Essays on Corporate Governance and Asset Pricing

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Abstract

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The first chapter of my thesis examines the effect of corporate governance on performance using nonprofit hospitals as an economic environment with muted external governance mechanisms and patient survival of a heart attack as an unambiguous measure of performance. I find that a one standard deviation increase in strength of governance reduces the probability of death by 0.86 percentage points after controlling for patient characteristics.

The second chapter of my thesis examines why a stock's market exposure, beta, varies across return frequencies. We provide a risk-based explanation for this frequency dependence of beta by introducing uncertainty about the effect of systematic news on firm value (opacity) into a frictionless model. We document a robust relationship between the frequency dependence of betas and proxies for opacity.

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DEDICATION

to my patient and loving wife

Chapter 1

HOW IMPORTANT IS GOVERNANCE? EVIDENCE FROM HEART ATTACK SURVIVAL

Internal governance is a set of policies put in place to align managerial interests with claimants' interests. Estimating the causal effect of internal governance is difficult. Strong governance could lead to strong performance, or firms with strong expected performance could choose strong governance. A simple regression approach to estimate the effect of governance is unable to distinguish a causal relationship from a simple correlation. In this study I estimate the marginal effect of internal governance on performance in an economic environment free of many confounding factors, with an unambiguous measure of performance, using an instrumental variable regression to establish causality.

I estimate the marginal effect of internal governance in the context of nonprofit hospitals. This setting provides an excellent testbed because many of the traditional external governance mechanisms are muted. In the nonprofit universe there is a weakened market for corporate control, which can reduce managerial slack through the threat of takeover (Bertrand and Mullainathan, 2003). There are no institutional investors to discipline management (Holderness, 2003) or do the Wall Street walk and divest their shares. There are no activist investors or blockholders to petition for a seat on the board of directors in order to change the operating performance of the organization. With many external governance mechanisms weakened or missing, the effect of internal governance on performance becomes more prominent.

Much of the existing literature on corporate governance limits itself to studying public firms, an environment where there are numerous external governance mechanisms acting as substitutes for internal governance. In these studies the availability of substitute governance mechanisms reduces the economic importance of internal governance (Rediker and Seth, 1995). This reduction in the economic importance of internal governance is not uniform across firms. Within the universe of public firms there is considerable heterogeneity in the availability of external governance mechanisms both across firms and across time. For example the probability of a takeover varies through time, which results in some periods when internal governance is more prominent. In this study I use the nonprofit environment to look at the economic importance of governance at the extreme; how important is internal governance without the disciplinary role of an explicit residual claimant?

While the lack of external governance mechanisms in the nonprofit universe allows me to isolate the effect of internal governance, it comes at a cost: many traditional measures of governance are not applicable. I remedy this by constructing a measure of the strength of internal governance based on the involvement of the board in the compensation setting process of the CEO. This measure uses the presence or absence of pertinent policies to measure the board's involvement in setting the manager's compensation package.

The choice of strength of governance is likely co-determined with unobserved hospital characteristics. In this study I explicitly address endogeneity through an instrumental variable (IV) regression. I use governance spillovers of geographically local public firms to instrument for nonprofit hospital governance. These spillovers act as a source of exogenous variation in governance, which I use to identify the effect of governance on performance. This estimate is free of correlated omitted variables and simultaneity issues that plague research on corporate governance. By focusing on the nonprofit economic environment I can identify the direction of the spillovers; governance spillovers flow from public firms to nonprofit hospitals, not from nonprofit hospitals to public firms.

The existing literature on the effect of corporate governance on performance is mixed and suffers from methodological complications. The current literature uses stock returns, Tobin's Q, or operating performance metrics such as return on assets (ROA) to measure the effect of corporate governance on performance. While residual claimants are ultimately concerned about residual cash flows, using residual cash flows to measure the effectiveness of governance presents complications. The effectiveness of governance is not in how it changes the financial performance of an organization, but rather in how it changes the performance of a manager. In this sense the change in financial performance of an organization is an outcome of a change in managerial performance; an outcome that is affected by many factors well outside the control of a manager. In this study I use a direct measure of performance. I use patient survival of an acute myocardial infarction (AMI), commonly known as a heart attack, to measure performance and the effectiveness of internal governance. In particular I estimate the effect of internal governance using patient level medical records for 86,503 AMI patients at 62 hospitals in Arizona and Florida.

By estimating the effect of governance on performance in an economic environment where the importance of internal governance is magnified, with a direct measure of performance, and using an estimation technique that explicitly addresses endogeneity, I am able to cleanly estimate the effect of internal governance on performance. The effect is non-trivial in magnitude. A one standard deviation increase in internal governance corresponds to a 0.86 percentage point increase in the probability of a patient surviving three days. Relative to a 4.4 percent probability of death, this represents a 20 percent reduction in the probability of death. One channel identified by these data is through better medicinal treatment of AMIs as measured by a reduction in adverse drug reactions. This is consistent with hospitals with stronger governance providing a higher quality of care, which in turn increases the probability of a patient surviving an AMI.

This study makes contributions to three distinct strands of literature. The first contribution is to the corporate governance literature. While the corporate governance literature has provided strong evidence that governance affects financial and accounting performance, this study goes one step further and shows that governance has an economically significant effect on performance at the operational level. This evidence supports the existing corporate governance literature and shows that improvements at the production level are one possible source of value creation due to corporate governance.

The second contribution is to the nonprofit finance literature. In 2010 the nonprofit organizational form controlled $4.5 trillion dollars in assets and recognized $2.1 trillion dollars in revenue in the United States. Nonprofit hospitals alone controlled $926 billion dollars in assets and recognized $773 billion dollars in revenue (Blackwood et al., 2012). The magnitude of the assets under control by nonprofit organizations make these economically significant organizations, yet the nonprofit organizational form has received limited attention from the finance literature (Brickley and Horn, 2002; Eldenburg et al., 2004).

This study advances our understanding of the magnitude of the agency costs in nonprofit organizations and shows that effective board monitoring is crucial to the provision of high quality healthcare. Further, this study demonstrates that despite nonprofit organizations having an unclear objective function, the costs of agency conflicts are mitigated in a similar fashion to those at traditional for-profit firms.

The third contribution of this study is to the peer-effects and corporate externalities literature. This study documents strong geographic clustering in strength of governance in public firms. This supports the nascent literature on intra-firm spillovers in governance. I extend the evidence of governance externalities and show that governance spillovers cross both industry and organizational form boundaries.

1.1 Literature Review

Research on the effects of corporate governance falls in two primary categories. The first category is the effect of corporate governance on a firm's stock return or Tobin's Q. Gompers et al. (2003) construct an index of shareholder's rights, referred to hereafter as the GIndex, and find that firms with strong governance outperform firms with weak governance as measured by abnormal stock returns. Bebchuk et al. (2009) identify the value relevant provisions of the GIndex and design an entrenchment index, referred to hereafter as the EIndex. Their results support Gompers et al. (2003) and find that firms with strong governance outperform firms with weak governance. Gompers et al. (2003) and Bebchuk et al. (2009) focus on the effect of internal governance mechanisms such as anti-takeover provisions and CEO compensation packages. Cremer and Nair (2005) incorporate institutional ownership as an external governance mechanism and find that internal and external governance mechanisms are complements. They find that firms only outperform in the presence of both strong internal and strong external governance.

Core et al. (2006) question the causal interpretation of the association between governance and stock returns and provide evidence that is not consistent with a causal relationship. Stock returns and strength of governance are potentially endogenously related. Bhagat and Bolton (2008) address these endogeneity concerns through instrumental variables and do not find a significant relationship between governance and returns. In short the evidence of a causal effect of corporate governance on stock returns is mixed.

The evidence of governance being associated with Tobin's Q is more uniform: stronger governance is associated with higher Q. This result is supported by Gompers et al. (2003); Bebchuk and Cohen (2005); Bebchuk et al. (2009) and numerous other papers. While the association between governance and Q is well established, the direction of causality is not. Bebchuk et al. (2009) address this explicitly on page 811: "although our evidence is consistent with an effect of entrenchment on value, it does not establish the direction of causation. The issue of simultaneity is one that clearly calls for further examination." The simultaneity arises because governance is not set in a vacuum, but rather is co-determined with firm and managerial characteristics. A few examples of these characteristics include managerial power (Hermalin and Weisbach, 1998), board characteristics (Hermalin and Weisbach, 2001), and institutional ownership (Chung and Zhang, 2011).

There are a number of established techniques in the corporate finance literature to address simultaneity and endogeneity more broadly. One often used identification strategy, and indeed used in Bebchuk et al. (2009), is to use lagged values of governance variables under the assumption that lagged values are uncorrelated with contemporaneous realizations of omitted variables. This is a strong assumption, especially with highly persistent variables such as governance (Roberts and Whited, 2012). Another often used identification strategy is to use an arguably exogenous shock to a particular governance mechanism to act as a natural experiment. Examples include changes in board independence requirements due to Sarbanes-Oxley (Chhaochharia and Grinstein, 2007), changes in business combination laws (Giroud and Mueller, 2010), and changes in regulatory restrictions (Kole and Lehn, 1997). A third method to address simultaneity, and the method used in this study, is to use an instrumental variables approach. Examples of this approach include Bennedsen et al. (2007), Duchin et al. (2010), and Smith (2013).

The second category of existing research is on the effect of corporate governance on firm decisions or operating performance as measured by accounting metrics. A standard method to test the effect of governance on operating performance is to regress return on assets (ROA) on measures of governance such as the GIndex or EIndex. The evidence points to a robust positive association between the strength of governance and ROA (Bhagat and

Bolton, 2008; Giroud and Mueller, 2011). Another strand of literature has looked at the sources, uses, and value of cash as a function of governance. Dittmar and Mahrt-Smith (2007) find that the market value of cash holdings by firms with weak governance is half the value of cash held by firms with strong governance. Harford et al. (2008) find that firms with weak governance invest 1.6 percent more in capital expenditures than their industry peers and invest less in research and development. This spending pattern is consistent with wasted corporate resources as a result of weak governance.

Using stock returns, Q, or accounting metrics to measure performance results in numerous methodological complications. Estimating the effect of corporate governance through stock returns is complicated by the fact that returns are based on expectations of the market. In order for corporate governance, a firm characteristic, to manifest as an abnormal return the market must have improper expectations of future cash flows, or corporate governance must be acting as a proxy for an omitted risk factor. Under the first alternative we cannot draw conclusions on the actual effect of corporate governance but rather draw conclusions on the improper expectations of market participants. Under the second alternative we are not measuring the effect of corporate governance but rather the exposure to an unobserved risk factor and improperly calling that the effect of governance. Q regressions suffer from similar problems in that Q is based on market expectations and is noisily measured.

Estimating the effect of corporate governance through accounting metrics is complicated by the fact that managers can and do manipulate financial disclosures. Burgstahler and Dichev (1997) find a discontinuity in the distribution of earnings around zero. They estimate that 30 to 44 percent of firms that are expected to have small losses in pre-managed earnings manipulate earnings in order to report positive earnings. Further, earnings manipulation is systematically related to governance. Agrawal and Chadha (2005) document a negative relationship between earnings restatements and strength of governance as measured by independent directors with financial expertise. The results of Efendi et al. (2007) support a positive relationship between governance and truthful reporting. They find that the likelihood of financial restatement is higher at firms where the CEO is also the chairman of the board. With imperfect detection of malfeasance, estimates of the effect of governance will be biased towards zero. Firms with the weakest governance will experience the most manipulation of accounting metrics, which will result in governance appearing to have a smaller effect than it actually does. In short we are drawing conclusions on the effect of corporate governance based on metrics that we know are subject to manipulation by managers and the degree of manipulation is a function of our explanatory variable. This observation limits our ability to draw meaningful inference when using accounting metrics as outcome variables in governance research.

My study overcomes many of the aforementioned problems by focusing on a direct and unambiguous measure of performance. This study does not draw conclusions based on market expectations that may be improper or measured with error. Managerial manipulation of performance is limited in this study because the manager does not have discretion in determining if a patient is alive or dead.

Causality is difficult to establish in research on corporate governance. In this study I argue that causality runs from strength of governance to performance. I determine this by using governance spillovers from geographically local public firms as a source of exogenous variation in the strength of governance in nonprofit hospitals. There is a growing body of literature on governance spillovers. Aggarwal et al. (2011) document international spillovers in corporate governance, which operates through institutional investor activism. Albuquerque et al. (2014) continue this line of research and examine governance spillovers through foreign direct investment. They find positive spillovers in strength of governance from cross-border M&A activity. Cheng (2011) builds a model of earnings inflation based on peer firm strength of governance. He finds the incidence of fraud is lower when peer firms have stronger governance. The transmission mechanism in Cheng (2011) does not rely on the presence of an explicit residual claimant. Rather the spillovers occur due to relative performance evaluation and the career concerns of managers. Dicks (2012) is similar to Cheng (2011) in that the channel for governance spillovers is through the labor market for executives and the crafting of executive compensation packages.

There is another line of literature that examines channels of governance spillovers that are geographically localized. John and Kadyrzhanova (2009) look at the geographically local governance environment of public firms and find positive spillovers. They conclude that good governance begets good governance, in that good governance of local peer firms positively affects a firm's governance. Bouwman (2011) examines overlapping directors and finds that the probability of being a director is significantly more likely if the director is geographically local. Additionally Bouwman (2011) finds convergence in governance practices of firms with overlapping directors and attributes this to overlapping directors exerting influence over governance practices. Knyazeva et al. (2013) examine the supply of outside directors and find a strong geographic segmentation in the supply of directors, which is especially pronounced in smaller firms. In this study I assert that the regional variation in governance practices, either due to spillovers or segmentation in the market for directors, is orthogonal to the probability of a patient surviving an AMI, save for through its effect on a hospital's strength of governance. This regional variation therefore acts as a source of exogenous variation in a hospital's strength of governance and is an appropriate instrumental variable.

The economic testbed that I use to examine the effect of governance on performance is the nonprofit economic environment. There has recently been a renewed interest in studying nonprofit organizations directly, as well as using the nonprofit economic environment to study central questions in the finance literature. Adelino et al. (2014) take advantage of the large financial portfolios nonprofit hospitals hold to examine how exogenous cash flow shocks affect investment decisions. They find that nonprofit hospitals behave in a similar fashion to traditional public firms. A central question that is unresolved in the nonprofit literature is, what is the objective function of a nonprofit organization. Chang and Jacobson (2011) use a seismic retrofit mandate in California to reject popular theories such as nonprofit organizations are "for-profits in disguise", or pure altruistic entities. Another line of literature studies university endowments, which are economically important nonprofit organizations. Current work is being done on the theoretical side by Gilbert and Hrdlicka (2013) and on the empirical side by Brown and Tiu (2013).

1.2 Data

I use patient level medical records in conjunction with hospital financial statements to study the real effects of governance. The sample of hospitals revolves around patient level medical records from the Arizona and Florida State Inpatient Databases (SID), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for the years

2006 through 2010. The data provided by HCUP contains 331 healthcare facilities that accept inpatients. I am able to match 254 of those healthcare facilities to physical hospitals based on the addresses provided by the Centers for Medicare & Medicaid Studies and a manual query to the American Hospital Association (AHA) hospital profile web interface.[1] I then restrict the sample to remove specialty clinics, rehabilitation centers, and healthcare facilities that do not provide emergency services. This reduces the sample to 227 facilities. I then remove hospitals that are run by the federal, state, or local government. This reduces the sample to 196 hospitals. In this paper I focus on nonprofit hospitals in order to exploit an economic environment that has limited external governance mechanisms. Removing public for-profit hospitals and privately owned for-profit hospitals reduces the sample to 96 nonprofit hospitals.

I gather data from many sources, which I discuss in detail in the following section. A summary of these sources is presented in Table 1.1.

1.2.1 Patient Data

The patient data I use is age, gender, primary expected source of payment, race, pre-existing conditions, income quartile in the patient's zip code by state, and the type of AMI. To be included in the sample the inpatient event must be the initial hospitalization for a primary diagnosis of acute myocardial infarction, and be classified as an emergency.[2] I require a hospital to have a minimum of 36 AMI diagnoses over the five year window to be included in the sample. This reduces my sample from 96 to 80 hospitals.

In this study I examine three and seven day survival rates. I define a patient as surviving three days if the patient does not die or transfer to hospice care in the first three days of an inpatient stay, or if the patient is discharged alive in the first three days. Seven day survival is defined similarly; if a patient does not die or transfer to hospice within the first seven days of an inpatient stay, or if the patient is discharged alive in the first seven days, I define the patient as surviving seven days. To fix ideas, if a patient is admitted with an

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[1] http://www.ahadataviewer.com/

[2] I define a diagnosis of AMI as a single level CCS diagnosis code equal to 100.

AMI, survives four days, and then dies, I code the patient as surviving three days but not surviving seven days.

A limit of my analysis is that I do not observe if the patient dies between the day of discharge and three (seven) days after the initial AMI. For example, if a patient is admitted with an AMI, is discharged alive on day four, and then dies on day five, I would erroneously code the patient as surviving both three days and surviving seven days. This measurement error will only affect inferences if hospitals have differential discharge policies and those policies are correlated with governance. I mitigate concerns of effects due to unobserved differential discharge policies by focusing on both short-term (three day) and medium-term (seven day) survival. Short-term survival estimates will suffer less from any potential distortions due to differential discharge policies than medium-term survival estimates. The average inpatient stay is 5.19 days and 29.2% (75.8%) of my sample is discharged before three (seven) days.

My analysis of performance revolves around the treatment of AMI patients. I restrict the sample to initial inpatient stays with a primary diagnosis of an AMI for three reasons. First, AMI survival is a headline metric; it is likely that a manager is aware of the hospital's performance along this dimension. The Centers for Medicare & Medicaid Studies offers the service Hospital Compare through Medicare.gov that allows prospective patients to evaluate hospitals based on the quality of care the hospital provides. Two prominent measures that Hospital Compare uses to evaluate hospital quality are the readmission rate of AMI patients and the risk adjusted death rate of AMI patients. If patients undergoing discretionary medical care, such as cancer therapies or joint replacement surgery, are influenced by these prominent measures of quality, then it is likely the board of directors and manager are concerned about performance along this dimension. For the board of directors, and especially outside directors, the importance of AMI care is magnified. In my sample nearly all outside directors receive zero monetary compensation, or stated differently, all compensation is in the form of human capital. This serves to tie an outside director's human capital to the performance of the hospital, of which AMI survival is a key metric.

The second reason for focusing on AMI survival in this study is the manager must have the ability to affect outcomes in order for governance to affect performance. Curry et al.

(2011) interview key hospital staff in order to determine what characteristics differentiate the best performing hospitals from the worst performing hospitals in AMI treatment. They document that the formal medical policies and procedures are not differentiating features. Rather the distinguishing features of high performing hospitals include level of managerial involvement, organizational values of excellence, and the flow of information from front-line workers to managers. These are all attributes that are within a manager's control, and allow him to influence the quality of care a patient receives.

The third reason for focusing on AMIs in this study is that an AMI is an acute condition that is non-discretionary in nature. Approximately 50 percent of AMI patients receive treatment within four hours of the onset of systems (Roger et al., 2012). The urgency of the condition to some extent limits self-selection by patients and patient selection by hospitals.

1.2.2 Financial Data

Nonprofit organizations that are not religious institutions and have gross receipts greater than \$200,000 or total assets greater than \$500,000 must file IRS Form 990 annually.[3] IRS Form 990 contains standard balance sheet and income statement information such as total assets, debt outstanding, total liabilities, revenues, expenses, managerial compensation, etc. The form also contains soft information such as the mission statement, organizational structure, and notes on the operations of the hospital. For the years 2008 through 2010 I hand collect balance sheet, income statement, and governance data from IRS Form 990.[4] For the years 2006 and 2007 I use a mix of data compiled by GuideStar and hand collected data.[5] I restrict the sample to short-term acute care hospitals with more than \$50M in fixed assets for an average year in the sample.

