ESSAYS ON CORPORATE FINANCE ISSUES

by

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ABSTRACT

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This dissertation consists of two essays on corporate finance issues. In the first essay (Chapter 1), I explore whether business group affiliations affect the covariance structure of stock returns in Korea. I find that the stock returns of firms belonging to the same business group show positive and significant comovement. The strong comovement between group returns and firm returns is explained by correlated fundamentals. I find strong comovement among business group affiliate earnings. Moreover, variance decomposition of returns shows that cash flow news plays a relatively more important role in explaining group comovement than discount rate news, suggesting a link between stock return comovement and the "tunneling" and "propping" behaviors of business groups. Finally, return comovement increases when a firm joins a business group.

In the second essay I show that, based on the decomposition of a model's R^2, latent manager qualities play a less important role than firm qualities in explaining the variation in innovation productivity. Labor economists argue that the average ability of managers who are raided should be higher than the average ability of managers who die suddenly. Our results show that the average change in innovation productivity following manager raids is not significantly different from that following manager deaths. The difference in abnormal returns surrounding manager raids between high and low innovation firms is similar to that surrounding manager sudden deaths. Assuming that exceptionally innovative managers are scarce, our results imply that managerial ability to promote innovation is not a sufficient determinant of manager quality. Overall, our evidence suggests that firm attributes matter more for stimulating corporate innovation than managerial attributes.

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Acknowledgements

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Chapter 1

Stock Return Comovement and Korean Business Groups

1.1 INTRODUCTION

Large, diversified business groups are a prominent feature of the economic landscape in many countries, particularly in Asia. A business group is a consortium of firms that are connected, often through common share ownership of member firms. It is common for a single individual or family to control all member firms, and cross holdings among member firms are also typical. The role of business groups has attracted considerable academic attention, with researchers presenting evidence in favor of both value-creating and value-destructive functions of business groups. However, relatively little attention has been paid to correlations among member firm stock returns.

In this study, we explore whether business group affiliations impact the covariance structure of stock returns for business groups in South Korea. Focusing only on Korean business groups (known as *chaebol*) provides two advantages. First, chaebol firms are clearly defined. The Korea Fair Trade Commission (KFTC) publishes business group membership each year, identifying member firms and ranking groups by total assets. Second, focusing on Korean markets helps to control for differences in country-level institutional environments that may introduce endogeneity issues and confound results (Joh 2003).

Using stock returns and business group composition data for Korean firms during the period 2002-2011, we find that stock returns for firms within the same business group exhibit significant comovement, beyond market-wide movements. Furthermore, when we control for industry-wide movement the effect of group affiliation on chaebol firm comovement remains positive and significant. Our findings are consistent with related studies which suggest that corporate governance mechanisms permitting concentrated ownership over member firms is associated with increased stock return comovement (Morck et al. 2000, Jin and Myers 2006, Fernandes and Ferreira 2008, 2009).

We next examine the sources of the business group return comovement. Vijh (1994) shows evidence that return comovement could arise from fundamental (economic) or sentimental (noneconomic) factors. It is likely that stock return comovement within Korean business groups stems from the correlation of the affiliates' fundamentals. Firms within Korean business groups are connected by mutual cross holding agreements. These crossholding arrangements might be an underlying factor affecting return comovement, because even though a controlling shareholder does not have an incentive to manipulate the performance of affiliates, the fundamentals of affiliates maybe affected through equity cross holdings (Bae et al. 2008). Thus, if strong return comovement of business group affiliates is significantly influenced by these activities, then the fundamentals of affiliates would also exhibit strong comovement. To test the link between return comovement and fundamentals, we measure comovement in group members' earnings. We find strong positive comovement in business group firm earnings, consistent with the fundamental explanation of business group return comovement.

We further explore the sources of chaebol stock return comovement by evaluating the relative importance of two fundamental components of stock returns, cash flow news and discount rate news (Campbell 1991). Stock returns change due to innovations in expected future cash flows which measures real activity and innovations in the discount rate applied to those cash flows, which measures financial activity. Therefore, we decompose unexpected stock returns into expected cash flow and discount rate news by utilizing the return decomposition framework in Vuolteenaho (2002). We find that stock return comovement is, on average, more strongly related to cash flow news comovement than discount rate news comovement, suggesting that real activity is more important than financial activity in explaining chaebol stock return comovement.

To validate our evidence that the comovement of stock returns of affiliates is attributable to the chaebol group affiliation effect, we examine a subsample of affiliates that changed their group affiliation during the sample period. Our investigation is motivated by recent studies that have explored the "index inclusion effect" on the comovement of stock returns. For example, Barberis et al. (2005) find that corporations newly added to the S&P 500 index experience a significant increase in stock return comovement with the rest of the index. Empirical analysis of firms that are newly added to (or removed from) a Korean business group would provide a more rigorous setting for verifying robustness of the group affiliation effect on the comovement of stock returns. We find that stock returns of firms that newly join a Korean business group comove positively with the returns of the group they join. Prior to joining the chaebol, these firms exhibit an insignificant degree of comovement with returns of that group.

Our study is related to a working paper by Kim et al. (2014), who focus on comovement before and after the 1997 Asian financial crisis. The authors find that business group comovement increased following the crisis, which they attribute to being in investors' preferred "habitat" along the lines of Barberis et al. 2005. In addition, Kim et al. find that comovement is not related to simple fundamental measures such as ROA, cash flow, and related party transactions. We extend Kim et al.'s results by decomposing business group comovement into cash flow news and discount rate news. Our results contrast with those of Kim et al. in that we find substantial evidence that business group comovement is related to fundamental factors, as evidenced by group earnings comovement as well as our evidence from the decomposition of group returns.

Our results contribute to the literature on return comovement in three areas. First, our results provide new insight into the relationship between business group affiliations and the covariance structure of stock returns. Second, we show evidence that stock return comovement among chaebol firms is driven by comovement in fundamental factors of member firms. Finally, our study makes an important distinction between cash flow news and discount rate news, and provides compelling evidence that cash flow news is more relevant than discount rate news in the comovement of stock returns among chaebol members.

The rest of the paper is organized as follows. Section 2 briefly reviews relevant literature. Section 3 describes the data employed in our study. Section 4 documents the group comovement of stock returns for firms that are affiliated with Korean business groups. In section 5 we explain the decomposition framework of stock returns, and we test whether group returns comovement is more strongly associated with cash flow or discount rate news comovement. Section 6 examines changes in business group affiliation, and section 7 concludes.

1.2. LITERATURE REVIEW

Existing literature has examined the value implications of business groups. One collection of studies suggests that business groups have the potential to perform a value creating function among member firms. For example, in countries where external capital markets are not well developed and have severe information asymmetry, business groups can facilitate more efficient allocation of internal capital or sharing of resources and risks. Khanna (2000) reviews the literature on business groups in emerging markets and reports that they can enhance social welfare in countries that lack certain institutions. Khanna argues that business groups may partially replace contract and property rights enforcement mechanisms that are more established in developed countries. Khanna and Palepu (2000) study business groups in India and find similar results, that business groups can help overcome imperfect markets.

Other studies find evidence that business groups may exploit the weaker institutions of the countries in which they operate, taking advantage of minority shareholders. This stream focuses on the agency problems that arise from the separation of cash flow and control rights, a defining feature of many business groups. This discrepancy in cash flow and control rights can create incentives for the controlling shareholder of the group to expropriate wealth from member firms, which researchers have termed “tunneling.” Johnson et al. (2000) review the legal treatment of tunneling and find that it is prevalent in both developed and emerging countries. Furthermore, the authors find that it is often conducted legally, despite being in conflict with minority shareholder interests. Examples of such legal tunneling cited by Johnson et al. include the sale of assets from a firm to its controlling owner at below-market prices, loan guarantees collateralized by the firm's assets, and excessive executive compensation. Bertrand et al. (2002) find evidence of tunneling in Indian business groups. Their methodology is based on how firms respond to performance shocks. In contrast, Siegel and Choudhury (2012) question several aspects of Bertrand et al.'s methodology. Most notably, they argue that differences in firm business strategy must be considered, or else firm responses to industry shocks may be misinterpreted as tunneling. The disparity in the conclusions of these two studies suggests that the role of business groups as vehicles for tunneling has not yet been resolved.

A few studies have looked specifically at chaebol firms in Korea for evidence of tunneling. Bae et al. (2002) study chaebol firms and find that when a chaebol firm acquires another firm, the chaebol firm's stock price tends to fall. However, other firms that belong to the chaebol tend to have positive abnormal returns around the acquisition. Given that the controlling owner of the chaebol has an ownership interest in all member firms, the owner benefits overall from the acquisition, consistent with the tunneling hypothesis. Almeida et al. (2011) find similar results for chaebol firms, and posit that the shares of such firms trade at a discount because they are sometimes used as a vehicle for value-destroying acquisitions. Tunneling is not the only negative side effect of business group affiliation. Kim and Yi (2006) find that greater separation of ownership and control at chaebol firms is associated with more severe earnings management.

Firms that belong to business groups may also benefit from the financial resources of other member firms. It is conceivable that firms facing potential financial distress may receive financial backing from other member firms; this "reverse tunneling" is referred to as propping by existing literature. Studies in this segment contend that a controlling shareholder of a business group may help member firms experiencing financial difficulty by providing private funds or internal capital, so as to reduce the default risk of the firm and ensure group survival. Bae et al. (2008) examine earnings announcements of chaebol firms and find that a negative earnings announcement by a firm has a negative effect on the market value of all firms that belong to the chaebol, consistent with investor pricing of propping within a chaebol. Friedman et al. (2003) find that controlling shareholders prop up member firms as a means to future expropriation of wealth from those firms.

Researchers have identified comovement among stock returns, citing various factors that contribute to return comovement. Kim et al. (2014) study return comovement among Korean business groups. Their analysis is based on average pairwise correlations among member firms vs. industry firms. The authors find that business group stock returns commove more than industry-level stock returns, and that comovement increased after the 1997 Asian financial crisis. Kim et al. argue that group comovement cannot be explained by fundamental factors, which they measure using firm return on assets (ROA), cash flow, and related party transactions. As described in section 5.2 below, we find that business group comovement is significantly related to firm fundamentals.

Prinsky and Wang (2006) find comovement among firms whose corporate headquarters are in the same geographic location. Interestingly, they find that when a firm moves the location of its headquarters, the firm's returns comove with returns of firms in the new location after the move. This event study context is an appealing way to demonstrate robustness, and we employ it below. Heston and Rouwenhorst (1994) present evidence that country level factors explain return comovement much more than industry level factors. Bekaert et al. (2009) use a linear factor model to analyze international stock return comovement, and they also find that country of origin explains comovement. Chan et al. (2007) find that firms in the same industry exhibit return comovement, where industry is measured according to several popular classification schemes. Karolyi and Stulz (1996) use high frequency intraday trading data to measure comovement between U.S. and Japanese stocks. They find that comovement is high during large market movements, and they conclude that international diversification does not protect against broad market shocks.

Researchers have also attempted to separate comovement drivers into fundamental and sentimental sources. Barberis and Shleifer (2003) develop a model where firms within the same “style” comove, even though their cash flows may be uncorrelated. They find that firms added to the S&P 500 experience a significant increase in comovement with other S&P 500 firms. This result builds on Vijh’s (1994) results and is consistent with the sentiment based view of return comovement. Similarly, Greenwood (2008) looks at firms that are overweighted in the Nikkei 225 index and finds that overweight stocks comove significantly with other Nikkei 225 stocks. In addition, being overweight is negatively associated with comovement with stocks outside the index. Kumar and Lee (2006) also find support for the sentiment based comovement view by analyzing retail investor stock trades.

Another approach to explaining comovement is by decomposing stock returns into different types of news. Viewing the intrinsic value of an asset as the present value of a stream of future cash flows, that asset's value may fluctuate due to (i) changes in expected future cash flows, and (ii) changes in the discount rate applied to those cash flows. Campbell (1991) looks at aggregate New York Stock Exchange returns and develops a vector auto regression for decomposing index returns into cash flow news and discount rate news. Voulteenaho (2002) elaborates on Campbell's work by decomposing individual stock returns. He finds that cash flow news is more important for explaining firm-level stock returns than discount rate news. In addition, discount rate news is driven mainly by market wide forces.

1.3. DATA

To investigate the relationship between Korean business group membership and stock return comovement, we begin with all publicly traded firms listed on the Korean Stock Exchange (KSE), taken from Data Guide Pro. The sample period is 2002-2011. We delete firm observations that are missing stock returns or financial information. We also exclude financial firms because they are subject to heavy government regulation and are more likely to have different financial policies such as capital and ownership structures than other non-financial firms in Korea. After these screens, our initial sample includes 893 firms listed in the KSE over the sample period.

From our initial sample, we identify firms belonging to Korean business groups using data published by the Korea Fair Trade Commission (KFTC). To identify business group affiliations, we first obtain the information regarding the ranking of Korean business groups and the list of affiliates from the KFTC over the sample period. The list of group affiliates announced by the KFTC includes both listed and unlisted affiliates, but we consider only listed affiliates. We exclude business groups owned by the Korean government. We also require that a business group have at least two affiliates in order to be included in our sample.

KFTC reports group affiliation once a year, usually in April. However, in practice a chaebol may sell an affiliate or add a new member firm during the year. If there is a large discrepancy in the date of group affiliation from KFTC's announcement, we use reports from daily newspapers to verify changes in group affiliation. We follow the KSE's industry classification standard, which is roughly equivalent to the two digit Standard Industrial Classification (SIC) scheme. Results are not materially affected if we use the SIC classification standard. In total, we identify 40 Korean business groups with 209 affiliates in our sample which meet all of the above criteria.

Table 1 presents descriptive statistics for Korean business groups and their member firms in our sample. Panel A shows the total number of firms listed in the KSE and the distribution of the firms which belong to chaebols in the sample, as well as the total number of chaebols. The total number of firms listed in the KSE varies over time. Starting in 2002 there were685listedfirms in our sample, and at the end of the sample period in 2011 there were 743. Also, the total number of affiliates listed in the KSE increased from 118 in 2002to 178 in 2011, and also the number of Korean business groups expanded from 25groups to 34 groups. However, not all firms belonging to Korean business groups are listed on the KSE. The average proportion of listed firms in a chaebol is only 20%.

Chaebols have a mean group size of 4.5 firms. Panel B of Table 1shows the characteristics of 18industry groups over the sample period. The mean number of industries per chaebol is 3.3, with a maximum of 16 industries, suggesting that business groups in the sample tend to be diversified across industries.

1.4. BUSINESS GROUP AND STOCK RETURN COMOVEMENT

1.4.1 Evidence of Stock Return Comovement

In this section, we examine the impact of Korean business group affiliation on the covariance structure of stock returns. Following existing literature, we employ the capital asset pricing model (CAPM) as our baseline model, and begin our analysis by evaluating the degree of the return comovement using the slope coefficients from a regression of stock returns on the returns of other stocks in the same chaebol.[1] We build a set of equally weighted portfolio return indices for each chaebol. We use the returns of all affiliates listed in the KSE in the same business group when constructing the return indices. For each stock that belongs to a chaebol, we estimate a stock-level time-series regression at daily, weekly, monthly, and quarterly return frequencies:

$$R_{i,t} = \alpha_i + \beta^{GR} R_t^{GR} + \beta^{MKT} R_t^{MKT} + \varepsilon_{i,t} \tag{1}$$

[1] Kim et al. (2014) calculate pairwise correlations for business groups and average the correlations within each business group. We find it advantageous to use a modified market model that controls for industry and market comovement.

where, $R_{i,t}$ denotes the excess return of a particular stock i at time t, and R_t^{GR} and R_t^{MKT} denote the excess return of the stock's corresponding business group, and the excess return of the market at time t, respectively (Prinsky and Wang 2006). We exclude the return of the firm whose returns are the dependent variable when computing its return relative to the rest of the business group (R_t^{GR}) to avoid introducing spurious correlations.

As discussed above, existing literature finds that the returns of firms in the same industry exhibit comovement (Chan et al. 2007). Given that chaebols tend to be diversified across industries, it is unlikely that our results are driven by such industry effects. Nevertheless, we control for possible industry effects by adding a return index for each industry by equally weighting the return of the firm's corresponding industry group in our regression model, and we estimate a regression which is an extension of equation (1):

$$R_{i,t} = \alpha_i + \beta^{GR} R_t^{GR} + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t} \qquad (2)$$

where R_t^{IND} is the excess return of the firm's corresponding industry. β^{GR} is our measure of comovement, which is the sensitivity of the member firm returns to the return of the rest of the chaebol after controlling for other variables in the regression model. We run the above regressions using daily, weekly and monthly return frequencies.

Table 2 reports the time series regression estimates of equations (1) and (2) and the averages of the estimated coefficients, with t-statistics in parentheses. Results show that the stock returns of chaebol firms exhibit robustly positive comovement even after controlling for both market and industry effects. Group betas (β^{GR}) are highly significant across both models and all data frequencies. Average group betas vary from 0.309 to 0.515

over the various specifications. Industry betas (β^{IND}) are between 0.382 and 0.546 across specifications. Group betas remain highly significant after controlling for industry effects, suggesting that the strong positive return comovement among firms in the same chaebol is not due to industry comovement.

