ONLINE APPENDIX (NOT for publication)
for "Competitive Differentiation Effects of Board Network Distance"

Appendix A1: Unexpected Director Death Variation

Data used to construct the director death instrumental variable comes from the BoardEx Individual Profiles Detail dataset. When applicable, BoardEx collects the date of death of a director and encodes it into the *dod* variable. These observations typically include the day, month, and year of the death. For some observations in which only the year of death was encoded, we used the month and day of death found from the press release of the firm. There were 4,578 such death occurrences from 2002-2014 as recorded by BoardEx. We keep only the S&P 1500 set of firms from the same time period and only directors whose death occurred while simultaneously serving on the board of at least 2 S&P 1500 firms. Finally, we use Lexis-Nexis to verify that these deaths were unexpected. A total over 300 deaths between S&P 1500 firm-pairs are part of the final sample set.

Generally, there are no succession plans for directors in the event of an unexpected departure. When a director dies, most corporate bylaws stipulate that the position will remain vacant until the following annual shareholder's meeting, see Microsoft's Corporate Bylaws as an example.[1] Thus, if a director dies unexpectedly while holding the position, the position generally will remain vacant until the board presents nominees to replace the director at the next shareholders meeting. In practice, this means that a vacant position could remain vacant for up to a year if a

[1] Microsoft Corporate Bylaws 2019: Section 4.2 Appointment and Term of Office. The Board shall appoint the officers of the Corporation annually at the first meeting of the Board held after each annual meeting of the shareholders. If officers are not appointed at such meeting, such appointment shall occur when possible thereafter, or may be left vacant. Each officer shall hold office until a successor shall have been appointed and qualified or until said officer's earlier death, resignation, or removal.

director unexpectedly dies right after being appointed and there is no requirement to fill a vacant position. Given that a director's affiliations intricately link various corporate boardrooms, we use these instances of unexpected director deaths as an exogenous shock to a firm's board network structure.

Using deaths as an exogenous shock to the composition of a board has been well established in the literature. Most recently, Fracassi, 2017 and Fracassi & Tate, 2012 used unexpected director deaths as exogenous shocks to board social ties to examine changes in corporate financial policies and corporate governance polices. Borokhovich, Boulton, Brunarski, and Harmon, 2014 examines the incentives of grey directors using executive deaths as exogenous shocks to firm values. Salas, 2010 measures executive entrenchment through exogenous shocks to stock prices dues to unexpected executive deaths. Bennedsen, Nielsen, Perez-Gonzalez, and Wolfenzon, 2007 use deaths of family members of CEOs as exogenous shocks to CEO focus to evaluate the value that a CEO brings to the firm. However, none of these papers use director deaths to analyze the changes in indirect connections, which allows us to exploit more variation coming from these director deaths.

To ensure that the director deaths are unexpected, we search for press release and announcements of unexpected director deaths from 2002-2014. Specifically, we search for and preserve observations that include terms such as *unexpected*, *accident*, *or heart attack* and exclude observations with terms that include *cancer*, *on leave*, or *absent*.

Appendix A2: OLS-IV comparison with Measurement Error Correction

In this section we provide a detailed discussion of the comparison of our OLS and IV estimates and a comparison of their magnitudes. To begin, we note that all our main specifications use firm-pair level fixed effects to control for permanent differences across firm-pairs. Therefore, the OLS specification can be written as:

$$\Delta y_{ij,t} = \beta \cdot \Delta X_{ij,t} + \Delta \epsilon_{\mathrm{ij,t}} \tag{1}$$

where $\Delta y_{ij,t}$ is the change in our competitive differentiation measures (Product Segment Similarity, Product Description Similarity, Patenting Similarity, Patent Citations), $\Delta X_{ij,t}$ is the change in board network distance and $\Delta \epsilon_{\mathrm{ij,t}}$ the change in errors. Since we use pair fixed effects throughout, we will refer to the first differences specification in (1) as "OLS". An important limitation of any type of OLS is the presence of classical measurement error, for example from errors in self-reported values, data entry or data processing errors. As is well-known, such measurement errors can have an especially large impact on OLS estimators as in (1), see Hausman and Grilliches (1986), Pischke (2007), Jennings et al., (2023). To illustrate this problem, let us begin with the classical measurement error model in which the measured board network distance variable $\tilde{X}_{ij,t}$ is given by:

$$\tilde{X}_{ij,t} = X_{ij,t} + u_{ij,t}$$

where the measurement error $u_{ij,t}$ is assumed to be iid. At the same time, the true distance $X_{ij,t}$ is persistent, due to persistence of directors in their positions:

$$X_{ij,t} = \rho_X \cdot X_{ij,t-1}$$

with autocorrelation coefficient $\rho_X \in (0,1)$. Then OLS with classical measurement error is given by:

$$\Delta y_{ij,t} = \beta \cdot \Delta \tilde{X}_{ij,t} + \Delta \epsilon_{\mathrm{ij,t}} \tag{2}$$