I restrict the sample of hospitals to those with greater than \$1M in total compensation to the top management team for an average year in the sample. The top management team is defined by the IRS and includes all officers, directors, and key employees. A key employee is defined as an employee who earns greater than \$150,000, and controls more

[3]Instructions for IRS Form 990 http://www.irs.gov/pub/irs-pdf/i990.pdf

[4]Additional details on financial data collection and variable construction can be found in Appendix A.

[5]GuideStar is an information provider and research organization in the field of nonprofits.

than 10 percent of the hospital's resources. This skews my sample towards larger hospitals where formal governance mechanisms are more likely to be implemented. The combination of the minimum of $50M in fixed assets and a minimum of $1M in total compensation to the top management team reduces my sample to 71 hospitals.

1.2.3 Governance Measurement

I create a measure of the strength of governance based on the board's involvement in the compensation setting process of the CEO. I isolate four provisions that pertain to the pay setting process: the use of a compensation committee, the use of an independent compensation consultant, the use of a compensation survey, and the use of the written contracts of comparable organizations in setting compensation (hereafter denoted comparable contract). The presence of each provision is consistent with more involvement by the board in the pay setting process.

I follow the literature and construct a managerial discretion index, hereafter referred to as the DIndex, in the spirit of Gompers et al. (2003); Bebchuk et al. (2009); Aggarwal et al. (2009). For each provision present I add one point to a hospital's DIndex and then divide the total by four to facilitate interpretation. A higher DIndex is indicative of stronger governance, which is in contrast to the GIndex and EIndex where a lower value is indicative of stronger governance.

I am data limited in my measure of governance. The reporting requirements of nonprofit organizations changed in 2008 when the IRS overhauled Form 990. In 2008 the IRS required details of the compensation setting processes to be reported in Schedule J. Prior to 2008 this data was not reported on IRS Form 990. To allow for the use of the entire patient dataset spanning the years 2006 through 2010 I fix the DIndex of a hospital as its DIndex in 2008. I assume that governance is slow moving and the strength of governance is reasonably well captured by using the mid-point of the dataset. This is consistent with these data in that there is little variation in a hospital's DIndex between 2008 and 2010.

1.2.4 DIndex Analysis

The DIndex has a maximum value of one and a minimum value of zero. Table 1.2 presents summary statistics for the index and a breakdown of each component of the index.[6] 96% of hospitals have a compensation committee, 88% use a compensation consultant, and 80% use a compensation survey in the setting of managerial compensation. These provisions are prevalent among all hospitals. The use of a comparable compensation contracts is not nearly as pervasive, with only 47% of the sample. Figure 1.1 presents the distribution of DIndex in my sample. The distribution of DIndex has a mean of 0.78, a standard deviation of 0.201, and significant mass at a DIndex of 0.75.

Table 1.3 presents the mean values of hospital characteristics for the full sample of hospitals and hospital subsets by mean DIndex. Hospitals with strong governance and weak governance are similar along most dimensions. The sample is predominately urban hospitals because the filters tend to exclude small hospitals.

Patient self selection is a concern. Patients with a particularly severe AMI may opt to attend strong or weak governance hospitals. This concern is partially mitigated by the time to treatment sensitivity of an AMI. Table 1.4 presents the mean values of select patient characteristics for the full sample of patients and subset by mean DIndex. Patients are of similar age but slightly fewer women are admitted to high DIndex hospitals than low DIndex hospitals, 38 percent versus 40 percent. While this difference in female admissions is statistically significant, the economic significance is likely small. High and low DIndex hospitals admit similar fractions of Medicare patients as well as private insurance patients. Both types of hospitals have similar fractions of patients classified as obese, as well as similar fractions of patients classified as having chronic heart failure.

The data is sufficiently rich that I am able to determine the exact type of AMI that a patient had. For example I can determine if the patient had a subendocardial infarction, which has an unconditional seven day survival probability of 0.98, or an AMI with unspecified location, which has an unconditional seven day survival probability of 0.84. The richness of

[6] There are only 62 hospitals in my final sample due to restrictions on the construction of the instrumental variable.

the data and the ability to observe the exact type of AMI mitigates the possibility of omitting a patient characteristic that is of first order importance in determining three or seven day survival. There are two broad categories of AMIs, ST-elevation myocardial infarction (STEMI) and non-ST-elevation myocardial infarction (NSTEMI) AMI, which subsume the ten categories of the locations of the heart where the AMI occurred. Within these two classes of AMIs I do not find statistically significant differences in patient composition at hospitals with strong governance and hospitals with weak governance. In general Table 1.4 shows a lack of meaningful differences along numerous highly detailed dimensions of patient characteristics, and provides strong suggestive evidence that patient self-selection is not a first-order concern.

1.3 Governance and Performance

Does strength of governance affect performance and if so how important is it? I make this broad question testable by using AMI survival as an unambiguous measure of performance. My hypothesis is that the probability of survival is increasing in the strength of governance.

1.3.1 Methodology

A hospital produces a given quality of care that results in some probability of AMI survival. I chose patient survival as the primary measure because it is an unambiguous, observable measure and it acts as a summary for other unobservable measures of performance that is free from many measurement complications. Using the survival of patient p, in hospital j, at time t ($S_{p,j,t}$), I work under the assumption that survival is a function of the quality of the hospital $\lambda_{j,t}$, observable patient characteristics c_p, unobservable patient characteristics c_p^U, and an idiosyncratic component $\eta_{p,j,t}$. I follow Gowrisankaran and Town (1999) and estimate patient survival using a linear model.

$$S_{p,j,t} = \lambda_{j,t} + \rho c_p + \rho^U c_p^U + \eta_{p,j,t} \tag{1.1}$$

The economic process behind the quality of care is what is of interest. I define quality of care as a function of baseline quality α, strength of governance D_j, industry shocks in a state $\tau_{s,t}$, observable hospital characteristics $H_{j,t}$, unobservable hospital characteristics $H^U_{j,t}$, and an idiosyncratic term $\omega_{j,t}$.

$$\lambda_{j,t} = \alpha + \phi D_j + \tau_{s,t} + \delta H_{j,t} + \delta^U H^U_{j,t} + \omega_{j,t} \tag{1.2}$$

Substituting in the parametrized quality of care and collapsing into the error term the individually unidentifiable idiosyncratic terms for unobserved patient characteristics, unobserved hospital characteristics, patient mortality, and hospital quality my estimating equation becomes

$$S_{p,j,t} = \alpha + \phi D_j + \tau_{s,t} + \delta H_{j,t} + \rho c_p + \rho^U c^U_p + \delta^U H^U_{j,t} + \omega_{j,t} + \eta_{p,j,t} \tag{1.3}$$

$$S_{p,j,t} = \alpha + \phi D_j + \tau_{s,t} + \delta H_{j,t} + \rho c_p + \nu_{p,j,t} \tag{1.4}$$

My hypothesis is quality of care is increasing in strength of governance. This would manifest itself as a positive coefficient on ϕ. Complicating the estimation process of ϕ is the concern that a hospital's strength of governance, D_j, is correlated with unobserved hospital characteristics, $H^U_{j,t}$, or is correlated with unobserved patient characteristics, c^U_p. For example if governance is correlated with unobserved government involvement and survival of an AMI is also correlated with unobserved government involvement then the estimated $\hat{\phi}$ will be biased. Additionally patient choice of hospital is not fully randomized. While approximately 50 percent of AMI patients receive treatment within four hours of the onset of symptoms (Roger et al., 2012), patients do have limited ability to select which hospital they go to. If strength of governance is a determinant of quality of care and patients self-select into a hospital population then the estimated $\hat{\phi}$ will be biased.

1.3.2 Instrumental Variable Theory

To estimate consistent coefficients of the survival function I use an instrumental variables approach. I construct a set of instrumental variables (IVs) that are orthogonal to unobserved hospital characteristics and unobserved patient characteristics. The IVs I construct affect an AMI patient's probability of survival only through their effect on the hospital's strength of governance, and provide a source of exogenous variation in strength of governance. I use this exogenous variation to estimate the effect of governance on patient survival and interpret the regression as a causal relationship.

I exploit geographic variation in public firm governance to instrument for nonprofit hospital governance. I hypothesize that geographic clustering in public firm strength of governance spills over to nonprofit hospital strength of governance. This provides a source of variation in a hospital's strength of governance that is exogenous to other hospital characteristics.

I begin my analysis by first demonstrating that there is geographic clustering of public firm governance that is relevant to this study. To measure geographic variation in corporate governance I use all governance data available in RiskMetrics in 2004. I chose the governance data as of 2004 because this data is pre-sample period, which mitigates any unobserved contemporaneous shocks concerns. RiskMetrics did collect public firm governance in 2008, the year of my hospital governance data, but RiskMetrics' data collection methodology changed in 2007 such that it is inappropriate to compare data collected after 2007 to data collected before 2007, and requires different assumptions in the construction of the GIndex. To my knowledge there has not been a systematic reconciliation of pre-2007 and post-2007 data. By choosing 2004 public firm governance I can stay consistent with the literature as well as not introduce a new variation of the GIndex.

With positive spatial autocorrelation in governance, firms that are geographically closer to each other are more likely to have similar governance than firms further apart. This will manifest as clusters of particularly strong governance in some parts of the country, and clusters of particularly weak governance in others. Governance, as measured by the GIndex, could appear to be spatially autocorrelated even if there are no spillovers due to industry clustering. I therefore adjust each firm's GIndex by the industry mean at the three digit SIC code level, which I denote GIndex$'$. Figure 1.2 presents a map of GIndex$'$. In Figure 1.2 an arbitrary grid is overlaid on a map of the United States. If a box has five or more firms within its boundaries, I estimate the mean GIndex$'$ for all firms located within that box. Boxes that have higher average GIndex$'$, indicative of weaker governance, are shaded red, while boxes that have lower GIndex$'$, indicative of stronger governance, are shaded blue. Under a null of no spatial autocorrelation I would expect most boxes to be white, which is indicative of an even mix of strong and weak governance. Figure 1.2 shows that this is not the case. Areas such as Tampa, FL and San Fransisco, CA tend to have strong governance, while areas such as Pittsburgh, PA and Chicago, IL tend to have weak governance.

Moran's I is a test statistic that quantifies the spatial autocorrelation in GIndex$'$ that is visually evident in Figure 1.2. The test statistic is based on the distribution of GIndex$'$, as well as an adjacency matrix, denoted w.

$$\text{Moran's } I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(GIndex'_i - \overline{GIndex'})(GIndex'_j - \overline{GIndex'})}{\sum_i (GIndex'_i - \overline{GIndex'})^2} \tag{1.5}$$

In my sample Moran's I is 0.096. Unlike a traditional autocorrelation the expected value of Moran's I only goes to zero in the limit. Additionally the test statistic is not invariant to changes in the adjacency matrix. To estimate an expected value and distribution under a null of no spatial autocorrelation, I simulate the test statistic holding the adjacency matrix constant and drawing a random sample from the distribution of GIndex$'$. Figure 1.3 presents the results of this simulation using a binary adjacency matrix with firms closer (further) than 200 kilometers equal to 1 (0). The realized Moran's I of 0.096 is far in the right tail of the distribution and is indicative of positive spatial autocorrelation relative to the expected value of 0.04. Under the null of no spatial autocorrelation the realized Moran's I is statistically significant with a t-statistic of 12.9. This result is consistent with the clustering visually evident in Figure 1.2.

I take geographic variation in strength of governance as given and hypothesize that there are governance spillovers from geographically-local public firms to nonprofit hospitals. One potential channel for cross organizational form, cross industry governance spillovers is through the labor market for directorships. The sample average board has 24.9 directors with 79% of those directors classified as independent. Among public firms Ferris et al. (2003) find that the average outside director holds 1.89 total directorships. Assuming a similar pattern holds true for nonprofit board members then on average a nonprofit board has a connection to 18 other boards through its outside directors.[7] If board members are more likely to sit on boards that are geographically close then the local overlap in board

[7] The representative board will have 19.7 independent members ($24.9 * .79$) who will hold 17.5 outside directorships ($19.7 * (1.89 - 1)$). This calculation assumes there is no overlap of outside boards.

membership could act as a channel for local governance spillover.

A concrete example of this channel for geographic governance spillovers is the board of Banner Health, a Phoenix, Arizona based hospital system in the sample. In total the board members currently hold or have held over 65 outside directorships.[8] Of those 65 directorships, 11 are directorships on boards of publicly traded firms. An excerpt from the biography of a current Banner Health board member explicitly details the potential for governance spillover: "[Michael] Garnreiter is a designated financial expert according to the rules of the Securities and Exchange Commission and is chairman of the audit committee and member of the governance committee for three public company boards." The directorships that Michael Garnreiter holds are at Taser International based out of Scottsdale, Arizona; Amtech Systems based out of Tempe, Arizona; and Knight Transportation in Phoenix, Arizona. The cities of Scottsdale and Tempe are suburbs of Phoenix. The overlap of directors of public firms and the directors of nonprofit hospitals represents one channel through which governance of public firms could spillover to nonprofit hospitals.

1.3.3 Instrumental Variable Estimation

I construct two instrumental variables that I use to estimate the causal effect of governance on AMI patient survival. The first IV is local GIndex′, which is defined as the local average, industry adjusted public firm GIndex. For hospital j I calculate the average GIndex′ of all public firms located within 200 kilometers of hospital j.[9] The second IV is the local average, industry adjusted rate of the CEO of a public firm also being the chairman of the board of directors. This instrument is constructed in the same manner as local GIndex′. I denote this second IV local dual CEO-Chairman′. Both instruments capture the extent in which discretion is passed to the CEO. A high GIndex is indicative of entrenched managers who may have excess discretion in the operation of the firm. Similarly a CEO who is also chairman of the board has more discretion in the operation of the firm than a CEO who is not also the chairman of the board.

[8] These data were taken from the biographies on Banner Health's website: http://www.bannerhealth.com/About+Us/Banner+Leadership/Board+of+Directors.htm

[9] Additional details on geographic calculations can be found in Appendix B.

In all analysis I require there to be a minimum of five local public companies with governance data to be included in the sample. This restriction reduces the final sample to 62 hospitals with 288 hospital years and 86,503 AMI events.

The instrumental variables estimation methodology is two-stage least squares (TSLS). In the first stage for the most complete specification I estimate:

$$\begin{aligned}
\text{DIndex}_{j,t} = {} & \alpha_1 + \beta_1 \left(\text{local GIndex}'_{j,t}\right) + \beta_2 \left(\text{local dual CEO-Chairman}'_{j,t}\right) \\
& + \delta_1^{(1)} \left(\ln(\text{fixed assets})_{j,t-1}\right) + \delta_2^{(1)} \left(\text{teaching status}_j\right) + \delta_3^{(1)} \left(\text{urban hospital}_j\right) \\
& + \delta_4^{(1)} \left(\text{leverage}_{j,t-1}\right) + \delta_5^{(1)} \left(\frac{\text{investments}_{j,t-1}}{\text{fixed assets}_{j,t-1}}\right) + \delta_6^{(1)} \left(\frac{\text{cash}_{j,t-1}}{\text{fixed assets}_{j,t-1}}\right) \\
& + \delta_7^{(1)} \left(\ln(\text{real GDP})_{j,t}\right) + \delta_8^{(1)} \left(\ln(\text{average wage})_{j,t}\right) + \delta_9^{(1)} \left(\text{unemployment rate}_{j,t}\right) \\
& + \text{state-year FE} + \rho_1 c_p + \nu_{1,p,j,t}
\end{aligned} \tag{1.6}$$

where c_p are patient characteristics which include 29 pre-existing conditions, expected source of payment, quartile of median income for the patient's zip code by state, and a full set of interactions between the type of AMI, age, gender, and if white.[10] The sample and included instruments (i.e. hospital characteristics, patient characteristics, and state-year fixed effects) are identical for the first and second stage. This is a requirement for consistent estimation (Wooldridge, 2002). As a result the included instruments vary across specifications but first and second stage estimates always have the same sample and included instruments.

In the second stage I regress patient survival on the fitted value of hospital j's DIndex and the included instruments.

$$\begin{aligned}
S_{p,j,t} = {} & \alpha_1 + \phi \left(\widehat{\text{DIndex}}_{j,t}\right) + \delta_1^{(2)} \left(\ln(\text{fixed assets})_{j,t-1}\right) \\
& + \delta_2^{(2)} \left(\text{teaching status}_j\right) + \delta_3^{(2)} \left(\text{urban hospital}_j\right) + \delta_4^{(2)} \left(\text{leverage}_{j,t-1}\right) \\
& + \delta_5^{(2)} \left(\frac{\text{investments}_{j,t-1}}{\text{fixed assets}_{j,t-1}}\right) + \delta_6^{(2)} \left(\frac{\text{cash}_{j,t-1}}{\text{fixed assets}_{j,t-1}}\right) + \delta_7^{(2)} \left(\ln(\text{real GDP})_{j,t}\right) \\
& + \delta_8^{(2)} \left(\ln(\text{average wage})_{j,t}\right) + \delta_9^{(2)} \left(\text{unemployment rate}_{j,t}\right) \\
& + \text{state-year FE} + \rho_1 c_p + \nu_{1,p,j,t}
\end{aligned} \tag{1.7}$$

[10] For example I create an indicator for a white woman, between the ages of 65 and 75, with a Type 6 AMI.

The second stage estimates of $\hat{\phi}$ represent the causal effect of a hospital's strength of governance on AMI survival. For all hypothesis testing I cluster standard errors at the hospital level.

1.3.4 Results

Table 1.5 presents the first stage regressions in estimating TSLS. For expositional symmetry with the second stage regressions I report duplicate first stage regressions for the three day and seven day survival specifications. The excluded instruments local GIndex$'$ and local dual CEO-Chairman$'$ load negatively. A low GIndex and the absence of a dual CEO-Chairman in public firms can be indicative of strong corporate governance, while a high DIndex in nonprofit hospitals is indicative of strong governance. The negative relationship means that when local public firms have strong governance, a local nonprofit hospital is also likely to have strong governance. These results are consistent with both local GIndex$'$ and local dual CEO-Chairman$'$ capturing a common element of local governance spillovers.

Identification using an instrumental variables approach requires that the instrumental variables meet the relevance and exclusion restrictions. Shea's partial R^2 is a useful summary statistic to gauge the relevance of an IV. Table 1.5 contains Shea's partial R^2 (Shea, 1997), which is between 0.13 and 0.19 depending on the specification. This is consistent with the chosen IVs meeting the relevance condition. An additional heuristic is that the first stage of TSLS has an F-statistic ~ 10. This heuristic is generally met once hospital characteristics are accounted for. The exclusion restriction is more difficult to test, but with an over-identified model (i.e. with more instruments than endogenous variables) the Sargan-Hansen test is able to test the null hypothesis that the instruments are uncorrelated with the error term and are correctly excluded. A rejection of this null hypothesis casts doubt on the validity of an instrument. In the over-identified case presented in Table 1.5 the null of hypothesis is not rejected and has a p-value between 0.24 and 0.81 depending on the specification. While failure to reject the null hypothesis is not evidence that the null is in fact true, it is does remove one source of doubt. Finally while in Table 1.5 the coefficients on local GIndex$'$ and local dual CEO-Chairman$'$ are not individually statistically significant at conventional levels, when the IVs are used individually the coefficients load negatively, are significant at the 1 percent level, and as I will show in the robustness section my inferences are unchanged. By using both IVs in the first stage I gain the ability to test the exclusion restriction through the Sargan-Hansen test.

Table 1.6 presents the results of estimating the second stage of TSLS using local geographic variation in strength of governance as an instrument. I find the effect of DIndex is both statistically and economically significant. In all specifications the coefficient on the instrumented DIndex is positive and statistically significant at conventional levels. The economic significance is non-trivial. A one standard deviation increase in DIndex yields approximately a 0.86 percentage point increase in the probability of surviving three days after an AMI. To put this number in perspective this represents a 20 percent decrease in the probability of death relative to an unconditional average of 4.4 percent.

