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# Influence of financial distress on foreign exchange exposure

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## Abstract

**Purpose** – The purpose of this paper is to investigate whether a non-monotonic relationship may exist between financial distress and foreign exchange (FX) exposure. The authors hypothesize that firms with higher FX exposures are those with the lowest levels of financial distress because the costs of hedging exceed the benefits and those with highest levels of financial distress due to the conflict of interest between shareholders and bondholders.

**Design/methodology/approach** – The methodology allows for the possibility of a non-monotonic relation between financial distress and FX exposure for firms known to have ex-ante exposures. The approach is to include a Black-Scholes-Merton financial distress measure and standard accounting-based financial distress measures.

**Findings** – The results support the hypothesis of a non-monotonic relationship between financial distress and exposure; companies with the lowest and highest levels of financial distress are willing to bear greater FX exposures.

**Originality/value** – The authors examine whether a non-monotonic relationship may exist between distress and FX exposure. Intuition for this non-monotonic relationship is provided by Stulz (1996) as he describes the risk management practices of firms with low, medium, and high default probabilities.

**Keywords** Default, Risk management, Currency hedging, Financial distress, Foreign exchange exposure, Bankruptcy

**Paper type** Research paper

## 1. Introduction

The objective of this study is to investigate whether corporate foreign exchange (FX) exposure is influenced by financial distress. In particular, we examine whether a non-monotonic relationship may exist between distress and exposure. The intuition for this non-monotonic relationship is provided by Stulz (1996) as he describes the risk management practices of firms with low, medium, and high default probabilities.

In the presence of transactions costs, a firm with a low level of financial distress may conclude that the expected benefit of risk management does not outweigh its cost. In effect, this is in accordance with the Smith and Stulz (1985) theory that hedging to reduce a risk exposure may have little value for a firm with a low probability of default. In the mid-range of financial distress, a value-maximizing firm may be less willing to bear risk exposure and thus initiate risk management activities in order to avoid the expected costs of financial distress.

**JEL Classifications — F23, F31**

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For firms with high levels of financial distress, the work by Jensen and Meckling (1976) helps predict that firms with high levels of financial distress are less likely to undertake actions to reduce their risk exposure. Jensen and Meckling describe how a conflict of interest between shareholders and bondholders may lead managers-shareholders of a high distress firm to undertake actions that increase the volatility of the firm's assets. Campbell and Kracaw (1990) examine how the conflict of interest between shareholders and bondholders can influence the hedging decision. They develop a model to evaluate the impact of observable risk on this so-called "asset substitution problem" and find that increases in observable exposure provide incentives for managers-shareholders to also increase unobservable exposure. The study by Fang and Zhong (2004) also provides evidence that firms with high or low levels of financial distress subsequently increase their risk to a greater extent than other firms. Additionally, Fehle and Tsyplakov (2005) develop a dynamic hedging model that incorporates financial distress costs, taxes, and transaction costs associated with hedging. While they mainly focus on the multi-period hedging decisions at the firm level, their work is suggestive of a cross-sectional non-monotonic relationship between financial distress and risk management; firms with high levels of financial distress are less likely to undertake hedging actions to reduce their risk exposure.

The specific risk context that we investigate is exposure to FX risk, a risk dimension that can affect corporations through both direct and indirect channels. Our hypothesis is that firms willing to bear higher FX risk exposures are: those with the lowest levels of financial distress because the costs of hedging exceed the benefits; and those with highest levels of financial distress due to the conflict of interest between shareholders and bondholders.

There are empirical studies that provide support for our investigation of the specific link between distress and FX exposure. Géczy *et al.* (1997) concentrate on the determinants of currency derivative usage by firms. While they find that firms with extensive FX exposure, growth opportunities, and financing constraints are more likely to use currency derivatives, they do not find proxies for financial distress to be significant factors. He and Ng (1998) find that keiretsu firms have greater FX exposure than non-keiretsu firms and attribute this result to different hedging motives. Insightfully, they conclude that, because keiretsu firms have a lower bankruptcy probability, keiretsu firms are more likely to bear exposure to exchange rate risk. Lel (2012) examines the role of corporate governance on the use of currency derivatives, but he also provides some insight on the impact of distress on currency derivative use. He shows that financial leverage, as a proxy for distress, is inversely related with FX derivate usage, thus should be directly related to FX exposure. He further finds that weakly governed firms with greater distress costs are less likely to use derivatives, thus presumably more likely to have FX exposure. One explanation he provides is that equity holders benefit from increasing the exposure of the firm in cases where the firm is near bankruptcy.

We believe our methodology and data provide a more direct assessment of the linkages between FX exposure and the probability of financial distress in four important ways. First, our methodology allows for the possibility of a non-monotonic relation between financial distress and FX exposure. Second, our analyses include a Black-Scholes-Merton financial distress measure used by Vassalou and Xing (2004), Hillegeist *et al.* (2004), Duffie *et al.* (2007), and Huang and Lee (2013), as well as the standard accounting-based financial distress measures of Altman (1968) and Ohlson (1980). The Black-Scholes-Merton measure is especially useful since it provides an overall assessment of the degree of financial distress by the financial market.