1.5. SOURCES OF GROUP RETURN COMOVEMENT

Having demonstrated evidence of positive stock return comovement among firms in the same chaebol, we continue our analysis by looking at comovement from the perspective of the intrinsic value of an asset, where innovations in both expected future cash flows (fundamentals) and expected discount rates of a firm determine changes in stock returns.

1.5.1. Comovement of Earnings

In this section, we examine the sources of group return comovement by investigating the association between firm fundamentals and business group comovement. If comovement of chaebol firm stock returns is driven by fundamentals, then the cash flows of firms in the same chaebol could also be systematically correlated. Chaebol member firms are legally independently firms whose shares are separately traded in the Korean stock market. However, in practice it is believed that member firms serve as subdivisions of a controlling shareholder, resulting in close economic relationships among affiliates (Chang and Hong 2000). If strong group comovement of stock returns is driven by group-wide activities which decrease or increase innovations in the fundamentals of affiliates, then it is possible that firm fundamentals would also exhibit strong comovement within the same business group.

Following Prinsky and Wang (2006), we use quarterly earnings of group members as a proxy for firm fundamentals and investigate whether the group effect on return comovement of affiliates is driven by the comovement of firms' fundamental cash flows. We construct three earnings measures. For each firm in our sample, we first calculate the change in the level of earnings over the past one, two and four quarters. We then scale each earnings change variable by the firm's book value of equity, and denote these three earnings growth rates*Earning1*, *Earning2*, and *Earning4*, respectively. Using these three firm-level earnings change variables, we create market, industry, and group earnings change indices by equally weighting the earnings changes of all firms within a chaebol, industry, and market, denoted as$Earning_k^{MKT}$, $Earning_k^{IND}$, and $Earning_k^{GR}$, where k = (1, 2, 4). We exclude each firm's earnings growth ratio from the group and industry index to which it belongs. We also delete all firms with fewer than 16 quarterly earnings during the sample period. We then estimate a time-series regression for each stock:

$$R_{i,t} = \alpha_i + \beta^{GR} Earning_{k,t}^{GR} + \beta^{MKT} Earning_{k,t}^{MKT} + \beta^{\mathrm{IND}} Earning_{k,t}^{IND} + \varepsilon_{i,t} \qquad (3)$$

Table 3 reports the cross-sectional means of market, industry, and group earnings betas. Results show a significant positive association between a firm's earnings growth rate the earnings growth rates of the business group to which it belongs. Average group betas (β^{GR}) are between 0.2876 and 0.5016across earnings growth rates, with t-statistics all greater than 3. Interestingly, the magnitudes of the market and industry factors are lower, and significance of those betas is not as robust. Overall, results are consistent with the argument that strong comovement of returns is driven by correlation of chaebol firm fundamentals. These results contrast with those of Kim et al. (2014), who do not find evidence of a relation between group comovement and firm fundamentals, as measured by ROA, cash flow, and related party transactions.

1.5.2. Decomposition of Returns

We have presented evidence that the stock returns of chaebol firms exhibit positive comovement, and that this comovement is consistent with comovement in the fundamentals of group members. We further explore sources of return comovement through variance decomposition, separating firm stock returns into cash flow news and discount rate news components. We then evaluate the relative importance of the two return components in explaining group comovement.

1.5.2.1 Return Decomposition[2]

Based on Campbell's (1991) linear approximation that decomposes firm stock returns into cash flow news and discount rate news, Vuolteenhao (2002) implements a log-linear valuation model based on accounting data by replacing dividends with the clean surplus identity (Callen et 2010):

[2]See Vuolteenhao (2002) and Callen and Segal (2010) for more details of this method. Callen and Segal (2010) provide well documented summary of variance decomposition method. They also support SAS programs for estimating variance decompositions from cross sectional time-series data in the appendix.

$$bm_{t-1} = (r_t) - \ (roe_t) + bm_t \tag{4}$$

$$bm_{t-1} \ = \sum_{j=0}^{\infty} \rho^j \left(r_{t+j}\right) - \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j}\right) \tag{5}$$

Where bm_t, r_t, and roe_t denote the log book to market ratio, log stock returns, and log return on equity at time t, and ρ^j denotes the discount coefficient term.[3] Equation (4) separates price into expected future cash flow and discount rate news. In order to analyze return, Vuolteenhao further derives the model by taking the change in expectation of Equation (4) from *t-1* to *t* and rearranging:

$$r_t - E_{t-1}(r_t) = \Delta E_t \textstyle\sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right) - \ \Delta E_t \textstyle\sum_{j=1}^{\infty} \rho^j r_{t+j} \tag{6}$$

$$r_t - E_{t-1}(r_t) = Ncf_{t+1} - Ndr_{t+1} \tag{7}$$

where ΔE_t denotes the change in expectation from period t-1 to t.

The return decomposition in equation (7) can be conveniently operationalized via vector autoregression. Following Vuolteenaho (2002), we implement the return decomposition by employing stock returns, earnings divided by book value of equity, and book-to-market ratio as state variables in the VAR model assuming following form:

$$r_t = \alpha_1 r_{t-1} + \alpha_2 roe_{t-1} + \alpha_3 bm_{t-1} + \eta_{1t} \tag{8}$$

$$roe_t = \beta_1 r_{t-1} + \beta_2 roe_{t-1} + \beta_3 bm_{t-1} + \eta_{2t} \tag{9}$$

$$bm_t = \gamma_1 r_{t-1} + \gamma_2 roe_{t-1} + \gamma_3 bm_{t-1} + \eta_{3t} \tag{10}$$

[3]Following existing literature, our study assumes that $\rho = 1$ for simplicity.

Notation for the equations above is more convenient in matrix form, and an individual firm's state vector is assumed as follows:

$$Z_t = \Gamma Z_{t-1} + \eta_t \tag{11}$$

where

$$Z_t = \begin{pmatrix} r_t \\ roe_t \\ bm_t \end{pmatrix}, \quad \Gamma = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{pmatrix}, \quad \eta_t = \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{pmatrix}$$

Following Vuolteenaho (2002), we compute cash flow news and discount rate news:

$$Ne_t = (e_1 + \lambda_1)'\eta_t$$

$$Nr_t = \lambda_t{}'\eta_t$$

where $e_k' = (1,0,\ldots,0)$is a vector whose first element is one and whose other elements are zero, and $\lambda_k{}' = e_k{}'\rho\Gamma(I - \rho\Gamma)^{-1}$ with $(I - \rho\Gamma)^{-1}$ being the matrix equivalent of the present value of the sum.

We decompose quarterly stock returns into cash flow and discount rate news by estimating the first order VAR model in equation (7). Following Vuolteenaho (2002), we estimate the VAR from panel data using a weighted least squares (WLS) approach and one pooled prediction regression per state variable. We weigh each cross-section equally by deflating the data for each firm-quarter by the number of firms in the corresponding cross-section. We calculate a set of equally weighted indices for group-, market-, and industry-level cash flow and discount rate news comovement for each quarter. Similar to equation (2), we then measure the degree of comovement of cash flow and discount rate news for each firm by estimating the following firm level time-series regressions:

$$CF_{i,t} = \alpha_i + \beta^{GR} CF_t^{GR} + \beta^{MKT} CF_t^{MKT} + \beta^{\mathrm{IND}} CF_t^{IND} + \varepsilon_{i,t} \tag{12}$$

$$DR_{i,t} = \alpha_i + \beta^{GR} DR_t^{GR} + \beta^{MKT} DR_t^{MKT} + \beta^{\mathrm{IND}} DR_t^{IND} + \varepsilon_{i,t} \tag{13}$$

1.5.2.2. The Relative Importance of Cash Flow and Discount Rate News

We evaluate the relative importance of cash flow news and discount rate news on group comovement by comparing the magnitude of the coefficients in the cross-sectional regression models that include either cash flow news or discount rate news comovement variables. Given that cash flow news is computed by the sum of innovations in current and future earnings, we further break down cash flow news into current period and future period cash flow news. We examine the relative contribution of these proxies for real activity and financial activity to provide more detailed evidence on the source of cash flow news for group comovement (Callen and Segal 2010). We consider the following cross-sectional regression model with various firm and group characteristics as control variables and compare the magnitude of the coefficients:

$$GCI_i = \alpha_i + \beta^{CF} CF_i + \beta^{DR} DR_i + \beta^{Firm} Firm_i + \beta^{Group} Group_i + \varepsilon_i \tag{14}$$

where GCI_i is the business group stock return comovement beta from equation (2), CF_i is the is the cash flow news comovement beta from equation (12), DR_i is the discount rate news comovement beta from equation (13), *Firm*$_i$ are firm-level control variables, *Group*$_i$ are group-level control variables, and ε_i is an error term. We consider a set of firm and group characteristics that have been documented to be associated with return comovement. *Earnings correlation* is the index of earnings comovement as measured using equation (3). *Size* is the natural log of the firm's market capitalization measured at the end of the previous quarter. *Book-to-market ratio* is the ratio of book value of equity over market value of equity calculated at the end of the previous quarter. *Leverage* is the ratio of total debt to total assets. *ROA* is return on assets. *Group Assets* is the total business group assets reported by KFTC. *No. Firms* is the natural log of the total number of affiliates in the business group. *HHI* is the degree of industry diversification of the business group, measured by the Herfindahl index. *Institutional Ownership* is the equity ownership held by mutual fund managers in Korea.

We average all independent variables over the sample period, then standardize them by subtracting the sample mean and dividing by the standard deviation to give the variables a zero mean and unit variance (Hirshleifer et al. 2009; Chava and Purnanandam 2010). This approach allows direct comparison of the regression coefficients since they represent a one standard deviation change in each variable. We estimate eight different cross-sectional model specifications to capture the combined explanatory power of these fundamentals for group comovement. This methodology allows us to compare a set of factors that best explain variations in group comovement.

Table 4 presents correlations between the dependent variables (cash flow news, current cash flow news, future cash flow news, and discount rate news) and other firm and group control variables. We observe several relations. First, although group stock return comovement is positively associated with both cash flow and discount rate news comovement variables in univariate analysis, cash flow news comovement is more strongly associated with group comovement than with discount rate news comovement. Second, future cash flow news comovement is more strongly related to group comovement than current cash flow news comovement. Lastly, the correlation among firm and group specific variables is relatively low, with the highest correlation of -0.482 between ROA and Leverage, giving us a level of confidence in using independent firm and group variables in our models.

Table 5 reports results of the cross-sectional regressions of business group stock return comovement on cash flow news comovement and discount rate news comovement. The first two columns estimate the relative contribution of cash flow news and discount rate news on group comovement, while the other columns (columns (3)-(8)) further decompose cash flow news into current period and future period cash flow news. We find substantial evidence that chaebol stock return comovement is more strongly associated with cash flow news than discount rate news, after controlling for both firm and group characteristics. The coefficients on cash flow news in columns (1) and (2) are positive and statistically significant, and they are about five times greater in absolute value than the coefficient on discount rate news. Because all independent variables are standardized, the coefficients represent the effect of a one standard deviation change, and the difference in magnitudes suggests that cash flow news is more important in driving stock return comovement than discount rate news.

We also find that the coefficient of current cash flow news in columns (3) and (4) shows little explanatory power for the dependent variable. Neither of the coefficients on current cash flow news in column (3) and (4) are statistically significant. Interestingly, when future cash flow news is added to the model as shown in column (7) and (8), the coefficient of future cash flow news shows considerable explanatory power, suggesting that the explanatory power of real activity for group comovement is mainly driven by future real activity. Finally, all models except those in columns (1) and (2) show that the coefficient on discount rate news is not significant, further evidence that real activity explains stock returns comovement more so than financial activity.

Overall, VAR analysis suggests that cash flow news comovement plays a more important role in explaining Korean business group stock return comovement than discount rate news. In other words, real activity that drives cash flows to equity holders appears more strongly associated with return comovement than financial activity, represented by the firm's cost of equity. Nevertheless, the evidence does not rule out the possibility that such a phenomenon can also be jointly driven by both unobserved "tunneling" and "propping" behavior of a business group. Our finding that return comovement is positively related to earnings comovement is consistent with the findings of Kim and Yi (2006) that earnings management is more prevalent among chaebols. It is plausible that the comovement of affiliated stock returns in Korean business groups could be driven by tunneling behavior of the controlling shareholders of chaebols. Djankov et al. (2008) shows that business groups provide direct opportunities to expropriate wealth through tunneling using related party transactions. If such tunneling behavior decreases innovations in the cash flows of chaebol members and increases comovement in cash flow news, then the observed comovement of chaebol firm stock returns may also reflect propping behavior.

Byun et al. (2013) demonstrate that chaebol firms have a considerably lower cost of debt in the Korean capital market and argue that this is because investors perceive enhanced protection from firms belonging chaebols, as membership is a credible signal that a troubled firm will receive financial assistance from other member firms. If this group-wide propping activity reduces the default risk of member firms in the business group, it is likely that the discount rates of member firms would eventually comove within the same business group resulting in the comovement of discount rate news. However, distinguishing these explanations for the group comovement phenomenon is beyond the current scope of the study.

1.6. CHANGE IN GROUP MEMBERSHIP

We further examine return comovement using a subset of firms that either joined or left a chaebol during the sample period. If affiliation with a chaebol drives the covariance structure of a firm's stock returns, then analysis of the subsample of firms that change group membership could provide a more rigorous setting for testing of the group comovement effect.

We identify firms that join or leave chaebols by comparing the KFTC list of Korean business groups in two consecutive years. We then manually verify the date the firm joins or leaves the group using major newspapers and the database compiled by the Korean Listed Companies' Association (KLCA). Our final subsample of firms that change group membership consists of 40addition and 17 removal events over the sample period. To assess the effect of changes in chaebol membership on return comovement, for each addition and removal we estimate the following regression separately for the 3 years before and 3 years after the event:

$$R_{i,t} = \alpha_i + \beta^{GR} R_t^{GR} + \beta^{DUM} D^{GR} + \beta^{DGR} D^{GR} R_t^{GR} + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t} \quad (15)$$

$R_{i,t}$ is the excess return of a stock i, R_t^{GR} is the excess return of the stock's business group, R_t^{MKT} is the return on the market portfolio, and R_t^{IND} is the equally weighted index of the stock's industry. D^{GR} is a dummy variable identifying the firm's addition to or removal from the business group. To clarify the interpretation of the dummy variable, we define it in two different ways, according to whether a firm was added to or removed from a chaebol. The dummy variable for addition to a chaebol takes a value of 0 if the firm stays out of the business group, and 1 when it is added to the group. If a firm is removed from a chaebol, we assign the value of 0 when the firm stays in the group, and 1 when the firm leaves the group. We are most interested in the interaction between addition/deletion and comovement, and the effect of this change in business group affiliation on return comovement is measured by β^{DGR}. We run the above regression for daily, weekly and monthly return frequencies. We exclude the 6 month period ending the month before and after the addition or removal announcement to reflect the time for incorporation and diffusion of information to investors.

Table 6 presents the results of regressions with the chaebol addition and removal dummy. Panel A shows the average of the estimated betas with respect to the various indices when affiliates are *added* to a business group, and panel B shows the average of the estimated betas when they are *removed* from a business group. Although removal from a business group is not significantly associated with changes in comovement, results show that firms newly added to a chaebol experience a significant increase in sensitivity to that chaebol's stock returns (β^{DGR}). This result holds for daily, weekly and monthly return frequencies. The increase in β^{DGR} is between 0.111and 0.181 across return frequencies. This result supports the evidence presented earlier using the full sample, implying that a firm's addition to a business group has a significant and positive effect on that firm's comovement with other firms in the same business group, consistent with Kim et al. (2014).

7. CONCLUSION

Despite the increased academic interest in the role of business groups in a country's economy, the impact of business group affiliations on the stock prices of member firms is relatively unexplored. This study investigates whether the Korean business group affiliations affect the covariance structure of underlying stock returns. We find positive and significant comovement in the stock returns of firms belonging to the same Korean business group. We also demonstrate that our findings are robust to a subsample of affiliate firms that changed their group affiliation.

We also examine the comovement of chaebol member firm fundamentals. Consistent with the fundamental-based explanations, our results indicate that the comovement of stock returns can be explained by comovement in corporate earnings. These findings suggests that investors take into account other consider firms belonging to the same business group as relevant since the unique governance and structural system of Korean business groups allows coordination of firm activities within the group.

Finally, given that strong comovement in the stock returns of group affiliates is attributed to correlation of fundamentals, we further explores more detailed sources of the group returns comovement by examining the relative importance of cash flow and discount rate news. We find that cash flow news plays a greater role in explaining stock return comovement than discount rate news. Our evidence that Korean business group return comovement is driven by the relative importance of two fundamental return factors contrasts sharply with the results of Kim et al. (2014) and may have important implications about the widely documented tunneling and propping behaviors of business groups. That is, our results might imply that the comovement of cash flow and discount rate news are closely related to unobserved tunneling and propping behaviors of business groups, respectively. However, although our study suggests a possible linkage between two return decomposing components and tunneling and propping behaviors, whether tunneling or propping effects contribute significantly to the phenomenon of group comovement is an interesting issue that warrants future research.