Included in each TSLS regression are detailed patient characteristics which allow me to account for variation in mortality risk. Those characteristics include indicators for 29 preexisting conditions, expected source of payment, quartile of median income for the patient's zip code by state, and a full set of interactions between the type of AMI, age, gender, and if white. The patient level medical records allow me to risk adjust at the patient level and mitigates concerns of heterogeneous patient populations.

Specifications 2 and 5 of Table 1.6 include hospital level characteristics that may be relevant to the quality of care provided to patients. These specifications include an indicator if the hospital is a teaching hospital, an indicator if the hospital is urban, as well as one period lagged log fixed assets, leverage, lagged cash to fixed assets ratio, and lagged investments to fixed assets ratio. Specification 3 and 6 of Table 1.6 include contemporaneous local macroeconomic factors that could affect the quality of care provided to patients, either through the budget constraint of the hospital or the unobserved health of patients. These local macroeconomic variables include log real GDP of the county, log average wage for all firms in the metropolitan statistical area (MSA), and the unemployment rate of the MSA. The inclusion of the hospital specific characteristics and local macroeconomic factors does not affect inferences on the marginal effect of DIndex.

1.3.5 The Channel

The TSLS results of Table 1.6 are consistent with strong governance resulting in a higher probability of AMI survival. The natural follow up question is, "how does strong governance at the CEO level translate into a higher probability of AMI survival?" Through interviews with key hospital staff, Curry et al. (2011) document that key differentiating features between the best and worst hospitals are characteristics such as managerial involvement, organizational values of excellence, and the flow of information from front-line workers to managers. These are policies that are under a manager's control and are correlated with higher quality of care provided to AMI patients. Ultimately though, the policies in and of themselves do not affect patient outcomes, but rather the policies facilitate the higher quality of care provided to patients by medical professionals.

In order to identify the channel through which governance affects patient survival, I first ask if patients are systematically treated differently at hospitals with differing strength of governance. There are two broad classes of treatment for AMIs. The first class is invasive procedures such as coronary artery bypass grafting (CABG), commonly known as open heart surgery, or percutaneous transluminal coronary angioplasty (PTCA), commonly known as angioplasty. The second class is non-invasive treatment where the AMI is treated medicinally through anticoagulants and other drug based treatments.

To test if patients are systematically treated differently at hospitals with differing strength of governance I estimate a linear probability model via TSLS with an indicator for an invasive treatment as the dependent variable. The methodological setup is identical to the TSLS procedure of Table 1.6 except for the dependent variable is an indicator for an invasive treatment. Column (1) of Table 1.7 presents the results of this analysis. The marginal effect of governance is positive but statistically insignificant. This fails to support the hypothesis that patients are treated systematically differently with respect to invasive procedures.

If choice of treatment (i.e. invasive or non-invasive) is not driving the results of Table 1.6, perhaps hospitals with strong governance have particularly good outcomes conditional on a treatment. Columns (2) and (3) of Table 1.7 estimate the 3 and 7 day survival probability via TSLS of patients that were treated with a non-invasive treatment. Columns (4) and (5) of Table 1.7 repeat this analysis but only on the subset of patients who were treated with an invasive procedure. The point estimates of the marginal effect of governance on survival is positive for both patients who receive either type of treatment; however the point estimates are only statistically significant at conventional levels for patients who receive non-invasive treatment.

Why are patients who receive non-invasive treatment at strong governance hospitals more likely to survive? One answer could be that the medical professionals are better at prescribing and delivering the appropriate type of medicine. Unfortunately these data do not have details on the drugs administered, but I can infer the appropriateness of the prescribing behavior by the incidence of adverse reactions to therapeutic drugs.[11] Column (6) of Table 1.7 estimates a linear probability model via TSLS of the probability of an adverse drug reaction in a patient who is treated non-invasively. The marginal effect of governance on the incidence of an adverse drug reaction is negative and statistically significant at conventional levels. This result supports the hypothesis that the medical professionals are better at prescribing and delivering the correct type of medicine, which I observe through a lower incidence of adverse drug reactions. Further Engelberg et al. (2014) provide supportive evidence and shed light on one mechanism through which governance at the CEO level could translate into a lower probability of an adverse drug reaction. In their paper they show that doctors' prescribing behavior is systematically affected by financial incentives put in place by pharmaceutical companies. The incentives put in place by strong governance at the CEO level could translate to appropriate incentive systems put in place at the doctor level to combat pay-for-prescription behavior that is detrimental to the care patients receive.

For completeness I repeat the analysis for patients who receive invasive treatment in column (7) of Table 1.7. The marginal effect of governance on the incidence of a surgical misadventure is negative but is not statistically significant at conventional levels.[12] Despite the lack of statistical significant the result is directionally correct in that stronger governance reduces the incidence of surgical misadventures.

[11] Adverse drug reaction is defined as a primary external injury code between 930 and 949.

[12] Surgical misadventure is defined as a primary external injury code between 870 and 876.

Pulling these results together, stronger governance results in a higher survival probability in AMI patients. The choice of treatment (invasive or non-invasive) is not driving this result. Rather a lower probability of an adverse drug reaction, an observable signal of more appropriate treatment, results in patients who receive non-invasive treatment having a higher probability of survival. Patients who receive invasive treatments at strong governance hospitals are more likely to survive and are less likely to incur a medical misadventure, though the point estimates are not statistically significant at conventional levels.

1.4 Robustness

1.4.1 Components of the DIndex

The DIndex of a hospital is composed of four provisions that measure the control the board has over the pay setting process. I take each individual provision as a signal of the strength of a hospital's governance. In this section I explore each provision's effect on survival in isolation.

One method to determine the effect of each provision would be to substitute an indicator for each provision into the TSLS regression. This method would allow me to determine the marginal impact of any given provision conditional on the presence or absence of other governance provisions in the DIndex. The difficulty with this method is that in order to identify the marginal effect of four provisions I need four instrumental variables. This is problematic because in this study I only have two IVs. To overcome this I estimate each provision of the DIndex separately in an independent TSLS regressions.

The results from this methodology have to be interpreted with care. Economic theory suggests that governance provisions implemented should not be interpreted in isolation but rather the entire governance system should be analyzed as a whole because a firm will choose the portfolio of governance provisions that implements the desired strength of governance at the lowest cost (Agrawal and Knoeber, 1996). This means that all governance provisions are codetermined and omitting provisions from the analysis will result in a correlated omitted variables problem. While estimating each provision of the DIndex individually does not invalidate the estimated coefficients, it does change the interpretation of them. Under this methodology I am not estimating the causal impact of the adoption of a particular provision; rather I am estimating the causal impact of strength of governance using a particular provision as a signal about the underlying strength of governance.

Table 1.8 presents a summary of the results of each independently estimated TSLS regression. Each row of Table 1.8 are the coefficients from an independently run set of TSLS regressions paralleling Table 1.6 using just the provision as the variable of interest. The results presented in Table 1.8 are indicative of each provision acting as a signal of stronger governance. All of the 24 point estimates are positive and generally of the same order of magnitude as those in Table 1.6. The power for testing for statistical significance in Table 1.8 varies with the strength of the relationship between the set of IVs with a particular provision and the cross-sectional variation in the particular provision. The wide spread adoption of having a compensation committee, using a compensation consultant, and commissioning a compensation survey reduces the cross-sectional variation, which results in the positive point estimates generally not being statistically significant at conventional levels. The comparable contract provision is less widely adopted and provides more cross-sectional variation. Using this provision as a signal of the strength of a hospital's governance, I find a strong and statistically significant effect of AMI survival. Despite the lack of statistical significance on a number of the provisions the point estimates are positive and of the same order of magnitude, which is consistent with the main result that stronger governance leads to better survival outcomes.

1.4.2 Single Instrumental Variable

The instrumental variables that I use to identify the causal effect of corporate governance on AMI survival are local GIndex$'$ and local dual CEO-Chairman$'$. Both instruments are constructed under the intuition that higher GIndex or a dual CEO-Chairman is indicative of the CEO having more discretion in the operation of the firm, and therefore more discretion to misappropriate resources. If each instrument is a valid IV then using either IV in isolation should provide similar estimates of the marginal effect of governance to the estimates when the IVs are used in conjunction.

Table 1.9 presents the second stage of a TSLS estimate of patient survival on hospital and patient characteristics. Specifications 1 through 6 use local GIndex$'$ as the single IV, while specifications 7 through 12 use local dual CEO-Chairman$'$ as the single IV. Using each IV in isolation provides similar estimates of the marginal effect of governance on AMI survival. This is consistent with both instruments being valid IVs and the documented marginal effect of governance being robust to instrument specification.

In unreported results the construction of the IVs was varied to insure that inferences were robust to the details of the IV construction. These variations included industry adjusting at the two digit SIC code level instead of the three digit SIC code level; using 100 kilometers as the definition of local instead of 200 kilometers; and using the subset of the GIndex that composes the Bebchuk et al. (2009) EIndex. All variations on the construction of the IVs result in support for a statistically significant and economically important effect of governance on AMI survival.

1.4.3 IV Probit Results

The main result of this paper is that governance has an economically and statistically significant effect on performance as measured by AMI survival. The econometrics behind this result are based on a linear probability model. The benefit of a linear probability model in this context is that I am able to risk adjust AMIs using a vast number of patient controls. This benefit comes at the cost of the possibility of estimated survival probabilities that are greater than one or less than zero.

To test the robustness of my main result to the shortcomings of a linear probability model I estimate an IV probit regression. In order to obtain convergence in the likelihood function I use a reduced number of patient controls. In particular I include 29 pre-existing conditions, expected source of payment, quartile of median income for the patient's zip code by state, the type of AMI interacted with gender, age, and an indicator if the patient is white. Table 1.10 presents the results of this analysis. These results support the inferences from the linear probability model; strength of governance has an economically and statistically significant effect on performance.

Additionally I re-estimate the results of Table 1.7 using an IV probit regression in order to check the robustness of the channel to the econometric methodology. The results are presented in Table 1.11 and confirm the inferences of the TSLS approach. AMI patients who receive non-invasive treatments have a higher probability of survival and a lower probability of having an adverse drug reaction when a hospital has strong governance. One difference in the IV probit results from the TSLS results is that the coefficient on DIndex is positive and statistically significant at conventional levels for 7 day survival in patients who receive invasive treatment. The coefficient for 3 day survival is also positive and is larger in magnitude but not statistically significant. These results hint that strong governance also improves the outcomes of patients who receive invasive treatment but I have insufficient power to detect a statistically significant effect.

1.5 Conclusion

Estimating the effect of internal governance on performance is difficult. This study addresses the difficulties by focusing on an economic environment with muted external governance mechanisms, using an unambiguous measure of performance, and estimating the effect in an instrumental variables regression. The effect of internal governance is economically significant; a one standard deviation increase in governance corresponds to a 0.86 percentage point reduction in the unconditional probability of death within three days of an AMI. Relative to a 4.4 percent probability of death, this represents a 20 percent reduction in the probability of death. One channel identified by these data is through better medicinal treatment of AMIs as measured by a reduction in adverse drug reactions. This is consistent with hospitals with stronger governance providing a higher quality of care, which in turn increases the probability of a patient surviving an AMI.

As part of this study I document that there are significant geographic spillovers in corporate governance. These spillovers cross industry boundaries as well as organizational forms. I use these spillovers to construct an instrumental variable that allows me to consistently estimate the marginal effect of corporate governance on performance. This is a novel instrumental variable that to the best of my knowledge has not been exploited in the finance literature.

Figure 1.1: This figure presents the distribution of the DIndex.

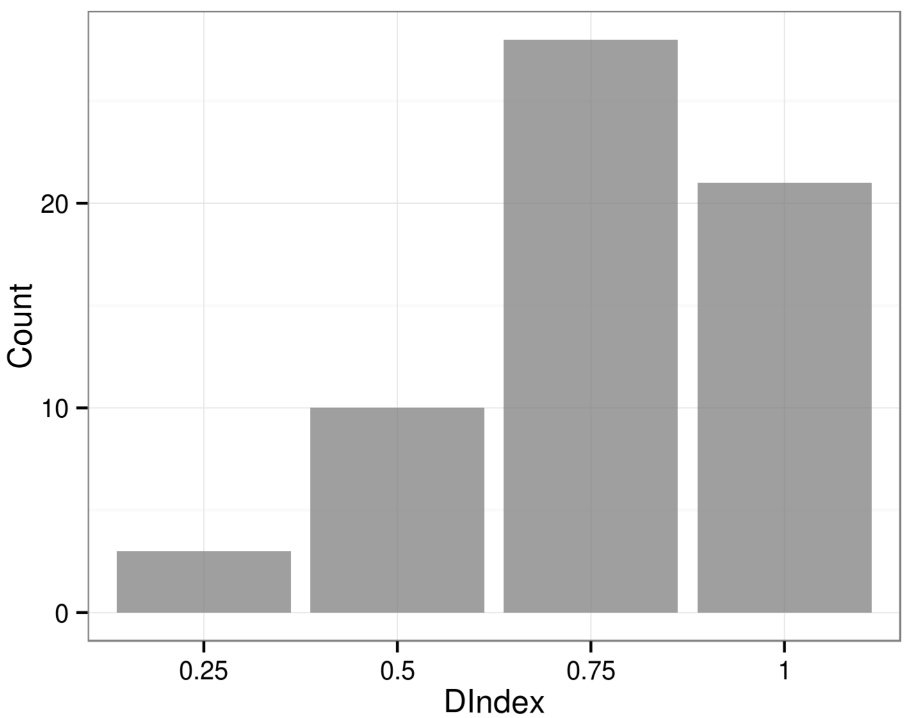

Figure 1.2: This figure presents the spatial distribution of industry adjusted GIndex in 2004 for firms headquartered in the United States. Within each box with more than five firms located within the boundaries of the box, I estimate the mean industry adjusted GIndex. Boxes shaded red have a higher mean industry adjusted GIndex (indicative of weaker governance), while boxes shaded blue have a lower mean industry adjusted GIndex (indicative of stronger governance).

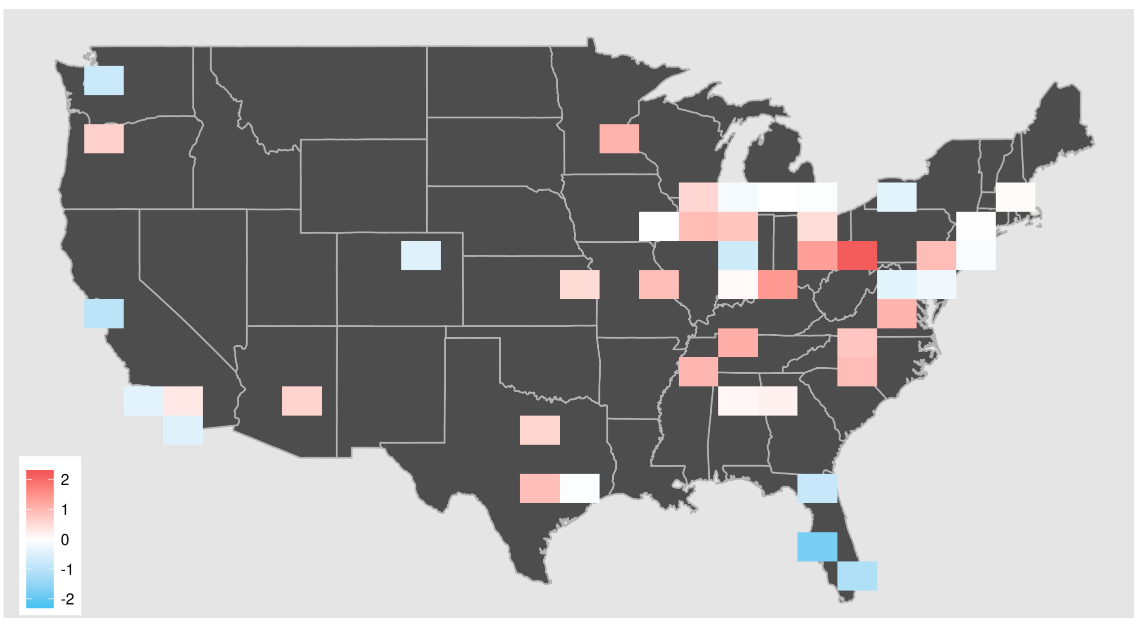

Figure 1.3: This figure presents the results of a simulation of Moran's I which holds the adjacency matrix constant and randomly draws industry adjusted GIndex from the empirical distribution. The adjacency matrix is a binary matrix with firms closer (further) than 200 kilometers equal to 1 (0) The realized Moran's I of 0.096 is denoted by the dashed line.

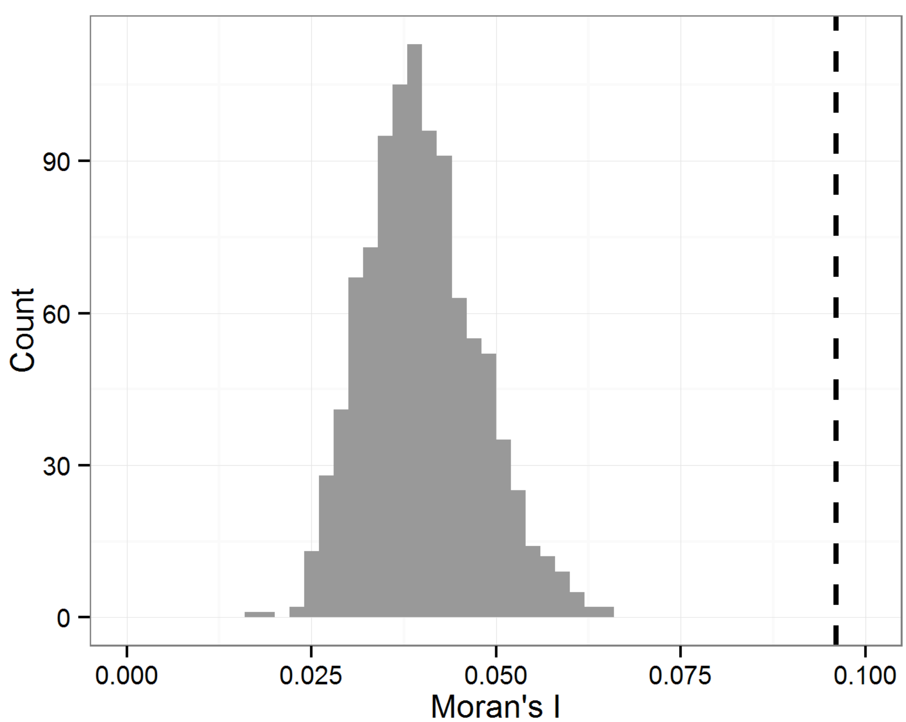

Table 1.1: Sources of Data

This table reports the sources of data and years the data is used.

Data	**Years**	**Source**
Patient Records	2006-2010	State Inpatient Databases (SID), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality
Financial Data	2006-2007	IRS Form 990 GuideStar database, supplemented by hand
Financial Data	2008-2010	IRS Form 990 hand collected
Hospital Governance Data	2008-2010	IRS Form 990 Schedule J, only available 2008-2010
Public Firm Governance Data	2004	RiskMetrics through Wharton Research Data Services (wrds)
Public Firm Location	-	CorpWatch API
Geolocation Data	-	Zip-Codes.com
Local Unemployment	2006-2010	US Bureau of Labor Statistics
Local Real GDP	2006-2010	US Bureau of Economic Analysis
Local Average Wage	2006-2010	US Census Bureau

Table 1.2: DIndex Summary Statistics

This table presents the fraction of hospitals that use each provision that composes the DIndex. The DIndex is composed of four data items. The four provisions are the use of a compensation committee, the use of a compensation consultant, the use of a comparable contract, and the use of a compensation survey.

