. Here we find a stronger negative, rather than positive, response. Interestingly, the greatest negative response is found in the censoring decile portfolio 0.4<c<0.6 with 13.3% of the stocks recording significant estimates. This in contrast to the results discussed thus far in this section that indicate a stronger asymmetric and time-variation response in stocks that have a small proportion of zero daily returns.

3.3.2 Exchange Rate Results

The results presented in Tables 5 and 6 exhibit some evidence of asymmetry and time variation. Once again, beginning with the base model (Eq.1), we note a stronger positive exchange rate response than negative response. In addition, reflecting the market exposure results, the largest percentage of stocks recording significant (positive) exchange rate exposure is noted in the censoring deciles with the lower percentages of zero daily returns. For example, almost 22% of the stocks in the decile portfolio 0.1<c<0.2 record positive exchange rate exposure. This is the strongest result. Conversely, zero stocks record exchange rate exposure (positive or negative) in the portfolio c>0.6.

Turning our attention to the results of the asymmetry model (Eq. 2) reported in Table 5, we again find relatively strong evidence of positive exchange rate exposure. Although overall the evidence is relatively weaker than in the base model (Eq. 1), the pattern of stronger exposure in deciles with a lower proportion of zero daily returns persists. However, both positive and negative asymmetric exchange rate exposure is reported in this table. Although these results are not strong, asymmetric exposure is found across most of the deciles with no discernible pattern emerging.

The overall exchange rate exposure is notably weaker in the findings of the time-varying model (Eq. 3). There is some evidence of both positive and negative exchange rate risk with the greatest proportion of significant positive (negative) estimates noted in the decile $0.1<c<0.2$ ($0.2<c<0.3$). Once again no exchange rate exposure is reported in the $c>0.6$ decile portfolio. The time-variation response is also weak. Although positive estimates occur more frequently than negative, overall no generalisations can be made.

Finally, when considering the composite specification (Eq. 6) the results presented in Table 6 reflect the results already discussed above. A positive exchange rate response is found in more cases than a negative response, and the censoring decile portfolio $0.1<c<0.2$ records the largest proportion of significant positive estimates (12.4%). Further, although there is some evidence of asymmetry and time variation across the censoring deciles, we cannot make any generalisation about either. We note both positive and negative exchange rate exposure, with the no censoring decile portfolio recording a proportion of greater than 10% in either the time-variation or the asymmetry results in this table. This is also true for the findings of the time-varying downside exchange rate risk variable.

4. Conclusion

In this study we undertake a comprehensive analysis of the exchange rate risk exposure of Australian firms. Specifically, the study analyses the time-varying and asymmetric nature of exchange rate risk implementing a vector GARCH specification that allows for both time varying and asymmetric market and exchange rate exposures. This approach varies from previous studies in this area that only allow for asymmetry and time variation in exchange rate exposures. Further, we test our sample of 476 firms using three classification approaches – industry portfolios, size deciles and censoring deciles portfolios.

Generally our results indicate that a greater proportion of Australian firms experience positive exchange rate risk exposure rather than negative exposure. We find this to be the case across each of the three methods of classification. However, while we find that not all industry portfolios experience the same degree of (positive) exposure (we find the strongest evidence of exposure in the materials, energy and industrial sectors), we report relatively consistent (positive) exchange rate exposure across all of the (size) deciles portfolios. In addition, we find that the censoring portfolios containing stocks with the least proportion of zero daily returns exhibit the strongest (positive) exposure.

Further, our results suggest some asymmetry and time-variation in the exchange rate risk exposure of Australian firms. Specifically, we find (i) a (positive) time-varying asymmetric effect primarily in the utilities sector; (ii) time-varying (positive) exposure in the materials and energy sector; and (iii) a (negative) asymmetric effect in the technology sector. However, unlike previous studies, for example Koustmos and Martin (2006), we find very little evidence of time variation or asymmetry in the exchange rate risk exposure across size decile portfolios. This is also true of our censoring portfolio analysis.

Finally, one of the distinguishing factors of this study is the provision of time varying and asymmetric market risk exposure. Interestingly, although we find a strong (positive) asymmetric response across each of the three classification analyses, we find limited evidence of time-varying market exposure

Table 1: Significant parameter estimate proportions by industry for base model, asymmetry model and time varying model at the 5% significance level