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Table 1
Summary Statistics

Panel A provides the total number of firms in a Korean business group in the sample as well as the distribution of the number of firms per business group over the sample period. Panel B reports the distribution of the total number of industries in each business group. The sample includes domestic common stocks listed on the KSE from 2002 to 2011 with coverage in DataGuide.

Panel A: Number of firms in a Korean business group

Year	No. KSE-listed firms	No. KSE-listed firms belonging to a business group	No. business groups	Number of firms per business group		
				Mean	Max	Min
2002	685	118	25	4.7	17	2
2003	694	124	26	4.8	17	2
2004	693	140	30	4.7	16	2
2005	684	141	31	4.5	14	2
2006	684	144	32	4.5	14	2
2007	696	152	34	4.5	15	2
2008	710	160	34	4.7	15	2
2009	729	168	34	4.9	16	2
2010	742	184	34	5.4	18	2
2011	743	178	34	5.2	17	2

Panel B: Distribution of the total number of industries

Year	Number of Industries	Number of Industries per business group		
		Mean	Max	Min
2002	18	3.2	15	1
2003	18	3.3	16	1
2004	18	3.2	15	1
2005	18	3.1	11	1
2006	18	3.2	13	1
2007	18	3.0	13	1
2008	18	3.1	11	1
2009	18	3.2	12	1
2010	18	3.5	12	1
2011	17	3.3	9	1

Table 2
Business Group Comovement

For each stock in the sample, we estimate a time-series regression of stock returns on the returns of a business group index, the market portfolio, and industry indices. Cross-sectional averages of the estimated coefficients are reported, with t-statistics in parentheses. The group index (GR) is the equally weighted return of all stocks from the firm's corresponding business group, excluding the firm itself. The market index (MKT) is the return index of all stocks listed in the Korean stock market. The industry index (IND) is the equally weighted return of the stock's corresponding industry, according to the KSE 18-industry classification. The sample period is 2002 to 2011.

Frequency	β^{GROUP}	β^{MKT}	β^{IND}
Daily	0.344	0.7056	
	(18.27)	(29.40)	
	0.309	0.3579	0.382
	(17.22)	(11.13)	(13.31)
Weekly	0.370	0.6937	
	(15.11)	(21.42)	
	0.335	0.2931	0.433
	(14.30)	(6.91)	(12.24)
Monthly	0.486	0.5795	
	(11.78)	(10.44)	
	0.432	0.1030	0.546
	(10.49)	(1.58)	(7.26)
Quarterly	0.515	0.4838	
	(9.58)	(7.72)	
	0.473	0.0863	0.456
	(7.30)	(0.82)	(4.34)

Table 3
Business Group Earnings Comovement

For each stock in the sample, we estimate time-series regressions of its earnings growth rate on group, industry and market earnings growth indices. Earning1, Earning2, and Earning4 are the earnings change from the previous 1, 2, and 4 quarters, respectively, scaled by the lagged book value of equity. The group and industry earnings-growth indices include all stocks from the firm's corresponding business group and industry, excluding the firm itself, and the market earnings growth index includes all stocks in the Korean stock market. Average values of the estimated coefficients are reported with t-statistics in parentheses. The sample includes domestic common stocks traded on KSE from 2002 to 2011 with coverage in Data Guide.

	Group Earnings Growth	Market Earnings Growth	Industry Earnings Growth
Earning1	0.2876	0.0989	0.1668
	(3.56)	(1.65)	(2.10)
Earning2	0.4852	0.0182	0.0658
	(5.77)	(0.80)	(1.00)
Earning4	0.5016	0.072	0.0747
	(3.10)	(1.31)	(0.81)

Table 4
Correlation Matrix

This table presents correlations. Group comovement is the sensitivity of a firm's stock returns to the stock returns of the other firms belonging to the same business group. Cash flow news and discount rate news are based on Vuolteenaho's (2002) stock return decomposition. Size is the log of firm market capitalization. Leverage is the ratio of total debt to total assets. Book to market is the ratio of book to market equity. ROA is return on assets. Earning comovement is the sensitivity of a firm's earnigns to the earnings of the other firms belonging to the same business group. Group assets is the total assets of the firm's business group. No. Firms is the log of the number of firms in the business group. Institutional ownership is the equity ownership held by mutual fund managers in Korea.

	Group Comovement	Cash Flow News	Current Cash Flow News	Future Cash Flow News	Discount Rate News	Size	Leverage	Book to Market	ROA	Earnings Comovement	Group Assets	No. Firms	Herfindahl Index	Institutional Ownership
Group Comovement	1.000													
Cash Flow News	0.533	1.000												
Current Cash Flow News	0.061	-0.177	1.000											
Future Cash Flow News	0.513	0.836	-0.128	1.000										
Discount Rate News	0.268	-0.106	0.178	-0.009	1.000									
Size	-0.027	0.105	0.014	0.104	0.102	1.000								
Leverage	-0.008	-0.042	0.145	-0.148	-0.254	-0.023	1.000							
Book to Market	0.016	0.098	-0.144	0.072	-0.034	-0.454	-0.190	1.000						
ROA	-0.051	-0.066	-0.077	0.007	0.232	0.367	-0.482	-0.254	1.000					
Earning Comovement	0.040	-0.055	0.379	0.151	0.044	-0.112	0.110	0.012	-0.097	1.000				
Group Assets	0.011	-0.037	0.088	-0.011	0.143	0.471	-0.011	-0.401	0.176	0.050	1.000			
No. Firms	-0.031	-0.029	0.100	-0.044	0.086	0.245	-0.088	-0.231	0.106	0.032	0.688	1.000		
Herfindahl Index	-0.136	-0.026	0.023	-0.036	0.023	0.088	-0.195	-0.180	0.133	0.010	0.208	0.525	1.000	
Institutional Ownership	0.103	0.052	0.022	0.082	0.074	0.043	-0.040	-0.085	0.038	0.020	0.204	0.121	0.047	1.000

Table 5
Business Group Comovement and Stock Return Decomposition

The dependent variable is the degree of stock return comovement with a firm's business group. Cash Flow News and Discount Rate News are based on the return decomposition of Vuolteenaho (2002). We standardize all independent variables over the sample period. Coefficient estimates are reported with t-statistics in parentheses. The sample includes domestic common stocks traded on KSE from 2002 to 2011 with coverage in Data Guide.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cash Flow News	0.7368	0.6978						
	(9.39)	(9.06)						
Current Cash Flow News			0.0614	0.0739			0.0554	0.067
			(0.78)	(0.98)			(0.82)	(1.02)
Future Cash Flow News					0.647	0.5955	0.6461	0.594
					(6.98)	(6.42)	(6.96)	(6.41)
Discount Rate News	0.1443	0.121	0.2124	0.1798	0.1038	0.0882	0.0972	0.0799
	(2.91)	(2.55)	(3.40)	(2.97)	(1.87)	(1.62)	(1.73)	(1.45)
Size	0.0241	0.0098	0.0971	0.0783	0.0481	0.0309	0.0479	0.0299
	(0.87)	(0.34)	(2.85)	(2.17)	(1.60)	(0.95)	(1.59)	(0.92)
Leverage	0.1263	0.09	-0.0168	-0.1204	0.1056	0.0359	0.0862	0.0071
	(0.54)	(0.38)	(-0.06)	(-0.40)	(0.41)	(0.14)	(0.33)	(0.03)
Book to Market	0.0678	0.0957	0.1105	0.1315	0.0646	0.0903	0.0692	0.0956
	(1.47)	(1.99)	(1.85)	(2.14)	(1.26)	(1.68)	(1.34)	(1.77)
ROA	5.8642	5.6724	0.4559	-0.1881	1.6919	1.6023	1.987	1.9285
	(1.50)	(1.46)	(0.09)	(-0.04)	(0.40)	(0.38)	(0.46)	(0.45)
Earning Comovement	0.0794	0.0712	0.0556	0.0453	0.0189	0.0158	0.0068	0.0012
	(2.29)	(2.11)	(1.16)	(0.98)	(0.49)	(0.41)	(0.16)	(0.03)
Group Asset		0.099		0.1297		0.1192		0.1247
		(1.88)		(1.93)		(2.03)		(2.12)
No. Firms		-0.0028		-0.0062		-0.0045		-0.0049
		(-0.80)		(-1.39)		(-1.16)		(-1.27)
Herfindahl Index		-0.0852		-0.1057		-0.0842		-0.0811
		(-1.10)		(-1.07)		(-0.97)		(-0.94)
Institutional Ownership		3.7059		5.2461		2.972		2.904
		(2.16)		(2.41)		(1.53)		(1.50)
Intercept	0.7565	1.2485	2.4402	2.9837	1.2623	1.7673	1.2692	1.7923
	(-0.96)	(-1.56)	(-2.48)	(-3.00)	(-1.47)	(-1.99)	(-1.47)	(-2.02)
Adjusted R^2 (%)	47.63	51.12	13.28	20.60	36.21	39.39	36.06	39.40
Number of Obs.	149	149	149	149	149	149	149	149

Table 6
Changes in Stock Return Comovement for Firms that Join or Leave Business Groups

We identify a sample of 57 firms that either join or leave business groups between 2002 and 2011. For each stock in the sample we estimate a time-series regression for the 3 years prior to and the 3 years subsequent to the event (inclusion or deletion from business group). Panel A reports results for firms that join a business group; in this panel, DUM takes a value of 1 if a firm joins a business group. Panel B reports results for firms that leave a business group; in this panel, DUM takes a value of 1 if a firm leaves a group. DGR is the interaction between group comovement and the indicator for joining/leaving a group. The group index (GR) is constructed as the equally weighted return of all stocks from the firm's corresponding business group, excluding the firm itself. The market index (MKT) is the return index of all stocks listed on the KSE. The industry index (IND) is the equally weighted return of the stock's corresponding industry, according to the KSE 18-industry classification. Cross-sectional averages of coefficient estimates are presented, with t-statistics in parentheses.

Sample	β^{GROUP}	β^{DUM}	β^{DGR}	β^{MKT}	β^{IND}
Panel A: Additions					
Daily	0.036	0.400	0.111	0.359	0.618
t-stat	(1.43)	(3.04)	(4.19)	(4.14)	(8.19)
Weekly	0.037	0.091	0.132	0.726	0.298
t-stat	(0.70)	(0.30)	(2.34)	(6.66)	(3.47)
Monthly	0.078	-1.638	0.181	0.186	0.749
t-stat	(0.78)	(2.11)	(2.01)	(4.92)	(1.32)
Panel B: Deletions					
Daily	0.177	-0.110	-0.051	0.267	0.588
t-stat	(3.50)	(0.37)	(0.82)	(2.97)	(6.20)
Weekly	0.126	0.467	0.017	0.899	0.017
t-stat	(1.60)	(1.46)	(0.20)	(0.16)	(7.20)
Monthly	0.214	3.792	0.084	0.018	0.770
t-stat	(1.06)	(2.52)	(0.43)	(0.06)	(3.08)

Chapter 2

Do Managers Matter for Corporate Innovation?

> *"We are asking you to see the success of visionary companies – at least in part – as coming from underlying processes and fundamental dynamics ... not primarily the result of a single great idea or some great, all-knowing, godlike visionary who made great decisions, had great charisma, and led with great authority."*
>
> - Collins and Porras (2002)

2.1. INTRODUCTION

It is widely recognized that innovation is a significant driver for long-run economic growth. In his seminal paper, Solow (1956) shows that technological innovation contributed over 80% of the U.S.'s economic growth between 1909 and 1949 and that technological improvements are necessary for sustained economic growth. Recent financial research finds that innovation is vital to firm survival (Eisdorfer and Hsu, 2011), competitive advantage (Porter, 1992), and is positively associated with firm value (Hall, Jaffe, and Trajtenberg, 2005) as well as stock returns (Rossi, 2006). Despite the importance of innovation for firms and to society as a whole, we know little about the key factors that drive innovation. Is it latent abilities of the CEO and top management or the firm's culture and environment that spur corporate innovation? The goal of our study is to assess the relative importance of time invariant firm and manager characteristics in explaining firms' innovation productivity.

Businesses thrive when firms innovate. Popular media and practitioners suggest that top management is important in building a framework for successful innovation. For example, recent media sentiment deifies innovative managers and speculates about the next great innovator or the next Steve Jobs[4]. These media stories suggest that extraordinary latent qualities in top executives are important for innovation. Other practitioners emphasize a firm's physical environment and/or a corporate culture that reinforces thinking and idea generation as important determinants of innovation[5]. It is undeniable that all these firm and manager qualities, while latent, are necessary to encourage corporate innovation.

Existing empirical research finds that firm or managerial characteristics, including year effects, can explain up to about 54% of the cross-sectional variation in innovation productivity, leaving a substantial portion of the variation unexplained[6]. The quote from Collins and Porras (2002), at the start of the paper,

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[4] See The Book of Jobs, \The Economist, Jan. 28th 2010; \How to hire the Next Steve Jobs," Inc.com, Oct.30, 2013; \Je_ Bezos isn't the next Steve Jobs," CNNMoney, Dec. 3, 2013; A Google search for \the next Steve Jobs" yields about 1.5 million results.

[5] See \Why corporate culture is important for innovation," by Je_rey Phillips, Senior Leader at OVO Innovation, December 29, 2012; http://www.innovationexcellence.com/blog/2012/12/29/why-corporate-culture-is-important-for-innovation/. See, also, \Why environment matters for innovation," by J. Phillips, December 30, 2012; http://www.innovationexcellence.com/blog/2012/12/20/why-environment-matters-to-innovation/.

[6] For example, studies show that firm-level characteristics, such as stock market liquidity (Fang, Tian, and Tice, 2013), equity market development (Hsu, Tian, and Xu, 2013), analyst coverage (He and Tian, 2013), anti-takeover provisions (Chemmanur and Tian, 2013), local banking competition (Cornaggia et al., 2013), firm alliances (Schilling and Phelps, 2007), business groups (Belenzon and Berkovitz, 2010), and institutional ownership (Aghion, Reenen, and Zingales, 2009) matter for innovation. Others suggest that managerial characteristics, such as CEO overconfidence (Galasso and Simcoe, 2011; Hirshleifer, Low, and

implies that firm success is not primarily the result of unobservable managerial fixed effects such as managerial skills, charisma, and talents, but is "at least in part" the result unobservable firm fixed effects such as firm culture and the underlying processes and fundamental dynamics of a firm. The evidence presented in this paper is largely consistent with this view. Manager fixed effects, while still important, explain a smaller portion of the variation in firm level innovation productivity than firm fixed effects in the majority of our tests.

A few empirical studies have looked beyond observable characteristics to understand the role of managers in explaining corporate policies. For example, Bertrand and Schoar (2003) show that the role of CEOs and top executives is more important in determining some corporate decisions than others. When adding manager fixed effects to models of corporate policies that have already incorporated both observable and unobservable time invariant firm characteristics, they show that the adjusted R^2's increase by more than four percentage points. Graham, Li, and Qiu (2012) provide evidence that firm and, especially, manager fixed effects explain a substantial portion of the variation in executive pay. Coles and Li (2012) find that manager fixed effects have varying explanatory powers for several corporate policies. All these studies mainly show the importance of manager fixed rather than firm fixed attributes in corporate policies and decision-making. In contrast, Kaplan, Sensoy, and Stromberg (2009) show that firm fixed effects are more critical than manager fixed effects in startups and early stage

Teoh, 2012), managers' compensation structure (Xue, 2007; Manso, 2011; Lerner and Wulf, 2007), and managers' motives (Sauermann and Cohen, 2010), can explain variation in innovation productivity.

ventures. However, none of these studies examines the extent to which manager or firm fixed effects influence innovation.

In this study, we conduct a thorough analysis to determine the contributions of unobservable manager and firm fixed effects to corporate innovation beyond those of their observable characteristics. We gauge the extent of a firm's innovation productivity by the number of patents and patent citations available from the NBER Patent Citations Database (Trajtenberg, 1990; Hall and Ziedonis, 2001; Hall, Jaffe, and Trajtenberg, 2005) and use the information on executives from ExecuComp. After merging the two databases, our sample contains 75,491 firm-year observations with complete data for the period of 1992 to 2006. Our main tests employ Abowd, Kramarz, and Margolis's (1999, henceforth AKM) method to determine the proportion of the model R^2 attributable to observable and time-invariant unobservable firm and managerial characteristics[7]. The AKM approach improves on the mover dummy variable (MDV) method developed by Bertrand and Schoar (2003), who study a subset of data that comprises only managers who change firms (henceforth the mobility sample), while including manager, firm, and year fixed effects in the model specification. Specifically, the AKM approach expands and draws inferences from the mobility sample to a "connected sample", which includes both movers and non-movers, thus increasing the sample size and reducing the potential selection bias created by examining only managers that switch firms.

[7] The AKM method is employed by Graham, Li, and Qiu (2012) and Coles and Li (2012).