	Mean
Compensation Committee	0.96
Compensation Consultant	0.88
Comparable Contract	0.47
Compensation Survey	0.80
Hospitals	62

Table 1.3: Hospital Characteristics Summary Statistics: DIndex Subsamples

This table presents the mean values of select hospital characteristics. Columns denoted High (Low) DIndex indicate above (below) mean DIndex hospitals. Refer to the glossary for variable definitions. Significance is determined with standard errors clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

Variable	Overall	High DIndex	Low DIndex	Difference
DIndex	0.78	1.00	0.66	0.34***
Fixed Assets	612.37	533.33	653.77	-120.43
Leverage	0.99	0.84	1.06	-0.22
Cash / Fixed Assets	0.32	0.31	0.33	-0.02
Investments / Fixed Assets	0.76	1.19	0.53	0.66*
Teaching Hospital	0.38	0.36	0.39	-0.03
Urban Hospital	0.98	1.00	0.97	0.03

Table 1.4: Patient Characteristics Summary Statistics: DIndex Subsamples

This table presents the mean values of select patient characteristics. Columns denoted High (Low) DIndex are patients that are admitted to an above (below) mean DIndex hospital. Unless otherwise denoted all statistics are percent of patient population. Refer to the glossary for variable definitions. Significance is determined with standard errors clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

Variable	Overall	High DIndex	Low DIndex	Difference
Age (Years)	68.75	68.83	68.71	0.12
Female	39.25	37.87	39.98	-2.11**
White	77.21	72.29	79.77	-7.47
Survived 3	95.62	95.79	95.53	0.26
Survived 7	93.33	93.56	93.21	0.35
Medicare	60.28	59.68	60.60	-0.92
Private Insurance	23.81	25.37	23.00	2.37
Obese	12.05	12.01	12.08	-0.07
Chronic Heart Failure	0.67	0.70	0.65	0.04
AMI Type - STEMI	43.10	42.93	43.40	-0.47
AMI Type - NSTEMI	53.60	53.71	53.40	0.31
AMI Type - Unspecified	3.31	3.36	3.21	0.16

Table 1.5: Survival Estimation: TSLS First Stage

This table presents the results of the first stage of a two-stage least squares of patient survival on hospital and patient characteristics. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex′ and local dual CEO-Chairman′. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Omitted for exposition are indicator variables for pre-existing conditions, expected source of payment, quartile of median zip code income by state, and a full set of interactions of type of heart attack, age, gender, and if white. *p*-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

DIndex	(1)	(2)	(3)	(4)	(5)	(6)
Local GIndex′	-0.13522	-0.20305*	-0.15773	-0.13522	-0.20305*	-0.15773
	(0.261)	(0.094)	(0.125)	(0.261)	(0.094)	(0.125)
Local CEO is BOD Chair′	-0.61301	-0.30940	-0.84032	-0.61301	-0.30940	-0.84032
	(0.260)	(0.608)	(0.130)	(0.260)	(0.608)	(0.130)
Lag Log Fixed Assets		-0.03979	-0.00862		-0.03979	-0.00862
		(0.132)	(0.780)		(0.132)	(0.780)
Teaching Status		0.00368	0.04224		0.00368	0.04224
		(0.937)	(0.271)		(0.937)	(0.271)
Urban Hospital		0.11225	0.31937**		0.11225	0.31937**
		(0.134)	(0.046)		(0.134)	(0.046)
Lag Leverage		0.00076	0.02862		0.00076	0.02862
		(0.983)	(0.505)		(0.983)	(0.505)
Lag Investments / Fixed Assets		0.03099*	0.03181		0.03099*	0.03181
		(0.100)	(0.114)		(0.100)	(0.114)
Lag Cash / Fixed Assets		0.17594**	0.13976*		0.17594**	0.13976*
		(0.034)	(0.077)		(0.034)	(0.077)
Log Real GDP			0.00586			0.00586
			(0.801)			(0.801)
Log Average Wage			-0.58729*			-0.58729*
			(0.066)			(0.066)
Unemployment Rate			-1.17809			-1.17809
			(0.228)			(0.228)
Patient Controls	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
Patients	86,503	86,503	86,503	86,503	86,503	86,503
N. Hospitals	62	62	62	62	62	62
F-statistic	3.36	13.12	9.47	3.36	13.12	9.47
R^2	0.17	0.26	0.33	0.17	0.26	0.33

Table 1.6: Survival Estimation: TSLS Second Stage

This table presents the results of the second stage of a TSLS regression of patient survival on hospital and patient characteristics. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex′ and local dual CEO-Chairman′. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Specifications 1 through 3 are estimated with 3 day patient survival. Specifications 4 through 6 are estimated with 7 day patient survival. Omitted for exposition are indicator variables for pre-existing conditions, expected source of payment, quartile of median zip code income by state, and a full set of interactions of type of heart attack, age, gender, and if white. p-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

	Patient 3 Day Survival			Patient 7 Day Survival		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{DIndex}}$	0.04532***	0.05078**	0.04285***	0.05030***	0.05229**	0.04417**
	(0.005)	(0.012)	(0.008)	(0.007)	(0.030)	(0.023)
Lag Log Fixed Assets		0.00247	0.00118		0.00183	0.00014
		(0.265)	(0.619)		(0.543)	(0.964)
Teaching Status		0.00003	-0.00118		-0.00069	-0.00225
		(0.992)	(0.706)		(0.864)	(0.552)
Urban Hospital		-0.00448	-0.01181		-0.00014	-0.01061
		(0.393)	(0.194)		(0.984)	(0.339)
Lag Leverage		-0.00041	-0.00124		-0.00204	-0.00325
		(0.871)	(0.609)		(0.518)	(0.272)
Lag Investments / Fixed Assets		-0.00382**	-0.00383**		-0.00439**	-0.00457**
		(0.029)	(0.034)		(0.040)	(0.046)
Lag Cash / Fixed Assets		-0.01284***	-0.01050***		-0.01195*	-0.00922
		(0.007)	(0.009)		(0.079)	(0.111)
Log Real GDP			0.00020			0.00042
			(0.909)			(0.827)
Log Average Wage			0.02079			0.02720*
			(0.132)			(0.075)
Unemployment Rate			0.09564			0.08186
			(0.283)			(0.342)
Patient Controls	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
N. Patients	86,503	86,503	86,503	86,503	86,503	86,503
N. Hospitals	62	62	62	62	62	62
Hansen's J	0.06	0.43	0.15	1.21	1.40	0.83
Hansen's J (p-value)	0.81	0.51	0.70	0.27	0.24	0.36
Shea's R^2	0.17	0.13	0.19	0.17	0.13	0.19

Table 1.7: The Channels: TSLS Second Stage

This table presents the results of the second stage of a two-stage least squares regression. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex′ and local dual CEO-Chairman′. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Specification 1 estimates a linear probability model of a patient receiving invasive treatment. Specifications 2 and 3 (4 and 5) estimate a linear probability model of 3 or 7 day survival conditional on receiving non-invasive (invasive) treatment. Specification 6 (7) estimate a linear probability model of the incidence of an adverse drug reaction (surgical misadventure) conditional on receiving non-invasive (invasive) treatment. Omitted for exposition are indicator variables for pre-existing conditions, expected source of payment, quartile of median zip code income by state, and a full set of interactions of type of heart attack, age, gender, and if white. p-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

	Treatment Choice	Non-Invasive Treatment		Invasive Treatment		Medical Mistakes	
	Invasive	Survived 3	Survived 7	Survived 3	Survived 7	Drug	Surgical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{\text{DIndex}}$	0.13273	0.07489***	0.07861**	0.00632	0.00814	-0.05105**	-0.02469
	(0.311)	(0.008)	(0.034)	(0.267)	(0.130)	(0.017)	(0.709)
Lag Log Fixed Assets	0.01946	0.00278	0.00063	-0.00084	-0.00100	-0.00814*	-0.01101*
	(0.283)	(0.553)	(0.923)	(0.224)	(0.284)	(0.078)	(0.086)
Teaching Status	0.05247**	-0.00463	-0.00695	-0.00283**	-0.00401***	0.00629	-0.00507
	(0.046)	(0.377)	(0.295)	(0.019)	(0.006)	(0.222)	(0.654)
Urban Hospital	0.08951	-0.01521	-0.01946	0.00217	0.01066**	-0.02179	-0.01527
	(0.242)	(0.324)	(0.314)	(0.496)	(0.012)	(0.219)	(0.698)
Lag Leverage	-0.05936***	0.00076	-0.00030	0.00237*	0.00110	0.00595	0.02248**
	(0.003)	(0.845)	(0.950)	(0.057)	(0.483)	(0.143)	(0.037)
Lag Investments / Fixed Assets	-0.02119	-0.00424	-0.00554	-0.00087	-0.00077	0.00538**	0.00789
	(0.213)	(0.186)	(0.204)	(0.342)	(0.499)	(0.042)	(0.290)
Lag Cash / Fixed Assets	-0.02544	-0.01591**	-0.01565	-0.00291	-0.00112	-0.00758	-0.00867
	(0.543)	(0.028)	(0.128)	(0.197)	(0.712)	(0.377)	(0.609)
Log Real GDP	0.00133	-0.00121	-0.00066	0.00041	0.00004	0.00539**	0.00761
	(0.947)	(0.659)	(0.840)	(0.458)	(0.953)	(0.045)	(0.175)
Log Average Wage	0.28715	0.01477	0.01725	0.00525	0.01112**	-0.00709	-0.02081
	(0.139)	(0.522)	(0.528)	(0.341)	(0.038)	(0.707)	(0.733)
Unemployment Rate	0.51496	0.09911	0.08924	0.04193	0.01966	0.54557***	0.01757
	(0.422)	(0.617)	(0.651)	(0.266)	(0.686)	(0.000)	(0.944)
Patient Controls	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y
N. Patients	86,503	44,969	44,969	41,534	41,534	44,969	41,534
N. Hospitals	62	62	62	53	53	62	53
Hansen's J	3.75	0.80	0.00	3.16	0.41	2.39	3.08
Hansen's J (p-value)	0.05	0.37	0.97	0.08	0.52	0.12	0.08

Table 1.8: Survival Estimation: TSLS Second Stage (DIndex Components)

This table presents the results of the second stage of a two-stage least squares regression of patient survival on hospital and patient characteristics. The effect of each provision of the DIndex is seperately estimated and correspond to a row. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex$'$ and local dual CEO-Chairman$'$. Refer to Section 1.3.3 for a description of the instrumental variables. Specifications 1 through 3 are estimated with 3 day patient survival. Specifications 4 through 6 are estimated with 7 day patient survival. ***, **, and * denote significance at the 1, 5, and 10 percent level using p-values clustered at the hospital level.

	Patient 3 Day Survival			Patient 7 Day Survival		
	(1)	(2)	(3)	(4)	(4)	(6)
Compensation Committee	0.08225	0.10734	0.07695	0.07057	0.09818	0.08052
Compensation Consultant	0.49602	0.05653	0.04113	0.68307	0.07528	0.05189
Comparable Contract	0.01480***	0.02188***	0.02383**	0.01757***	0.02376**	0.02349*
Compensation Survey	0.04420	0.01626	0.03321*	0.03565	0.00858	0.03098
Hospital Controls	N	Y	Y	N	Y	Y
Area Controls	N	N	Y	N	N	Y
Patient Controls	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y

Table 1.9: Survival Estimation: TSLS Second Stage (Single IV)

This table presents the results of the second stage of a two-stage least squares regression of patient survival on hospital and patient characteristics. Nonprofit hospital j's DIndex is instrumented for with local GIndex′ in specifications 1 through 6, and local dual CEO-Chairman′ in specifications 7 through 12. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Specifications 1, 2, 3, 7, 8 and 9 are estimated with 3 day patient survival. Specifications 4, 5, 6, 10, 11, and 12 are estimated with 7 day patient survival. Omitted for exposition are indicator variables for pre-existing conditions, expected source of payment, quartile of median zip code income by state, and a full set of interactions of type of heart attack, age, gender, and if white. p-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

	Instrumental Variable: Local GIndex′						Instrumental Variable: Local Dual CEO-Chairman′					
	Patient 3 Day Survival			Patient 7 Day Survival			Patient 3 Day Survival			Patient 7 Day Survival		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{\text{DIndex}}$	0.04384***	0.04766**	0.04009**	0.04289**	0.04634*	0.03660*	0.04665***	0.06066**	0.04516**	0.05693***	0.07109**	0.05051**
	(0.007)	(0.017)	(0.012)	(0.025)	(0.055)	(0.070)	(0.010)	(0.031)	(0.015)	(0.006)	(0.023)	(0.018)
Lag Log Fixed Assets		0.00228	0.00105		0.00147	-0.00023		0.00307	0.00129		0.00298	0.00045
		(0.299)	(0.655)		(0.618)	(0.940)		(0.224)	(0.596)		(0.390)	(0.891)
Teaching Status		-0.00005	-0.00122		-0.00085	-0.00236		0.00030	-0.00114		-0.00017	-0.00216
		(0.987)	(0.689)		(0.827)	(0.519)		(0.934)	(0.720)		(0.970)	(0.581)
Urban Hospital		-0.00454	-0.01160		-0.00025	-0.01003		-0.00429	-0.01199		0.00022	-0.01109
		(0.376)	(0.192)		(0.970)	(0.356)		(0.448)	(0.197)		(0.977)	(0.328)
Lag Leverage		-0.00044	-0.00123		-0.00209	-0.00324		-0.00032	-0.00124		-0.00186	-0.00326
		(0.861)	(0.608)		(0.506)	(0.276)		(0.904)	(0.610)		(0.568)	(0.273)
Lag Investments / Fixed Assets		-0.00362**	-0.00364**		-0.00402*	-0.00406*		-0.00443**	-0.00398**		-0.00556**	-0.00500**
		(0.038)	(0.043)		(0.061)	(0.078)		(0.031)	(0.035)		(0.023)	(0.034)
Lag Cash / Fixed Assets		-0.01240***	-0.01015**		-0.01111	-0.00827		-0.01423**	-0.01079**		-0.01460*	-0.01002*
		(0.007)	(0.010)		(0.102)	(0.158)		(0.012)	(0.011)		(0.053)	(0.090)
Log Real GDP			0.00019			0.00040			0.00020			0.00043
			(0.911)			(0.833)			(0.907)			(0.823)
Log Average Wage			0.02006			0.02520*			0.02140			0.02887*
			(0.128)			(0.098)			(0.141)			(0.067)
Unemployment Rate			0.09536			0.08110			0.09588			0.08250
			(0.279)			(0.339)			(0.286)			(0.348)
Patient Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N. Patients	86,503	86,503	86,503	86,503	86,503	86,503	86,503	86,503	86,503	86,503	86,503	86,503
N. Hospitals	62	62	62	62	62	62	62	62	62	62	62	62
F-statistic (First Stage)	3.36	13.08	9.91	3.36	13.08	9.91	3.79	10.21	8.95	3.79	10.21	8.95
Shea's R^2	0.15	0.13	0.16	0.15	0.13	0.16	0.15	0.10	0.17	0.15	0.10	0.17

Table 1.10: Survival Estimation: IV Probit Regression

This table presents the results of an IV probit regression of patient survival on hospital and patient characteristics. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex′ and local dual CEO-Chairman′. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Specifications 1 through 3 are estimated with 3 day patient survival. Specifications 4 through 6 are estimated with 7 day patient survival. Omitted for exposition are indicator variables for 29 pre-existing conditions, expected source of payment, quartile of median income for the patient's zip code by state, the type of AMI interacted with gender, age, and an indicator if the patient is white. *p*-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

	Patient 3 Day Survival			Patient 7 Day Survival		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{DIndex}}$	0.55287***	0.61663**	0.53404***	0.49773***	0.50156**	0.43490**
	(0.004)	(0.016)	(0.008)	(0.004)	(0.040)	(0.021)
Lag Log Fixed Assets		0.03052	0.01654		0.01565	0.00192
		(0.272)	(0.561)		(0.578)	(0.945)
Teaching Status		0.00317	-0.01067		-0.00333	-0.01650
		(0.937)	(0.777)		(0.929)	(0.633)
Urban Hospital		-0.04284	-0.12539		-0.00451	-0.09059
		(0.510)	(0.248)		(0.944)	(0.360)
Lag Leverage		-0.00332	-0.01185		-0.01600	-0.02543
		(0.917)	(0.698)		(0.579)	(0.348)
Lag Investments / Fixed Assets		-0.04471**	-0.04559**		-0.03662*	-0.03842*
		(0.041)	(0.035)		(0.074)	(0.063)
Lag Cash / Fixed Assets		-0.14832**	-0.12187**		-0.10769*	-0.08431
		(0.013)	(0.014)		(0.086)	(0.111)
Log Real GDP			0.00110			0.00243
			(0.957)			(0.882)
Log Average Wage			0.25628			0.24355*
			(0.128)			(0.077)
Unemployment Rate			1.65376			1.13880
			(0.153)			(0.193)
N. Patients	85,881	85,881	85,881	85,881	85,881	85,881
N. Hospitals	62	62	62	62	62	62

Table 1.11: The Channels: IV Probit Regression

This table presents the results of the second stage of an IV probit regression. Nonprofit hospital j's DIndex is instrumented for with two IVs: local GIndex′ and local dual CEO-Chairman′. Refer to Section 1.3.3 for a description of the instrumental variables, and the glossary for variable definitions. Specification 1 estimates an IV probit model of a patient receiving invasive treatment. Specifications 2 and 3 (4 and 5) estimate an IV probit model of 3 or 7 day survival conditional on receiving non-invasive (invasive) treatment. Specification 6 (7) estimate an IV probit model of the incidence of an adverse drug reaction (surgical misadventure) conditional on receiving non-invasive (invasive) treatment. Omitted for exposition are indicator variables for 29 pre-existing conditions, expected source of payment, quartile of median income for the patient's zip code by state, the type of AMI interacted with gender, age, and an indicator if the patient is white. *p*-values are clustered at the hospital level. ***, **, and * denote significance at the 1, 5, and 10 percent level.