This proximity to default measure takes into consideration, for example, the influence of various industry and competitive factors on the value of the firm's assets. Third, we select firms known to have ex-ante exposure, as do Géczy *et al.* (1997). Fourth, our cash-flow-based method allows us to examine the exposures of firms without natural hedges that may eliminate their exposures.

For a set of US-based MNCs known to have FX cash flow exposures in the eurozone, we examine the cross-sectional influence of market-based and accounting-based measures of default on FX cash flow exposure. For those firms willing to bear risk exposure, we find that those with the highest likelihood of default choose to bear higher levels of exposures to FX risk and those with the lowest likelihood of default are more willing to bear FX exposure, likely because the expected benefits of FX risk management do not outweigh the transactions and other costs. Thus, we conclude that the proximity to default can affect the willingness of MNCs to bear FX exposure, and our results support a non-monotonic influence.

The remaining paper is organized as follows. Section 2 explains how we determine the degree of FX exposure. The description of the sample and the empirical method for estimating FX exposure are contained in this section. In Section 3, we describe our measures of financial distress. Section 4 presents our statistical analyses and reports the results, and Section 5 concludes the paper.

## 2. Estimating the degree of FX exposure net of hedging

We start with identifying a sample of firms with ex-ante exposure to exchange rate risk. We presume that US MNCs with a substantial degree of foreign sales are, ipso facto, exposed to FX rates on an ex-ante basis. Without screening for ex-ante exposure, we could not conclude that the firm with no empirically detectable exposure had chosen to hedge, since plausibly that firm simply may not be materially exposed. In other words, if a firm does not hedge with financial instruments or with operational strategies, we expect to find cash flow sensitivity to changing exchange rates. As described in Section 2.2, we detail our method on identifying those firms with cash flow sensitivity to changing exchange rates.

Our approach empirically assesses the degree of exposure, net of hedging. While we are not able to measure directly the extent of hedging, we regard the line of causality from financial distress to exposure net of hedging to be empirically fruitful. From a broader perspective in Finance, there is interest in how financial stress affects the willingness of firms to bear exposure. With regard to FX risk, it is common to separately discuss transaction exposure and economic exposure. Firms can adopt a range of approaches, including the use of currency derivatives and international cash management, to hedge transaction exposure. However, longer-term economic or operational exposures are typically managed by changing the structure of the MNC's cross border input, output, and financial sourcing flows. Support for our view is provided, for example, when Petersen and Thiagarajan (2000, p. 5) state, "In practice, the problem [measurement of risk exposure] is more difficult, since risk exposure can only be seen through the firm's financial disclosures, which might not fully reflect the true economic exposure […]".

### *2.1 Sample selection*

We identify US MNCs that generate substantial foreign sales in Europe, since this is a region where US firms are actively involved, thus permitting a reasonable sample size. Furthermore, focussing on a specific region may improve our ability to measure exposure because we can measure it with respect to a bilateral exchange rate instead of a broad exchange rate index. Due to an averaging out effect, broadly defined exchange rate indexes may obscure the detection of exposure (e.g. Bartov and Bodnar, 1994; Allayannis and Ofek, 2001; Priestley and Odegaard, 2007).

To identify our sample of US MNCs with heavy European involvement, we obtained data from Compustat's Research Insight database for all US firms in 1997 that had at least 20 percent of total sales from Europe and total sales of at least \$10 million. The year 1997 is selected because it is the latest point in time when geographic segment disclosure was required. Until 1998, disclosure of geographic information was required under SFAS No. 14. The FASB changed segment reporting requirements when it issued SFAS No. 131, which became effective for fiscal years beginning after December 15, 1997. Effectively, firms are no longer required to report both line of business and geographic segment information. SFAS No. 131 requires segment disclosure according to the type of segments that management uses in assessing operations, which may or may not include geographic segments.

The 409 US MNCs that meet these criteria are screened further to ensure that adequate quarterly operating income before depreciation and amortization data are available to estimate company cash flow exposures. We select our period of analysis, 1992-2002, to be centered around 1997. This period allows for using up to five years of data before and after 1997. Our additional requirement, of at least 28 (or seven years) contiguous quarterly operating income observations, assures robust estimation and results in a sample of 211 firms.

Studies show considerable variation in FX exposures within the same industry for industries comprised of firms with large exposures; for example, see Tufano (1996) for gold mining companies and Haushalter (2000) for oil and gas producers. Some firms choose to remain entirely unhedged, while other firms choose to hedge the great majority of their exposures. Firms with a strict policy of hedging their entire exposures are not likely to be sensitive to financial distress. Similarly, firms with natural hedges that effectively eliminate their exposures are also not likely to be sensitive to financial distress. We identify and focus on a subset of firms that demonstrate statistically significant cash flow sensitivity to FX risk.