Contrary to popular press and to the existing evidence on corporate policies but consistent with Collins and Porras (2002), we find unobservable firm fixed effects play a larger role in innovation productivity. However, manager fixed effect also appear to be important but perhaps to a lesser degree. Our empirical results indicate firm fixed effects, as opposed to manager fixed effects, explain the majority of the variation in firm innovation productivity, even after incorporating observable firm and manager attributes as well as year effects into the models. Depending on the empirical methodology employed (AKM vs MDV), firm fixed effects contribute about 50% and 70%, while manager fixed attributes account for about 30% and 14%, of the explained variation in firm innovation productivity respectively. Our findings are robust to a subsample of firms that were granted at least one patent and to another subsample that consists of only CEOs in firms with at least one patent. These robustness tests help eliminate the possibility that unobservable differences between firms with and without patents, or managers that would not be expected to contribute to innovation, such as CFOs, are not driving our main results.

We also examine the impact of manager/firm separations on corporate innovation productivity. Labor economists suggest that raided managers are more likely to be of higher quality (Lazear 1986; Hayes and Schaefer 1999). Thus, building on Hayes and Schaefer, we compare the change in corporate innovation following manager raids (i.e., a manager leaves for a similar position at another firm) to the change in corporate innovation following manager sudden deaths. Sudden deaths are likely to occur randomly. Hence, a sample of managers that suddenly die is likely to be of average quality. If raided managers, on average, are indeed of higher quality and their ability to innovate is an important factor in determining quality, we would expect corporate innovation output to fall after manager raids relative to the change in innovation output for a sample of firms whose managers die suddenly. Our results do not find that innovation productivity falls more following manager raids compared to that following manager deaths, suggesting that on average managers' ability to innovate is not a major determinant of manager quality or innovation productivity.

Further, if managers are matched to firms based on their ability to innovate, we would expect that raids of managers from firms with high innovation productivity, on average, would have a larger impact on firm value than raids of managers from firms with low innovation productivity, as exceptionally innovative managers are likely to be scarce. We thus compare the difference between abnormal stock returns surrounding manager raids and manager deaths in firms with high versus low innovation productivity. Our findings indicate no significant difference in firm valuation effects between raids of managers from firms with high innovation productivity and those from firms with low innovation productivity. Overall, the results are consistent with our earlier key finding using the AKM and MDV methodologies that firm characteristics matter more for innovation than manager characteristics.

This paper expands the existing literature in several directions. First, our study adds to the literature that examines the effects of manager characteristics on firm performance. In particular, Bertrand and Schoar (2003) find that manager fixed effects are related to accounting measures of firm performance, whereas Coles and Li (2012) show that managerial characteristics explain 30% to 50% of the variation in return on assets and Tobin's Q. Further, managers have previously been shown to improve operating performance of small textile firms (Bloom et al., 2013), and national leaders have been linked to national growth (Jones and Olken, 2005). In contrast to these studies, we find relatively less contribution from manager fixed effects to patented innovation, a performance metric that is less likely to be manipulated by managers.

Second, our paper offers new insights on the literature investigating the relative importance of non-human and human assets. Consistent with our evidence, Kaplan, Sensoy, and Stromberg (2009) find that, at the margin, firm-level characteristics matter more for the success of early- stage companies, compared to managerial characteristics. Our work expands the prior literature in that our sample is not confined to a single industry (Bloom et al., 2013), or to early-stage companies (Kaplan, Sensoy, and Stromberg, 2009), but it covers a broad range of publicly-traded U.S. companies, which are more representative of the economy as a whole.

Finally, this paper also contributes to the growing literature on the determinants of corporate innovation. A large body of recent research finds that firm-level characteristics, such as stock market liquidity (Fang, Tian, and Tice, 2013), equity market development (Hsu, Tian, and Xu, 2013), analyst coverage (He and Tian, 2013), anti-takeover provisions (Chemmanur and Tian, 2013), local banking competition (Cornaggia et al., 2013), firm alliances (Schilling and Phelps, 2007), business groups (Belenzon and Berkovitz, 2010), and institutional ownership (Aghion, Reenen, and Zingales, 2009), explain variation in innovation productivity. Other research suggests that managerial characteristics, such as CEO overconfidence (Galasso and Simcoe, 2011; Hirshleifer, Low, and Teoh, 2012), managers' compensation structure (Xue, 2007; Manso, 2011; Lerner and Wulf, 2007), and managers' motives (Sauermann and Cohen, 2010), explain variation in innovation productivity. However, our study provides evidence as to which type of characteristics identified by prior studies (firm or manager) is more important in explaining the variation in innovation productivity of large U.S. corporations.

The rest of the paper is organized as follows. The next section describes the data and methodology. Section 3 discusses the empirical results, and Section 4 concludes the paper.

2.2. DATA AND METHODOLOGY

2.2.1. Sample Construction

Our main sample starts with the intersection of the following three databases: The NBER Patent Citations Database, ExecuComp, and Compustat. We first collect firms' patents and citations – the main variables of interest in this study – from the NBER Patent Citations Database. This database provides information of all utility patents and citations granted by the United States Patent and Trademark Office (USPTO) from 1976 to 2006. From this database, we obtain the following information: the name of patent assignee, the application and grant date, and other patents that cite or are cited by the patent in question. The database also contains an identifier link between patent assignees and the Compustat universe, so we can track the timing, quantity and quality of patents filed by a company in Compustat.[8]

Before examining any potential impact of unobservable manager effects on firm innovation, we first need to control for the effects of observable manager characteristics. Our study obtains manager information from ExecuComp, including managers' demographic information such as gender, job title, and the starting (ending) year of his or her tenure. We also collect information on managerial compensation from ExecuComp, including total salaries, bonus, and stock options that are granted and exercised, as managerial incentives are well documented to affect corporate performance and innovation. Finally, firms' accounting information, including firm size, liquidity, profitability, capital structure and investment, comes from Compustat; data on firms' stock returns and volatility are from CRSP. The final sample contains 75,491 firm-year observations and 20,116 unique managers from 1992 to 2006.[9]

For robustness, our analysis also employs two additional pieces of information: managers who die suddenly and those who are raided. The information on sudden deaths comes from Bereskin and Hsu (2013), Combs et al. (2007), and ExecuComp. Bereskin and Hsu identify a total of 16 sudden deaths, where the previous CEO died from an accident, a heart attack, aggressive cancer, during sleep without a disclosed cause, or a recent illness. Combs et al. report a total of 73 unexpected CEO deaths from firms listed on US stock exchanges between January 1978 and August 2001. Finally, we obtain the list of managers

[8] For details of this database, see the website https://sites.google.com/site/patentdataproject/ and Hall, Jae, and Tratjenberg (2001).

[9] We follow Chen, Huang, and Wei (2012) and start the sample period from 1993 because ExecuComp's coverage is incomplete in 1992, its starting year of coverage. Similarly, the sample ends in 2005 because the coverage of patents and citations is incomplete in 2006 in the NBER Patent Citations Database.

who left office due to death based on the ExecuComp variable REASON. Using the list of manager deaths from ExecuComp, we search LexisNexis and Proquest to identify the death announcement dates and classify each death according to whether the death was sudden or not.[10] After merging the sudden deaths with the patent and firm level data, we are left with a sample 75 manager sudden deaths.

In order to identify managers who were raided, we examine every single case in ExecuComp where the GVKEY associated with a given manager changes compared to that of the prior year.[11] We then search LexisNexis and Proquest to examine news reports and firm disclosures in order identify the announcement date, the move date, and the nature of the manager's move. Managers are considered to be raided if an article infers that the manager was raided, or if we cannot find evidence that the change in GVKEY was the result of a termination, acquisition, spin-off, or other reorganization event. After merging the sample of raided managers with the patent and firm level data, our sample consists of 152 manager raids.

2.2.2. Main Variables

In this subsection, we briefly describe the main variables used in this study and provide their summary statistics.

i. *Mobility of Top Managers*

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[10] We classify sudden deaths as those resulting from accidents, heart attacks, strokes, other sudden illnesses, or the article states the death was unexpected.
[11] We eliminate all managers that have multiple GVKEYs assigned to the same year (for example, the same manager in two different firms at the same time).

We identify the mobility of all named managers from one firm to another for all firms that are covered in ExecuComp database between 1993 and 2006. The selected sample period is constrained by the availability of patents and citations information from the NBER Patent Citations Database. Table 1 provides summary statistics of the mobility of top managers in our sample. Panel A reports the distribution of the number of times a manager moves. Among the 20,116 managers in our sample, 95.32% of them (i.e., 19,175) make zero move; that is, they stay in the same company and thus are "non-movers". The remaining 4.68% (i.e., 941) serves as top executives in at least two companies and are therefore classified "movers". A closer look at the distribution of these movers reveals that the vast majority (877 managers) moved only once, with the largest number of moves made by a single manager equal to 3. Panel B shows the number of managerial moves by firm. Among our sample of 2,083 companies (that contain the aforementioned 20,116 managers and 79,491 firm-year observations), 1,059 (50.84%) do not have any movers, where the remaining 1,024 firms have at least one mover. Overall, the summary statistics related to manager moves are consistent with those reported by Graham, Li, and Qiu (2012).[12]

ii. *Patents and Citations*

The main variable of interest in this study is corporate innovation, which measures the realization of a firm's long-term research and development investments and is an indicator of the firm's long-term competitiveness. Hall, Jaffe, and Tratjenberg (2005) and Rossi (2006) show that corporate innovation is positively associated with a firm's market value. Patents offer a rich source of information about the nature and influence of a firm's

[12] As in Graham, Li, and Qiu (2012) we are only able to capture manager moves within the ExecuComp sample due to data limitations.

innovation and thus are widely used in the literature as the standard measure of corporate innovation. In our study, we construct two measures of corporate innovation based on the number of patent counts:

(1) the natural logarithm of one plus a firm's number of patents (LPatents), which is the number of (eventually granted) annual patents in an application year t filed by firm i, and (2) Industry-Adjusted LPatents, defined as the natural logarithm of the ratio of number of patents to the mean number of patents of all firms in year t and industry j. Aghion et al. (2013) and Hall, Jaffe, and Tratjenberg (2005) indicate that a firm's patent citations provide a good measure of the value of innovations. We therefore construct two citation-based measures: (3) LCitations, defined as the natural logarithm of one plus the number of total patent citations in year t by firm i, and (4) Industry Adjusted LCitations, defined as the logarithm of the ratio of number of citations to the mean number of citations per patent in year t in the same industry j.

iii. *Firm, Industry, and Manager Characteristics*

We follow the innovation literature and control for potential observable firm and industry characteristics that may affect a firm's innovation output. These control variables include a firm's size measured by total assets (Size), firm age (Age), profitability measured by return on assets (ROA), R&D investments (R&D), capital expenditures (Capx), asset tangibility (Tang), leverage (Lev), a firm's Tobin's Q (Q), industry concentration proxied by the Herfindahl index based on sales and the squared Herfindahl index (H and HH2), stock return (Retn), return volatility (Vol), financial constraints proxied by the Kaplan and

Zingales index (1997) (KZ), liquidity measured using the cash over assets ratio (Cash), and institutional ownership (IOwn).

In addition, we control for observable manager characteristics documented in the literature. These characteristics include pay slice (the difference between a manager's annual compen- sation and the median of all other managers' annual compensation in a firm) (PSlice), the length of a manager's tenure (Tenure), the sensitivity of CEO compensation to stock price volatility (Vega), the sensitivity of CEO compensation to stock prices (Delta), a female dummy (equal to one if the manager is female) (Female), a CEO dummy (equal to one if the manager is the CEO of the company) (CEO), and a CEO-Chair dummy (equal to one if the manager is both the CEO and the board chairperson of the company) (Chairman). Appendix A details the variable definitions.

The AKM and MDV methodologies depend on the mobility of managers to separately identify firm and manager fixed effects. Whereas the MDV method can only separately identify the fixed effects for managers that switch firms, the AKM method is able to use the information in manager moves to estimate the fixed effects for non-movers within the same firm. This sample of movers and connected non-mover managers is referred to as the connected sample. It is a subset of the full ExecuComp sample with data. Thus, in order to gauge the plausibility that our results, based on the connected sample, extend to the full sample of ExecuComp firms, Table 2 summarizes representativeness of the connected sample relative to the full ExecuComp sample with available data.

Following, the methodology in Graham, Li, and Qiu (2012) we present the mean, median, and standard deviation of the above variables employed in our analyses for both the full sample and the connected sample. We then examine the quintile means and the percent of firms in the connected sample that are in each quintile based on the full sample breakpoints. On average, firms in the connected sample are larger, more innovative, and have higher average stock returns than those in the full sample. For example, the average innovation productivity as measured by patents (citations) is 29.79 (467.24) for the connected sample and is 18.71 (285.66) for the full sample. Thus our results are based on the largest and most innovative firms.

The connected sample of firms has an average annual stock return of 0.31, compared with 0.24 for the full sample. However, examining the quintiles, the connected and full samples look similar along this dimension. For manager-related variables, we find that manager characteristics in the connected sample are not vastly different from those in the full sample. For example, the pay slice is 0.19 for the connected sample and 0.20 for the full sample. The Vegas and Deltas for both samples are fairly close. Managers in the connected sample have an average Vega of $0.060 million and an average Delta of $0.396 million, and those for the hold out sample are $0.047 million and $0.357 million. In general, the descriptive statistics are broadly similar for the two samples, suggesting that overall the connected sample is a fair representation of the full sample.

Panel C of Table 2 reports the correlation matrix of the above main variables with the full sample presented below the diagonal and the connected sample above the diagonal. The size and direction of the correlation coefficients for all variables are consistent across the two samples of firms. We find that firms with high R&D intensity are smaller in size, have lower accounting performance (as measured by returns on assets), but are associated with larger market values (proxied by Tobin's Q), stock return volatility, and cash holdings. Further, firms with higher cash holdings experience lower leverage, greater market values, and larger stock return volatilities. These correlations are generally consistent with those documented in the existing literature.

2.2.3. Empirical Methodology

This section describes the rationale for each of our major tests. We briefly describe the AKM method for the purpose of distinguishing the relative importance of unobservable firm and manager fixed effects. We then discuss the reasons for examining the different effects of manager raids and sudden deaths on corporate innovation productivity and stock returns.

i. *AKM methodology*

To distinguish the relative importance of unobservable firm and manager fixed effects, we employ an approach developed by Abowd, Kramarz, and Margolis (1999) for its capability to increase sample size and reduced the selection bias associated with only examining the mobility sample.[13] In the regression framework, the typical method to address the potential omitted variables problem (due to unobservable firm and manager characteristics) is to create a dummy variable for each unique firm-manager combination. This so-called "spell" approach mitigates possible endogeneity concerns and enhances explanatory power. However, it can only measure the combined influence of both firm and manager fixed effects without separating and gauging their relative importance. Bertrand and Schoar (2003) provide an alternative solution to separate these various effects by considering only the sample with managers who move from one company to another (these

[13] See Graham, Li, and Qiu (2012) and Coles and Li (2012) for more details of this method.

managers are called movers), while including manager, firm, and year fixed effects in the regressions. This mover dummy variable (MDV) approach helps separate manager-fixed effects from firm-fixed effects, but may induce potential sample selection bias as the "movers" sample might comprise only a small proportion of overall observations, thus making it problematic to generalize the inference obtained from movers to non-movers.

The AKM approach mitigates the small sample bias that plagues the MDV approach by expanding the "movers" sample to a larger "connected" sample, which contains both movers and non-movers. As long as a non-mover works in companies that hires at least one mover, she is in the "connected" sample. Therefore, a small number of movers can generate a larger connected sample. AKM further show that connectedness is the necessary and sufficient condition for separating person and firm fixed effects. As such, given sufficient manager mobility, using the AKM approach with a larger connected sample increases the precision of model estimates.

We apply the AKM approach to evaluating the relative importance of firm innovation's determinants by estimating the following empirical model.

$$y_{i,t+1} = F_{i,t}\lambda + M_{m,t}\beta + \phi_i + \theta_m + \gamma_t + \varepsilon_{i,t} \tag{1}$$

In Eq. (1), $y_{i,t+1}$ is one of our innovation measures for firm i, $F_{i,t}$ is firm i's observable characteristics, $M_{m,t}$ is manager m's observable attributes, ϕ_i and θ_m denote firm and manager time-invariant latent characteristics, respectively, γ_t represents year-fixed effects, and $\varepsilon_{i,t}$ is the residual error. To quantify the contribution of each determinant class to the total variation in firm innovation, we follow Graham, Li, and Qiu's (2012) approach and decompose the model R^2 as follows.

$$
\begin{aligned}
R^2 &= \frac{Cov(y_{i,t+1}, \hat{y}_{i,t+1})}{Var(y_{i,t+1})} \\
&= \frac{Cov(y_{i,t+1}, F_{i,t}\hat{\lambda} + M_{m,t}\hat{\beta} + \hat{\phi}_i + \hat{\theta}_m + \hat{\gamma}_t)}{Var(y_{i,y+1})} \\
&= \frac{Cov(y_{i,t+1}, F_{i,t}\hat{\lambda})}{Var(y_{i,y+1})} + \frac{Cov(y_{i,t+1,}M_{m,t}\hat{\beta})}{Var(y_{i,y+1})} + \frac{Cov(y_{i,t+1}, \hat{\phi}_i)}{Var(y_{i,y+1})} + \frac{Cov(y_{i,t+1}, \hat{\theta}_m)}{Var(y_{i,y+1})} \\
&+ \frac{Cov(y_{i,t+1}, \hat{\gamma}_t)}{Var(y_{i,y+1})} \qquad (2)
\end{aligned}
$$

Note that the covariance values in Eq. (2) correspond to the fractions of the model sum of squares attributable to specific determinant classes.

ii. *Manager raids vs. sudden deaths*

Based on the work in labor economics (Harris and Holmstrom, 1982; and Lazear, 1986), we also assume that on average managers who are raided have greater ability than managers who suddenly die.