	Treatment Choice	Non-Invasive Treatment		Invasive Treatment		Medical Mistakes	
	Invasive	Survived 3	Survived 7	Survived 3	Survived 7	Drug	Surgical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{\text{DIndex}}$	0.40345	0.53023**	0.42879*	0.39272	0.35753**	-0.59670**	0.25702
	(0.385)	(0.015)	(0.054)	(0.186)	(0.023)	(0.027)	(0.582)
Lag Log Fixed Assets	0.05849	0.01616	-0.00197	-0.03050	-0.02594	-0.08383*	-0.02864
	(0.303)	(0.646)	(0.957)	(0.332)	(0.337)	(0.061)	(0.507)
Teaching Status	0.16162*	-0.03738	-0.04361	-0.09545*	-0.09151**	0.04221	0.05147
	(0.051)	(0.340)	(0.255)	(0.055)	(0.027)	(0.357)	(0.400)
Urban Hospital	0.39089	-0.14514	-0.13076	0.07873	0.22892*	-0.19021	0.14551
	(0.111)	(0.206)	(0.239)	(0.635)	(0.083)	(0.260)	(0.430)
Lag Leverage	-0.18163***	0.00971	0.00249	0.09993*	0.03356	0.06581*	0.03447
	(0.004)	(0.756)	(0.931)	(0.061)	(0.433)	(0.051)	(0.552)
Lag Investments / Fixed Assets	-0.06516	-0.03174	-0.02997	-0.04345	-0.02076	0.05952**	-0.00059
	(0.246)	(0.200)	(0.245)	(0.370)	(0.555)	(0.015)	(0.988)
Lag Cash / Fixed Assets	-0.07525	-0.11191**	-0.08497	-0.12993	-0.04814	-0.02664	-0.13575
	(0.583)	(0.045)	(0.167)	(0.223)	(0.581)	(0.814)	(0.196)
Log Real GDP	0.00231	-0.00553	-0.00116	0.01057	-0.00646	0.04129*	0.04672
	(0.971)	(0.790)	(0.951)	(0.688)	(0.710)	(0.079)	(0.143)
Log Average Wage	0.88728	0.10211	0.08863	0.24242	0.30901*	-0.06616	0.18802
	(0.154)	(0.586)	(0.607)	(0.371)	(0.060)	(0.766)	(0.589)
Unemployment Rate	1.41885	1.24963	1.02849	2.06604	0.38061	2.38247*	0.24757
	(0.474)	(0.396)	(0.379)	(0.245)	(0.793)	(0.060)	(0.826)
N. Patients	85,881	85,881	85,881	85,881	85,881	85,881	85,881
N. Hospitals	62	62	62	62	62	62	62

Chapter 2

DAILY DATA IS BAD FOR BETA: OPACITY AND FREQUENCY DEPENDENT BETAS

With the increase in high-frequency trading and the reduction in investment horizons, measuring a security's instantaneous and possibly time-varying riskiness in terms of its market exposure (beta) has increased in importance. The contemporaneous reduction of microstructure frictions, such as bid-ask bounce and nonsynchronous trading (Chordia, Roll, and Subrahmanyam, 2011), has reinforced the notion that increasing the sampling frequency by using higher-frequency return data improves the accuracy with which beta is measured. The realized volatility literature has explicitly derived the potential of using ever more finely sampled realized returns to measure beta perfectly in the limit (e.g., Nelson and Foster, 1994; Andersen et al., 2001, 2003, 2005, 2006). Similarly, Lewellen and Nagel (2006) suggest accounting for time variation in the market risk exposure by estimating conditional quarterly market betas using daily returns. Underlying all these approaches is the assumption that beta does not depend on the return frequency. Similarly, the question of whether or not the Capital Asset Pricing Model (CAPM) or the Fama-French-Carhart factor model is the appropriate model to price assets is typically not addressed as a function of the frequency of the returns the model is asked to explain.[1]

We reexamine this common assumption of frequency-independent betas. We find that "opaque" firms have high-frequency betas that are smaller than their low-frequency betas, while the opposite applies to "transparent" firms. This frequency dependence of betas does not arise because of standard microstructure frictions but it arises due to uncertainty about the effect of systematic news on opaque firms. If investors are risk-averse, this uncertainty, while temporary, affects the prices of opaque firms at high frequencies. At sufficiently low

[1]Exceptions include Handa, Kothari, and Wasley (1989), Kothari, Shanken, and Sloan (1995), Longstaff (1989), Brennan and Wang (2010), Li (2012), Boguth et al. (2013), and Savor and Wilson (2013). A related literature explores the role of investment horizon for asset pricing (e.g., Lee, 1976; Lee et al., 1990; Brennan and Zhang, 2013; Kamara et al., 2013).

frequencies, though, the effect of systematic news is revealed for all firms. The opacity of some firms therefore drives a wedge between the high- and low-frequency market betas of all firms. Even more importantly, asset pricing models such as the CAPM or factor models such as the Fama-French-Carhart model that might be appropriate at low frequencies will not price assets correctly when applied at high frequencies as the effect of opacity-induced uncertainty is not captured by betas.

Our analysis begins with documenting substantial differences between high-frequency, in particular daily, and low-frequency, in particular quarterly, market betas. Sorting stocks based on the difference between their quarterly and daily beta estimates, $\Delta\beta$, we find that a portfolio that is long high $\Delta\beta$ stocks and short low $\Delta\beta$ stocks yields large positive CAPM alphas when using daily returns but significantly lower alphas when using quarterly returns.[2] Prior research has attributed the frequency dependence of measured beta to firm size, (e.g., Roll, 1981; Hawawini, 1983; Handa, Kothari, and Wasley, 1989), microstructure frictions such as nonsynchronous trading (e.g., Scholes and Williams, 1977; Dimson, 1979; Lo and MacKinlay, 1990) and bid-ask bounce (e.g., Blume and Stambaugh, 1983; Roll, 1983), as well as the multiplicative nature of arithmetic returns (e.g., Levhari and Levy, 1977; Longstaff, 1989). However, our results extend beyond small firms and illiquid stocks. We obtain similar results for large firms and liquid stocks, including firms with an equity market capitalization above \$1 billion. We find similar results after applying the beta measurement corrections of Scholes and Williams (1977) and Dimson (1979) designed to address microstructure biases. All of our empirical tests account for the multiplicative nature of arithmetic returns as a source of beta differences across frequencies.

Having ruled out the above existing explanations, we consider an alternative, risk-based explanation for the frequency dependence of betas as well as the apparent mispricing of $\Delta\beta$-sorted portfolios that does not rely on microstructure frictions. Specifically, in our model additional risk arises because for opaque firms the effect of systematic news on these firms is revealed with a delay, while the revelation of the impact of systematic news is immediate for transparent firms.

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[2]We focus on the CAPM throughout the paper, but provide similar results for the Fama-French-Carhart factor model in the Online Appendix.

Consider, for example, the market betas of Berkshire Hathaway and Exxon Mobil estimated using daily, monthly, and quarterly return data. Panel A of Figure 2.1 reveals that Berkshire has a market beta below 0.60 when estimated with daily return data but a much higher beta of about 0.95 when estimated with quarterly data. On the other hand, the market exposure of Exxon drops as the return frequency decreases. Since the annualized average returns are essentially constant across frequencies (Panel B), the beta differences between the two firms lead to sizable differences in CAPM alphas at higher frequencies, but not at the quarterly frequency (Panel C). We hypothesize that market participants require more time to understand the implications of systematic news for Berkshire Hathaway, a complex, multi-industry conglomerate, than they do for Exxon Mobil.

We formalize our intuition by developing a rational expectations equilibrium model in which differences in information processing for opaque firms (like Berkshire) and transparent firms (like Exxon) lead to the beta and alpha patterns we observe in the data. Specifically, while opaque and transparent firms may have the same exposure to underlying systematic news on average, at any given point in time the impact of systematic news on transparent firms, which make up the majority of firms in the market, is known immediately, while for opaque firms the impact is known only at a later point. The delayed revelation of the impact of systematic news on opaque firms constitutes an additional source of uncertainty that risk-averse investors care about at high frequencies, while no additional uncertainty exists at low frequencies.[3]

Our model does not contain any trading frictions or behavioral biases: prices correctly reflect all available information at all frequencies and times for both opaque and transparent firms. The model nevertheless produces frequency-dependent unconditional market betas. Differences in unconditional betas across frequencies are generated as the conditional riskiness of opaque firms varies at high frequencies when opacity matters, but does not vary at low frequencies. The riskiness and the expected returns of transparent firms do not vary with good or bad systematic news. However, opaque firms have higher risk

[3]Opacity, i.e., the delayed revelation of the impact of systematic news, could be due to opaque firms' complexity, which makes it very costly or even impossible to understand the impact of systematic news on firm value. Alternatively, the delay could be due to market participants requiring additional systematic news to understand its impact on the value of opaque firms.

and hence expected returns following better than expected systematic news. As a result of these higher expected returns, the short-term realized returns of opaque firms are lower in response to good news. Since transparent firms make up most of the market, the realized returns of opaque firms co-move less with the market at high frequencies. This dampens the betas of opaque firms, making them smaller at high frequencies, and has the opposite effect for transparent firms (due to the adding up constraint). These differences in betas lead to differences in CAPM alphas: positive for opaque firms and negative for transparent firms at high frequencies but zero for all firms at low frequencies. This means that, at high frequencies, the unconditional beta is not a sufficient measure of risk and therefore the unconditional CAPM fails, while it holds at low frequencies.

We empirically confirm that, in the cross-section, differences between low- and high-frequency betas are significantly related to proxies for opacity. In particular, we find that beta differences are larger for firms with more managerial discretion (Hambrick and Abrahamson, 1995) or higher abnormal accrual variance (Jones, 1991). Microstructure effects, of course, matter in reality and contribute to the observed frequency dependence of market betas, but the association between beta differences and opacity is robust to a large number of size and liquidity controls.

Our model suggests that the apparent mispricing at high frequencies relative to the CAPM reflects the unconditional CAPM's failure to capture opaque and transparent firms' risk exposures correctly. This limitation exists even for the conditional CAPM at high frequency when betas are determined conditional on systematic news, i.e., the lagged realization of systematic news, which is the only state variable in our model that affects the conditional return distribution.

Finally, we show that high-frequency mispricings are eliminated in the model and significantly reduced empirically when the CAPM is augmented by an additional $\Delta\beta$-factor that captures the opacity-induced uncertainty. Since all news is revealed at low frequency, opacity does not matter and this additional $\Delta\beta$-factor is not needed at low frequency.

Our findings have several important implications. First, in the presence of opacity and risk-averse investors, high-frequency market betas are not better or more precisely estimated proxies of betas; instead they are distinct economic quantities relative to low frequency betas. Specifically, our results show that unconditional as well as conditional market betas estimated from high-frequency returns are poor measures of risk. Therefore, for purposes of estimating fundamental risk exposures, ever higher frequency return data are less useful than is often thought.

Tests of the CAPM that rely on high-frequency return data (e.g., Bali and Engle, 2010, 2012; Ang and Kristensen, 2012) can be confounded by the effect of opacity. For example, Lewellen and Nagel (2006) use daily returns to calculate conditional betas and conclude that the conditional CAPM fails. Our results indicate, though, that the use of high-frequency returns to estimate conditional betas can contribute to the failure of the conditional CAPM. That is, it is possible that the conditional CAPM holds at low frequency, but not at high frequency as high-frequency betas are poor proxies for risk. The results in Lewellen and Nagel (see their Table 4 Panel A) reveal frequency dependence of conditional betas that is very similar to the patterns we document.[4] These conditional beta differences across measurement frequencies affect the fit of the conditional CAPM. Absolute conditional alphas are large when daily or weekly returns are used, but smaller when monthly returns are used (see their Table 3). Furthermore, for opaque assets, the maximum plausible unconditional alpha that Lewellen and Nagel report in their Table 1 is biased downward by the effect of opacity. Accounting for this effect can yield substantially larger alphas that are closer to those observed in the data.[5] As a result, opacity biases asset pricing tests in favor of rejecting the conditional CAPM when using high-frequency data.

Second, our results are related to the vast literature on information quality and price discovery (see, e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Zhang, 2006). In particular, our rational expectations model offers a possible risk-based explanation of Cohen and Lou (2012), who show that the returns of less complex firms can be used to predict

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[4]Lewellen and Nagel (2006) report average conditional betas, whereas we report unconditional betas. But their results reveal that the difference between the two is on average small (see their Tables 2 and 4).

[5] To see this, make the simplifying assumption that the frequency dependence of beta can be thought of as a proportional scaling (up or down) of a firm's low frequency beta (that accurately measures economic risk) based on the measurement frequency. The dampening effect can be quite large. Using the ratio of betas measured using daily returns to those measured using monthly returns (their Table 4 Panel A), the dampening effect is about two-thirds for their portfolio of small stocks and about one-sixth for their "small minus big" portfolio.

the returns of more complex firms in the same industry, and Hou and Moskowitz (2005), who show that firms that respond to market returns with a delay command a significant return premium, as well as papers that ascribe lead-lag patterns in returns to investor inattention (e.g., Hong, Torous, and Valkanov, 2007; Cohen and Frazzini, 2008). In contrast, in our model, a high-frequency trading strategy of buying (selling) opaque firms after positive (negative) factor realizations does *not* constitute a profit opportunity as its alpha represents risk that is not captured by high-frequency betas.

Third, our findings more generally indicate that the appropriate linear approximation of changes in marginal utility used for asset pricing tests depends on the return frequency at which the model is applied. Different linear asset pricing models are potentially needed to price assets at different frequencies. Differently from Longstaff (1989) who shows that the continuous-time CAPM becomes a multi-factor model when using discrete returns, we find that in the presence of opacity an additional factor is needed when applying the CAPM to high-frequency data.[6]

Lastly, there are important practical implications for measuring systematic market risk with high-frequency returns, for example, in event studies (e.g., Brown and Warner, 1985) and as part of the measurement of idiosyncratic volatility (e.g., Ang, Hodrick, Xing, and Zhang, 2006). Applying valid low-frequency asset pricing models to high-frequency returns can be problematic in the presence of opacity. Additional factors, such as the $\Delta\beta$-factor we introduce, offer one possible solution.

The remainder of this paper is organized as follows. We document significant differences in betas and alphas across return frequencies in Section 2.1. In Section 2.2, we present a rational expectations equilibrium model with opaque and transparent firms that produces the observed differences in betas and alphas in the absence of trading frictions. In Section 2.3, we empirically verify that the cross-sectional variation in the frequency dependence of beta is associated with variation in opacity across firms. In Section 2.4, we explore the asset pricing implications of opacity at high and low frequencies. We conclude in Section 2.5.

[6]Similarly, Handa et al. (1989) and Kothari et al. (1995) demonstrate that the French-French factors are less important for pricing assets at the annual frequency relative to the monthly frequency. This implication is also consistent with Kamara et al. (2013), who ask whether long-horizon investors can profit from systematic risk factors, which are priced over short horizons but not over long horizons.

2.1 Differences in Betas and Alphas Across Return Frequencies

We begin our empirical analysis by examining whether market betas and thereby CAPM alphas change as a function of the frequency of the underlying returns. Our null hypothesis is that betas are frequency independent. For logarithmic (additive) returns, market betas would indeed be identical across all frequencies under the null and in the absence of estimation error. Since we use arithmetic (multiplicative) returns throughout, we have to account for the variation of betas across frequencies due to the multiplicative structure of returns as demonstrated by Levhari and Levy (1977). In addition, the implementation of our null also accounts for estimation error, such as nonzero realized auto-correlation created by chance return realizations.

More specifically, under our null hypothesis, arithmetic returns are generated by sampling at discrete intervals without measurement error from a geometric Brownian motion with time-invariant parameters. By using standard errors generated under this null via bootstrapping, we ensure that statistically significant differences in betas and alphas across frequencies cannot be explained by the multiplicative nature of returns (Levhari and Levy, 1977) or estimation error. Appendix C provides a detailed discussion of how we construct test statistics for differences in betas and alphas across frequencies.

Even under our null, if prices are observed with error due to lack of trade and other microstructure frictions, high-frequency estimates of betas and alphas will be biased, leading to frequency dependence of measured betas and mispricings. While we do not model the various forms of possible microstructure frictions directly, we analyze subsamples of stocks that are unlikely to suffer from these frictions to test whether betas and alphas depend on return frequencies even in the absence of microstructure effects.

2.1.1 Differences in Betas Across Return Frequencies

For all NYSE/AMEX/NASDAQ-listed stocks with a market capitalization of at least $5 million, we estimate CAPM betas at the end of every calendar year between 1969 and 2010 using quarterly returns over the previous five years (60 months) and requiring at least 15 quarters of data for a stock to be included. For the remainder of the paper, we refer to such betas as quarterly betas. We do the same with daily return data to estimate betas (requiring at least 945 days of data), which we henceforth refer to as daily betas.[7] We then sort stocks into five quintile portfolios based on the difference between their lagged low-frequency (quarterly) beta and their high-frequency (daily) beta. We rebalance these portfolios at the end of each year. Throughout the paper, we focus on quarterly returns as the low frequency and daily returns as the high frequency and define $\Delta\beta$ as the difference between quarterly and daily CAPM betas.[8]

Table 2.1 reports summary statistics (pooled averages) for the stocks included in the five $\Delta\beta$-sorted portfolios. The quarterly beta of stocks in Portfolio 1 is lower than their daily beta ($\Delta\beta = -0.38$), while the quarterly beta of stocks in Portfolio 5 is much larger than their daily beta ($\Delta\beta = 1.49$). We see that, as $\Delta\beta$ increases, the firms in the portfolios have smaller market capitalization and lower liquidity. This pattern is consistent with the notion that differences in betas can in part be driven by trading frictions and correlated with firm size, two effects we control for in further tests. However, as highlighted by the 1st and the 99th percentiles of market capitalization, there is substantial size variation within all portfolios. For example, Portfolio 5 includes firms with a market capitalization of more than \$4 billion. This variation suggests that small stocks are unlikely to be the sole driver of our findings.

We form portfolios based on lagged $\Delta\beta$ (estimated over the previous five years) and calculate value- or equal-weighted portfolio returns. We then estimate unconditional full-sample daily and quarterly betas, as well as the difference between betas across frequencies for each of the five portfolios.[9] Panel A of Table 2.2 reports results when using value-weighted returns. We see that Portfolio 1 exhibits a significant decrease in beta of 0.14 as the return frequency decreases, similar to Exxon Mobil, whereas Portfolio 5 exhibits

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[7] The daily and monthly excess returns of the market portfolio are from Kenneth French's website. We compound monthly returns to obtain quarterly returns of all assets.

[8] Similar results are obtained by sorting stocks based on the difference between monthly betas and daily betas. The results are weaker when sorting on the difference between quarterly and monthly betas, consistent with our model in Section 2.2.

[9] The differences in betas in Table 2.2 are smaller than those in Table 2.1 because these are post-formation portfolio betas, whereas those in Table 2.1 report pre-formation values used to sort stocks into portfolios.

a significant increase in beta of 0.27, similar to Berkshire Hathaway in Figure 2.1.[10] The difference between these differences in beta can be assessed by building a $5-1$ portfolio that is long Portfolio 5 and short Portfolio 1. The difference in beta across frequency for Portfolio $5-1$ of 0.41 is both economically and statistically significant. Panel B reports results for the equal-weighted portfolios. The similarity between Panel A and Panel B of Table 2.2 suggests that other factors beyond size likely contribute to the observed differences.

We reproduce Panels A and B after excluding small and illiquid firms from the portfolio construction. Specifically, we include only stocks that have market capitalization above the median in each year, that are traded every day, and that have a $5 minimum price. In Table 2.2, Panels C (value-weighted) and D (equal-weighted) show that relative to the full sample, beta differences across return frequencies are reduced but remain statistically and economically significant. Hence, the frequency dependence of beta is not limited to small and illiquid stocks but occurs also in large and liquid stocks.

2.1.2 Differences in Alphas Across Return Frequencies

The above results show that an asset's beta can be significantly lower or higher at the daily frequency than at the quarterly frequency. If the asset's annualized expected returns are approximately the same across all frequencies, then these results imply that the CAPM cannot price assets equally well at all frequencies.

In Table 2.3, we examine this prediction. The first three rows of Panel A report estimates of CAPM alphas (α) for the five value-weighted portfolios sorted by $\Delta\beta$ as well as Portfolio $5-1$, which is again long Portfolio 5 and short Portfolio 1 at three different return frequencies (daily, monthly, and quarterly).[11] To facilitate comparison between the different frequencies, daily and monthly alphas are compounded to quarterly values. The last three rows of Panel A compare alphas across different frequencies and test whether the difference is statistically

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[10] All standard errors for differences in betas across return measurement frequencies are bootstrapped under the null that arithmetic returns are generated by a geometric Brownian motion, as explained in Appendix C.

[11] All daily alphas are positive, suggesting that our sample (due to standard filters) differs from the CRSP market portfolio.

significant.[12]

We compare alphas along two dimensions. The first dimension is a comparison across $\Delta\beta$ portfolios. The long-short Portfolio $5 - 1$ summarizes this dimension. The second dimension, and for our purposes the more important dimension, is a comparison of alphas across estimation frequency within a given portfolio. Finally, using the long-short $5 - 1$ portfolio, we report a difference-in-difference in the lower right corner to summarize the overall difference in alphas across portfolios and frequencies.

At the daily frequency, the alpha of Portfolio 1 is 2.3 basis points (bps) per quarter and statistically insignificantly different from zero. As $\Delta\beta$ increases, alpha increases from 2.3 bps for Portfolio 1 to 68.1 bps for Portfolio 5. At the quarterly frequency, alphas are overall lower. Indeed, differences between daily and quarterly alphas are statistically significant for all portfolios. Furthermore, all alphas are insignificant at the quarterly frequency, suggesting that CAPM performs better at the quarterly frequency relative to the daily frequency. The spread in alphas between Portfolios 5 and 1 (the alpha of Portfolio $5 - 1$) decreases by 50.6 bps, from 65.8 bps at the daily frequency to a difference of 15.2 bps at the quarterly frequency, which suggests that the spread in mispricing between $\Delta\beta$-sorted portfolios is significantly larger at high frequency than at low frequency.

Panel B of Table 2.3 reports corresponding results for equal-weighted portfolios. The alphas across all frequencies, as well as the difference in alphas between Portfolio 5 and 1, are larger compared to value-weighted portfolios. The performance of the CAPM again improves and the alpha of Portfolio $5-1$ decreases, as we move from high- to low-frequency returns.