Industry Group		*Base Model*			*Asymmetry Model*							*Time-varying Model*						
	No	β_i	γ_i		β_i	β_i^D		γ_i		γ_i^D		b_{1i}	b_{2i}		c_{1i}		c_{2i}	
			+	-		+	-	+	-	+	-		+	-	+	-	+	-
Consumer Discretionary	69	75.4	8.7	1.4	47.8	11.6	14.5	7.2	0.0	4.3	5.8	69.6	2.9	15.9	5.8	0.0	1.4	5.8
Consumer Staples	21	85.7	4.8	14.3	47.6	4.8	4.8	4.8	9.5	4.8	0.0	71.4	0.0	9.5	4.8	0.0	0.0	0.0
Energy	35	80.0	28.6	2.9	31.4	20.0	0.0	8.6	2.9	0.0	2.9	51.4	5.7	5.7	2.9	2.9	8.6	0
Financials	121	73.6	10.7	2.5	40.5	15.7	0.0	4.1	1.0	3.3	1.7	53.7	9.9	21.5	2.5	4.1	5.8	1.7
Health Care	41	80.5	0.0	2.4	46.3	22.0	0.0	0.0	4.9	0.0	2.4	73.2	2.4	24.4	0.0	4.9	2.4	0.0
Industrials	65	78.5	15.4	1.5	40.0	24.6	1.5	9.2	1.5	3.1	1.5	63.1	0.0	15.4	0.0	0.0	1.5	0.0
Information Technology	25	72.0	4.0	0.0	36.0	24.0	0.0	8.0	4.0	4.0	8.0	76.0	0.0	24.0	8.0	4.0	0.0	4.0
Materials	79	67.1	44.3	0.0	34.2	25.3	1.3	21.5	1.3	2.5	2.5	45.6	10.1	5.1	10.1	2.5	8.9	1.3
Telecommunications Services	9	88.9	0.0	11.1	66.7	0.0	0.0	0.0	11.1	0.0	0.0	77.8	0.0	22.2	0.0	11.1	0.0	0.0
Utilities	11	90.9	0.0	0.0	72.7	9.1	9.1	0.0	9.1	9.1	0.0	45.5	27.2	0.0	0.0	0.0	0.0	9.1
Overall	**476**	75.6	16.0	2.3	41.6	18.3	1.1	8.2	2.3	2.9	2.7	59.6	5.9	15.3	4.0	2.5	4.2	1.9

Parameter estimates are from the following equations:

Base Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{xt} + \varepsilon_{it}$ (Equation 1)

Asymmetry Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \beta_i^D D_m R_{mt} + \gamma_i R_{xt} + \gamma_i^D D_x R_{xt} + \varepsilon_{it}$ (Equation 2)

Time-varying Model: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + \varepsilon_{it}$ (Equation 3)

Table 2: Significant parameter estimate proportions by industry for model including both asymmetry and time varying exposures at the 5% significance level

Industry Group	b_{1i}	b_{2i}		b_{1i}^{D}		b_{2i}^{D}		c_{1i}		c_{2i}		c_{1i}^{D}		c_{2i}^{D}	
		+	-	+	-	+	-	+	-	+	-	+	-	+	-
Consumer Discretionary	42.0	5.8	8.7	13.0	1.4	0.0	5.8	8.7	2.9	5.8	5.8	1.4	2.9	5.8	0.0
Consumer Staples	47.6	0.0	4.8	4.8	0.0	4.8	4.8	0.0	0.0	0.0	0.0	0.0	0.0	4.8	0.0
Energy	22.8	8.6	0.0	17.1	0.0	0.0	8.6	8.6	0.0	0.0	2.9	0.0	0.0	2.9	5.7
Financials	31.4	5.0	8.3	14.9	1.0	1.0	4.1	2.5	1.7	1.7	2.5	1.0	1.0	1.0	1.0
Health Care	46.3	0.0	17.1	14.6	0.0	2.4	4.9	0.0	2.4	0.0	0.0	2.4	2.4	2.4	0.0
Industrials	32.3	0.0	3.1	26.2	0.0	0.0	7.7	4.6	3.1	3.1	1.5	3.1	4.6	3.1	1.5
Information Technology	36.0	0.0	4.0	20.0	0.0	0.0	8.0	4.0	0.0	0.0	4.0	0.0	8.0	0.0	0.0
Materials	24.1	3.8	1.3	27.8	1.3	0.0	10.1	6.3	1.3	11.4	0.0	2.5	1.3	1.3	7.6
Telecommunications Services	66.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Utilities	45.1	9.1	0.0	0.0	0.0	9.1	0.0	9.1	9.1	0.0	9.1	9.1	0.0	9.1	0.0
Overall	34.5	3.6	5.9	17.6	1.0	1.0	6.3	4.6	1.9	3.6	2.3	1.7	2.1	2.5	2.1

Parameter estimates are from the following equations: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + b_{1i}^{D} D_m Rmt + b_{2i}^{D} D_m R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + c_{1i}^{D} D_x R_{xt} + c_{2i}^{D} D_x R_{xt}/h_{xt}\ \varepsilon_{it}$ (Equation 6)