In Harris and Holmstrom's (1982) dynamic model, risk neutral firms partially insure a risk averse employees' ability related risk via downward rigid wages. If the employee's ability is revealed to be high, then the firm must revise the employee's wage upward to ward off other potential employers. On the other hand, if the employee's ability is revealed to be low, then the firm is bound by contract to keep the employee and the firm suffers negative profits.

In Lazear's (1986) model, however, inter-firm mobility is determined by a matching process, where managers are matched to firms that can best use the managers' abilities. Suppose firm A wishes to raid a high type manager, as long as the manager's ability generates more value in firm A than in the manager's current firm. Firm A will be able to pay the manager enough to satisfy the manager's participation constraint. Now suppose firm A wishes to raid a low type manager. If the low type manager generates value in firm A that is below his current wage, then it is not efficient for firm A to raid the low type manager even though the low type manager would improve the value of firm A. That is, the partial insurance in the manager's contract makes the market for low type managers inefficient. As pointed out by Hayes and Schaefer (1999), raids of low type managers would occur when the manager's ability strongly favors the raider (in order to offset the partial insurance). However, raids of high type managers can occur any time. Thus, compared to a random sample, the average ability level of a sample of raided managers would be higher.

If innovation is a highly coveted managerial ability, and thus a major determinant of overall manager quality, then on average we would expect a drop in firm level innovation productivity following manager raids compared to a random sample of manager/firm separations such as manager sudden deaths. Additionally, given the evidence that innovation improves firm value (Hall, Jaffe, and Trajtenberg, 2005), we would expect lower stock returns surrounding manager raids compared to those surrounding manager sudden deaths. This difference should be especially pronounced in highly innovative firms if managers are matched to firms based on their ability to promote innovation and the exceptionally innovative managers are scarce. The above discussion thus motivates the two following hypotheses.

Hypothesis 1: On average, firm level patent and citation productivity are lower following the firm losing its manager to another firm than to sudden death.

Hypothesis 2: On average, abnormal stock returns surrounding manager raids should be lower than those associated with manager sudden deaths, especially in firms with high innovation productivity.

2.3. EMPIRICAL RESULTS

2.3.1. The Determinants of Firm Innovation

We begin our analysis by examining the determinants of firm innovation using the full sample of ExecuComp firms with available data. We regress firm innovation on a set of observable firm-level variables that have previously been found to be significant determinants of firm innovation. We employ our earlier defined proxies for firm innovation: the number of patents and the number of citations. Drawn from the existing literature, the determinants of innovation are firm size (Size), return on assets (ROA), research and development (R&D), capital expenditure (Capx), tangible assets (Tang), leverage (Lev), Tobin's Q (Q), a firm's Herfindahl index (HH), the square of the Herfindahl index (HH2), stock return (Retn), stock volatility (Vol), Kaplan and Zingales's (1997) measurement of a firm's reliance on external financing (KZ), liquidity (Cash), institutional ownership (IOwn), the natural logarithm of firm age (Age), pay slice (PSlice), the natural logarithm of a manager's tenure at the firm (Tenure), Vega, and Delta, a dummy indicator if the manager is a female (Female), a CEO (CEO), and a dummy indicator if the manager is a CEO who also holds the position of chairman of the board (Chairman).

Table 3 reports results from pooled OLS regressions, regressions including firm fixed effects, Manager fixed effects, and finally both firm and manager fixed effects are included in the model. All regression models include year fixed effects to capture unobservable variation in economic environments and other plausible year differences related to firm innovation. In Models 1 and 2, we focus only on the explanatory power of observable firm and managerial attributes and hence, estimate the models without firm and manager fixed effects. The adjusted R^2s of these models are between 33.8% and 32.7%. However, when we account for unobservable time invariant firm heterogeneity by incorporating firm fixed effects into Models 3 and 4, their adjusted R^2 increases correspondingly to 83.3% and 74.4%. Similarly, adding manager instead of firm fixed effects to Models 5 and 6 also improves the adjusted R^2 to 83.4%-76.1%. When we incorporate both firm and manager fixed effects using the "Spell" method in models 7 and 8, the explanatory power goes up to 85.9% and 78.4%. These results suggest that the firm and manager attributes explain the majority of the variation in corporate innovation measured in terms of the number of patents and the number of citations. They also indicate that unobservable time invariant firm (for e.g., firm culture, firm quality, firm environment, among others) and managerial qualities (for e.g., managerial leadership quality, managerial creativity, talents, and abilities, etc.) play a much more important role in explaining firm innovation than observable firm and managerial characteristics.

To put our results into perspective, we compare them with those of the existing literature and find the explanatory powers of observable and unobservable determinants of firm innovation to be broadly consistent with the adjusted R^2s reported in prior studies. For example, Atanassov (2013) shows that about 83.1% (61.8%) of the cross-sectional variation in innovation measured in terms of the number of patents (citations) can be explained by the dummy variables that capture the passing of antitakeover laws, firm control variables, and time and firm fixed effects for the 1976-2000 period. Shen and Zhang (2013) find that promotion-based tournament incentives affect firm innovation (measured by the number of patents and patent citations granted in t to t + 3) during the 1993-2002 period. With industry and year fixed effects incorporated, their model specifications generate an adjusted R^2 of 46.3%-55.6%; the adjusted R^2 value increases in the length of time patents are filed or citations are received. He and Tian (2013) obtain an adjusted R^2 of 83.3% in their regression of firm innovation on analyst coverage, firm control variables, and firm and year fixed effects for the 1993-2005 period. Coles and Li (2013) evaluate the relative importance of observed and unobserved firm and manager specific characteristics in explaining a host of corporate policies, including R&D. For models with R&D as the dependent variable, their adjusted R^2s are 28% (without firm and manager fixed effects), 77% (with firm fixed effects) and 78% (with manager fixed effects).

Overall, the substantially improved adjusted R^2s in the estimated model specifications with time invariant firm and managerial qualities suggest that compared with their observable counterparts, these unobservable qualities have a significantly larger explanatory power for firm innovation. Aditionally, it is worth noting that several of the coefficients change dramatically when including firm and/or manager fixed effects in the model. For example, the economic importance of Size, ROA, R&D, Lev, Cash, and CEO are reduced when including firm and/or manager fixed effects while Capx, HH, HH2, Vol, switch signs. These differences across models underscore the importance of controlling for unobserved firm and manager qualities when studying the determinants of corporate innovation productivity. Finally, comparing models 3 and 4 (firm fixed effects) to models 7 and 8 (firm and manager fixed effects) we see much smaller differences in the aforementioned coefficients, this may suggest that firm fixed effects are more important than manager fixed effects in explaining corporate innovation than manager fixed effects. However, because the "Spell" methodology is unable to separately identify firm and manager fixed effects. We thus turn our attention to the connected sample in order to separately identify the importance of firm and manager fixed effects in determining corporate innovation productivity.

2.3.2. Relative Importance of Firm and Managerial Attributes

In the preceding section, we have established the significant role of unobservable firm and managerial qualities for firm innovation. We now turn to evaluating their relative importance by conducting AKM regressions on the connected subsample. All our AKM regressions reported in Table 4 include the observable variables employed in Table 3, as well as firm and/or manager and year fixed effects. Similar to Table 3, Table 4 also shows a larger model R^2 for estimated specifications using the number of patents than the number of citations as the innovation proxy. It is also worth noting that the magnitudes of the coefficients in Table 3 are similar to those in Table 4 further assuaging concerns related to the representativeness of the connected sample.

Panel B of Table 4 presents the R-squared decomposition of models 7 and 8 estimated using the AKM method. The model R^2 is decomposed according to expression (2) above that allows us to compute the component normalized covariance with the dependent variable and percentage of the model R^2 attributable to each class of determinants, namely firm fixed effects, manager fixed effects, observable components, which include observable time variant variables and the year fixed effects, and residuals. firm fixed effects contribute the most to the model R^2, with its normalized covariance representing 52.58% and 48.30% of the explained variation in firm innovation, whereas manager fixed effects contribute 30.89% and 30.21% depending on the measure of innovation examined. The observable time variant characteristics, together contribute 16.53% and 21.49% of the model R^2. These findings suggest that compared to firm effects, manager effects, while still significant, play a less important role in explaining firm innovation.

We next perform several robustness tests that broadly confirm our main results. As discussed in Graham, Li, and Qiu (2012) the AKM method relies on the information about movers to determine the non-mover fixed effects. Limited mobility within the sample will result in noisy estimates of the non-mover fixed effects. That is they may not be "truly purged of firm-level influences." Thus the contribution of manager fixed effects to model R^2 estimated above may be overstated. In order to address this concern we conduct the analysis in Table 4 using the MDV methodology on the mobility sample. It should be noted that the mobility sample contains the same firms as the connected sample, but, it does not contain the non-mover managers and is thus free from the potential contamination issue discussed above.

The results from the regressions using the MDV approach are reported in Table 5. The regression results in Table 5 are broadly consistent with those reported in Table 4. One notable, exception is that the R^2 in the manager fixed effects regressions (models 5 and 6) is much lower than that reported in the firm fixed effects regressions (models 3 and 4). This result suggests that manager fixed effects explain less of the variation in innovation productivity than firm fixed effects. Indeed, the R^2 decomposition in Panel B of Table 5 shows a stark contrast in the explanatory power of

firm and manager fixed effects. Firm fixed effects contribute 70.78% and 69.76% while manager effects contribute only 15.85% and 13.21% to model R^2 where the dependent variable is LPatents and LCitations respectively. The results are consistent with manager fixed effects playing a much smaller role in innovation productivity compared to firm fixed effects.

It is plausible that our results may be driven by the sample of low innovative firms or firms with no patents. That is, if managers are matched to firms based on their ability to innovate then our estimate of firm and manager fixed effects as well as the coefficients on the time varying observable characteristics are biased as the omitted variables related to matching are likely to be correlated with innovation productivity. To rule out this possibility, we replicate our results using the sample of firms within the connected sample that were assigned at least one patent during the sample period. The results are reported in the top panel of Table 6. Broadly consistent with the original results, firm fixed effects account for 41.59% and 30.04% of the variation in innovation productivity. While, manager fixed effects account for 28.09% and 30.95%. The observable variables together with year fixed effects constitute 30.32% and 39.01% of the model R^2.

The results using this subsample with patents suggest a smaller difference in the importance of firm and manager fixed effects in explaining innovation productivity, however they are consistent with our main results that managers are important but, firm characteristics may matter slightly more. By examining only firms with patents we eliminate some of the matching concerns, i.e. that our results are driven by differences in omitted time varying variables due to firm/manager matching in firms with and without patents.[14] As in Graham, Li, and Qiu (2012), we acknowledge that a test of this nature cannot completely eliminate matching concerns. However, Graham, Li, and Qiu (2012) also point out that if matching is based on unobservable time invariant firm and manager characteristics than including both firm and manager fixed effects should address the problem.

We also conduct two other tests to ensure the robustness of our main findings. It is plausible that the main results are driven by chief financial officers (CFOs) or other named executive officers (NEOs), who are not expected to contribute to innovation. It should be noted that we include CEO dummies in all of our regressions to control for the importance of this position. However, to further examine this possibility, we conduct the same analysis using only the connected sample of CEOs. As shown in the middle panel of Table 6, CEO fixed effects appear to explain the majority of the variation in innovation productivity in this subsample. CEO fixed effects account for 50.09% and 50.53% of the variation while

[14] Following Graham, Li, and Qiu (2012) we also run several tests were we restrict the sample to managers that move to firms with similar average patent productivity. The unreported results of these test suggest that manager fixed effects matter more than firm fixed effects. However, the majority 75% of the firms in these test have no patent productivity so they are difficult to interpret as patenting firms are likely to be different than non-patenting firms. If we eliminate those firms without patents we are left with on the order of 30 managers and 60 firms. Thus we do not believe that these results are representative of the entire sample of firms. Specifically, we run four separate analyses excluding movers if the average firm level patent productivity during their tenure in the new firm is 10%, 15%, 20%, or 25% different from the average firm level patent productivity during their tenure in their old firm.

firm fixed effects only account for 25.71% and 26.43%. However after controlling for unobservable differences between firms with and without patents, the bottom panel of Table 6 reports that CEO fixed effects account for 26.72% and 34.93% of model R^2 while firm fixed effects account for 46.82% and 38.41%. The results of these CEO subsample tests are again broadly consistent with our main findings CEOs matter, but firms characteristics appear to matter more especially after controlling for differences in firms with and without patents.

The overall evidence is consistent with our earlier quote from Collins and Porras (2002) that a firm's success relies "at least in part" on its "underlying processes and fundamental dynamics" and is not primarily the result of a single executive, who has great ideas and made good decisions, is charismatic, and has led with authority. Our finding of the importance of firm attributes relative to managerial attributes in explaining firm innovation productivity is also in accord with the results shown by Kaplan, Sensoy, and Stromberg (2009). These authors find that the success of startup companies depends more on the business than on the management. They argue that their findings are in line with the views of Hart and Moore (1994) and Holmstrom (1999) that nonhuman capital assets, such as identifiable lines of business and intellectual property, are critical for the early stage of a firm's life and that they remain relatively stable even as specific human capital assets turnover.[15] In line with their arguments, our results therefore suggest that a firm's innovation productivity still depends on the same, perhaps broadened, business and firm expertise it had when it started.

[15] They cite examples such as, Apple, eBay, Cisco, and Google that are in the same businesses they started in, but are managed by non-founders after their start up.

On the other hand, our findings contrast those of prior studies. For example, Bertrand and Schoar (2003) find that manager fixed effects matter for a number of corporate decisions, including investment, R&D, financial, and organizational practices. Graham, Li, and Qiu (2012) also reach a similar conclusion in their analysis of executive compensation determinants. However, Coles and Li (2012) show that the importance of unobservable manager and firm fixed effects varies with the type of corporate issue in question. For example, unobservable manager characteristics can explain a large extent of the heterogeneity in executive wealth-performance sensitivity, board independence, board size, and sensitivity of expected executive compensation to firm risk, whereas unobserved firm attributes contribute to a large proportion of variation explained for dividend payout, antitakeover defenses, book and market leverage, and corporate cash holdings.

2.3.3. Evidence from Manager Raids/Sudden Deaths

This section applies a concept from labor economics to test the robustness of our key finding that a firm's underlying processes and fundamentals play a more critical role than management in determining corporate innovation. We construct two samples of firms that allow us to evaluate the managerial contribution to corporate innovation: one sample consists of firms whose managers are raided by other firms, and another consists of firms whose managers die suddenly. As we discussed in Section 2.3 above, the sample of raided managers is not random, but the sample of sudden deaths ought to be random. We then examine the innovation productivity of the firm around the time when its manager is being raided by another firm versus when its manager dies suddenly. Labor economists argue that the average ability of a sample of managers who are raided should be higher than a sample of firms where the manager dies suddenly. Hence, comparing corporate innovation productivity or cumulative abnormal returns (CARs) across these groups should provide a measure of the differences in managerial ability. However, if the ability to promote innovation is not a major determinant of manager quality, we should not see differences between these two groups.

2.3.3.1. Innovation productivity and manager raids/sudden deaths

We first evaluate the effects of manager raids/sudden deaths on innovation productivity (measured in terms of the number of patents and the number of patent citations as well as with industry-adjusted patents and citations) by regressing innovation productivity on the indicator variables Post, Raid, and their interaction, Post×Raid. Post equals 1 for the two years following the raid/sudden death year and 0 for the two years prior to the raid/sudden death year. Raid equals 1 if a manager is raided by another public company and 0 if a manager dies suddenly. One potential issue with this analysis is that the departing manager may have contributed to the patents filed by the firm following the manager's departure, which would contaminate our results. In order to mitigate this concern, we employ a two-year lag for manager raids/sudden deaths relative to the patent filing year. Additionally, we exclude the filing year that is two years following the manager's departure, as this year most likely contains a combination of the old and new managers' contributions to the firm's innovation productivity. For example, if a manager is raided in 1999, we compare the raided firm's innovation productivity in 1999 and 2000 to that in 2002 and 2003. Furthermore, we control for various firm attributes that were used in Table 4; however, managerial attributes are excluded from these regressions because

ExecuComp has limited or no information on these managerial variables (PSlice, Tenure, Vega, and Delta) for the sample of firms whose managers are raided and whose managers die suddenly before 1992. These firm-specific variables are defined in the appendix. All regressions are estimated with year and industry fixed effects, and the t-statistics associated with regression coefficients are reported in parentheses. The regression results are reported in Table 7.