In the Online Appendix, we reproduce Table 2.3 using the Fama-French-Carhart four-factor model (Fama and French, 1993; Carhart, 1997) to price the same $\Delta\beta$ portfolios as above. The results are very similar. Portfolio 1 is priced correctly at all frequencies. However, high-frequency alphas are larger than the lower-frequency alphas across all other portfolios, with the largest change in alpha occurring for Portfolio 5. Looking at Portfolio

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[12] All standard errors for differences in alphas across return measurement frequencies are again bootstrapped under the null that arithmetic returns are generated by a geometric Brownian motion as explained in Appendix C.

$5-1$, the spread in alpha between Portfolio 5 and Portfolio 1 is reduced when moving from the daily frequency to the monthly or quarterly frequency.

2.1.3 Robustness

Handa, Kothari, and Wasley (1989) show similar alpha patterns across frequencies when stocks are sorted into portfolios based on size rather than $\Delta\beta$. In our results, the summary Portfolio $5-1$ experiences bigger beta and alpha changes across frequencies for equal-weighted than value-weighted portfolios, consistent with small firms being particularly strongly affected. We therefore address concerns that size or microstructure frictions cause our results by performing several robustness checks.

Table 2.4 compares CAPM betas (Panel A) and alphas (Panel B) across frequencies for Portfolio $5-1$ using value- and equal-weighted returns, after applying several filters in the portfolio construction as well as a standard measurement correction for daily betas. In particular, we use the following filters: (i) stocks that trade every single day; (ii) stocks with an Amihud illiquidity measure below the cross-sectional median for the year; (iii) stocks with a market capitalization of at least \$1 billion; (iv) stocks with a share price of at least \$5; and (v) stocks that trade every day, have a market capitalization of at least \$1 billion, and a share price of at least \$5. Additionally, we use the Dimson (1979) correction to address nonsynchronous trading when estimating daily betas.[13]

Irrespective of the filter, union of filters, or correction used, our main result remains: the spread in beta and alpha between high $\Delta\beta$ stocks and low $\Delta\beta$ stocks is larger when using daily returns compared to quarterly returns. Indeed, the differences between high-frequency betas and alphas and the corresponding low-frequency counterparts remain statistically and economically significant in all cases. Hence, our findings are not fully explained by nonsynchronous trading, illiquidity, or small size.[14]

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[13]The Dimson (1979) correction is implemented with two daily leads and lags. In untabulated results, we also use the Scholes-Williams (1977) correction to address systematic stale pricing, with no qualitative difference in results. For a recent generalization of the Scholes-Williams correction, see Chen, Ferson, and Peters (2010).

[14]For robustness tests using the Fama-French-Carhart factor model, see the Online Appendix.

2.2 A Model of Frequency-Dependent Risk Exposure and Opacity

Given that microstructure effects alone are unlikely to explain the difference in betas and alphas across frequencies that we document in the previous section, we develop a model where uncertainty about the effect of systematic news on the value of opaque firms causes betas and the overall risk structure to differ across frequencies. More specifically, we allow assets to have random time-varying exposures to systematic cash flow shocks. The realization of this exposure occurs immediately for certain firms that we call transparent, while the realization of this exposure for other firms that we call opaque occurs with a delay, which is exogenous to the model. This information structure captures the idea that transparent firms respond immediately and fully to systematic events. In contrast, opaque firms immediately respond by the correct amount on average, but time must elapse before the full response to the systematic news is revealed.

The conditional riskiness of opaque firms varies at high frequencies when opacity matters, but does not vary at sufficiently low frequencies when the effect of systematic news is known for all firms. This variation in risk adds another dimension to the price distribution of opaque firms compared to transparent firms at high frequencies. However, at low frequencies, all the information has been revealed about both the transparent and opaque firms and the price distribution of both types of firms is identical. These different price distributions at different frequencies lead to different (correctly measured) unconditional betas at high versus low frequencies. Specifically, opaque firms exhibit a lower unconditional beta at high frequencies relative to low frequencies, while unconditional beta estimates for transparent firms are higher at high frequencies relative to low frequencies. At high frequencies, the unconditional beta is not a sufficient measure of risk and the unconditional CAPM fails, while it holds at low frequencies.

These beta differences and asset pricing implications are on the surface similar to those caused by nonsynchronous trading. However, they occur even without the frictions of nonsynchronous trading, allowing us to rationalize the empirical findings of the previous section, namely that beta and alpha patterns commonly attributed to nonsynchronous trading persist in large and liquid stocks that are unlikely to be affected by such frictions.

2.2.1 Model Setup

We consider an economy populated by a continuum of identical risk-averse agents indexed by $j \in [0,1]$ who value only terminal wealth $W_{j,T}$. All agents have exponential utility:

$$u[W_{j,T}] = -\exp[-\gamma W_{j,T}], \tag{2.1}$$

where γ is the agents' coefficient of absolute risk aversion. The economy has $T+1$ dates: 0, 1, ..., T. At all dates before T, agents trade a risk-free bond and N risky assets. At the terminal date T, agents consume their terminal wealth $W_{j,T}$.

Assets

The risk-free bond pays 1 with certainty and serves as the numeraire. Each risky asset i pays a single cash flow at terminal date T. At every date following date 0, each risky asset i accrues a portion of its terminal cash flow. The cash flow accrued at date t is determined by an economy-wide systematic shock (event or news), denoted by $\tilde{f}_t$, and an asset-specific exposure to that shock, denoted by $\tilde{b}_{i,t}$. This asset level exposure is time-varying in realization, but constant in distribution. The final cash flow to asset i therefore is:

$$\tilde{C}_{i,T} = \sum_{\tau=1}^{T} \tilde{b}_{i,\tau} \tilde{f}_{\tau}. \tag{2.2}$$

There are two types of risky assets: M transparent assets and $(N-M)$ opaque assets, and there is one net share of each risky asset.

For tractability, we assume a finite set of states and restrict the systematic shock to be either f^u or f^d, where $f^u > f^d$. Similarly the individual firm level exposures are assumed to be either b^H or b^L, where $b^H > b^L$. The systematic shocks are i.i.d. across periods with f^u occurring with probability P_f^u and f^d with probability $P_f^d = 1 - P_f^u$. The firm level exposures are independent across time and independent across firm types. Exposures within firm types are assumed to be positively correlated, such that the exposure effect cannot be diversified away as the number of firms increases. However, the firm level exposures are independent of the systematic shock $\tilde{f}$. The probability of the high exposure state, b^H, is P_b^H and that of the low exposure state, b^L, is $P_b^L = 1 - P_b^H$.

Information Structure and Opacity

The information structure of this model is the main innovation to capture the effect of opacity. All agents have the same information set. At each date t, the systematic realization, $\tilde{f}_t$, is revealed. When a piece of systematic news is announced, agents must consider each firm's exposure to that specific shock. For transparent firms, the time-varying firm-specific exposure, $\tilde{b}_{i,t}$, is also revealed at t. However, for opaque firms, each firm's specific exposure, $\tilde{b}_{i,t}$, is revealed at $t+1$, i.e. opacity is a delay in the processing of information about the effect of systematic news on firm value. Thus for each systematic news event, the market must process both its overall importance (magnitude) and how the shock affects each firm individually. Opacity affects this second step of determining $\tilde{b}_{i,t}$ as it introduces a delay-driven uncertainty about the effect of systematic news on the value of opaque firms.

Our information structure captures the idea that transparent firms are easy to understand. The market instantaneously evaluates the impact of systematic news on transparent firms and incorporates the exposure to this particular systematic shock into their prices. This information structure also captures the intuition that opaque firms are harder to understand at high frequencies. Specifically, the delay with which systematic news affects opaque firms could be due to their complexity, which makes it very costly or even impossible to understand the impact of systematic news on firm value. Alternatively, the delay could be due to the need for additional information to understand the impact of systematic news on the value of opaque firms.

A firm's unconditional, (long term) risk is set by the average level of its systematic exposure, $\bar{b}_i$. Importantly, opacity is not related to a firm's overall level of long-term risk. There can be risky firms that are opaque and risky firms that are transparent. For simplicity, we assign both firm types the same unconditional long-term risk and we also assume that a firm is either transparent or opaque with respect to all systematic news. In reality, firms could be transparent for some types of systematic news and opaque for others.

Agent's Problem and Equilibrium

Let each agent begin with wealth $W_{j,0}$, and let $S_{j,t}$ denote the vector of shareholdings for agent j at date t. Furthermore, let P_t denote the vector of risky asset prices at date t and C_T denote the vector of terminal cash flows of the assets.

Each agent solves the following problem at each date t:

$$\max_{\{S_{j,\tau}\}_{\tau=t}^{T-1}} E_t[-\exp(-\gamma \tilde{W}_{j,T})] \tag{2.3}$$

subject to the price process P_t and the following wealth transition equations:

$$W_{j,t+1} = S'_{j,t} P_{t+1} + (W_{j,t} - S'_{j,t} P_t), \tag{2.4}$$

$$W_{j,t+2} = S'_{j,t+1} P_{t+2} + (W_{j,t+1} - S'_{j,t+1} P_{t+1}), \tag{2.5}$$

$$\vdots$$

$$W_{j,T} = S'_{j,T-1} C_T + (W_{j,T-1} - S'_{j,T-1} P_{T-1}). \tag{2.6}$$

An equilibrium in this economy is a series of shareholding policies $\{S_{j,0}, \ldots, S_{j,T-1}\}$ for each agent that solves the agent's problem and a price process P_t that clears the market at each state and date:

$$\int_{j=0}^{1} S_{j,t} dj = 1. \tag{2.7}$$

The pricing equations generated by this equilibrium are standard, as are the CAPM beta and alpha calculations. Details of both can be found in Appendix D.

2.2.2 Model Results

We solve the model in closed form. Due to the large state space, the closed-form solutions are long and cannot be conveniently reported. Therefore, we present the results of our model for specific parametrizations.[15] In all cases, the systematic shocks are assumed to be $f^u = 1$ and $f^d = 0$ with associated marginal probabilities $P_f^u = P_f^d = 0.5$. This captures the fact that the expected cash flows of firms have a positive mean, consistent with limited

[15]To compare across model parametrization, we normalize appropriately to keep both the amount of risk in the economy relatively constant and the priced assets of the same relative size. See Appendix D for further details.

liability.[16] Firm-level exposures are assumed to be $b^H = 1$ and $b^L = 0$ with marginal probabilities $P_b^H = P_b^L = 0.5$. These two values capture the fact that sometimes a firm is strongly exposed to a piece of systematic news, while at other times it is not.

Base Case Results

For our base case, we set the number of subperiods, T, to three, the number of risky assets, N, to five, and agents' risk aversion, γ, to five. Table 2.5 reports the model results in terms of (unconditional) expected returns, market betas, and CAPM alphas for each type of asset, as well as the expected market return. We first consider the case when there are only transparent assets and no opaque assets ($M = N = 5$). We consider a single subperiod as the high-frequency period and the total of all subperiods (T) as the low-frequency period. Columns (1) and (2) present low- and high-frequency results.[17] In the absence of opaque assets, expected returns, betas, and alphas are the same across frequencies. The CAPM prices all assets correctly and alphas are zero.

In columns (3) and (4) of Table 2.5, we consider the case of four transparent assets and one opaque asset, i.e., the fraction of the market that is opaque equals 20%. At the *low* frequency (column (3)), the presence of the opaque asset does not change the results relative to the case of no opaque assets. Furthermore, expected returns, betas, and alphas are the same for transparent and opaque assets, as differences with respect to the revelation of the asset-specific exposure, $\tilde{b}_{i,t}$, to systematic shocks, do not matter at the low frequency. However, at the *high* frequency (column (4)), the addition of the opaque asset changes the beta of both types of assets. The beta of the transparent asset is now 1.024 instead of 1.000, while the beta of the opaque asset is 0.907 as opposed to 1.000. That is, in our model, transparent assets are associated with a negative $\Delta\beta$ of -0.024 and opaque assets with a positive $\Delta\beta$ of 0.093, where $\Delta\beta$ is defined as in our empirical tests as the low-frequency

[16] Note that due to the multiplicative nature of cash flows in our model, model results are not invariant to translations in the values of f. Standard exponential utility models with purely additive cash flows are invariant to such normalization.

[17] The high-frequency expected returns as well as alphas we present are scaled by the number of subperiods, T. This scaling is akin to the compounding of our daily alphas to a quarterly frequency in our empirical section.

beta minus the high-frequency beta. Since unconditional expected returns do not differ between frequencies or asset types, the beta differences at the high frequency lead to non-zero CAPM alphas at the high frequency, while the expected unconditional market return remains unaffected by opacity.

Discussion

To explore the underlying mechanism of our model that leads to frequency-dependent betas as well as the failure of the CAPM at the high frequency, consider the specific parametrization of our model. The average exposure, $\bar{b}$, of all firms is 0.5, the average between 0 and 1. At the moment systematic shocks are realized, the exposure of transparent assets is also revealed. The exposure of opaque assets, on the other hand, is not revealed at the same time, but only in the next period. In the case of *good* (higher than expected) systematic news, $f = 1$, risk-averse investors demand additional compensation for the uncertainty about the opaque assets' exposure to the systematic shock, such that *conditional* on $f = 1$ the expected return of opaque assets increases to 0.476 (untabulated here) from the unconditional expected return of 0.293. Therefore, at the time of good systematic shocks, the net price change (i.e., the realized return) of opaque firms reflects positive news about future dividends (cash flow channel), but bad news about the temporarily increased uncertainty (discount rate channel). In contrast, in the case of *bad* systematic news, $f = 0$, the uncertainty about the unrevealed exposure of opaque firms matters less due to the smaller size of the systematic shock. In the particular case of $f = 0$, the uncertainty of the firm level exposure is completely irrelevant, as the opaque firms' dividend will be zero for *any* value of b. Consequently, *conditional* on $f = 0$, the expected return of opaque assets decreases to 0.232 (untabulated here) relative to the unconditional expected return of 0.293.[18] There-

[18]Conditional on $f = 0$, the expected return of the opaque asset is lower than both its unconditional return and the (un)conditional return of the transparent asset (both expected returns are 0.293). To see why this occurs, compare the expected return of the opaque asset to that of the transparent asset. Expected returns are driven by the amount of risk resolved, which is itself determined by the amount of information released for each firm. In the period following an $f = 0$ realization, the transparent firms have information released about the new systematic shock and their new idiosyncratic shock. In contrast, following a realization of $f = 0$, the opaque firms effectively only have information released about the new systematic shock, because their firm-specific exposure to the previous $f = 0$ no longer matters. The lower amount of effective information released lowers their expected return.

fore, at the time of bad systematic shocks, the net price change (i.e., the realized return) of opaque firms reflects negative news about future dividends (cash flow channel), but good news about the temporarily reduced uncertainty (discount rate channel). Hence, at high frequency, realized returns of opaque firms reflect the effect of the cash flow channel, as well as the partly offsetting effect of the discount rate channel.

The offsetting nature of the discount rate effect (due to variation of expected returns) for opaque firms does not depend on the specific choice of 0 and 1 we have used for f, but obtains for all combinations of f with a positive mean. As long as the mean of f is positive, which is justified by the limited liability nature of stocks, expected returns of opaque firms will increase following good news (large f) but decrease following bad news (small f).

In contrast, for transparent assets, the simultaneous revelation of the systematic shock, f, and the assets' specific exposure, b, means prices of transparent assets only respond to the cash flow effect, which is now bf rather than the $\bar{b}f$ for opaque assets. The expected returns of transparent assets are therefore constant, i.e., they do not change as a function of realizations of f since transparent assets lack the discount rate dimension of price variation at high frequencies.

At the *high* frequency, the additional discount rate effect in the price movement of the opaque firms dampens the comovement between the returns of the opaque and transparent assets. Since transparent assets make up a relatively larger fraction of the market, this dampened comovement between the returns of the two security types dampens the return comovement between the opaque assets and market, while accentuating the comovement between the transparent assets and the market. Therefore, in our model of otherwise identical assets, unconditional high-frequency betas of transparent assets are larger than those of opaque assets.

At the *low* frequency, the return length is long relative to the lag over which the firm-level exposure to shocks is revealed. Thus, the systematic shock and asset-specific exposures are effectively revealed simultaneously. All comovement between assets therefore reflects only cash flow effects, making the low-frequency betas solely measures of cash flow exposures. Both types of firms have the same risk exposures and the same market betas at the low frequency and the CAPM prices both types of assets correctly. High-frequency betas are confounded by the discount rate generated price changes of the opaque assets, causing the CAPM to underprice opaque assets and to overprice transparent ones at high frequencies. Across frequencies, therefore, opaque assets have lower high-frequency betas relative to low-frequency betas, while transparent assets have higher high-frequency betas relative to low-frequency betas.[19]

Additional Model Results

The results in our model are driven by uncertainty about the effect of systematic news on the value of opaque firms. Risk-averse agents properly account for this additional, even though temporary, risk when they set prices in equilibrium. Importantly, in our model, prices are always correct and are accurately "observed" by the econometrician even at the high frequency, allowing for accurate high-frequency beta calculations. The failure of the high-frequency CAPM to price assets is therefore not due to mismeasurement or agents mispricing assets. Instead, agents' risk-aversion is essential for our model to produce the frequency dependence of beta and alpha. To see the importance of risk-aversion, we calculate results when agents are risk-neutral in our model with one opaque and four transparent assets (untabulated). The difference in betas across frequencies disappears for both transparent and opaque firms when agents are risk-neutral since all expected (excess) returns are zero. Thus there is no discount rate channel to generate our effect.

Finally, we explore two additional dimensions of our model: the fraction of opaque assets in the economy and the length of the low-frequency period relative to the length of the high-frequency period. Panel A of Figure 2.2 presents results for different fractions of the market composed of opaque assets. In addition to the preceding case in which one out of five assets is opaque, we explore economies in which either one out of seven or one out of nine assets is opaque. All other parameters are unchanged relative to the base case. The left plot of Panel A shows CAPM betas of the transparent and opaque assets at the highest frequency (1 period) and at the lowest frequency (T periods), while the right plot shows CAPM alphas of both types of assets across both frequencies. The values for the opaque

[19]We discuss the conditional high frequency CAPM in Section 2.4.

assets are shown in thick (gray) lines and the values for the transparent assets are shown in thin (black) lines. The magnitude of the differences between high and low frequency beta and alphas decreases as the fraction of the market that is opaque decreases, reflecting the diminished importance of opacity as a source of high-frequency risk. The pattern is consistent with the effect completely vanishing in the absence of opaque firms (columns (1) and (2) of Table 2.5).

Panel B of Figure 2.2 shows corresponding results when varying the number of subperiods between 3, 4, and 5, while holding all other parameters constant relative to the base case, including the fraction of the market that is opaque at 20%. The magnitude of the differences between high- and low-frequency beta and alphas increases when the period length of the low-frequency sample grows relative to the period length of the high-frequency sample. This is consistent with our empirical results that the effect is generally stronger between the daily and quarterly frequency than between the daily and monthly frequency.

2.3 Opacity and $\Delta\beta$

Our model demonstrates that opacity, which is the uncertainty about the effect of systematic news on firm value, generates differences between high and low frequency market betas ($\Delta\beta$) similar to those found in actual data. In this section, we provide empirical evidence at the firm-level that $\Delta\beta$ is indeed related to proxies of opacity and that this relationship is robust to controlling for size, as well as microstructure and trading frictions.

2.3.1 Opacity Proxies

Our first measure of opacity is the managerial discretion measure from Hambrick and Abrahamson (1995). They measure managerial discretion, or latitude of action, at the industry level. The managerial discretion score is based on questionnaires completed by both academic researchers in strategic management and security analysts. The score is based on a seven-point scale with one being extremely little discretion and seven being extremely great discretion. Our assumption is that managerial discretion increases the cost of processing public information about a firm because the production function of the firm is more difficult to discern. The Hambrick and Abrahamson questionnaire focuses on managerial discretion at the industry level between 1985 and 1989 for 31 industries as defined by two-digit SIC codes. We assign the managerial discretion measure to all firms in our sample between 1969 and 2010, based on the firm's two-digit SIC code. All firms in the same industry therefore receive the same score.

