Online Appendix to: "Global Engagement and Returns Volatility"

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Appendix A: Estimation of firm-specific conditional volatility

We also explore fitting firm-specific GARCH models to estimate the conditional volatility of stock returns to be used as the dependent variable in a static fixed effects panel modelling framework. It is worth noting that conditional volatility has the advantage of producing a forward-looking estimator of volatility over their unconditional counterparts.

We therefore estimate firm-specific conditional volatility models for the 1,474 firms in our sample. We start with GARCH (1,1) as a reference model, since previous research has established that this model tends to perform better than a wide range of other ARCH-type models in terms of forecasting ability (Hansen and Lunde, 2005). As a competing alternative to GARCH (1, 1) we also estimate a higher-order "pure" ARCH model for each firm. After some preliminary investigation based on a small sample of firms, we choose ARCH (3) as a reasonable choice, because a more parsimonious ARCH model entails fewer restrictions to ensure that all coefficients are positive. As a third competing model, we consider a more general model that nests GARCH (1,1), namely the (exponential) EGARCH (2, 1) model. This model not only allows for two-lags of conditional variance terms, but also for asymmetric (leverage) effects between positive and negative shocks to the stock returns. While it is theoretically possible to estimate even more general models, these require more stringent parameters restrictions, which in turn often make it difficult for the maximum likelihood procedure to converge.

We start our estimation of the three ARCH-type models with a constant-only specification for the conditional mean for the sake of model parsimony. For each of the 1,474 firms in the sample, we then conduct model adequacy tests by checking for the absence of serial correlation in the standardized residuals and standardized residuals squared (e.g. see Tsay, 2005 p.109). At this stage any model with standardized residual terms that do not form sequences of i.i.d. random variables is deemed inadequate and therefore discarded. Amongst the adequate models, and again for each firm, we pick the one with the lowest value of the Akaike information criterion and use the fitted values of conditional volatility variable in the subsequent panel data analysis. We find that 973 returns series can be adequately modelled with either GARCH(1,1), EGARCH(2,1) or ARCH(3), with these models providing the best fit for 522, 231 and 220 firms respectively.

For the remaining 501 firms with serially correlated residuals, we re-estimated the three ARCH-type models, but this time with higher order lag terms in the specification of the conditional mean model. After some experimenting on a subsample of firms, an ARMA(4,2) model was found to be adequate in the sense of making the model residual terms behave like i.i.d. random variables. We then proceed to estimate the three ARCH-type models with the conditional mean equation specified as ARMA(4,2), and for each of the 501 firms, and again we chose the model with the lowest value of the Akaike information criterion. This exercise reveals that GARCH (1, 1), EGARCH (2, 1) and ARCH (3) provide the best fit for 222, 116 and 163 firms respectively.

Table A.1 presents the results of our benchmark specification and our external finance dependence regressions when we use the GARCH-based measure of conditional volatility as our dependent variable. Despite these caveats, the results reported are consistent with our main message that the intensity of global engagement has a positive and significant effect on firm-level volatility.

Table A.1: Volatility of stock returns and global engagement intensity — using a GARCH-based estimate for conditional volatility

	Baseline regression	Low external finance industries	High external finance industries
	(1)	(2)	(3)
Export intensity	0.072***	0.096***	0.063***
	(0.016)	(0.025)	(0.019)
Horizontal FDI intensity	0.049***	-0.044	0.074***
	(0.018)	(0.036)	(0.019)
Size	0.033***	0.028**	0.035***
	(0.008)	(0.012)	(0.008)
Leverage	-0.067***	-0.183***	-0.024
	(0.018)	(0.032)	(0.017)
Return on assets	0.003***	0.002***	0.003***
	(0.000)	(0.001)	(0.000)
Age	-0.028***	-0.042***	-0.025***
	(0.006)	(0.013)	(0.007)
Exchange rate volatility	0.160***	0.087**	0.191***
	(0.033)	(0.035)	(0.041)
North American stock market volatility	0.007***	0.002	0.009***
	(0.002)	(0.002)	(0.002)
European stock market volatility	-0.004***	-0.005*	-0.004***
	(0.001)	(0.003)	(0.001)
Asian stock market volatility	-0.000	-0.003	0.001
	(0.001)	(0.002)	(0.001)
Other stock markets volatility	0.001	0.003	0.001
	(0.001)	(0.002)	(0.001)
Observations	163,823	50,098	113,725

Panel fixed effects estimates with standard errors adjusted for cross-sectional dependence and within-firm serial correlation; standard errors in parenthesis. All specifications include firm, year, and month-specific fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References

Hansen, P. R. and A. Lunde (2005): "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)?" *Journal of Applied Econometrics*, 20, 873-889.

Tsay, R. (2005): *Analysis of Financial Time Series*, 2nd Edition. John Wiley and Sons Inc.