The OLS estimate of (2) is given by

$$\hat{\beta}_{OLS} = \beta \cdot \frac{\sigma_{\Delta X}^2}{\sigma_{\Delta X}^2 + \sigma_{\Delta u}^2} \tag{3}$$

Equation (6) is the classical measurement error formula for panel data and is similar to its well-known counterpart in the cross-section, in that classical measurement error will tend to bias any parameter estimate towards zero. However, in panel data, this bias can be strongly magnified. To calculate (3), it is useful to note that:

$$\sigma_{\Delta X}^2 = 2 \cdot \sigma_X^2 \cdot (1 - \rho_X) \tag{4}$$

and

$$\sigma_{\Delta \mathrm{u}}^2 = 2 \cdot \sigma_u^2 \tag{5}$$

Substituting (4) and (5) in (3) gives:

$$\hat{\beta}_{OLS} = \beta \cdot \frac{2 \cdot \sigma_X^2 \cdot (1 - \rho_X)}{2 \cdot \sigma_X^2 \cdot (1 - \rho_X) + 2 \cdot \sigma_u^2} \tag{6}$$

$$= \beta \cdot \left(\frac{1}{1 + \frac{\sigma_u^2}{\sigma_X^2} \cdot \frac{1}{(1 - \rho_X)}} \right)$$

Equation (6) expresses the attenuation bias in brackets as function of the noise-to-signal ratio (σ_u^2/σ_X^2) and the persistence in the board network distance variable ρ_X. We note that at this point, neither of the two parameters is related the dependent variable $\Delta y_{ij,t}$, and can therefore not explain differences in the bias of OLS across different dependent variables.

Once the two parameter values (σ_u^2/σ_X^2), ρ_X are set, it is possible to evaluate the importance of measurement error in OLS and even to provide a measurement error corrected OLS estimate. The latter is given by:

$$\beta = \hat{\beta}_{OLS} \cdot \left(1 + \frac{\sigma_u^2}{\sigma_X^2} \cdot \frac{1}{(1 - \rho_X)} \right) \tag{7}$$

To evaluate the importance of measurement error, we calibrate the parameters according to the following principles. First, for the noise-to-signal ratio (σ_u^2/σ_X^2) we set a value of 1, which implies that around half of the variation in board network distance is due to measurement error.

We obtain this value from Bloom et al., (2019), who report a noise-to-signal ratio for quantitative variables such as revenue and payroll reported to the mandatory Annual Survey of Manufacturing (ASM). Bloom et al., (2019) estimate this noise-to-signal ratio based on a sample of firms who were sent the mandatory survey forms twice due to a mistake by the US Census. Board network distance data and the underlying director data is likely to be more noisy, due to at least two different factors. First, BoardEx collects data only partially from regulatory filings and needs to supplement regulatory data with public data sources, such as company websites and news sources. This is likely to introduce more noise into the data, due to differences in spelling, data processing errors, and similar factors. Second, all of our baseline analysis relies on only indirectly connected firm-pairs, which means that at least two directors need to be accurately measured. The influence of measurement error will increase board network distance, for example one director is assigned to a wrong company, which makes measurement error even more quantitatively important.

For the persistence of board network connections ρ_X, we start from the stylized fact that the average director tenure is 8 years in the US, which implies a half-life of 5.54 years ($= 8 \cdot \log(2)$) , which in turn implies a value $\rho_X = 0.8823 \left(= \exp\left\{-\frac{\log(2)}{5.54}\right\}\right)$. Using both calibrated values in (7) gives:

$$\begin{aligned} \beta &= \hat{\beta}_{OLS} \cdot \left(1 + 1 \cdot \frac{1}{(1 - 0.8823)}\right) \\ &= \hat{\beta}_{OLS} \cdot 9.502 \end{aligned}$$

In other words, measurement error correction suggests that the true OLS effect is about 9.5 times larger than the estimated OLS effect. This measurement error correction will reduce the relative magnitude of OLS to IV, since IV automatically corrects for measurement error, which is a form of omitted variables bias, see Angrist and Pischke (2009).