*2.2 Measuring FX exposures*

We adopt a method of estimating FX exposure that measures the sensitivity of cash flows generated by the firm to changing exchange rates. Martin and Mauer (2003a, b) advocate an approach that decomposes exposure into transaction exposure and economic exposure by including contemporaneous and lagged effects of exchange rate movements. The cash flow sensitivities to contemporaneous or near-term exchange rate movements represent net transaction exposure, while the cash flow sensitivities to longer-term lagged exchange rate movements represent net economic exposure. The cash flow sensitivity measures are estimates of exposures that remain after the firm has engaged in both financial and operational hedging.

Following this approach, an optimal lag length for each company is established using the maximum likelihood criterion developed by Akaike (1973). Subsequently, the polynomial distributed lag technique developed by Almon (1965) is applied to estimate the FX exposures, $w(q)$, for each MNC as described below. A third degree polynomial is adopted as sufficiently accommodating a wide range of lag patterns:

$$UI_t = c + \sum_{q=0}^{L} w(q)X_{t-q} + u_t \quad (1)$$

where $UI_t$ is the standardized unanticipated operating income before adjustment for depreciation for time $t$; $X_{t-q}$ the percent change in the European exchange rate for time $t-q$; the ECU/USD rate is used to 1999 and EUR/USD thereafter; $c$ the intercept; $w(q)$ the weights or FX exposure for time $q$, where $q = 0$ to $L$; $L$ the lag length determined by the Akaike (1973) criterion that ranges from 0 to 12; $u_t$ the error term for time $t$.

$UI_t$ is calculated as the residuals $ui_t$ divided by their standard deviation in the regression of current operating income on the operating income four periods prior $I_t = \theta_1 + \theta_2 I_{t-4} + ui_t$, where $I_t$ is operating income before adjustment for depreciation at time $t$ and $ui_t$ is the residual or unanticipated operating income at time $t$, and $\theta_1$ and $\theta_2$ are regression coefficients. The transformation of the raw cash flow data into the standardized unanticipated operating income variable has the effect of minimizing spurious correlations that may arise from the use of lagged exchange rates as independent variables.

Significant FX exposure is assessed by the $F$-statistic generated from estimating Equation (1). We define significance as at the 10 percent level or below. In cases where the model is statistically significant, the sum of the weights, $w(q)$, is interpreted as the degree of FX exposure net of financial and operational hedging activities. It can be interpreted that the firm is willing to bear FX exposures if the model is statistically significant.

To maintain consistency in our cross-sectional analyses, we compute the mean absolute foreign exchange exposure ($MAFX$) for each company as follows:

$$MAFX = \frac{\left|\sum_{q=0}^{L} w(q)\right|}{L+1} \tag{2}$$

Absolute values are taken because large values, either positive or negative, indicate high degrees of exposure. In other words, it is not the direction of influence but the degree of impact that is important. The $MAFX$ over the entire lag structure, $MAFX_{0\text{-}12}$, is our primary dependent variable in the cross-sectional analyses. For alternate dependent variables, we also compute and utilize exposure measures that are close in concept to transaction and economic exposures. $MAFX$ for lags of up to one year, $MAFX_{0\text{-}4}$, can be viewed as capturing the short-term consequences of exchange rate risk (i.e. transaction exposure). $MAFX$ for lags eight to 12, $MAFX_{8\text{-}12}$, can be viewed as a measuring the impact of longer-term effects of exchange rate risk (i.e. economic exposure).

## 3. Measures of financial distress

To evaluate whether firms willing to bear FX risk exposure are those with low and high levels of financial distress, it is necessary to estimate the degree of distress. For each firm, we compute a market-based measure of financial distress and two accounting-based measures using readily available data. Following Vassalou and Xing (2004), Hillegeist *et al.* (2004), Duffie *et al.* (2007), and Huang and Lee (2013), we derive a market-based measure of default likelihood from the Black and Scholes (1973) and Merton (1974) option pricing model. The two accounting-based measures are the Altman (1968) *Z*-score and Ohlson (1980) *O*-score.

### *3.1 Market-based measure of financial distress*

The market-based measure of financial distress is a default likelihood indicator that is based on information embedded in equity prices, and thus should contain forward-looking information and provide an overall assessment of the degree of financial distress by the financial market. Furthermore, the option pricing model approach incorporates the important volatility factor. Specifically, we estimate this market-based default measure, *BSMDM*, for each MNC per day as:

$$BSMDM = N\left(-\frac{\ln(V_{A,t}/X_t) + (\mu - \frac{1}{2}\sigma_{A,t}^2)T}{\sigma_{A,t}T}\right) \quad (3)$$

where $V_{A,t}$ is the market value of assets on day $t$, $X_t$ is the book value of total liabilities and gathered for each year from Compustat, $\mu$ is the drift and calculated as the daily rolling mean of the change in $\ln V_A$ over the previous year, $\sigma_{A,t}$ is the annualized standard deviation of daily asset returns, $T$ is time to maturity and set equal to one, and $N$ is the cumulative density function of the standard normal distribution. The two unobservable variables, $V_{A,t}$ and $\sigma_{A,t}$, are estimated simultaneously using the iterative process described below.

