Boardroom Centrality and Systematic Risk of Firms

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Internet Appendix 1: Time-series regression analyses

In this section, we conduct time-series regressions of the risk-free rate-adjusted monthly returns of a long–short portfolio constructed according to boardroom centrality. This approach enables us to examine how higher stock returns, particularly the alpha coefficient of the time-series regression, change when the market factor is controlled for in the time-series regression. The monthly return data of 3,202 unique firms are obtained from the CRSP database from July 1997 to December 2020; these data are matched with the boardroom centrality data for fiscal year $t-1$ with the returns from July of year t to June of year $t+1$. We first construct five portfolios by categorizing firms into quintiles according to their boardroom centrality value, where firms with the highest (lowest) boardroom centrality value are assigned a rank of 5 (1). Next, for each portfolio, we calculate the equal-weighted average monthly returns adjusted using the monthly risk-free rate. Finally, we use the highest and lowest quintiles to construct a long–short zero-cost strategy portfolio.

The results are shown in Table A1. We first regress the time-series risk-free rate-adjusted long–short spreads between the portfolios of firms in the highest quintile (*Board_Centrality = 5*) and the lowest quintile (*Board_Centrality = 1*) on a constant term. Standard errors are adjusted using the approach employed by Newey and West (1987) with six lags. Column (1) reports that the alpha (coefficient of the constant term) is 0.0026 and statistically significant at the 5% level, indicating that firms with higher boardroom centrality earn excess stock returns.

Next, we introduce the time series of the market factor, which is measured as the value-weighted market-index monthly returns with dividends (including all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ) adjusted using the 1-month treasury bill rate (*Rm_Rf*), to the regression and re-estimate the regression. The results in Column (2) demonstrate that the alpha for the re-estimated regression is smaller than that for the first regression and is statistically insignificant. The coefficient of the market factor is 0.1009, statistically significant at the 5% level, suggesting that the excess stock returns of firms with higher boardroom centrality is attributable to their higher systematic risk exposure as the higher stock returns of these firms diminish after controlling for market factors.

Column (3) presents the results incorporating the Fama–French five factors and the momentum factor as control variables.[1] The regression results are similar to the previous analysis; however, the alpha value is of a smaller compared to the aforementioned regression. Moreover, a coefficient difference test (employing a seemingly unrelated estimation method) between Columns (1) and (3) shows a *p*-value of 0.088, denoting a significant difference upon adding the market factor. Finally, we introduce a column that excludes the market factor (*Rm_Rf*), and find that the *Alpha* in Column (4) remains statistically significant at 0.0021. The coefficient difference test results (using a seemingly unrelated estimation method) between Columns (1) and (4) show a *p*-value of 0.560, indicating the market factor's paramount importance. These findings affirm that the higher stock returns of firms with higher boardroom centrality decrease because of their increased systematic risk exposure.

Finally, as shown in Columns (5)–(8), the results remain robust even when the standard errors are not adjusted using the Newey and West (1987) approach.

[1] The five factors in the Fama and French (2015) five-factor model are as follows: (1) the value-weighted market-index returns adjusted using the risk-free return rate (*Rm_Rf*); (2) the difference between the returns of small and large firms (*SMB*); (3) the difference between the returns of high and low book-to-market stocks (*HML*); (4) the difference between the returns of stocks with robust and weak operating profitability (*RMW*); and (5) the difference between the returns of conservative and aggressive investment stocks (*CMA*).

Table A1: Time series regressions for the returns of a long-short portfolio based on boardroom centrality