Table A1 reports the magnitudes of OLS and IV estimates and the ratio of both estimates before and after correcting for measurement error of board network distance. Importantly, column (5) documents that the ratio of IV to OLS estimates is substantially smaller, once measurement error in OLS is taken into account. This result is sensible because board network distance as an independent variable is likely to be heavily influenced by measurement error. At the same time, the fact that the ratio of IV to OLS has a reasonable magnitude is reassuring about the quantitative implications of our causal estimates. Our IV estimates are broadly much larger than OLS estimates even after correcting for reasonable degrees of measurement error in OLS. This finding supports the notion that our IV strategy is indeed necessary to uncover causal effects and that the IV estimates are not merely driven by weak instruments problems, which would bias results towards OLS, see Angrist and Pischke (2009).

Appendix A3: Linking Compustat to I/B/E/S and Constructing the Public Firm Opacity Measure

To conduct a deeper analysis on the presence of information sharing, we hypothesize that the incremental value of private information flows through board networks is lower if firms are more transparent. To test this hypothesis, we construct measures of public firm opacity based on analyst data from the Institutional Brokers' Estimate System (I/B/E/S). Our main firm opacity measure is constructed using the earnings per share forecasts by sell-side analysts. To ensure that our results are not driven by issues in the data, we follow the literature and make the following data adjustments. First, we exclude any analyst forecasts in which the announcement date of the forecast occurs after the fiscal period end date as this is likely due to database error. Second, to ensure that estimates are not stale and are up-to-date, we ignore forecasts that have not been updated or revised with 105 days of the forecasting period date, as noted by McNichols & O’Brien, 1997. Stale and unrevised forecasts are likely to contain outdated information and these old forecasts are unlikely to reflect current information about the firm. Third, we follow Jegadeesh & Titman, 1993 in eliminating stocks priced lower than $5 per share to minimize bid-ask bounce.

To construct the opacity measure, we consider the sell-side analyst’ earnings per share forecast for the firm’s fiscal year end period. For each analyst, we keep only the forecast for the fiscal year end and only the last forecast issued by the analyst for that forecast period as this is likely to contain the most up-to-date information about the firm. These forecasts are then matched to Compustat by the firm's securities identifier CUSIP and the fiscal year-end date. This matching algorithm yields approximately an 80% match rate which we verify by hand.

The firm opacity measure of Table 6 in the main text is the analysts' EPS forecast dispersion, which is the standard deviation of the EPS forecast estimates by the analysts. We also construct an alternative firm opacity measure based on the forecast error dispersion which is the standard deviation of the forecast error by the analyst. This alternative firm opacity measure gives the same qualitative results as Table 6.

Table A2 reports summary statistics for our firm opacity measures, while Figure A1 presents the distribution of average firm opacity across industries. Note that in order to be able to calculate forecaster dispersion, we need at least two analysts to cover a specific firm, which is why our sample of firms is restricted to firms with at least two analysts in the IBES data. Despite this potential sample selection, we find that the forecaster dispersions vary a lot across firms, giving us sufficient variation for our interaction term analysis.