The Black-Scholes-Merton option pricing model is used to compute the two unobservable variables, $V_A$ and $\sigma_A$, since equity is viewed as a call option on the value of the firm's assets:

$$V_E = V_A N(d_1) - Xe^{-rT}N(d_2) \quad (4)$$

where $V_E$ is the market value of equity from *CRSP*, $r$ is the risk-free rate and represented by the end of month nominal one-year US Treasury bill rates from the Federal Reserve, $d_1$ and $d_2$ are defined below, and the remaining variables have been previously defined:

$$d_1 = \frac{\ln(V_A/X) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A T} \quad (5)$$

$$d_2 = d_1 - \sigma_A\sqrt{T} \quad (6)$$

The values of $V_A$ and $\sigma_A$ are estimated simultaneously by an iterative process outlined in Hillegeist *et al.* (2004). This iterative process uses a Newton search algorithm to estimate $V_A$ and $\sigma_A$ from Equation (4) and the optimal hedge equation, $\sigma_E = (V_A\, e^{-T}N(d_1)\sigma_A)/V_E$. As an initial value for $\sigma_A$, we use $\sigma_A = \sigma_E V_E/(V_E + X)$, where $\sigma_E$ is the annualized volatility computed as the standard deviation of daily equity returns multiplied by the square root of the number of trading days in the year. We then use the estimated values of $V_A$, $\sigma_A$, and $\mu$, along with T and X, to calculate the default measure using Equation (3).

Using this procedure, we calculate the *BSMDM* each day over the 1992-2002 sample period for each MNC. Then, as a way to represent the financial distress of the company over the full sample period, the mean of the *BSMDM*s is calculated and used in the regression analysis as a determinant of FX exposure.

### *3.2 Accounting-based measures of financial distress*

In addition to the market-based measure of financial distress previously described, we evaluate whether the standard accounting-based distress measures (*ADM*s) of Altman (1968) and Ohlson (1980) are significantly related to FX exposure. As a way to represent the financial distress of the MNC over the full sample period, mean *ADM*s are calculated and used in the regression analysis as determinants of FX exposure.

The Altman-*Z* and Ohlson-*O* scores are based on the statistical linkage between data on corporate defaults and such accounting measures as: liquidity ratios (the current ratio; working capital to total assets); asset productivity measures (EBIT to total assets; net income to total assets); capital structure (market value of equity to total liabilities; total liabilities to total assets); profitability over time (retained earnings divided by total assets; the scaled year-to-year change in net income); and an interest coverage ratio (cash flow from operations to total liabilities). Data for these measures are gathered from Compustat's Research Insight database. See Altman (1968) and Ohlson (1980) for a full description of the methodologies to compute the *Z*-scores and *O*-scores, respectively. Our paper reports results using these original methods; however, the use of updated Altman and Ohlson equations do not change the conclusions of this study.

## 4. Cross-sectional link between financial distress and FX exposure

We hypothesize that there is a non-monotonic relation between the measures of financial distress and FX exposure. Using a cross-sectional framework, we assess whether firms willing to bear FX risk exposure are firms with low levels of financial distress and firms with high levels of financial distress.

In general terms, our cross-sectional model, summarized in Equation (7), relates financial distress to FX exposure, while controlling for European sales presence and a firm scale measure:

$$MAFX_i = f(BSMDM_i, ADM_i, ESALES_i, SIZE_i) \tag{7}$$

where $MAFX_i$ is the FX exposure for MNC $i$, $BSMDM_i$ is the Black-Scholes-Merton distress measure for MNC $i$, $ADM_i$ is the accounting-based distress measure for MNC $i$, $ESALES_i$ is the percent of total sales in Europe for MNC $i$, $SIZE_i$ is the natural log of total assets for MNC $i$.

The cross-sectional analyses use the three alternative dependent variables measuring FX exposure, $MAFX_{0\text{-}12}$, $MAFX_{0\text{-}4}$, and $MAFX_{8\text{-}12}$, that were developed in Section 2. Table I provides descriptive statistics for the three *MAFX* measures for the full sample of 211 MNCs in Panel A and for the subset of 91 MNCs with statistically significant exposure to European exchange rate risk in Panel B. The subset of 91 MNCs has demonstrated statistical significance in Equation (1) at the 10 percent level or below based on the *F*-test. Note that, for the full sample and the subset, a smaller number of companies had optimal lags longer than seven quarters.