This table reports the time series regressions for the returns of a long-short portfolio based on boardroom centrality. The dependent variable is the equal-weighted monthly returns adjusted by the monthly risk-free rate for the long-short portfolio (*Board_Centrality = 5 – Board_Centrality = 1*). We use Fama and French (1993), Carhart (1997) and Fama and French (2015) factor models, and thus have six independent variables that are the time series of monthly returns associated (1) with the value-weighted market index returns adjusted by the risk-free return rate (*Rm_Rf*), (2) with the difference in returns between small firms and large firms (*SMB*), (3) with the difference in returns between high and low book-to-market stocks (*HML*), (4) with the difference in returns between robust and weak operating profitability stocks (*RMW*), (5) with the difference in returns between conservative and aggressive investment stocks (*CMA*), and (6) with the difference in returns between stocks with a high prior return and those with a low prior return (*MOM*). The sample covers the period from July 1997 to December 2020. To ensure that firms' characteristic variables are known before the returns they are used to explain, we match the boardroom centrality data for all fiscal years t–1 with the returns for July of year t to June of year t+1. The composition of the portfolio results from sorting firms into quintiles according to their boardroom centrality value for fiscal year t–1, where firms with highest (lowest) boardroom centrality value are assigned a rank of 5 (1). The t-statistics in Columns (1)-(4), which are based on Newey and West (1987) standard errors with six lags, are reported in brackets; The t-statistics not adjusted by Newey and West (1987) standard errors in Columns (5)-(8) are reported in brackets. The coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	Portfolio*: Board_Centrality = 5 – Board_Centrality = 1*							
Variable	Adjusted by Newey and West standard errors				Not adjusted by Newey and West standard errors			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	0.0026**	0.0019	0.0001	0.0021*	0.0026**	0.0019	0.0001	0.0021**
	(2.01)	(1.54)	(0.14)	(1.90)	(2.01)	(1.51)	(0.15)	(2.01)
Rm_Rf		0.1009**	0.1940***			0.1009***	0.1940***	
		(2.58)	(8.58)			(3.78)	(7.86)	
SMB			0.0457	0.0716			0.0457	0.0716*
			(1.18)	(1.57)			(1.33)	(1.90)
HML			0.1426***	0.2106***			0.1426***	0.2106***
			(3.42)	(4.43)			(3.34)	(4.57)
RMW			0.2605***	0.1491***			0.2605***	0.1491***
			(6.09)	(2.99)			(5.78)	(3.15)
CMA			0.2995***	0.1492**			0.2995***	0.1492**
			(4.76)	(2.41)			(5.04)	(2.40)
MOM			-0.0428	-0.0826**			-0.0428**	-0.0826***
			(-1.38)	(-2.59)			(-2.17)	(-3.92)
Observations	282	282	282	282	282	282	282	282

Internet Appendix 2: Other robustness tests

This subsection presents the other robustness checks for the impact of boardroom centrality on the market beta. The control variables remain consistent with those in Table 4 but are not explicitly detailed here; the results are presented in Table A2.

Controlling for firms' business centrality

Boardroom centrality may simply reflect firms' business centrality, which may also affect their exposure to systematic risk. Hence, the positive effect of boardroom centrality on firms' market beta that we identified might stem from business centrality. Although we cannot obtain information on all individual firms' transactions along their supply chains, we note that a firm's business centrality may be strongly correlated with the centrality of the industry in which the firm operates. Following Ahern and Harford (2014) and Aobdia et al. (2014), we use the input–output (IO) tables provided by the Bureau of Economic Analysis (BEA) from 1997 (the first year for which data are available) to 2019. We define industries using the four-digit IO industry codes provided by the BEA to ensure adequate numbers of firms in each industry. The interindustry trading links for industries i and j can be represented in matrix form by matrix A with elements $A_{ij} = A_{ji} = 1$ and diagonal elements $A_{ii} = 0$; A is used to measure the influence of industries. Hence, like Ahern and Harford (2014) and Anjos and Fracassi (2015), we consider the heterogeneity in trade relationships and represent the links in A with measures of the strength of trade between two industries. Specifically, we compute the elements for each year as follows:

$$\boldsymbol{A}_{ij} = \frac{1}{4}\left(\frac{s_{ij}}{\sum_k s_{ik}} + \frac{s_{ij}}{\sum_k s_{kj}} + \frac{s_{ji}}{\sum_k s_{jk}} + \frac{s_{ji}}{\sum_k s_{ki}}\right) \tag{1}$$

where s_{ij} is the sales (in USD) of goods and services from industry i to industry j. The first (second) ratio measures the sales made by industry i to industry j as a percentage of industry i's total sales (industry j's total purchases), which shows whether industry j is an important customer of industry i (industry i is an important supplier to industry j). Similarly, the third and fourth ratios measure whether industry i is an important customer of industry j and whether industry j is an important supplier to industry i, respectively. The larger the value of A_{ij}, the stronger is the connection between industries i and j.

We measure an industry's position in the economy using Bonacich's (1972) eigenvector centrality metric. Higher centrality is indicative of an industry with strong trade connections to other industries that possess higher centrality. Specifically, industry *i*'s centrality (*Industry_Centrality*) is c_i for each year:

$$c_i = \frac{1}{\lambda} \sum_j \boldsymbol{A}_{ij} c_j \tag{2}$$

where λ is a normalization factor. An industry's centrality depends on the number of industries it trades with and the positioning of those industries within the overall economy. We then use the historical North American Industry Classification System industry codes in Compustat database to merge our firm-year-related data with our centrality measures available at the BEA four-digit industry level.

Subsequently, we incorporate *Industry_Centrality* into the regression and reestimate it. The results (reported in Panel A) are robust.