Our second measure of opacity is the variance of abnormal accruals. We estimate a five-year rolling variance of the residuals obtained from estimating the expected accrual model of Jones (1991). Our assumption is that the more managers make use of accruals to manage the firm's earnings, the harder it will be for investors to understand the impact of systematic news on firm value. A firm with high variance of abnormal accruals is opaque in the sense that investors require more information and hence more time to price the impact of news because, as above, the firm's production function is more difficult to discern.

We also considered using the number of analysts as a proxy for opacity, but we decided against it since it is endogenous, making ex-ante predictions unclear. For example, analysts might choose to focus on opaque firms as they can add more value for investors in those firms relative to the case of transparent firms, or they might choose to focus on transparent firms because they are easier to value.

2.3.2 Panel Regression Analysis

To test the effect of opacity on betas measured at different frequencies, we perform panel regressions of quarterly minus daily betas ($\Delta\beta$) on our proxies of opacity: managerial discretion and abnormal accrual variance. Our hypothesis is that $\Delta\beta$ is positively related to the level of opacity. The high-frequency betas of more opaque firms are smaller compared to their low-frequency counterparts.

In the regressions, we control for firm size with the natural log of the firm's equity market capitalization in addition to size quintile indicators. We also control for firm-level liquidity differences by including the Amihud (2002) illiquidity measure, the fraction of days with zero trading volume, the fraction squared, and turnover. To minimize the influence of potentially extreme measurement error, we drop observations in the top and bottom one percentile of both the $\Delta\beta$ and abnormal accrual variance distributions.[20] In the Online Appendix, we report summary statistics for all firms included in both the managerial discretion and the abnormal accrual variance samples.

Table 2.6 presents results from the following linear regression:

$$\Delta\beta_{i,t} = \alpha + \gamma_1\, Opacity_{i,t-1} + \gamma_2\, controls_{i,t-1} + \epsilon_{i,t}. \tag{2.8}$$

Each data point in the regressions is a firm-year observation and the explanatory variables are estimated based on the prior calendar year. The first two specifications report results without any control variables. The effect of managerial discretion (column (1)) is statistically significant and economically meaningful, implying an increase of about 0.14 in $\Delta\beta$ per one standard deviation increase in managerial discretion. Similarly, a one standard deviation increase in abnormal accrual variance is related to an increase in $\Delta\beta$ of about 0.11 when no controls are included (column (2)). The magnitude of the managerial discretion effect drops by about one-third (column (3)) and that of the abnormal accrual variance (column (4)) drops by slightly over one-half when all size and liquidity controls are included, but both remain highly statistically and economically significant. Interestingly based on the results in columns (3) and (4), a two standard deviation change in opacity implies a change in $\Delta\beta$ between 0.08 and 0.19 that is similar to the spread in "Quarterly β − Daily β" of 0.19 that we document at the portfolio level for big and liquid stocks (see Panels C and D of Table 2.2).

In Table 2.7, we perform a large number of robustness checks in order to rule out alternative explanations related to microstructure frictions, investor inattention, or asymmetric information. Specifications 1 and 2 exclude all firm-year observations where the stock does not trade during every single (trading) day of the year. Specifications 3 and 4 exclude all firm-year observations whose Amihud measure of illiquidity is above the cross-sectional median in that year. Specifications 5 and 6 exclude all firm-year observations whose share price falls below $5 at any point during the year. Specifications 7 and 8 exclude all firm-year observations whose market capitalization is below $1 billion. This stringent filter basically

[20] We obtain qualitatively similar results without winsorizing.

leaves us with the largest publicly traded firms for which trading frictions or investor inattention should not be material. Specifications 9 and 10 introduce an indicator variable for the post-2001 decimalization period when transaction costs were lowered. Finally, specifications 11 and 12 add the Adjusted PIN of Duarte and Young (2009) as a control for asymmetric information for a subsample of NYSE and AMEX stocks between 1984 and 2005.[21] The coefficient on the opacity measures remains positive and significant in all cases, including those cases where we focus on the largest and most liquid firms.

2.4 High-Frequency Asset Pricing and Opacity

Our results so far suggest that opacity poses significant challenges to asset pricing at high frequencies. In this section, we explore possible approaches to improve the pricing of assets at high frequencies. We first explore possible solutions within our model.

2.4.1 Model Results

We use our model to examine three possible solutions to price assets at the high frequency: traditional beta measurement corrections (e.g., Scholes and Williams, 1977; Dimson, 1979), a high-frequency conditional CAPM, and the unconditional CAPM augmented by a second factor based on the return spread between firms with positive and negative $\Delta\beta$. We present the different high-frequency model results in Table 2.8. To gauge how well a given approach works, column (1) repeats the baseline specification of our model from Table 2.5 that demonstrates the failure of the CAPM at the high frequency.

Scholes-Williams and Dimson Analog Betas

The beta and alpha patterns we document and model are similar to those that can occur in the case of nonsynchronous trading. However, in our model the mechanism generating these alpha and beta patterns is variation in conditional risk rather than measurement error created from inaccurately observed prices of securities that do not trade.

[21] The Adjusted PIN is an extension of the Easley et al. (1996) structural microstructure model or PIN model. Like the PIN, the Adjusted PIN identifies the probability of an informed trade using periods of abnormal order flow imbalance.

Nevertheless, we examine in our model whether the prescription of Scholes and Williams (1977) and Dimson (1979) to use covariances between asset returns and lead and lag market returns to correct the high-frequency beta improves the performance of the CAPM at high frequency in the presence of opacity. We create a single analog for the Scholes-Williams and Dimson beta corrections in our model, by essentially capturing all lead and lag effects. The details of this analog are in Appendix D.4.

In column (2) of Table 2.8, we show that the corrected betas fail to eliminate the mispricing under the CAPM at high frequency in the model. In particular, the correction leads to a beta for the transparent assets that is too low and to a beta for the opaque assets that is too high. As a result, the alphas change sign and become larger in absolute value. This failure is consistent with our empirical findings in Table 2.4, where the Scholes-Williams and Dimson beta corrections also fail to eliminate the mispricing.[22]

Conditional CAPM

In our model, differences in *unconditional* betas across frequencies are generated by high-frequency variation in conditional riskiness of opaque assets. The opaque assets have higher risk following good (higher than expected) systematic news and lower risk following bad (lower than expected) systematic news. This dampens the unconditional beta of opaque firms estimated from high-frequency returns (relative to their unconditional beta estimated from low-frequency returns), while it has the opposite effect for transparent firms. It could be, though, that the *conditional* CAPM prices assets accurately at the high frequency. We examine this possibility next. Specifically, we calculate beta conditional on the lagged realization of the systematic news, f, which takes on values of zero or one with equal probability.[23]

[22] In our model, the correction makes the alphas worse at high frequency while empirically the Scholes-Williams and Dimson betas somewhat reduce the high-frequency alphas. This empirical mitigation of the mispricing occurs because in reality there are microstructure effects, which the Scholes-Williams and Dimson corrections address, and our opacity effect, which they do not address. Empirically, the net of these two effects is a slight improvement of the high-frequency pricing of assets. However, since the microstructure effects are absent in our model, the mispricings can become worse.

[23] The one period lagged value of the systematic shock f is the only state variable that affects the conditional distribution of returns, and hence we only consider a conditional CAPM based on it. The other state variables (e.g., additional lagged values of the systematic factor f and firm-specific exposure realization

Columns (3) and (4) in Table 2.8 report the results of the CAPM conditional on the realization of f. Conditional market betas of opaque assets are indeed higher after good systematic news ($f = 1$) and lower after a bad systematic news ($f = 0$). Due to the adding-up constraint of market betas, the conditional betas of the transparent assets move opposite to those of the opaque assets.

Even though the conditional betas of the opaque assets correspond to the high-frequency variation in the conditional riskiness of opaque assets, the high-frequency conditional CAPM does not correctly price assets within the context of our model. Columns (3) and (4) in Table 2.8 report non-zero alphas for both transparent and opaque assets. For opaque assets, the positive conditional alphas suggest that conditional betas are too low relative to their riskiness. Transparent assets are likewise mispriced, but in the opposite manner, which suggests that their conditional betas are relatively too high.

To understand the failure of the conditional CAPM, note that conditional betas also measure the risk and expected return associated with the release of *new* systematic information. This information release creates new high-frequency variation in the conditional risk of the opaque assets. This variation again creates offsetting discount rate and cash flow effects. The two effects interfere with the conditional betas' ability to measure part of the risk in the same way they interfered in the unconditional case. Thus the conditional betas help, but do not fully capture the risk of assets at high frequency, leaving the conditional CAPM unable to price assets at high frequencies.

While the conditional CAPM does not resolve the challenges due to opacity at high frequency, we test whether the conditional beta patterns from our model exist in actual data. We do so because the predicted pattern in conditional betas presents an opportunity to test the risk-based mechanism of our model and to distinguish it from the nonsynchronous trading literature. In that literature, beta variation across frequencies is due to the fact that the returns of assets that trade infrequently lag the market return, and there are no predictions about differences in betas conditional on systematic shocks.

To empirically test this implication, we calculate the conditional beta of the lowest

the $b_{i,t}$) only affect agents' wealth levels, which do not affect returns due to the use of exponential utility.

$\Delta\beta$ portfolio (Portfolio 1, representing transparent assets) and the conditional beta of the highest $\Delta\beta$ portfolio (Portfolio 5, representing opaque assets). We use the previous month's market return as the conditioning variable since in the data, differently from the model, we are unable to observe the underlying systematic news shocks directly (i.e., the one period lagged f in the model). Past market returns are an imperfect but reasonable empirical proxy for the model's aggregate shocks $\tilde{f}$.

We present the conditional betas using the prior month's market return as the conditioning information in Table 2.9. Panel A presents the conditional betas when the prior period's market return is above or below the median. Panel B presents the results when the prior period's market return is above the 75th percentile or below the 25th percentile. Both sets of empirical conditional betas match our model's predictions (see columns (3) and (4) of Table 2.8). Indeed, the risk of opaque assets rises after positive shocks, as demonstrated by their increased conditional betas following high market returns. After negative shocks, the conditional betas of opaque assets falls and the opposite patterns exist for transparent assets. Moreover, by comparing across Panels A and B, we see that the more extreme the previous market returns, the more extreme the difference between the conditional betas. This increasing difference occurs because there is more conditional uncertainty accompanying opaque stocks the larger the magnitude of the underlying systematic shock.

$\Delta\beta$-Factor

The conditional CAPM fails because, conditioning on one period lagged systematic factor realizations, f, it is still confounded by the delayed information revelation of the opaque assets. To properly price assets, we need a way to disentangle the cash flow effects from the discount rate effects. Going long the opaque assets (high $\Delta\beta$) and short the transparent assets (low $\Delta\beta$) in the right proportions yields a zero investment portfolio that moves only with the discount rate effect since the cash flow effect has been netted out. We label this portfolio the $\Delta\beta$-factor. Augmenting the high-frequency unconditional CAPM by this $\Delta\beta$-factor allows the market factor to correctly capture the cash flow effect, while the $\Delta\beta$-factor will capture the discount rate effect. We present the details of this new factor's construction within the model and the calculation of the betas and alphas of this two-factor model in Appendix E.

In column (5) of Table 2.8, we report the results of using this two-factor model to price assets within the model. First, note that transparent assets load negatively on the $\Delta\beta$-factor, while opaque assets load positively, which is consistent with the factor's long-short construction. Importantly, adding the $\Delta\beta$-factor to the market factor produces a model that correctly prices all assets, i.e., all alphas in column (5) are zero. By stripping out the discount rate effect with the $\Delta\beta$-factor, the model yields market betas of one for both transparent and opaque assets (i.e., the same market betas as under the low-frequency CAPM). Thus, in the high-frequency two-factor model, the market factor is able to fully capture the risk of both assets. As can be seen from Table 2.8, the expected return of the second factor is zero. While the second factor is crucial for correcting the confounding of the market beta by the discount rate effect, in our model, it is designed such that it has no correlation with the true stochastic discount factor and therefore has no premium.[24] Finally, note that the unconditional CAPM prices both the transparent and opaque asset perfectly at low frequency. Thus, adding the $\Delta\beta$ factor to the low-frequency CAPM has no effect (untabulated result).

2.4.2 Empirical Tests of the $\Delta\beta$-Factor

Our model results suggest that out of the several possible solutions to price assets at the high frequency, only the unconditional CAPM augmented by the $\Delta\beta$-factor prices assets correctly at high frequency. We empirically explore the performance of such a $\Delta\beta$-factor. To do so, we construct the empirical $\Delta\beta$-factor as the difference between the value-weighted returns of portfolios of stocks in the top and bottom terciles of the $\Delta\beta$ distribution.[25] As before, betas are estimated at the end of the previous year using 60 months of data. We

[24]If the cash flow effect is not fully netted out in the construction of the $\Delta\beta$-factor, the factor premium would be nonzero due to remaining cash flow exposure. In our model, the netting out of the cash flow effect is accomplished by weighing the long (opaque assets) and short (transparent assets) position appropriately in the construction of the $\Delta\beta$-factor.

[25]Differently from the model, we do not know the appropriate weights to fully remove the cash flow effect from the $\Delta\beta$-factor. Therefore, the $\Delta\beta$-factor will likely have a non-zero risk premium in our empirical implementation.

rebalance this factor annually.

Our test consists of comparing CAPM alphas with the alphas after adding the $\Delta\beta$-factor to the CAPM, in particular at the high frequency where we expect the $\Delta\beta$-factor to play an important role. As test assets, we use the five value-weighted $\Delta\beta$ sorted portfolios from Section 2.1.

Table 2.10 reports the alphas for each of the five portfolios at the daily, monthly, and quarter frequency. As before, all alphas have been converted to quarterly frequency equivalents for comparison. The alphas in Panel A are for the CAPM, while the alphas in Panel B are for the CAPM augmented with the $\Delta\beta$-factor. Consistent with our prediction, we see a substantial drop in high-frequency alphas between Panel A and Panel B. More precisely, the addition of the $\Delta\beta$-factor leads to a 59% decrease in the sum of squared daily alphas, while the sum of squared monthly and quarterly alphas falls by a much smaller 19% and 30%, respectively.

In order to further disentangle our result from the effect of size and to control for the fact that $\Delta\beta$ is correlated with market capitalization, we present results in Panel C of Table 2.10 where the $\Delta\beta$-factor has been orthogonalized to the SMB factor.[26] We see that the addition of a size-orthogonalized $\Delta\beta$-factor leads to a 58% reduction in the sum of squared alphas at the daily return frequency compared to a 42% and 38% reduction in the sum of squared alphas at the monthly and quarterly return frequencies, respectively. In addition, note that a large fraction of the improvement in alphas happens in portfolios 4 and 5, which are the opaque high $\Delta\beta$ portfolios. Summarizing, the $\Delta\beta$-factor plays a significant role in reducing alphas at high frequencies and this role is reduced as the return frequency is lowered.

While these results based on the sum of squared alphas are consistent with our model, the measure has the disadvantage that it can be influenced by test assets with poorly measured alphas as the sum of squared alphas weights all test assets equally. As a robustness test and to assess the performance of the $\Delta\beta$-factor more formally, we compare the Hansen and

[26]Specifically, we run the regression $r_{OMT,t} = a + b * r_{SMB,t} + \epsilon_t$ over the entire sample period and consider our orthogonalized factor to be $r^O_{OMT,t} = r_{OMT,t} - b * r_{SMB,t}$. We consider the orthogonalized return to be that of a traded portfolio. In a robustness check, we consider this orthogonalized factor within the Hansen and Jagannathan (1997) distance methodology where there is no need to assume the factor is traded and find similar results.

Jagannathan (1997) distance of the CAPM to the one of the CAPM augmented with either the $\Delta\beta$-factor or the orthogonalized $\Delta\beta$-factor.[27] The results are in the Online Appendix. Using a wide set of test assets ($\Delta\beta$-sorted portfolios and the 30 Fama-French industries), we show that the presence of the $\Delta\beta$-factor greatly reduces the HJ distance compared to the CAPM and particularly so at high frequencies. In the Online Appendix, we show that these results are robust to the inclusion of the Fama-French-Carhart SMB, HML, and UMD factors in the base model.

Taken together, our results show that the addition of the $\Delta\beta$-factor, based on the difference in betas across frequencies, helps improve the pricing of assets at high frequencies while, consistent with our model, it is less important at low frequencies. Our results also underscore the challenges of using high-frequency data. Differently from the findings of Longstaff (1989), we show that *more* factors are needed when moving from low- to high-frequency data.

2.5 Conclusion

A stock's market exposure, beta, is not the same when measured across different return frequencies. Contrary to previous research, we show that beta differences across frequencies occur even in large and liquid stocks and cannot be explained by microstructure and trading frictions. We present a rational expectations model with no microstructure or trading frictions and no behavioral biases. In the model, opacity (i.e., uncertainty about the effect of systematic news on the value of opaque firms) gives rise to betas that differ between low and high frequencies, as we observe in the data. We show empirically that the frequency dependence of betas is associated with firm- and industry-level proxies of opacity.

Our model shows how opacity can generate differences in unconditional betas across frequencies. The apparent mispricing at high frequencies relative to the CAPM reflects the unconditional CAPM's failure to capture opaque and transparent firms' risk exposure correctly at high frequencies, while the unconditional CAPM does so perfectly at low fre-

[27] The Hansen-Jagannathan (HJ) distance was designed specifically to compare different asset pricing models; a lower HJ distance is associated with a better fitting model. The HJ distance is similar in concept to the sum of squared alphas, but the weighting scheme of the HJ distance is constant across models.

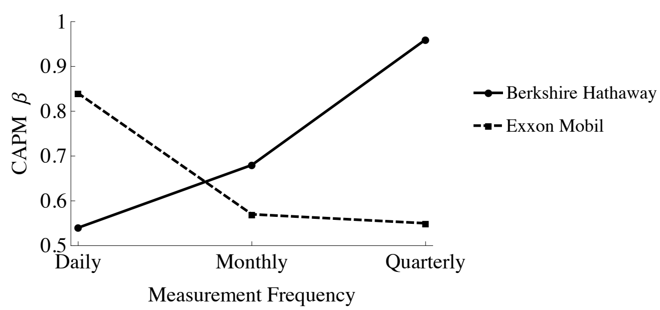
quencies. We also explore the conditional CAPM at high frequencies in our model. We find that although conditional high-frequency betas vary with systematic news (as in the data), at high frequencies the conditional CAPM is not able to price assets correctly. Overall, our results suggest that the effect of opacity can confound asset pricing tests and distort risk measures at high frequencies, while opacity has little impact at low frequencies.

Finally, we provide one possible solution for researchers using high-frequency return data. We show both within our model and empirically that augmenting linear asset pricing models such as the CAPM with a new $\Delta\beta$-factor improves the pricing of assets at high frequencies. Overall, we suggest that while the CAPM may be an appropriate asset pricing model at low frequencies, additional factors are necessary for pricing assets at high frequency.

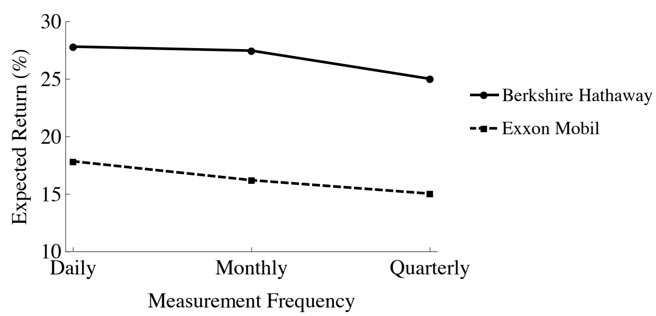
Figure 2.1: Berkshire Hathaway and Exxon Mobil Across Return Frequencies

This figure shows the full sample CAPM betas (Panel A), annualized expected returns (Panel B), and annualized CAPM alphas (Panel C) for Berkshire Hathaway and Exxon Mobil estimated using three different return frequencies (daily, monthly, and quarterly) between 1980 and 2010.