The coefficient on the interaction term Post×Raid is negative, suggesting that the productivity of a firm will fall more when its manager is being raided by another firm than when its manager dies suddenly, consistent with the manager's ability to innovate being an important determinant of quality. However, the coefficient on Post×Raid is not significantly different from zero, which implies no statistical difference between the effects of manager raids versus sudden deaths on corporate innovation productivity. These findings are maintained even after we adjust the measure of the change in a firm's productivity to account for industry productivity. Hence, the overall evidence indicates that firm level attributes, and perhaps to a lesser extent manager attributes, play an important role in encouraging corporate innovation.

2.3.3.2. Cumulative abnormal returns (CAR) and manager raids/sudden deaths

We now turn to assessing managerial contributions by examining the effects of manager raids/sudden deaths on a firm's CAR across different levels of innovation productivity. We employ four different benchmarks in measuring the firm's CAR: (i) the market-adjusted return, (ii) the market model, (iii) the Fama-French 3-factor model, and (iv) the Fama-French 4-factor model.

For all the above models, except the market-adjusted returns, we estimate the parameters over a 150-day period, which ends two weeks before CAR is computed. We define Day 0 as the date at which a manager raid or sudden death is announced, and CAR is computed between Day -2 and Day 2. For the market model, we regress a firm's stock return against the corresponding market return to obtain the regression parameters. For the Fama-French 3-factor model, we regress a firm's stock return against the corresponding three factors (i.e., the market, size, and book-to-market factors) to obtain the regression parameters, and for their 4-factor model, we include the fourth factor, the momentum factor.[16] Finally, for the market-adjusted returns, we compute the abnormal return as the difference between the stock return and market return and accumulate the abnormal return over Day -2 to Day 2.

Our sample consists of 152 manager raids and 75 manager sudden deaths. We divide these 227 firms into high and low innovative firms based on their total number of patents for the two years prior to a manager raid or a sudden death. A firm is assigned to a high-innovative group (High) if the number of its patents is larger than the median number of patents for the 227 firms. Similarly, if a firm's number of patents is equal or lower than the median, it falls into a low-innovative group (Low). Of the 152 firms whose managers depart for a similar position at another firm, 74 are low innovative firms and 78 are high innovative firms. Of the 75 firms whose managers die suddenly, 56 are low innovative firms and 19 are high innovative firms. We compute the cross-sectional average of the 5 Day CAR associated with each type of innovative firms and also the difference in CARs

[16] All the daily returns on these factors are obtained from Ken French's website.

between firms with manager raids and those with sudden deaths within the high and low innovative firms. Results are reported in Table 8.

On average, the 5-day CAR for firms with manager raids is consistently negative, whereas the 5- day CAR for firms with manager sudden deaths is mostly positive. For example, the 5-day CAR for manager raids is between -0.8% (Low innovative firms based on the Fama-French 3-factor approach) and -1.3% (High innovative firms based on the Fama-French 3-factor approach), suggesting that the market reaction is unfavorable when a firm loses its manager to another firm. On the other hand, the 5-day CAR for manager sudden deaths varies from -0.6% (High innovative firms based on the market model) to 1.6% (High innovative firms based on the Fama-French 4-factor approach), implying that the market reacts somewhat favorably when a firm suddenly loses its manager. While the difference in the market reaction between manager raids and manager deaths is insignificant, the results are broadly consistent with those obtained by Hayes and Schaefer (1999). These findings suggest that on average raided managers are of higher quality, compared with the quality of managers who die suddenly.[17] Finally, if managers' are matched to firms based on their ability to innovate and exceptionally innovative managers are scarce, we would expect that the difference between CARs surrounding manager deaths and raids would be higher for high innovative firms compared to low innovative firms. The last row of Table 8 indicates no statistical difference in the CARs surrounding manager raids and manager deaths between firms with high and low innovation productivity.

[17] Hayes and Schaefer (1999) report that manager raids are accompanied by an average abnormal return of -1:87%, while manager deaths are associated with an average abnormal return of +2:84% using a (-1, +1) day event window.

In Table 9, we reexamine the results of Table 8 in a multivariate setting. Specifically, we regress the 5-Day CAR on the previously defined indicator variable Raid, a high-innovative variable HInnov, the interaction between Raid and HInnov, and all the control variables employed in Table 7. HInnov equals one if the firm belongs to a highly innovative group and 0 if otherwise. All regressions include fixed effects and the t-statistics are computed based on robust standard errors clustered at the firm level. To conserve space, we present only the coefficients of these three key variables, together with their t-statistics. While the results show a consistently negative coefficient on the interaction term, consistent with the ability to innovate being a major determinant of manager quality, none of the coefficients is statistically significant at conventional levels. The multivariate results therefore suggest that while managers' ability to innovate may be an important quality it is not as important as other firm level characteristics. In summary, the evidence suggests that that firm characteristics, and to a lesser extent managerial ability, explain a large portion of the heterogeneity in firm level innovation productivity.

2.4. CONCLUSION

In this paper, we analyze the relative importance of firm and managerial attributes in determining corporate innovation productivity. A firm's innovation productivity is less likely to be manipulated by managers and thus serves as a less biased performance metric compared to traditional accounting-based performance measures. Using the AKM approach that calculates proportions of R^2 attributable to different firm and manager characteristics, we find that firm characteristics dominate manager characteristics in explaining the heterogeneity in innovation productivity.

We conduct several robustness tests to ensure that the finding is not driven by managers who are not expected to contribute to innovation (such as non-CEOs). We also do not find that our results are due to unobservable differences between firms with and with our patents. We also provide evidence using manager/firm separations that on average managers' ability to innovate is not a major determinant of manager quality or innovation productivity.

Finally, we don't want to under represent the role the managers play in innovation productivity. As shown in all of our results manager fixed effects are generally nearly as important as firm fixed effects. However, we would caution investors and corporate insiders that hiring the next Steve Jobs may not improve innovation productivity if the firms underlying traits and characteristics such as the firm culture, product nature, and competitiveness are not also conducive to innovation.

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Table 1
Mobility of Top Managers

This table shows the number of top managers who move (i.e., movers) or stay in our sample of firms. Panel A reports the number (percentage) of managers that move to another firm within the sample, and Panel B presents the number of firms with mobile managers. The sample period is from 1992 to 2006.

Panel A: Number of Times a Manager Moves

Number of Moves Made	Number of Managers	%
0	19,175	95.32
Number of Non-Movers	19,175	95.32
1	877	4.36
2	59	0.29
3	5	0.02
Number of Movers	941	4.68
Total Number of Managers	20,116	100.00

Panel B: Number of Managerial Moves in a Firm

Number of Movers in a Firm	Number of Firms	%
0	1,059	50.84
1-5	647	31.06
6-10	241	11.57
11-20	117	5.62
21-30	15	0.72
31-50	4	0.19
Total	2,083	100.00

Table 2
Representativeness of the Connected Sample

This table reports summary statistics of the major variables used in our analysis. Patent information comes from the NBER patent data set provided by Hall, Jaffe, and Trajtenberg (2001). This data set includes the number of patents by each firm and the number of citations received by each patent. Variable definitions are reported in the appendix. It provides the average, median, and standard deviation of each variable in the full and connected samples (i.e., the sample firms connected by mobile managers). It also shows the quintile averages of each variable and the percent of firms from the connected sample in each quintile. Quintiles are formed using the full sample.

Panel A: Representativeness of continuous variables

				Average and % in each quintile				
Variable	Mean	Median	SD	1	2	3	4	5
Patents								
Full	18.71	0.00	117.57		0.00		2.53	94.95
Connected	29.79	0.00	155.88		0.00		2.56	115.57
Connected %					56.50		18.10	25.40
Citations								
Full	285.66	0.00	2337.61		0.00		19.72	1417.84
Connected	467.24	0.00	3137.81		0.00		20.78	1793.65
Connected %					63.80		10.30	25.90
Total assets								
Full	4493.17	814.80	19635.31	152.53	404.31	845.60	2085.94	18979.19
Connected	6339.80	1289.66	21241.72	155.03	404.85	858.10	2132.76	20266.99
Connected %				13.90	16.00	19.00	23.50	27.60
ROA								
Full	0.14	0.14	0.13	-0.02	0.11	0.14	0.19	0.28
Connected	0.13	0.14	0.14	-0.02	0.11	0.14	0.19	0.27
Connected %				20.50	20.10	20.50	19.80	19.10
R&D								
Full	0.04	0.00	0.08		0.00	0.01	0.04	0.15
Connected	0.04	0.01	0.08		0.00	0.01	0.03	0.15
Connected %					43.70	11.60	21.70	23.00
Capx								
Full	0.07	0.05	0.06	0.02	0.03	0.05	0.08	0.16
Connected	0.07	0.05	0.06	0.02	0.03	0.05	0.08	0.16
Connected %				17.80	20.50	21.10	20.90	19.80

Table 2 - Continued

Variable	Mean	Median	SD	Average and % in each quintile 1	2	3	4	5
Tang								
Full	0.31	0.25	0.22	0.07	0.16	0.25	0.39	0.67
Connected	0.31	0.26	0.21	0.07	0.16	0.25	0.39	0.66
Connected %				18.80	19.80	20.20	20.70	20.50
Lev								
Full	0.22	0.20	0.19	0.00	0.09	0.20	0.31	0.50
Connected	0.23	0.22	0.19	0.00	0.09	0.21	0.31	0.49
Connected %				17.40	18.60	21.50	22.00	20.50
Q								
Full	2.21	1.66	1.93	1.02	1.34	1.67	2.25	4.77
Connected	2.21	1.65	2.06	1.02	1.34	1.67	2.25	4.86
Connected %				19.60	20.70	20.40	19.90	19.40
HH								
Full	0.06	0.04	0.06	0.03	0.03	0.05	0.06	0.14
Connected	0.06	0.04	0.07	0.03	0.03	0.05	0.06	0.15
Connected %				21.40	19.50	20.20	19.40	19.60
HH2								
Full	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.03
Connected	0.01	0.00	0.05	0.00	0.00	0.00	0.00	0.04
Connected %				21.40	19.50	20.20	19.40	19.60
Retn								
Full	0.24	0.03	12.46	-0.49	-0.17	0.03	0.25	1.58
Connected	0.31	0.03	16.94	-0.50	-0.17	0.03	0.25	1.96
Connected %				20.10	19.90	20.40	19.90	19.70
Vol								
Full	0.47	0.40	0.24	0.23	0.32	0.41	0.53	0.83
Connected	0.46	0.39	0.23	0.23	0.32	0.41	0.53	0.83
Connected %				22.10	20.40	19.50	18.50	19.50
KZ								
Full	-4.36	-0.83	59.10	-20.87	-3.19	-0.86	0.49	2.63
Connected	-4.05	-0.78	78.54	-20.23	-3.18	-0.87	0.49	2.92
Connected %				19.70	19.50	20.00	19.10	21.70

Table 2 - Continued

Variable	Mean	Median	SD	Average and % in each quintile 1	2	3	4	5
Cash								
Full	0.14	0.07	0.18	0.01	0.02	0.07	0.17	0.45
Connected	0.14	0.06	0.18	0.01	0.02	0.07	0.17	0.44
Connected %				20.50	20.00	20.80	18.80	20.00
IOwn								
Full	0.62	0.64	0.21	0.31	0.52	0.64	0.74	0.90
Connected	0.64	0.66	0.20	0.31	0.52	0.64	0.74	0.89
Connected %				16.50	19.00	21.10	22.30	21.00
Age								
Full	22.00	16.00	18.60	4.80	9.90	16.75	28.04	52.77
Connected	24.32	17.00	20.59	4.80	9.88	16.72	28.11	54.51
Connected %				21.60	17.80	18.30	17.30	24.90
PSlice								
Full	0.20	0.16	0.13	0.07	0.12	0.16	0.23	0.41
Connected	0.19	0.15	0.13	0.07	0.12	0.16	0.22	0.42
Connected %				22.70	20.60	19.20	18.00	19.60
Tenure								
Full	9.02	7.00	7.38	3.54	5.69	6.96	8.68	20.53
Connected	8.66	6.78	7.24	3.49	5.68	6.96	8.68	20.81
Connected %				25.00	18.10	19.70	19.40	17.80
Vega								
Full	47.41	13.19	176.39	1.31	5.89	13.51	31.28	185.04
Connected	60.24	17.36	218.91	1.35	5.97	13.58	31.66	195.80
Connected %				15.60	17.70	19.80	21.80	25.20
Delta								
Full	357.44	47.48	5655.6	6.12	21.17	48.71	118.80	1592.40
Connected	396.12	54.31	6170.2	6.23	21.20	48.97	119.11	1647.61
Connected %				17.40	19.20	20.10	21.70	21.60

Table 2 - Continued

Panel B: Representativeness of Indicator variables

Variable		Mean	Median	SD
Female	Full	0.04	0.00	0.20
	Connected	0.04	0.00	0.20
CEO	Full	0.18	0.00	0.39
	Connected	0.18	0.00	0.39
Chairman	Full	0.15	0.00	0.36
	Connected	0.15	0.00	0.36

Panel C: Correlation Matrix

This table presents the correlation matrix of the variables used in our analysis. Patent information comes from the NBER patent data set provided by Hall, Jaffe, and Trajtenberg (2001). Variable definitions are reported in the appendix. This data set includes the number of patents by each firm and the number of citations received by each patent. Pearson correlation coefficients within the hold out sample are above the diagonal and those within the connectedness sample are below the diagonal. * indicate significance at the 5% levels.

Var.	Size	ROA	R&D	Capx	Tang	Lev	Q	HH	HH^2	Retn	Vol	KZ	Cash	IOwn	Age	PSlice	Tenure	Vega	Delta	Female	CEO	Chairman
Size		0.19***	-0.30***	-0.03***	0.23***	0.25***	-0.16***	0.02***	0.02***	0.01**	-0.42***	0.04***	-0.38***	0.16***	0.44***	-0.04***	0.18***	0.26***	0.07***	-0.03***	0.02***	0.08***
ROA	0.14***		-0.47***	0.15***	0.14***	-0.08***	0.05***	-0.02***	-0.01*	0.00	-0.39***	0.05***	-0.21***	0.25***	0.06***	0.01*	0.14***	0.04***	0.02***	0.01	-0.00	0.01**
R&D	-0.27***	-0.46***		-0.03***	-0.26***	-0.21***	0.32***	-0.01	-0.03***	-0.00	0.37***	-0.03***	0.48***	-0.14***	-0.15***	0.01	-0.13***	-0.02***	0.00	-0.01	-0.00	-0.04***
Capx	-0.05***	0.16***	-0.06***		0.61***	0.04***	0.06***	-0.10***	-0.07***	-0.00	-0.09***	0.04***	-0.15***	-0.06***	-0.08***	0.01*	0.07***	-0.04***	-0.01**	0.00	-0.00	-0.00
Tang	0.20***	0.14***	-0.26***	0.63***		0.29***	-0.17***	-0.09***	-0.06***	0.00	-0.31***	0.06***	-0.43***	-0.05***	0.12***	0.00	0.17***	-0.02***	-0.03***	-0.03***	0.00	0.02***
Lev	0.28***	-0.08***	-0.20***	0.04***	0.27***		-0.19***	0.02***	0.01	0.00	-0.15***	0.06***	-0.42***	-0.02***	0.11***	-0.01*	0.03***	-0.01	-0.03***	-0.02***	0.00	0.02***
Q	-0.16***	0.11***	0.31***	0.05***	-0.17***	-0.21***		-0.05***	-0.04***	0.00	0.20***	-0.04***	0.38***	-0.00	-0.20***	0.02**	-0.06***	0.05***	0.08***	0.02***	-0.00	-0.02***
HH	0.01*	-0.03***	0.01**	-0.09***	-0.09***	0.01***	-0.03***		0.91***	-0.01	-0.08***	-0.00	-0.05***	-0.00	0.11***	-0.00	0.02***	-0.02**	-0.01**	-0.02***	-0.00	0.01
HH^2	0.02***	-0.02***	-0.01**	-0.06***	-0.06***	-0.00	-0.03***	0.89***		-0.00	-0.05***	-0.00	-0.03***	0.01*	0.08***	-0.00	-0.00	-0.01	-0.01	-0.01	0.00	0.01*
Retn	0.01*	0.00	-0.00	-0.00	-0.00	0.00	0.01*	-0.01	-0.00		0.02***	-0.00	0.02**	0.00	-0.04***	0.00	-0.01**	-0.00	-0.00	0.01	0.00	-0.01
Vol	-0.39***	-0.34***	0.35***	-0.06***	-0.27***	-0.13***	0.17***	-0.07***	-0.04***	0.02***		-0.04***	0.54***	-0.10***	-0.42***	0.00	-0.24***	-0.05***	0.01	0.04***	-0.00	-0.06***
KZ	0.04***	0.03***	-0.03***	0.05***	0.08***	0.07***	-0.05***	-0.01***	-0.01***	-0.00	-0.04***		-0.10***	0.02***	0.02***	-0.03***	0.02***	-0.00	-0.01	-0.00	-0.01	0.01
Cash	-0.36***	-0.20***	0.48***	-0.15***	-0.41***	-0.41***	0.38***	-0.03***	-0.00	0.02***	0.48***	-0.12***		-0.02***	-0.28***	0.01	-0.17***	-0.01	0.05***	0.04***	-0.01	-0.06***
IOwn	0.24***	0.20***	-0.12***	-0.07***	-0.06***	-0.01*	-0.00	-0.02***	-0.00	0.00	-0.08***	0.01**	-0.02***		0.02***	-0.01*	0.00	0.03***	-0.02***	0.05***	0.01*	0.01*
Age	0.45***	0.06***	-0.15***	-0.09***	0.11***	0.11***	-0.18***	0.09***	0.07***	-0.03***	-0.39***	0.01***	-0.27***	0.04***		-0.03***	0.20***	0.07***	-0.00	-0.03***	0.02***	0.06***
PSlice	-0.06***	0.01***	0.00	0.01***	-0.00	-0.02***	0.02***	0.00	-0.00	0.00	0.01**	-0.03***	0.02***	-0.02***	-0.04***		0.10***	0.19***	0.02***	-0.08***	0.61***	0.46***
Tenure	0.14***	0.13***	-0.13***	0.07***	0.15***	0.03***	-0.05***	0.02***	-0.00	-0.01***	-0.20***	0.02***	-0.14***	-0.01*	0.17***	0.12***		0.08***	0.05***	-0.04***	0.21***	0.23***
Vega	0.28***	0.04***	-0.01**	-0.04***	-0.03***	0.01*	0.05***	-0.01*	-0.00	-0.00	-0.05***	-0.00	-0.01**	0.06***	0.08***	0.18***	0.07***		0.16***	-0.02***	0.19***	0.18***
Delta	0.07***	0.02***	-0.00	-0.01***	-0.03***	-0.02***	0.06***	0.00	-0.00	-0.00	-0.01	-0.01	0.03***	-0.02***	0.00	0.03***	0.06***	0.13***		-0.01	0.06***	0.06***
Female	-0.03***	0.01	-0.00	-0.01*	-0.04***	-0.03***	0.03***	-0.01***	-0.00	0.01	0.04***	-0.00	0.04***	0.05***	-0.03***	-0.07***	-0.04***	-0.02***	-0.01*		-0.07***	-0.07***
CEO	0.02***	0.00	-0.01	-0.01	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.01	-0.01	-0.01*	0.01**	0.02***	0.59***	0.22***	0.18***	0.07***	-0.07***		0.68***
Chairman	0.08***	0.01***	-0.04***	-0.00	0.02***	0.02***	-0.01***	0.01**	0.01***	-0.00	-0.06***	0.01	-0.05***	0.01**	0.06***	0.43***	0.24***	0.17***	0.07***	-0.07***	0.65***	