Table 3: Significant parameter estimate proportions by size decile for base model, asymmetry model and time varying model at the 5% significance level

Decile #	*Base Model*			*Asymmetry Model*							*Time-varying Model*						
	$\boldsymbol{\beta_i}$	γ_i		$\boldsymbol{\beta_i}$			$\boldsymbol{\beta_i}$		γ_i		$\boldsymbol{\beta_i}$			$\boldsymbol{\beta_i}$		γ_i	
		+	-		+	-	+	-	+	-		+	-	+	-	+	-
Decile 1	96.0	18.0	6.0	82.0	12.0	6.0	12.0	6.0	4.0	2.0	80.0	14.0	20.0	2.0	2.0	4.0	0.0
Decile 2	94.0	24.0	4.0	62.0	20.0	0.0	6.0	6.0	6.0	0.0	72.0	16.0	16.0	6.0	2.0	2.0	0.0
Decile 3	88.0	14.0	0.0	64.0	24.0	2.0	6.0	0.0	2.0	2.0	72.0	6.0	12.0	2.0	4.0	6.0	4.0
Decile 4	88.0	16.0	2.0	54.0	20.0	0.0	8.0	0.0	0.0	2.0	78.0	4.0	16.0	8.0	0.0	4.0	8.0
Decile 5	84.0	18.0	4.0	46.0	14.0	0.0	8.0	0.0	2.0	4.0	62.0	2.0	14.0	8.0	4.0	4.0	4.0
Decile 6	64.0	12.0	2.0	30.0	26.0	2.0	10.0	2.0	6.0	6.0	56.0	4.0	20.0	8.0	2.0	4.0	2.0
Decile 7	66.0	12.0	0.0	20.0	14.0	0.0	6.0	4.0	2.0	0.0	44.0	6.0	12.0	0.0	2.0	4.0	0.0
Decile 8	64.0	14.0	2.0	18.0	18.0	0.0	8.0	2.0	0.0	2.0	46.0	2.0	16.0	0.0	4.0	2.0	0.0
Decile 9	54.0	18.0	2.0	18.0	18.0	0.0	10.0	0.0	0.0	6.0	42.0	2.0	14.0	4.0	2.0	6.0	0.0
Decile 10	42.3	11.5	0.0	3.8	15.4	0.0	7.7	3.8	11.5	3.8	30.8	0.0	11.5	0.0	3.8	7.7	0.0

Parameter estimates are from the following equations:

Base Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{xt} + \varepsilon_{it}$ (Equation 1)

Asymmetry Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \beta_i^D D_m R_{mt} + \gamma_i R_{xt} + \gamma_i^D D_x R_{xt} + \varepsilon_{it}$ (Equation 2)

Time-varying Model: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + \varepsilon_{it}$ (Equation 3)

Table 4: Significant parameter estimate proportions by size decile for model including both asymmetry and time varying exposures at the 5% significance level

Decile #	$\boldsymbol{\beta_{1i}}$	$\boldsymbol{\beta_{2i}}$		$\boldsymbol{\beta_{1i}^D}$		$\boldsymbol{\beta_{2i}^D}$		c_{1i}		c_{2i}		c_{1i}^D		c_{2i}^D	
		+	-	+	-	+	-	+	-	+	-	+	-	+	-
Decile 1	78.0	8.0	6.0	18.0	6.0	0.0	8.0	0.0	2.0	2.0	0.0	2.0	0.0	2.0	2.0
Decile 2	48.0	8.0	2.0	22.0	0.0	0.0	12.0	6.0	4.0	2.0	0.0	2.0	4.0	4.0	2.0
Decile 3	48.0	2.0	10.0	16.0	0.0	0.0	4.0	10.0	0.0	4.0	4.0	0.0	0.0	2.0	0.0
Decile 4	36.0	2.0	4.0	20.0	0.0	2.0	8.0	12.0	2.0	6.0	8.0	2.0	4.0	6.0	2.0
Decile 5	28.0	4.0	8.0	8.0	0.0	2.0	4.0	6.0	2.0	2.0	2.0	2.0	4.0	4.0	2.0
Decile 6	28.0	6.0	8.0	26.0	0.0	0.0	6.0	6.0	2.0	2.0	4.0	2.0	0.0	2.0	0.0
Decile 7	20.0	2.0	4.0	18.0	0.0	2.0	4.0	0.0	4.0	8.0	0.0	2.0	0.0	0.0	6.0
Decile 8	24.0	2.0	6.0	16.0	0.0	0.0	6.0	4.0	0.0	2.0	4.0	0.0	4.0	4.0	2.0
Decile 9	12.0	0.0	4.0	18.0	0.0	2.0	2.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
Decile 10	11.5	0.0	7.7	11.5	0.0	0.0	11.5	0.0	3.8	3.8	0.0	7.7	0.0	0.0	7.7