Figure A1

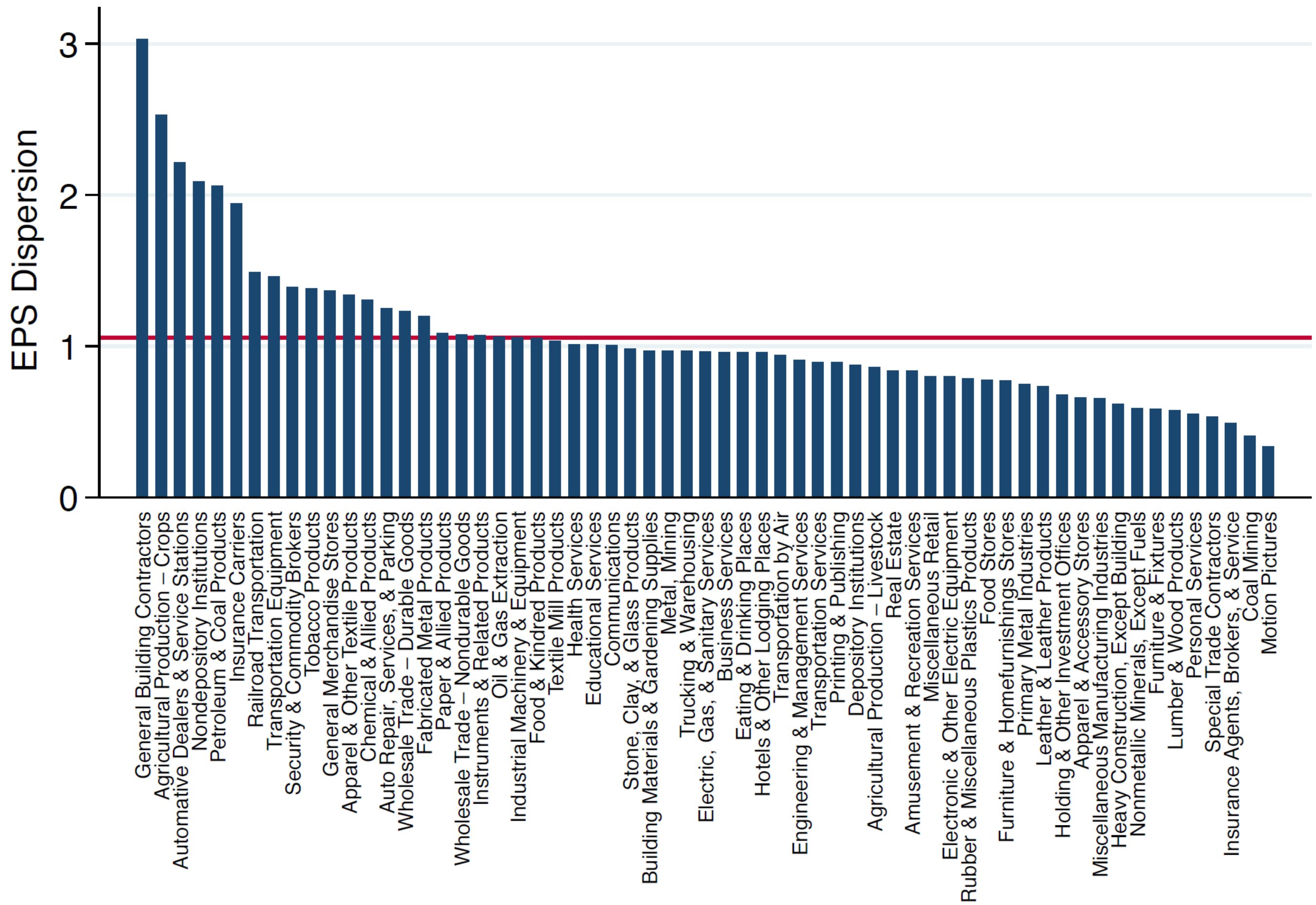

Figure A1: Average firm opacity measure across industries. Firm opacity is measures as earnings-per-share (EPS) forecast dispersion across analysts covering the same firm.

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Table A1: Ratio of IV to OLS

	OLS (uncorrected); from Table 4	OLS (corrected for meas. error)	IV from Table 5	Ratio of IV to OLS (uncorrected)	Ratio of IV to OLS (corrected for meas. error)
	(1)	(2)	(3)	(4)	(5)
Product Segment Similarity	0.00141	0.01341	0.06890	48.87	5.14
Product Description Similarity	0.00120	0.01141	0.02680	22.33	2.35
Patent Similarity	0.00123	0.01170	0.17300	140.65	14.79
Patent Citations	3.18700	30.30969	2.52200	0.79	0.08

Notes: Product Segment Similarity is measured using industry revenue similarity of firms in Compustat segments. Product Description Similarity is text similarity in 10-K filings, constructed by Hoberg and Phillips. Patent Similarity is measured using the similarity of the NBER technology classes of firm patents. Patent Citations captures the degree of citations of patents across firms. Measurement error correction assumes signal to noise ratio of 1 and average tenure of directors of 8 years, see text for details.

Table A2: Summary Statistics of Firm Opacity Measure

	Obs	Mean	Std. Dev	Min	Max
EPS Dispersion	1,072	1.057	1.131	0.013	17.217
Num. of Forecasters	1,072	26.097	16.661	2	104

Table A2: Summary statistics for firm opacity measure. Our baseline measure is the dispersion of earnings per share (EPS) forecasts by analysts.