Table 3
Determinants of Corporate Innovation Productivity (Full Sample)

This table presents the regression results on the determinants of corporate innovation productivity using the full sample. The results are from pooled OLS regressions with year fixed effects only and also with combinations of other fixed effects. All regressions are estimated with year fixed effects, and variable definitions are reported in Appendix A. All regressions are estimated with year fixed effects. The t-statistics reported in parentheses are based on robust standard errors clustered at the firm level. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Pooled OLS		**Firm Fixed Effects**		**Manager Fixed Effects**		**Firm and Manager Fixed Effects**	
	LPatents	LCitations	LPatents	LCitations	LPatents	LCitations	LPatents	LCitations
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Size	0.429***	0.563***	0.168***	0.197***	0.265***	0.367***	0.183***	0.254***
	(14.95)	(14.30)	(5.90)	(3.37)	(12.46)	(9.33)	(7.68)	(5.17)
ROA	1.680***	2.764***	0.170	0.653***	0.179*	0.538***	0.075	0.381*
	(7.23)	(7.57)	(1.40)	(2.61)	(1.84)	(2.66)	(0.76)	(1.82)
R&D	6.649***	10.640***	0.696**	1.500***	0.629***	1.281***	0.269	0.834*
	(10.93)	(10.93)	(2.29)	(2.64)	(2.72)	(2.79)	(1.18)	(1.76)
Capx	1.108***	1.628***	-0.045	-0.252	0.000	-0.135	-0.0534	-0.234
	(2.89)	(2.71)	(-0.29)	(-0.70)	(0.00)	(-0.47)	(-0.41)	(-0.81)
Tang	-0.925***	-1.463***	0.440***	1.135***	0.156	0.591**	0.378***	0.974***
	(-6.37)	(-6.85)	(2.73)	(3.25)	(1.14)	(2.29)	(2.78)	(3.43)
Lev	-0.440***	-0.780***	-0.125	-0.337**	-0.157**	-0.372***	-0.090	-0.278**
	(-3.84)	(-4.38)	(-1.49)	(-1.98)	(-2.29)	(-2.75)	(-1.30)	(-1.99)
Q	0.027**	0.045**	0.030***	0.055***	0.032***	0.053***	0.027***	0.044***
	(2.35)	(2.44)	(4.79)	(4.60)	(5.36)	(4.65)	(4.34)	(3.75)
HH	2.967***	4.710***	-1.184	-1.544	-0.585	-0.751	-1.388**	-2.329*
	(3.11)	(3.28)	(-1.59)	(-0.87)	(-0.89)	(-0.61)	(-2.25)	(-1.65)
HH^2	-2.902**	-4.868**	-0.089	-2.461	1.231	1.355	0.621	-0.023
	(-2.00)	(-2.33)	(-0.10)	(-1.11)	(1.21)	(0.77)	(0.85)	(-0.01)
Retn	-0.000	0.000	-0.001***	-0.002***	0.000	0.000	0.001	0.013
	(-1.32)	(1.03)	(-8.39)	(-6.81)	(0.17)	(0.78)	(0.12)	(1.05)
Vol	0.346***	0.429**	-0.032	-0.265	-0.091	-0.423**	-0.082	-0.395**
	(2.82)	(2.36)	(-0.43)	(-1.48)	(-1.62)	(-2.57)	(-1.42)	(-2.24)
KZ	0.000	0.000	-0.000**	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.91)	(1.00)	(-1.97)	(-0.99)	(-1.78)	(-0.99)	(-1.41)	(-0.84)
Cash	0.349**	0.551**	0.037	0.024	0.057	0.083	0.088	0.154
	(2.26)	(2.18)	(0.31)	(0.10)	(0.62)	(0.44)	(0.94)	(0.80)
IOwn	-0.145	0.040	0.208***	0.425***	0.016	0.108	0.107*	0.247*
	(-1.25)	(0.22)	(2.92)	(2.72)	(0.27)	(0.91)	(1.81)	(1.96)
Log(Age)	0.241***	0.351***	0.139**	0.223**	0.171***	0.203***	0.094**	0.075
	(7.19)	(7.05)	(2.53)	(2.20)	(4.71)	(3.31)	(2.22)	(0.89)
PSlice	0.033	0.028	0.000	0.013	-0.041	-0.025	0.030	0.109
	(0.71)	(0.35)	(0.02)	(0.30)	(-1.07)	(-0.33)	(0.89)	(1.53)
Log(Tenure)	0.014	0.001	0.015*	0.027	-0.037*	-0.025	-0.027	-0.034
	(0.60)	(0.04)	(1.70)	(1.64)	(-1.70)	(-0.59)	(-1.20)	(-0.71)
Vega	-0.000	-0.000**	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(-1.15)	(-2.19)	(-2.39)	(-2.65)	(-2.78)	(-3.51)	(-3.59)	(-3.98)
Delta	-0.000	-0.000	0.000	0.000	0.000*	0.000	0.000***	0.000
	(-0.40)	(-0.61)	(1.09)	(0.57)	(1.68)	(0.27)	(3.10)	(0.83)
Female	-0.141***	-0.253***	0.003	0.011				
	(-3.82)	(-4.60)	(0.18)	(0.38)				
CEO	0.029	0.069**	0.011*	0.024*	-0.005	-0.015	0.009	0.009
	(1.58)	(2.34)	(1.82)	(1.84)	(-0.33)	(-0.57)	(0.80)	(0.36)
Chairman	-0.068**	-0.116**	-0.007	-0.013	-0.076***	-0.150***	-0.038**	-0.084**
	(-2.29)	(-2.50)	(-0.89)	(-0.75)	(-3.81)	(-3.84)	(-1.98)	(-2.18)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	75,491	75,491	75,491	75,491	75,491	75,491	75,491	75,491
Adj. R^2	0.338	0.327	0.833	0.744	0.834	0.761	0.859	0.784

Table 4
Determinants of Corporate Innovation Productivity (Connected Sample)

This table presents the regression results on the determinants of corporate innovation productivity using the connected sample. The results are from pooled OLS regressions with year fixed effects only and also with combinations of other fixed effects. All regressions are estimated with year fixed effects, and variable definitions are reported in Appendix A. The t-statistics reported in parentheses are based on robust standard errors clustered at the firm level. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Determinant of Innovation Productivity (Connected Sample)

	Pooled OLS		**Firm Fixed Effects**		**Manager Fixed Effects**		**Firm and Manager Fixed Effects**	
	LPatents	LCitations	LPatents	LCitations	LPatents	LCitation	LPatents	LCitations
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Size	0.478***	0.625***	0.203***	0.223***	0.315***	0.422***	0.221***	0.295***
	(12.30)	(11.74)	(4.74)	(2.72)	(11.44)	(8.88)	(6.13)	(4.26)
ROA	1.840***	2.941***	0.296*	0.876**	0.366***	0.814***	0.180	0.562*
	(5.17)	(5.50)	(1.66)	(2.41)	(2.72)	(2.98)	(1.26)	(1.91)
R&D	6.553***	10.09***	0.852**	1.556**	0.915***	1.663***	0.431	1.063*
	(8.32)	(8.23)	(2.30)	(2.48)	(3.21)	(3.18)	(1.50)	(1.92)
Capx	1.527**	2.409**	0.135	-0.051	0.128	-0.045	0.021	-0.305
	(2.24)	(2.31)	(0.49)	(-0.08)	(0.56)	(-0.10)	(0.09)	(-0.62)
Tang	-1.352***	-2.061***	0.344	0.928*	-0.028	0.245	0.356	0.926**
	(-5.68)	(-6.00)	(1.36)	(1.76)	(-0.14)	(0.70)	(1.62)	(2.10)
Lev	-0.459***	-0.797***	-0.0164	-0.0936	-0.136	-0.318	-0.021	-0.153
	(-2.61)	(-3.08)	(-0.13)	(-0.38)	(-1.30)	(-1.60)	(-0.19)	(-0.71)
Q	0.032**	0.063***	0.033***	0.064***	0.037***	0.066***	0.031***	0.057***
	(2.15)	(2.81)	(4.28)	(4.78)	(5.41)	(5.86)	(4.37)	(4.98)
HH	3.950***	6.670***	-1.074	-0.514	-0.148	0.495	-1.245	-1.288
	(2.62)	(3.03)	(-0.94)	(-0.20)	(-0.16)	(0.31)	(-1.20)	(-0.57)
HH^2	-4.111**	-7.262***	-0.414	-3.628	0.806	0.307	0.415	-0.789
	(-2.15)	(-2.66)	(-0.33)	(-1.22)	(0.64)	(0.14)	(0.38)	(-0.33)
Retn	-0.000	0.000**	-0.001***	-0.002***	0.000	0.000*	-0.006	-0.001
	(-0.44)	(2.17)	(-5.25)	(-4.94)	(1.00)	(1.86)	(-0.78)	(-0.07)
Vol	0.576***	0.816**	-0.0279	-0.337	-0.0793	-0.529**	-0.110	-0.608**
	(2.66)	(2.53)	(-0.17)	(-0.99)	(-0.66)	(-2.23)	(-0.76)	(-2.03)
KZ	0.000	0.000	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.66)	(0.77)	(-2.17)	(-1.14)	(-1.27)	(-0.86)	(-1.02)	(-0.77)
Cash	0.435*	0.771**	-0.027	-0.168	-0.001	-0.090	0.050	0.024
	(1.79)	(1.97)	(-0.15)	(-0.47)	(-0.00)	(-0.33)	(0.34)	(0.08)
IOwn	0.0171	0.306	0.295***	0.740***	0.0305	0.244	0.159*	0.468***
	(0.09)	(1.10)	(2.80)	(3.32)	(0.38)	(1.54)	(1.84)	(2.66)
Log(Age)	0.329***	0.468***	0.178**	0.281*	0.196***	0.227***	0.156**	0.161
	(6.54)	(6.42)	(2.15)	(1.93)	(4.48)	(3.13)	(2.34)	(1.27)
PSlice	0.145**	0.226**	0.042*	0.088*	-0.052	-0.036	0.055	0.167*
	(2.39)	(2.26)	(1.66)	(1.69)	(-0.92)	(-0.35)	(1.15)	(1.75)
Log(Tenure)	0.026	0.007	0.015	0.018	-0.062**	-0.059	-0.027	-0.007
	(0.75)	(0.13)	(1.17)	(0.75)	(-2.19)	(-1.12)	(-0.95)	(-0.12)
Vega	-0.000	-0.000**	-0.000**	-0.000**	-0.000**	-0.000***	-0.000***	-0.000***
	(-1.54)	(-2.01)	(-1.97)	(-2.28)	(-1.96)	(-2.61)	(-2.80)	(-3.20)
Delta	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000**	0.000
	(0.80)	(0.33)	(0.47)	(-0.83)	(0.54)	(-0.78)	(2.14)	(0.03)
Female	-0.139**	-0.221***	0.024	0.093**				
	(-2.46)	(-2.71)	(0.99)	(2.13)				
CEO	0.026	0.055	0.003	0.007	-0.003	-0.014	0.000	-0.012
	(0.88)	(1.18)	(0.31)	(0.39)	(-0.15)	(-0.36)	(-0.01)	(-0.35)
Chairman	-0.093**	-0.141*	-0.008	-0.003	-0.114***	-0.189***	-0.062**	-0.093*
	(-1.99)	(-1.93)	(-0.69)	(-0.11)	(-3.83)	(-3.40)	(-2.19)	(-1.70)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	40,697	40,697	40,697	40,697	40,697	40,697	40,697	40,697
Adj. R^2	0.355	0.350	0.839	0.757	0.834	0.768	0.908	0.859

Table 4 - Continued

Panel B: R-Squared Decomposition (Connected Sample)

	LPatents	**LCitations**
	Cov(Innov, Determinant)	Cov(Innov, Determinant)
Determinant	Var(Innov)	Var(Innov)
	Connected Sample	
R^2	**0.908**	**0.859**
Firm fixed effects	0.477 (52.58%)	0.415 (48.30%)
Manager fixed effects	0.280 (30.89%)	0.259 (30.21%)
Observable time variant characteristics	0.150 (16.53%)	0.185 (21.49%)
Residuals	0.092	0.141
No. of Firms	1,024	1,024
No. of Managers	11,040	11,040
No. of Movers	941	941
No. of Obs.	40,697	40,697

Table 5
Determinants of Corporate Innovation Productivity (Mobility Sample)

This table presents the regression results on the determinants of corporate innovation productivity using the mobility sample. The results are from pooled OLS regressions with year fixed effects only and also with combinations of other fixed effects. All regressions are estimated with year fixed effects, and variable definitions are reported in Appendix A. The t-statistics reported in parentheses are based on robust standard errors clustered at the firm level. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Determinant of Innovation Productivity (Mobility Sample)