Parameter estimates are from the following equations: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + b_{1i}^D D_m Rmt + b_{2i}^D D_m R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + c_{1i}^D D_x R_{xt} + c_{2i}^D D_x R_{xt}/h_{xt} \varepsilon_{it}$ (Equation 6)

Table 5: Significant parameter estimate proportions by censoring portfolio for base model, asymmetry model and time varying model at the 5% significance level

Censoring Proportion		***Base Model***			***Asymmetry Model***							***Time varying Model***						
Degree of censoring	***n***	β_i	γ_i		β_i	β_i^D		γ_i		γ_i^D		b_{1i}	b_{2i}		c_{1i}		c_{2i}	
			+	-		+	-	+	-	+	-		+	-	+	-	+	-
c=0	110	87.4	18.0	3.6	59.5	18.0	1.8	5.4	1.0	1.8	1.8	75.7	10.8	20.7	1.8	1.0	3.6	0.0
0<c<0.1	62	96.8	16.1	3.2	72.6	21.0	4.8	8.1	6.5	6.5	0.0	82.3	9.7	14.5	6.5	1.6	1.6	4.8
0.1<c<0.2	97	84.5	21.6	4.1	52.6	23.7	0.0	10.3	2.1	2.1	2.1	71.1	3.1	13.4	8.2	2.1	3.1	4.1
0.2<c<0.3	94	72.3	18.1	0.0	18.1	20.2	0.0	12.8	0.0	2.1	5.3	53.2	2.1	14.9	3.2	6.4	8.5	1.1
0.3<c<0.4	53	61.1	13.0	1.9	20.4	13.0	0.0	9.3	1.9	0.0	5.6	33.3	5.6	16.7	1.9	3.7	5.6	1.9
0.4<c<0.6	45	33.3	2.2	0.0	13.3	8.9	0.0	2.2	4.4	4.4	2.2	24.4	2.2	8.9	2.2	0.0	2.2	0.0
c>0.6	15	30.8	0.0	0.0	7.7	7.7	0.0	0.0	0.0	7.7	0.0	7.7	0.0	7.7	0.0	0.0	0.0	0.0

Parameter estimates are from the following equations:
Base Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{xt} + \varepsilon_{it}$ (Equation 1)
Asymmetry Model: $R_{it} = \alpha_i + \beta_i R_{mt} + \beta_i^D D_m R_{mt} + \gamma_i R_{xt} + \gamma_i^D D_x R_{xt} + \varepsilon_{it}$ (Equation 2)
Time-varying Model: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + \varepsilon_{it}$ (Equation 3)

Table 6: Significant parameter estimate proportions by censoring portfolio for model including both asymmetry and time varying exposures at the 5% significance level

Censoring Proportion	b_{1i}	b_{2i}		b_{1i}^D		b_{2i}^D		c_{1i}		c_{2i}		c_{1i}^D		c_{2i}^D	
		+	-	+	-	+	-	+	-	+	-	+	-	+	-
c=0	51.4	6.3	7.2	19.8	1.8	0.0	4.5	1.8	1.0	1.8	1.8	0.0	1.0	1.0	1.0
0<c<0.1	54.8	4.8	4.8	17.7	1.6	1.6	1.6	3.2	3.2	3.2	1.6	3.2	0.0	1.6	1.6
0.1<c<0.2	43.3	3.1	10.3	17.5	0.0	3.1	3.1	12.4	0.0	4.1	5.2	2.1	4.1	7.2	3.1
0.2<c<0.3	20.2	0.0	4.3	20.2	0.0	0.0	6.4	4.3	4.3	7.4	2.1	2.1	4.3	2.1	2.1
0.3<c<0.4	13.0	1.9	3.7	14.8	0.0	0.0	0.0	1.9	0.0	3.7	0.0	0.0	0.0	0.0	1.9
0.4<c<0.6	6.7	2.2	2.2	13.3	0.0	0.0	13.3	2.2	2.2	0.0	2.2	2.2	2.2	2.2	0.0
c>0.6	15.4	7.7	0.0	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.4

Parameter estimates are from the following equations: $R_{it} = \alpha_i + b_{1i} R_{mt} + b_{2i} R_{mt}/h_{mt} + b_{1i}^D D_m Rmt + b_{2i}^D D_m R_{mt}/h_{mt} + c_{1i} R_{xt} + c_{2i} R_{xt}/h_{xt} + c_{1i}^D D_x R_{xt} + c_{2i}^D D_x R_{xt}/h_{xt}\ \varepsilon_{it}$ (Equation 6)

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