The independent variables are the financial distress measures, *BSMDM* and *ADM* developed in Section 3, along with two control variables: percent of European sales, and firm size. Table II reports descriptive statistics for the independent variables for the full sample of 211 MNCs (Panel A) and for the subset of 91 significantly exposed MNCs (Panel B). The Table II data suggest differences in the financial distress measures between the two panels. The median values of the accounting-based measures are at least 25 percent lower for Panel B, compared with the full sample, indicating a higher level of financial stress in the exposed MNCs as measured by the *ADM* variables. In contrast, the median values of the *BSMDM* measure suggest that the exposed MNCs have as a group a lower level of financial stress (lower by 25 percent) when compared with the full sample. Also, these summary statistics indicate

| | $MAFX_{0\text{-}12}$ | $MAFX_{0\text{-}4}$ | $MAFX_{8\text{-}12}$ |
|---|---|---|---|
| *Panel A: across the full sample of 211 MNCs* | | | |
| Mean | 0.0210 | 0.0211 | 0.0278 |
| Median | 0.0174 | 0.0169 | 0.0224 |
| Minimum | 0.0000 | 0.0000 | 0.0017 |
| Maximum | 0.0868 | 0.2644 | 0.0926 |
| $n$ | 211 | 211 | 92 |
| *Panel B: across the subset of 91 significantly exposed MNCs* | | | |
| Mean | 0.0360 | 0.0333 | 0.0400 |
| Median | 0.0318 | 0.0346 | 0.0314 |
| Minimum | 0.0208 | 0.0056 | 0.0042 |
| Maximum | 0.0767 | 0.0623 | 0.1543 |
| $n$ | 91 | 91 | 72 |

**Notes:** This table reports summary statistics for the *MAFX* measures across lag groups for the full sample and the subset of significantly exposed firms. The *MAFX* for each MNC is the average absolute value of the sum of the weights generated from the following model that is estimated using the Almon (1965) PDL technique:

$$UI_t = c + \left(\sum_{q=0}^{L} w(q)X_{t-q}\right) + u_t$$

$UI_t$ is the standardized unanticipated operating income before depreciation at time $t$ as a proxy for cash flows, $X_{t-q}$ is the percent change in the euro rate at time $t-q$, $c$ is the intercept, $w(q)$ are the response coefficients which represent the marginal sensitivity of cash flows to exchange rate risk at time 0 through $L$, $L$ is the optimal lag identified with the Akaike (1973) criterion, and $u_t$ is the stochastic error term. Statistical significance is defined when the model is significant at the 5 percent level

**Table I.**
Mean absolute foreign exchange exposure (*MAFX*) estimates

| | *BSMDM* | *ALTMANZ* | *OHLSONO* | *ESALES* | *ASSETS* ($M) |
|---|---|---|---|---|---|
| *Panel A: across the full sample of 211 MNCs* | | | | | |
| Mean | 0.0380 | −182.82 | −20.32 | 0.3476 | 3,542.9 |
| Median | 0.0085 | −7.88 | −0.80 | 0.2991 | 404.1 |
| Minimum | 0.0000 | −7,282.77 | −915.08 | 0.2011 | 6.4 |
| Maximum | 0.4056 | 7.83 | 124.55 | 0.9820 | 255,408.0 |
| $n$ | 171 | 194 | 202 | 211 | 199 |
| *Panel B: across the subset of 91 significantly exposed MNCs* | | | | | |
| Mean | 0.0282 | −318.81 | −42.18 | 0.3449 | 1,732.8 |
| Median | 0.0061 | −10.04 | −1.33 | 0.2893 | 399.8 |
| Minimum | 0.0000 | −7,282.77 | −915.08 | 0.2022 | 6.4 |
| Maximum | 0.4056 | 7.83 | 34.31 | 0.9820 | 21,453.0 |
| $n$ | 76 | 84 | 87 | 91 | 85 |

**Notes:** *BSMDM* is the average of daily Black-Scholes-Merton distress measures over the 1992-2002 period. *ALTMANZ* and *OHLSONO* are the averages of annual Altman-*Z* and Ohlson-*O* accounting-based distress measures over the 1992-2002 period. *ESALES* is the proportion of European sales in 1997. *ASSETS* is the average of total assets over 1992-2002. The number of observations, $n$, differ across variables due to data availability

**Table II.**
Summary statistics for independent variables

that there are outliers within Altman-*Z*, Ohlson-*O*, and level of assets. Thus, we winsorize Altman-*Z* and Ohlson-*O*, and transform assets by the natural logarithm.

Our first set of regression results is obtained using the OLS method in a traditional linear functional form to estimate the cross-sectional model described in Equation (7), presented in Table III. In these results, the financial stress variables are not segmented into low, medium, and high stress categories. Two separate models are evaluated since the two proxies for the accounting-based measures of financial distress, the Altman-*Z*