Controlling for persistence in governance practices

Given the persistence in board-related corporate governance practices (Hermalin and Weisbach, 1998), which suggests the nonindependence of annual firm observations, we follow Linck, Netter, and Yang (2008) and decrease the effects of intertemporal rigidity by calculating the results using observations from alternate years (i.e., 1997, 1999…, 2017, and 2019). The results reported in Panel B are robust after controlling for persistence in corporate governance practices.

Alternative measures

We test each boardroom centrality variable (*Quint(Degree)*, *Quint(Closeness)*, *Quint(Betweenness)*, and *Quint(Eigenvector)*) independently in the main regression. Panel C demonstrates the robustness of the results to each of these boardroom centrality variables.

Additionally, we explore alternative market beta variables. First, we estimate the market beta from CAPM using data on daily stock returns and market-index returns excluding dividends (*Beta_CAPM_ExDiv*) and data on equally weighted market-index returns including dividends (*Beta_CAPM_Equal*). Second, we estimate the market beta (*Beta_CAPM_Monthly*) using monthly data. The results shown in Column (1) to Column (3) in Panel D remain robust to these alternative variables representing market beta. Finally, we estimate the ratio of idiosyncratic risk (*Idio_Risk*) to total stock risk, where idiosyncratic risk is calculated from CAPM using daily stock returns including dividends and value-weighted market-index returns including dividends. The ratio of idiosyncratic risk is the standard deviation of the residuals of CAPM divided by the total stock risk, where the latter is measured as the standard deviation of daily stock returns. The results shown in Column (4) of Panel D indicate that boardroom centrality significantly reduces the ratio of idiosyncratic risk to total risk at the 1% level. This suggests that higher boardroom centrality reduces the ratio of a firm's specific risk, thereby increasing their exposure to systematic risk.

Table A2: Robustness tests

This table reports the results of the robustness tests. Panel A reports the results after controlling for the effect of business centrality on market beta. Panel B reports the results estimated using the sample comprising the observations from 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, and 2019, to control for the inter-temporal persistence of governance practices. Panel C reports the results estimated using the alternative boardroom centrality variables. Panel D reports the results estimated using the alternative dependent variables. The unreported control variables are the same as in Table 4. Appendix 1 provides the definitions of all variables. All regressions include firm and year fixed effects. Robust standard errors are clustered at the firm and year levels, and the *t*-statistics are reported in brackets. The coefficients marked with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for the effect of business centrality on market beta

Variable	*Beta_CAPM*	*Beta_FF3*	*Beta_FF5*
	(1)	(2)	(3)
Board_Centrality	0.022***	0.014***	0.016***
	(8.80)	(6.31)	(6.87)
Industry_Centrality	0.058***	0.016	-0.002
	(4.39)	(1.44)	(-0.19)
Controls	Included	Included	Included
Firm & Year FE	Included	Included	Included
Observations	25,916	25,916	25,324
Adjusted R^2	0.54	0.47	0.37

Panel B: Controlling for the inter-temporal persistence of governance practices

Variable	*Beta_CAPM*	*Beta_FF3*	*Beta_FF5*
	(1)	(2)	(3)
Board_Centrality	0.021***	0.013***	0.020***
	(5.42)	(3.91)	(5.33)
Controls	Included	Included	Included
Firm & Year FE	Included	Included	Included
Observations	13,451	13,451	13,189
Adjusted R^2	0.55	0.47	0.36

Panel C: Using the alternative boardroom centrality variables

Variable	Beta_CAPM				Beta_FF3				Beta_FF5			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Quint(Degree)	0.020***				0.013***				0.015***			
	(8.24)				(5.86)				(6.57)			
Quint(Closeness)		0.019***				0.014***				0.015***		
		(7.55)				(6.48)				(6.59)		
Quint(Betweenness)			0.018***				0.010***				0.009***	
			(7.93)				(3.99)				(4.22)	
Quint(Eigenvector)				0.017***				0.012***				0.016***
				(7.02)				(5.36)				(6.75)
Controls	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Firm & Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	26,841	26,841	26,841	26,841	26,841	26,841	26,841	26,841	26,247	26,247	26,247	26,247
Adjusted R^2	0.54	0.54	0.54	0.54	0.46	0.46	0.46	0.46	0.35	0.35	0.35	0.35

Panel D: Using the alternative dependent variables

Variable	Beta_CAPM_ExDiv	Beta_CAPM_Equal	Beta_CAPM_Monthly	Idio_Risk
	(1)	(2)	(3)	(4)
Board_Centrality	0.017***	0.016***	0.020***	-0.002***
	(6.51)	(5.13)	(2.76)	(-2.59)
Controls	Included	Included	Included	Included
Firm & Year FE	Included	Included	Included	Included
Observations	24,838	24,838	26,771	26771
Adjusted R^2	0.55	0.57	0.23	0.25