	Pooled OLS		**Firm Fixed Effects**		**Manager Fixed Effects**		**Firm and Manager Fixed Effects**	
	LPatents	LCitations	LPatents	LCitations	LPatents	LCitations	LPatents	LCitations
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Size	0.478***	0.625***	0.203***	0.223***	0.315***	0.422***	0.221***	0.295***
	(12.30)	(11.74)	(4.74)	(2.72)	(11.44)	(8.88)	(6.13)	(4.26)
ROA	1.840***	2.941***	0.296*	0.876**	0.366***	0.814***	0.180	0.562*
	(5.17)	(5.50)	(1.66)	(2.41)	(2.72)	(2.98)	(1.26)	(1.91)
R&D	6.553***	10.09***	0.852**	1.556**	0.915***	1.663***	0.431	1.063*
	(8.32)	(8.23)	(2.30)	(2.48)	(3.21)	(3.18)	(1.50)	(1.92)
Capx	1.527**	2.409**	0.135	-0.051	0.128	-0.045	0.021	-0.305
	(2.24)	(2.31)	(0.49)	(-0.08)	(0.56)	(-0.10)	(0.09)	(-0.62)
Tang	-1.352***	-2.061***	0.344	0.928*	-0.028	0.245	0.356	0.926**
	(-5.68)	(-6.00)	(1.36)	(1.76)	(-0.14)	(0.70)	(1.62)	(2.10)
Lev	-0.459***	-0.797***	-0.0164	-0.0936	-0.136	-0.318	-0.021	-0.153
	(-2.61)	(-3.08)	(-0.13)	(-0.38)	(-1.30)	(-1.60)	(-0.19)	(-0.71)
Q	0.032**	0.063***	0.033***	0.064***	0.037***	0.066***	0.031***	0.057***
	(2.15)	(2.81)	(4.28)	(4.78)	(5.41)	(5.86)	(4.37)	(4.98)
HH	3.950***	6.670***	-1.074	-0.514	-0.148	0.495	-1.245	-1.288
	(2.62)	(3.03)	(-0.94)	(-0.20)	(-0.16)	(0.31)	(-1.20)	(-0.57)
HH^2	-4.111**	-7.262***	-0.414	-3.628	0.806	0.307	0.415	-0.789
	(-2.15)	(-2.66)	(-0.33)	(-1.22)	(0.64)	(0.14)	(0.38)	(-0.33)
Retn	-0.000	0.000**	-0.001***	-0.002***	0.000	0.000*	-0.006	-0.001
	(-0.44)	(2.17)	(-5.25)	(-4.94)	(1.00)	(1.86)	(-0.78)	(-0.07)
Vol	0.576***	0.816**	-0.0279	-0.337	-0.0793	-0.529**	-0.110	-0.608**
	(2.66)	(2.53)	(-0.17)	(-0.99)	(-0.66)	(-2.23)	(-0.76)	(-2.03)
KZ	0.000	0.000	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.66)	(0.77)	(-2.17)	(-1.14)	(-1.27)	(-0.86)	(-1.02)	(-0.77)
Cash	0.435*	0.771**	-0.027	-0.168	-0.001	-0.090	0.050	0.024
	(1.79)	(1.97)	(-0.15)	(-0.47)	(-0.00)	(-0.33)	(0.34)	(0.08)
IOwn	0.0171	0.306	0.295***	0.740***	0.0305	0.244	0.159*	0.468***
	(0.09)	(1.10)	(2.80)	(3.32)	(0.38)	(1.54)	(1.84)	(2.66)
Log(Age)	0.329***	0.468***	0.178**	0.281*	0.196***	0.227***	0.156**	0.161
	(6.54)	(6.42)	(2.15)	(1.93)	(4.48)	(3.13)	(2.34)	(1.27)
PSlice	0.145**	0.226**	0.042*	0.088*	-0.052	-0.036	0.055	0.167*
	(2.39)	(2.26)	(1.66)	(1.69)	(-0.92)	(-0.35)	(1.15)	(1.75)
Log(Tenure)	0.026	0.007	0.015	0.018	-0.062**	-0.059	-0.027	-0.007
	(0.75)	(0.13)	(1.17)	(0.75)	(-2.19)	(-1.12)	(-0.95)	(-0.12)
Vega	-0.000	-0.000**	-0.000**	-0.000**	-0.000**	-0.000***	-0.000***	-0.000***
	(-1.54)	(-2.01)	(-1.97)	(-2.28)	(-1.96)	(-2.61)	(-2.80)	(-3.20)
Delta	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000**	0.000
	(0.80)	(0.33)	(0.47)	(-0.83)	(0.54)	(-0.78)	(2.14)	(0.03)
Female	-0.139**	-0.221***	0.024	0.093**				
	(-2.46)	(-2.71)	(0.99)	(2.13)				
CEO	0.026	0.055	0.003	0.007	-0.003	-0.014	0.000	-0.012
	(0.88)	(1.18)	(0.31)	(0.39)	(-0.15)	(-0.36)	(-0.01)	(-0.35)
Chairman	-0.093**	-0.141*	-0.008	-0.003	-0.114***	-0.189***	-0.062**	-0.093*
	(-1.99)	(-1.93)	(-0.69)	(-0.11)	(-3.83)	(-3.40)	(-2.19)	(-1.70)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	40,697	40,697	40,697	40,697	40,697	40,697	40,697	40,697
Adj. R^2	0.355	0.350	0.839	0.757	0.834	0.768	0.908	0.859

Table 5 - Continued

Panel B: R-Squared Decomposition (Mobility Sample)

	LPatents	**LCitations**
	Cov(Innov, Determinant)	Cov(Innov, Determinant)
Determinant	Var(Innov)	Var(Innov)
	Full Sample	
R^2	**0.903**	**0.853**
Firm fixed effects	0.640 (70.78%)	0.595 (69.76%)
Manager fixed effects	0.143 (15.85%)	0.113 (13.21%)
Observable time variant characteristics	0.121 (13.37%)	0.145 (17.02%)
Residuals	0.097	0.147
No. of Firms	1,024	1,024
No. of Managers	941	941
No. of Movers	941	941
No. of Obs.	5,659	5,659

Table 6
Robustness Tests

This table presents several robustness test on the relative importance of each class of determinants in explaining innovation productivity measured in terms of the number of patents and the number of citations. The determinants are all the variables used in Table 4, but are classified into: (i) firm fixed effects, (ii) manager effects, and (iii) Observable time variant characteristics, and (iv) residuals. The percentage of R^2 attributable to each group of determinants is reported in parentheses.

	LPatents	**LCitations**
Determinant	Cov(Innov, Determinant) / Var(Innov)	Cov(Innov, Determinant) / Var(Innov)
	Sample of Firms with Patents	
R^2	**0.893**	**0.843**
Firm fixed effects	0.371 (41.59%)	0.235 (30.04%)
Manager fixed effects	0.251 (28.09%)	0.261 (30.95%)
Observable time variant characteristics	0.271 (30.32%)	0.329 (39.01%)
Residuals	0.107	0.157
No. of Firms	526	526
No. of Managers	6,234	6,234
No. of Movers	435	435
No. of Obs.	22,879	22,879
	Sample of CEOs	
R^2	**0.908**	**0.859**
Firm fixed effects	0.235 (25.71%)	0.233 (26.43%)
Manager fixed effects	0.458 (50.09%)	0.446 (50.53%)
Observable time variant characteristics	0.221 (24.20%)	0.203 (23.04%)
Residuals	0.092	0.141
No. of Firms	161	161
No. of Managers	288	288
No. of Movers	84	84
No. of Obs.	1,198	1,198
	Sample of CEOs in Firms with Patents	
R^2	**0.907**	**0.868**
Firm fixed effects	0.425 (46.82%)	0.333 (38.41%)
Manager fixed effects	0.242 (26.72%)	0.303 (34.93%)
Observable time variant characteristics	0.240 (26.46%)	0.231 (26.66%)
Residuals	0.093	0.132
No. of Firms	75	75
No. of Managers	154	154
No. of Movers	38	38
No. of Obs.	634	634

Table 7
Impact of Manager Raids / Sudden Death on the Innovation Productivity

This table presents the regression results on the determinants of the innovation productivity (measured in terms of the number of patents and the number of patent citations) with respect to manager deaths and raids. The sample focuses only on firms whose executives die suddenly or are raided. Post is a dummy variable that indicates the period subsequent to year 0 in which a manager's sudden death or raid occurs, and Raid is an indicator variable that equals one if a manager is raided to join another company and 0 if a manager dies suddenly. All variables are defined in the appendix. All regressions are estimated with year effects, and the t-statistics associated with regression coefficients are reported in parentheses. These statistics are based on robust standard errors clustered at the firm level. Significance at the 1%, 5% or 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively

Variable	LPatents	LCitations	LPatents	LCitations
P ost	-0.059	-0.153	-0.087	-0.222
	(-0.34)	(-0.45)	(-0.53)	(-0.70)
Raid	0.229	0.368	0.145	0.283
	-0.9	-0.88	-0.59	-0.69
P ost × *Raid*	-0.146	-0.154	-0.085	-0.045
	(-0.72)	(-0.40)	(-0.46)	(-0.13)
Size	0.593∗∗∗	0.767∗∗∗	0.552∗∗∗	0.739∗∗∗
	-6.61	-5.55	-6.29	-5.6
ROA	2.417∗∗	2.883∗	2.168∗∗	2.119
	-2.49	-1.8	-2.37	-1.42
R&D	8.534∗∗∗	10.747∗∗∗	7.885∗∗∗	8.352∗∗
	-3.48	-2.78	-3.37	-2.32
Capx	0.624	1.407	0.357	0.474
	-0.28	-0.37	-0.17	-0.13
Tang	-0.335	-0.793	-0.161	-0.313
	(-0.45)	(-0.69)	(-0.23)	(-0.29)
Lev	-0.187	-0.657	0.025	-0.275
	(-0.35)	(-0.79)	-0.05	(-0.36)
Q	0.129∗∗	0.196∗	0.137∗∗	0.202∗∗
	-2	-1.96	-2.2	-2.11
HH	6.206	13.769∗	3.214	9.123
	-1.31	-1.69	-0.62	-1.07
HH^2	-7.512	-31.897∗	-3.495	-24.536
	(-0.83)	(-1.95)	(-0.37)	(-1.59)
Retn	0.027	0.002	-0.037	-0.111
	-0.35	-0.01	(-0.51)	(-0.84)
Vol	0.987	1.413	0.639	1.173
	-1.19	-0.97	-0.81	-0.86
KZ	0.005∗	0.009	0.005∗	0.007
	-1.67	-1.5	-1.78	-1.47
Cash	0.026	-0.104	0.163	0.358
	-0.04	(-0.09)	-0.26	-0.33
IOwn	-0.16	0.268	-0.218	0.11
	(-0.31)	-0.34	(-0.46)	-0.15
Log(Age)	0.213∗	0.122	0.221∗∗	0.164
	-1.83	-0.66	-2.01	-0.93
Year	Yes	Yes	Yes	Yes
No. of Obs	637	637	637	637
Adj. R^2	0.71	0.649	0.632	0.54

Table 8
Cumulative Abnormal Returns (CAR) Associated with Manager Deaths/Raids and Firms with High vs. Low Innovation Productivity

This table reports only the key regression coefficients from regressing 5-day cumulative abnormal returns (CAR) associated with the announcement of manager sudden deaths or raids on two variable indicators (*Raid* and *HInnov*) and their interaction as well as all the control variables used in Table 7. All variables are defined in the appendix. *Raid* is an indicator variable that equals one if a manager is raided by another company and 0 if a manager dies suddenly. *HInnov* is an indicator variable that equals one if the firm belongs to a highly innovative group and 0 if otherwise. We define highly innovative firms as those whose innovation productivity is above the median productivity in our sample of firms. We employ four different models to compute the parameters used in estimating CAR over a 150-day period: (i) market adjusted, (ii) the market model, (iii) the Fama-French 3-factor model, and (iv) the Fama-French 4-factor model. The 150-day period ends two weeks before CAR is computed. Assigning the announcement date as day 0, the CAR is computed between day -2 and day 2. All regressions are estimated with year and industry fixed effects and the t-statistics associated with the regression coefficients are reported in parentheses. These statistics are based on robust standard errors clustered at the firm level.

	Market Adjusted			**Market Model**			**Fama-French 3- Factor Model**			**Fama-French 4- Factor Model**		
Indicator	**All**	**High**	**Low**	**All**	**High**	**Low**	**All**	**High**	**Low**	**All**	**High**	**Low**
Raid	-0.011	-0.012	-0.011	-0.010	-0.011	-0.010	-0.011	-0.013	-0.008	-0.011	-0.011	-0.011
Death	0.011	0.005	0.013	0.007	-0.006	0.011	0.010	0.002	0.013	0.015	0.016	0.015
Diff(R-D)	-0.022	-0.017	-0.024	-0.017	-0.005	-0.021	-0.021	-0.015	-0.021	-0.026	-0.027	-0.026
	(-1.54)	(-0.69)	(-1.31)	(-1.19)	(-0.21)	(-1.16)	(-1.47)	(-0.67)	(-1.18)	(-1.79)	(-0.94)	(-1.47)
DID(H-L)		0.007			0.016			0.006			-0.001	
		(0.24)			(0.59)			(0.20)			(0.05)	

Table 9
Multivariate analysis of Cumulative Abnormal Returns (CAR) associated with Manager Deaths / Raids

This table reports only the key regression coefficients from regressing 5-day cumulative abnormal returns (CAR) asso- ciated with the announcement of manager sudden deaths or raids on two variable indicators (*Raid* and *HInnov*) and their interaction as well as all the control variables used in Table 7. All variables are defined in the appendix. *Raid* is an indicator variable that equals one if a manager is raided by another company and 0 if a manager dies suddenly. *HInnov* is an indicator variable that equals one if the firm belongs to a highly innovative group and 0 if otherwise. We define highly innovative firms as those whose innovation productivity is above the median productivity in our sample of firms. We employ four different models to compute the parameters used in estimating CAR over a 150-day period: (i) market adjusted, (ii) the market model, (iii) the Fama-French 3-factor model, and (iv) the Fama-French 4-factor model. The 150-day period ends two weeks before CAR is computed. Assigning the announcement date as day 0, the CAR is computed between day -2 and day 2. All regressions are estimated with year and industry fixed effects and the t-statistics associated with the regression coefficients are reported in parentheses. These statistics are based on robust standard errors clustered at the firm level.

	Market Adjusted	**Market Model**	**Fama-French 3- Factor Model**	**Fama-French 4- Factor Model**
Raid	-0.004	0.008	-0.005	-0.014
	(-0.18)	(0.37)	(-0.22)	(-0.54)
HInnov	0.000	-0.020	0.001	0.018
	(0.01)	(-0.67)	(0.04)	(0.48)
$Raid \times HInnov$	-0.028	-0.023	-0.026	-0.036
	(-0.86)	(-0.79)	(0.88)	(1.01)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
No. of Obs.	154	154	154	154
Adj. R^2	0.077	0.211	0.123	0.143

Appendix
Variable Definition

Variable	Definition	Data Source
Innovation		
LPatents	Natural logarithm of one plus aggregate number of patents filed in application year *t* by firm *i*	NBER Patent Dataset
LCitations	Natural logarithm of one plus aggregate adjusted number of citations received by the patents filed in year *t* by firm *i*, where adjusted number of citaton is computed by multi- plying each patent's raw citation by the weighting index from Hall, Jaffe, and Trajtenberg (2001, 2005)	NBER Patent Dataset
Firm Characteristics		
Size	Natural log of total assets of firm *i* in fiscal year *t*	Compustat
ROA	Earnings before interest and depreciation of firm *i* in fiscal year *t* divided by its book value of total assets in *t*	Compustat
R&D	Research and development expenditure divided by book value of total assets in year *t* and set to 0 if missing	Compustat
Capx	Capital expenditure scaled by book value of total assets in year *t*	Compustat
Tang	Tangibility defined as net property plant and equipment of firm *i* in fiscal year *t* divided by total assets in year *t*	Compustat
Lev	Total debt of firm i in fiscal year *t* divided by its book value of total assets in year *t*	Compustat
Q	Market value of equity plus book value of assets minus book value of equity minus balance sheet deferred taxes, divided by book value of assets in year *t*	Compustat
HH	Herfindahl index of firm *i* in fiscal year *t*, calculated as the sum of the squared share of each firm in total industry sales based on sales at the 4-digit SIC code	Compustat
HH2	Square of HH	Compustat
Retn	Firm *i*'s annual stock return	CRSP
Vol	Standard deviation of monthly returns over the past five years and then annualized by multiplying by the square root of 12	CRSP

Appendix
Variable Definition – Continued

Variable	Definition	Data Source
Firm Characteristics – Continued		
KZ	Firm i's Kaplan-Zingales index measured at the end of fiscal year t, calculated as -1.002*Cash Flows/K + 0.283*Q + 3.139*Leverage/Total Capital - 39:368*Dividends/K - 1.315*Cash/K, where Cash Flows = (Income before extraordinary items in t + total depreciation and amortization in t), K = PP&E in t - 1, Q = (market capitalization in t + total shareholder's equity in t - book value of common equity in t – deferred tax assets in t)/Total shareholder's equity in t, Debt = total long-term debt in t + notes payable in t + current portion of long-term debt in t, Dividends = total cash dividends paid in t (common and preferred), Cash = cash and short-term investments in t	Compustat
Cash	Cash of firm *i* in year *t* divided by total assets	Compustat
IOwn	Percentage of total shares outstanding held by 13f institutional investors	Thomson Reuters
Age	Firm *i*s age, approximated by the number of years from firms IPO as reported in CRSP	CRSP
Manager Characteristics		
PSlice	Pay slice defined as the difference between the total pay of the manager (TDC1) and the median total compensation of the other managers in year *t* by firm *i*	ExecuComp
Tenure	The number of years the manager has been with the company, which equals the difference between the year of the observation and the year when the individual joined the firm	ExecuComp
Vega	Change in the dollar value of the manager wealth for a one percentage point change in the annualized standard deviation of stock returns at the end of the fiscal year	ExecuComp
Delta	Change in the dollar value of the manager wealth for a one percentage point change in stock price at the end of the fiscal year	ExecuComp
Female	A dummy variable that equals one if the manager is a female and zero if otherwise	ExecuComp
CEO	A dummy variable that equals one if the manager is the CEO in a particular year and zero if otherwise	ExecuComp
Chairman	A dummy variable that equals one if the CEO of the firm is also the board chairman and zero if otherwise	ExecuComp

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