| | Overall exposure: $MAFX_{0\text{-}12}$ | | Transaction exposure: $MAFX_{0\text{-}4}$ | | Economic exposure: $MAFX_{8\text{-}12}$ | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 | Model 1 | Model 2 |
| *Panel A: full sample of MNCs* | | | | | | |
| Intercept | 0.0070 | 0.0105 | 0.0213 | 0.0208 | 0.0057 | 0.0049 |
| | (1.00) | (1.57) | (1.92*) | (1.95**) | (0.37) | (0.34) |
| *BSMDM* | 0.0421 | 0.0397 | 0.0017 | 0.0041 | −0.0413 | −0.0425 |
| | (1.83*) | (1.68*) | (0.05) | (0.11) | (−0.99) | (−1.03) |
| *ALTMANZ*[a] | −0.0021 | – | −0.0004 | – | 0.0022 | – |
| | (−1.47) | | (−0.18) | | (0.88) | |
| *OHLSONO*[a] | – | −0.0055 | – | −0.0072 | – | 0.0216 |
| | | (−0.48) | | (−0.40) | | (1.08) |
| *ESALES* | −0.0051 | −0.0057 | −0.0152 | −0.0146 | 0.0086 | 0.0061 |
| | (−0.56) | (−0.61) | (−1.03) | (−0.98) | (0.44) | (0.31) |
| *LNASSETS* | 0.0020 | 0.0016 | 0.0008 | 0.0009 | 0.0038 | 0.0040 |
| | (2.52***) | (2.12**) | (0.66) | (0.71) | (1.97**) | (2.29**) |
| *n* | 156 | 156 | 156 | 156 | 65 | 65 |
| *F* | 2.19* | 1.61 | 0.48 | 0.51 | 2.65** | 2.77** |
| Adj. $R^2$ | 0.0297 | 0.0155 | −0.0137 | −0.0128 | 0.0937 | 0.0995 |
| *Panel B: subset of significantly exposed MNCs* | | | | | | |
| Intercept | 0.0252 | 0.0265 | 0.0186 | 0.0200 | 0.0048 | 0.0090 |
| | (3.66***) | (3.86***) | (2.19**) | (2.35**) | (0.48) | (0.33) |
| *BSMDM* | 0.0782 | 0.0743 | 0.1170 | 0.1150 | −0.1591 | −0.1702 |
| | (2.82***) | (2.64***) | (3.42***) | (3.30***) | (−1.21) | (−1.29) |
| *ALTMANZ*[a] | 0.0003 | – | −0.0004 | – | 0.0016 | – |
| | (0.36) | | (−0.43) | | (0.65) | |
| *OHLSONO*[a] | – | 0.0045 | – | −0.0005 | – | 0.0202 |
| | | (0.79) | | (−0.78) | | (0.96) |
| *ESALES* | 0.0003 | −0.0007 | 0.0090 | 0.0087 | −0.0131 | −0.0173 |
| | (0.03) | (−0.08) | (0.82) | (0.79) | (−0.40) | (−0.52) |
| *LNASSETS* | 0.0014 | 0.0013 | 0.0014 | 0.0013 | 0.0070 | 0.0067 |
| | (1.81*) | (1.72*) | (1.46) | (1.33) | (2.09**) | (2.05**) |
| *n* | 72 | 72 | 72 | 72 | 55 | 55 |
| *F* | 2.62** | 2.76** | 2.93** | 2.87** | 2.33* | 2.48* |
| Adj. $R^2$ | 0.0835 | 0.0902 | 0.0979 | 0.0955 | 0.0900 | 0.0989 |

**Notes:** *BSMDM* is the average of daily Black-Scholes-Merton distress measures over the 1992-2002 period. *ALTMANZ* and *OHLSONO* are the averages of annual Altman-*Z* and Ohlson-*O* accounting-based distress measures over the 1992-2002 period. *ESALES* is the proportion of European sales in 1997. *LNASSETS* is the natural log of the average of total assets over 1992-2002. Model 1 (Model 2) includes the Altman-*Z* (Ohlson-*O*) score as the accounting-based measure of financial distress. The dependent variables are the three *MAFX* measures across lag groups that have been estimated over the 1992-2002 period. [a]For tabulating purposes, these coefficients have been scaled by a factor of E02. *,**,***Significant at least at the 10, 5 and 1 percent levels, respectively

**Table III.** Cross-sectional regression results and the Ohlson-*O*, are significantly correlated. Panel A shows the results for the full sample of 211 MNCs. Panel B examines the subset of 91 significantly exposed MNCs; the results of the subset are important because we have identified that these companies are willing to bear FX risk exposure.

The results for the full sample in Table III, Panel A show that the Black-Scholes-Merton financial distress indicator is marginally significant when examining overall exposure, $MAFX_{0\text{-}12}$. Thus, we have some support for the hypothesis that the degree of exposure is higher when financial distress is higher. The accounting-based measures are not statistically significant for any of the models. Firm size is found to be positive and significantly related to exposure. This result indicates that larger MNCs have greater exposure and seemingly is in contrast with studies purporting that economies of scale in hedging FX risk exist (e.g. Mian, 1996; Géczy *et al.*, 1997; Bodnar *et al.*, 1998; Dominguez and Tesar, 2006). However, our results may occur because large firms frequently are more complex in their cross-border flows and, through this complexity, inherently have higher levels of economic exposure. The previous studies have focussed on economies of scale in hedging transaction exposures. Here, it can be seen that the positive influence of firm size on exposure occurs with economic exposure as the dependent variable, and not with transaction exposure as the dependent variable. It is plausible that MNCs are not achieving economies of scale in hedging their economic exposures and/or that larger MNCs simply have a greater degree of economic exposure.

Panel B of Table III additionally shows the *BSMDM* factor to be positive and significant in models run on overall exposure, $MAFX_{0\text{-}12}$, and transaction exposure, $MAFX_{0\text{-}4}$. For the MNCs willing to bear FX risk exposure, the degree of exposure is higher when financial distress is higher. This finding supports the view that hedging is limited in the case of firms with greater financial distress. However, the Table III analysis constrains financial distress to affect exposure monotonically.

We hypothesize that the marginal effect of financial distress on exposure may differ across ranges of financial distress. More specifically, we expect that exposure is decreasing with financial distress over lower ranges of distress, and that exposure increases over the higher ranges of distress. To test this hypothesis, we adjust our analysis to specify Equation (7) to be piecewise linear. We divide our sample into quarters on the basis of the *BSMDM* measure and create two variables, *LOBSM* and *HIBSM*, to isolate the relationship over the lowest and highest quartile ranges of financial distress, respectively. We also divided our sample into quartiles on the basis of the Altman-*Z* and Ohlson-*O* scores to determine whether a piecewise linear relationship may exist with these variables. These results are omitted since these variables were not statistically significant.

*LOBSM* is defined as the *BSMDM* value for all observations falling in the first quartile, and for all other observations the highest *BSMDM* value in the first quartile is assigned. *HIBSM* is calculated as the *BSMDM* value for all observations falling in the fourth quartile minus the lowest *BSMDM* value in the fourth quarter, and for all other observations *HIBSM* is assigned zero. We also evaluated the relationship between *BSMDM* and exposure for observations in the middle quartiles to isolate the relationship over the middle range of financial distress. We did not find these middle quartile analyses to be statistically significant, and thus omit the results.

The results using the piecewise regression technique are displayed in Table IV. As in Table III, two separate models are evaluated that differ by the proxy used to represent *ADM*, the accounting-based measure of financial distress. And again,

| | Overall exposure: $MAFX_{0\text{-}12}$ | | Transaction exposure: $MAFX_{0\text{-}4}$ | | Economic exposure: $MAFX_{8\text{-}12}$ | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 | Model 1 | Model 2 |
| *Panel A: full sample of MNCs* | | | | | | |
| Intercept | 0.0053 | 0.0088 | 0.0209 | 0.0201 | 0.0100 | 0.0099 |
| | (0.70) | (1.17) | (1.71*) | (1.68*) | (0.57) | (0.59) |
| *LOBSM* | 4.3255 | 4.2112 | 2.3539 | 3.0834 | −9.5948 | −10.8895 |
| | (0.61) | (0.58) | (0.21) | (0.27) | (−0.66) | (−0.74) |
| *HIBSM* | 0.0519 | 0.0500 | −0.0071 | −0.0050 | −0.0430 | −0.0445 |
| | (1.89*) | (1.79*) | (−0.16) | (−0.11) | (−0.92) | (−0.95) |
| *ALTMANZ*[a] | −0.0021 | – | −0.0004 | – | 0.0024 | – |
| | (−1.48) | | (−0.18) | | (0.94) | |
| *OHLSONO*[a] | – | −0.0063 | – | −0.0074 | – | 0.0242 |
| | | (−0.55) | | (−0.40) | | (1.18) |
| *ESALES* | −0.0053 | −0.0058 | −0.0157 | −0.0151 | 0.0099 | 0.0072 |
| | (−0.57) | (−0.62) | (−1.06) | (−1.01) | (0.50) | (0.36) |
| *LNASSETS* | 0.0021 | 0.0017 | 0.0008 | 0.0009 | 0.0035 | 0.0038 |
| | (2.60***) | (2.22**) | (0.64) | (0.69) | (1.81*) | (2.09**) |
| *n* | 156 | 156 | 156 | 156 | 65 | 65 |
| *F* | 1.94* | 1.48 | 0.39 | 0.42 | 2.18* | 2.30* |
| Adj. $R^2$ | 0.0294 | 0.0152 | −0.0200 | −0.0191 | 0.0844 | 0.0920 |
| *Panel B: subset of significantly exposed MNCs* | | | | | | |
| Intercept | 0.0345 | 0.0367 | 0.0240 | 0.0257 | 0.0320 | 0.0416 |
| | (4.44***) | (4.68***) | (2.44**) | (2.57***) | (1.00) | (1.28) |
| *LOBSM* | −54.0197 | −58.0392 | −22.6954 | −24.2686 | −183.6481 | −203.7249 |
| | (−1.90*) | (−2.04**) | (−0.63) | (−0.67) | (−1.70*) | (−1.87*) |
| *HIBSM* | 0.0960 | 0.0911891 | 0.1347 | 0.1324 | −0.1326 | −0.1414 |
| | (3.24***) | (3.06***) | (3.59***) | (3.48***) | (−0.90) | (−0.97) |
| *ALTMANZ*[a] | 0.0004 | – | −0.0002 | – | 0.0019 | – |
| | (0.60) | | (-0.28) | | (0.75) | |
| *OHLSONO*[a] | – | 0.0066 | – | 0.0009 | – | 0.0260 |
| | | (1.19) | | (0.13) | | (1.25) |
| *%ESALES* | −0.0005 | −0.0018 | 0.0086 | 0.0081 | −0.0175 | −0.0236 |
| | (−0.05) | (−0.21) | (0.79) | (0.73) | (−0.54) | (−0.73) |
| *LNASSETS* | 0.0008 | 0.0006 | 0.0010 | 0.0009 | 0.0053 | 0.0046 |
| | (1.01) | (0.82) | (1.02) | (0.86) | (1.51) | (1.33) |
| *n* | 72 | 72 | 72 | 72 | 55 | 55 |
| *F* | 3.17*** | 3.44*** | 2.61** | 2.59** | 2.47** | 2.72** |
| Adj. $R^2$ | 0.1328 | 0.1464 | 0.1017 | 0.1009 | 0.1200 | 0.1375 |

**Notes:** *LOBSM* is the average of daily Black-Scholes-Merton distress measures over the 1992-2002 period if the measure is less than the bottom quartile value, otherwise it is the bottom quartile value. *HIBSM* is the average of daily Black-Scholes-Merton distress measures over the 1992-2002 period minus the top quartile value if this measure is greater than the top quartile, otherwise it equals zero. *ALTMANZ* and *OHLSONO* are the averages of annual Altman-*Z* and Ohlson-*O* accounting-based distress measures over the 1992-2002 period. *ESALES* is the percent of European sales in 1997. *LNASSETS* is the natural log of the average of total assets over 1992-2002. Model 1 (Model 2) includes the Altman-*Z* (Ohlson-*O*) score as the accounting-based measure of financial distress. The dependent variables are the three *MAFX* measures across lag groups that have been estimated over the 1992-2002 period. [a]For tabulating purposes, these coefficients have been scaled by a factor of E02. *,**,***Significant at least at the 10, 5 and 1 percent levels, respectively

**Table IV.**
Cross-sectional results using a piecewise regression technique

Panel A (Panel B) shows the results for the full sample of MNCs (subset of significantly exposed MNCs).

As in Table III, the full MNC sample in Table IV, Panel A does not show statistical significance in most of the financial distress variables. Only *HIBSM*, is marginally positive and significant, suggesting that firms in the highest financial distress quartile are associated with greater tolerance to FX risk. The results in this table also show the same significance pattern for the scale variable, *LNASSETS*, as was identified in the non-piecewise results seen in Table III. Specifically, the *LNASSETS* coefficients are positive and statistically significant in the models that use the overall exposure and economic exposure measures as dependent variables.

The piecewise results for the subset of statistically exposed MNCs in Table IV, Panel B provide evidence of a non-monotonic relationship between financial distress and FX exposure in the regressions on overall exposure. As a robustness check, we adjust the *t*-values using White's (1980) heteroskedasticity-consistent covariance matrix. The conclusion remains the same; White-adjusted *t*-statistics still show a non-monotonic relationship between financial distress and FX exposure.

For those firms willing to bear exposure (i.e. those MNCs with significant FX exposure that are examined in Panel B), the piecewise variables *HIBSM* and *LOBSM* are statistically significant for the $MAFX_{0\text{-}12}$ values. For *HIBSM*, the positive sign indicates that in the highest financial distress quartile, greater default likelihood is associated with greater tolerance to FX risk. In this analysis, *LOBSM* has a negative sign, consistent with increased willingness to bear risk exposures for firms with the lowest levels of financial distress. In the case of the regression on transaction exposure, $MAFX_{0\text{-}4}$, only the *HIBSM* variable is statistically significant and positive, which is again consistent with the asset substitution problem identified by Jensen and Meckling (1976). Lastly, the regression conducted on economic exposure, $MAFX_{8\text{-}12}$, finds the *LOBSM* to have a negative sign indicating that firms with the lowest levels financial distress may be less concerned with their economic exposures.

## 5. Conclusion

Based in part on the intuition provided by Stulz (1996) for a non-monotonic relationship between financial distress and risk management, we hypothesize that the relationship between default likelihood and the willingness of firms to bear FX risk exposure is non-monotonic. Our study contributes to the literature by empirically investigating this relationship.

For a set of US-based MNCs known to have FX cash flow exposures in the eurozone, we examine the cross-sectional influence of market-based and accounting-based measures of default on FX cash flow exposure. For those firms willing to bear risk exposure, we find that those with the highest likelihood of default choose to bear higher levels of exposures to FX risk, consistent with the asset substitution problem identified by Jensen and Meckling (1976); and those with the lowest likelihood of default are more willing to bear FX exposure, likely because the expected benefits of FX risk management do not outweigh the transactions and other costs associated with such management. The proximity to default can affect the willingness of MNCs to bear FX exposure, and our results support a non-monotonic influence.

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