Panel A: CAPM β



Panel B: Expected returns



Panel C: CAPM α

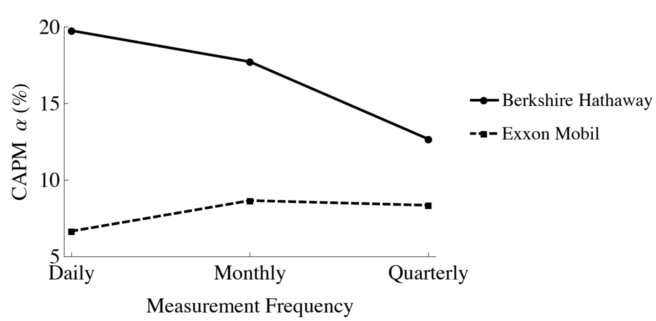
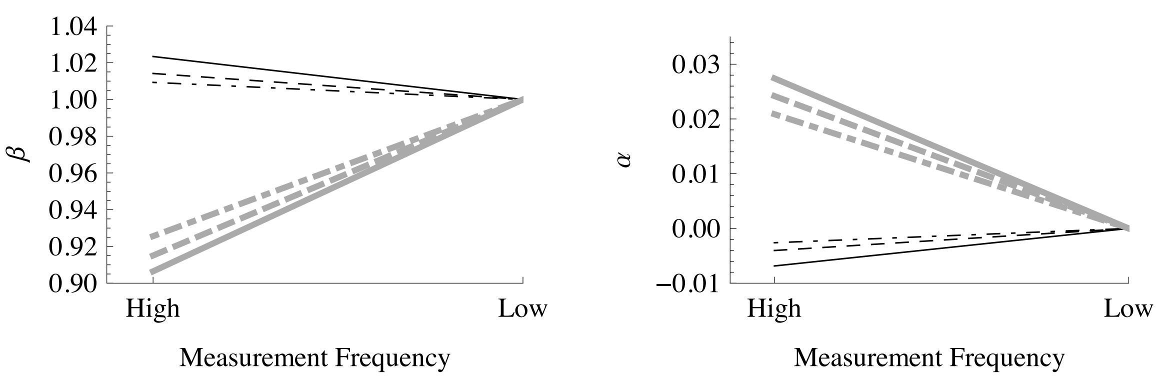


Figure 2.2: CAPM β and α Across Return Frequencies From the Model

This figure shows the model's CAPM betas and alphas measured across return frequencies (High to Low). Opaque assets are depicted by thick (gray) lines and transparent assets are depicted by thin (black) lines. Betas and alphas are presented for assets normalized to size 1, and alphas are "annualized" to the lowest frequency. Panel A shows how the magnitude of betas and alphas changes across measurement frequency as the fraction of the market composed of opaque assets decreases. The solid line is for 1/5 opaque assets, the dashed line is for 1/7 opaque assets, the dot-dashed line is for 1/9 opaque assets, and all three of these models use a total of three periods. Panel B shows how the magnitude of the betas and alphas changes across measurement frequency as the total number of periods increases. The solid lines depict the results for three periods, the dashed lines depict the results for four periods, the dot-dashed lines depict the results for five periods, and all three of these models use 1/5 opaque assets. Agents have a coefficient of risk aversion of five for all models.

Panel A: Variation across fraction of opaque assets



Panel B: Variation across number of periods

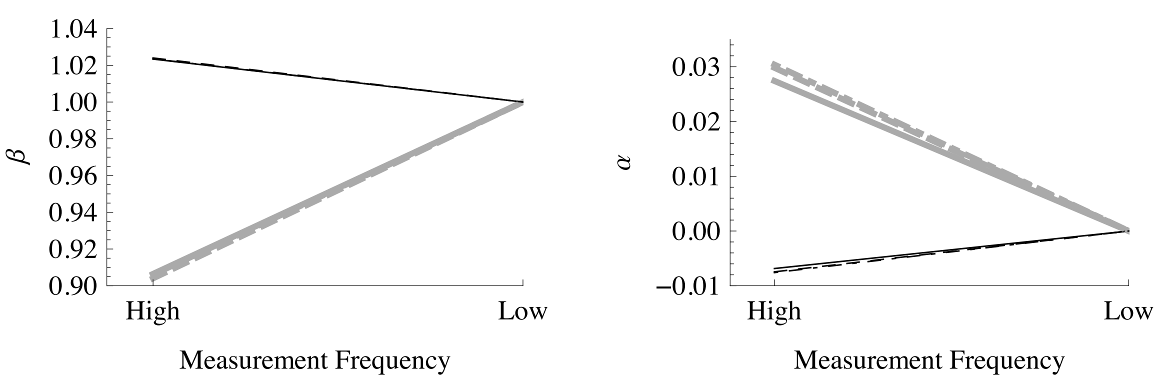


Table 2.1: Summary Statistics of $\Delta\beta$ Portfolio Constituents

This table reports summary statistics for the constituents of five value-weighted portfolios sorted by the difference between quarterly and daily betas ($\Delta\beta$ = Quarterly β − Daily β). The portfolios are formed annually based on each stock's $\Delta\beta$. Quarterly (daily) unconditional betas are estimated at the end of every calendar year using quarterly (daily) returns over the previous 60 months. The first market capitalization (MCap) row reports the average size of the portfolio constituents in millions of dollars. The second MCap row reports the 1st percentile (in millions of dollars), the median (in millions of dollars), and the 99th percentile (in billions of dollars) of the size of the portfolio constituents. Illiquidity is the percentage of days with zero trading volume for a given stock within a given year. The Amihud illiquidity measure is in units of absolute return per million dollars of daily volume. Below $5 is the percentage of months with end-of-month trading price below $5 for a given stock. Managerial discretion is an industry-level measure by Hambrick and Abrahamson (1995). Abnormal accrual variance is the five-year rolling variance of the residual from the expected accrual model by Jones (1991). The sample period is 1969-2010.

	Portfolios formed on $\Delta\beta$				
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5
Number of Firms	595	596	596	596	595
Daily β	0.98	0.76	0.70	0.72	0.83
Quarterly β	0.60	0.85	1.06	1.40	2.32
$\Delta\beta$ = Quarterly β − Daily β	-0.38	0.09	0.36	0.67	1.49
Share Price	$25.90	$38.57	$49.13	$25.56	$13.67
Market Capitalization (MCap $m)	2,964	2,261	1,465	709	317
MCap 1st/50th/99th Pct. ($ m/m/b)	9/432/48	9/350/37	8/221/24	7/114/11	7/65/4
Illiquidity	5.9%	8.4%	10.6%	11.4%	11.7%
Amihud Illiquidity	1.52	1.64	1.91	2.79	4.00
Below $5	12.1%	8.8%	9.9%	14.8%	27.8%
Managerial Discretion	4.52	4.54	4.73	4.95	5.16
Abnormal Accrual Variance	0.010	0.008	0.010	0.010	0.022

Table 2.2: Differences in CAPM β Across Return Frequency

This table presents estimates of unconditional β for five portfolios formed annually based on the difference between quarterly and daily CAPM β (estimated at the end of the previous year using 60 months of data), as well as Portfolio $5-1$ that is long Portfolio 5 and short Portfolio 1. Each panel reports time series estimates of β for each portfolio at the daily and quarterly return frequency, as well as the difference between them. Panel A (Panel B) provides full-sample estimates of daily and quarterly CAPM β, as well as the differences between them for the five value-weighted (equal-weighted) portfolios. Panel C (Panel D) mirrors Panel A (Panel B) but restricts stocks to have a greater than median market capitalization, have non-zero trading volume every day within the year, and have a price that is greater than \$5. The sample period is 1969-2010. All portfolios are rebalanced every year based on β estimates from the previous 60 months. All β estimates are statistically significant. Standard errors for the differences in beta are bootstrapped as described in Appendix C. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CAPM β (value-weighted)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. 5 − 1
Daily β	1.02	0.96	0.97	1.03	1.16	0.14
Quarterly β	0.89	0.94	1.03	1.14	1.43	0.55
Quarterly β − Daily β	-0.14***	-0.02	0.06**	0.11***	0.27***	0.41***

Panel B: CAPM β (equal-weighted)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. 5 − 1
Daily Returns β	0.94	0.78	0.75	0.75	0.85	-0.09
Quarterly Returns β	1.11	1.01	1.06	1.17	1.48	0.37
Quarterly β − Daily β	0.17***	0.23***	0.31***	0.42***	0.63***	0.46***

Panel C: CAPM β (value-weighted; large/liquid/min. price filters)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. 5 − 1
Daily Returns β	1.04	0.95	0.98	0.97	1.13	0.09
Quarterly Returns β	0.90	0.83	0.94	0.98	1.18	0.28
Quarterly β − Daily β	-0.14***	-0.12***	-0.05*	0.01	0.05*	0.19***

Panel D: CAPM β (equal-weighted; large/liquid/min. price filters)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. 5 − 1
Daily Returns β	1.04	0.92	0.90	0.92	1.09	0.05
Quarterly Returns β	0.99	0.89	0.91	0.96	1.20	0.21
Quarterly β − Daily β	-0.05**	-0.04*	0.01	0.05*	0.11***	0.16***

Table 2.3: CAPM α of Portfolios Formed on $\Delta\beta$

This table presents estimates of unconditional α (in basis points) for five portfolios formed annually based on the difference between quarterly and daily CAPM β (estimated at the end of the previous year using 60 months of data), as well as Portfolio $5-1$ that is long Portfolio 5 and short Portfolio 1. α represents the average pricing error relative to the CAPM. Each panel reports time series estimates of α at the daily, monthly, and quarterly return frequency, as well as the difference between them. Panel A uses value-weighted portfolios and Panel B uses equal-weighted portfolios. The sample period is 1969-2010. All portfolios are rebalanced every year based on β estimates from the previous 60 months. All alphas are compounded to quarterly alphas for comparison. Standard errors for the differences in alphas across frequencies are bootstrapped as described in Appendix C. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CAPM α (value-weighted)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. $5-1$
Daily Returns α	2.3	29.9**	41.4**	78.8***	68.1*	65.8
Monthly Returns α	-7.9	14.2	8.2	38.5	2.6	10.6
Quarterly Returns α	-10.0	14.2	5.0	36.6	5.2	15.2
Daily α $-$ Monthly α	10.2***	15.7***	33.2***	40.4***	65.4***	55.2***
Monthly α $-$ Quarterly α	2.1	0.0	3.2	1.9	-2.6	-4.6
Daily α $-$ Quarterly α	12.3***	15.7***	36.4***	42.3***	62.9***	50.6***

Panel B: CAPM α (equal-weighted)

	Portfolios formed on $\Delta\beta$					
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5	Port. $5-1$
Daily Returns α	214.6***	215.3***	253.2***	324.7***	434.6***	215.4***
Monthly Returns α	54.8*	96.7***	115.8***	149.8***	155.0***	99.8**
Quarterly Returns α	47.1	87.4**	107.2***	139.3***	134.4**	87.3
Daily α $-$ Monthly α	159.8***	118.6***	137.4***	174.8***	279.5***	115.6***
Monthly α $-$ Quarterly α	7.7**	9.3**	8.6**	10.6**	20.7***	12.6**
Daily α $-$ Quarterly α	167.5***	128.0***	146.0***	185.4***	300.2***	128.1***

Table 2.4: Robustness: CAPM β and α

This table presents estimates of unconditional CAPM betas (β) and alphas (α) (in basis points) for Portfolio $5-1$. Portfolio $5-1$ is long Portfolio 5 and short Portfolio 1 of five portfolios formed annually based on the difference between quarterly and daily CAPM β estimated at the end of the previous year using 60 months of data. Panel A reports the quarterly and daily β, as well as the difference between them. Panel B reports α at the daily, monthly, and quarterly return frequency as well as the difference between them. Each column shows the results for a different robustness check: Liquid – only stocks that trade every day; Amihud – only stocks below the annual cross-sectional median Amihud illiquidity measure; Min. Size – only stocks with market capitalization of at least \$1bn; Min. Price – only stocks with price above \$5; Liq./Size/Price is the union of the Liquid, Min. Size, and Min. Price filters; Dimson – daily betas are estimated as in Dimson (1979) using two daily lead and lag returns. The sample period is 1969-2010. All alphas are compounded to quarterly alphas to facilitate comparison. Standard errors for the differences in betas and alphas across frequencies are bootstrapped as described in Appendix C. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CAPM β

	Value-weighted Portfolio 5−1						Equal-weighted Portfolio 5−1					
	Liquid	Amihud	Min. Size	Min. Price	Liq./Size/Price	Dimson	Liquid	Amihud	Min. Size	Min. Price	Liq./Size/Price	Dimson
Daily Returns β	0.19	0.11	0.08	0.11	0.08	0.32	-0.01	0.05	0.07	-0.06	0.06	-0.10
Quarterly Returns β	0.53	0.46	0.17	0.49	0.16	0.55	0.45	0.31	0.16	0.29	0.14	0.37
Quarterly β − Daily β	0.33***	0.34***	0.09**	0.37***	0.08*	0.22***	0.45***	0.26***	0.09**	0.35***	0.08*	0.46***

Panel B: CAPM α

	Value-weighted Portfolio 5−1						Equal-weighted Portfolio 5−1					
	Liquid	Amihud	Min. Size	Min. Price	Liq./Size/Price	Dimson	Liquid	Amihud	Min. Size	Min. Price	Liq./Size/Price	Dimson
Daily Returns α	66.3	84.9*	76.9*	92.5*	78.7*	42.9	201.9***	121.9***	92.7**	211.6***	98.1***	191.9***
Monthly Returns α	15.6	49.8	44.2	49.5	54.0	10.6	104.5*	98.4**	53.7	134.1***	61.2	99.8**
Quarterly Returns α	12.0	54.1	44.1	51.6	51.6	15.2	51.6	93.0**	49.6	123.7***	55.5	87.3
Daily α − Monthly α	50.7***	35.2***	32.6***	43.0***	24.7***	32.3***	97.4***	23.5***	38.9***	77.6***	36.9***	92.1***
Monthly α − Quarterly α	3.6	-4.3	0.1	-2.1	2.3	-4.6	52.9***	5.4	4.1	10.4**	5.7	12.6**
Daily α − Quarterly α	54.3***	30.8***	32.8***	40.9***	27.1***	27.7***	150.4***	28.9***	43.0***	87.9***	42.7***	104.6***

Table 2.5: CAPM Within Our Model

This table shows the ability of the unconditional CAPM to price transparent and opaque assets at both high and low frequencies within our model. Columns (1) and (2) show the results for an economy composed entirely of transparent assets with measurements at low and high frequencies. Columns (3) and (4) show the results for an economy with 20% opaque assets with measurements at low and high frequencies. All models have three periods, five total assets, and agents with a risk aversion of five. High-frequency alphas and expected returns are "annualized" by multiplying by the number of high-frequency periods.

	(1)	(2)	(3)	(4)
Opaque Asset %	0	0	20	20
Measurement Frequency	Low	High	Low	High
Transparent Asset				
$E[R_i]$	0.293	0.293	0.293	0.293
$\beta_{MKT,i}$	1.000	1.000	1.000	1.024
α_i	0.000	0.000	0.000	-0.007
Opaque Asset				
$E[R_i]$			0.293	0.293
$\beta_{MKT,i}$			1.000	0.907
α_i			0.000	0.027
Market Factor				
$E[R_{MKT}]$	0.293	0.293	0.293	0.293

Table 2.6: $\Delta\beta$ Panel Regressions

This table presents results of a panel regression of annual, firm-level $\Delta\beta$ (i.e., the difference between quarterly and daily CAPM β) onto different measures of opacity (columns (1) and (2)) and lagged controls such as size, illiquidity, and illiquidity squared, turnover, as well as untabulated size quintile indicators (columns (3) and (4)). Quarterly (daily) β is estimated at the end of every year (t) using quarterly (daily) returns over the previous 60 months (i.e., years $t-4$ to t). Managerial discretion is a time-invariant measure of the amount of managerial discretion at the industry level by Hambrick and Abrahamson (1995). Abnormal accrual variance is the five-year rolling variance ($t-5$ to $t-1$) of the residual from estimating the expected accrual model by Jones (1991). Size is the natural log of the firm's equity market capitalization at the end of the previous year ($t-1$). Amihud illiquidity is from Amihud (2002) and is calculated based on the previous year ($t-1$). Illiquidity is the fraction of days with zero trading volume for a given stock in the previous year ($t-1$). Illiquidity squared is the square of illiquidity. Turnover is volume per month per share outstanding. To be included, a stock is required to trade at least 75% of trading days in a year. The sample period is 1969-2010. t-statistics are reported in parentheses based on standard errors clustered on firm and year. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Constant	-0.114***	0.392***	1.617***	1.924***
	(-3.13)	(26.37)	(6.54)	(7.43)
Managerial Discretion	0.122***		0.080***	
	(13.82)		(9.64)	
Abnormal Accrual Variance		6.409***		2.476***
		(11.96)		(6.38)
Size			-0.091***	-0.088***
			(-7.62)	(-7.27)
Amihud Illiquidity			0.469	0.592
			(1.14)	(1.39)
Illiquidity			-0.703	0.203
			(-0.95)	(0.29)
Illiquidity Squared			1.073	-2.384
			(0.41)	(-0.97)
Turnover			0.821***	0.775***
			(5.88)	(5.79)
Observations	79,878	88,463	79,878	88,463
R^2	0.030	0.019	0.132	0.120

Table 2.7: Robustness: $\Delta\beta$ Panel Regressions

This table presents $\Delta\beta$ regression results under different filters and specifications. See Table 2.6 for a description of the regression setup and for variable definitions. Specifications (1) and (2) require the stock to trade every day in a year. Specifications (3) and (4) require the stock to be below the cross-sectional median Amihud illiquidity measure in each year. Specifications (5) and (6) require the stock price to always be greater than \$5. Specifications (7) and (8) require the market capitalization to always be greater than \$1 billion. Specifications (9) and (10) interact an indicator variable if the observation is after the 2001 decimalization of stock prices. Specifications (11) and (12) add the one year lagged Adjusted PIN, which measures asymmetric information for NYSE and AMEX listed stocks. To be included in specifications (3)-(12), a stock is required to trade at least 75% of trading days in a year. The sample period is 1969-2010 for specifications (1) to (10) and 1984-2005 for specifications (11) and (12). t-statistics are reported in parentheses based on standard errors clustered by firm and year. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	1.645***	1.820***	2.075***	2.201***	2.068***	2.274***	1.507***	1.543***	1.654***	1.936***	2.007***	2.222***
	(7.12)	(7.76)	(12.95)	(12.49)	(9.40)	(10.08)	(6.22)	(6.40)	(7.10)	(7.93)	(7.60)	(9.06)
Managerial Discretion	0.076***		0.066***		0.071***		0.038***		0.079***		0.062***	
	(8.35)		(6.15)		(8.19)		(2.62)		(7.53)		(4.42)	
Abnormal Accrual Variance		3.403***		3.899***		3.497***		3.784***		1.562***		2.937***
		(7.28)		(6.58)		(8.03)		(3.02)		(3.54)		(5.39)
Post-2001									-0.016	-0.023		
									(-0.21)	(-0.51)		
Post-2001 x Manag. Disc.									0.005			
									(0.32)			
Post-2001 x Ab. Acc. Var.										3.366***		
										(3.56)		
Adjusted PIN											0.307***	0.397***
											(2.68)	(3.54)
Controls:												
Size and Size Quintile Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amihud Illiquidity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Illiquidity	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Illiquidity^2	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Turnover	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,728	57,860	40,695	45,004	61,170	71,205	15,753	17,804	79,878	88,463	23,552	28,206
R^2	0.153	0.137	0.113	0.099	0.132	0.126	0.069	0.059	0.132	0.121	0.139	0.130

Table 2.8: High-Frequency Factor Models Within Our Model

This table shows the ability of four models to price transparent and opaque assets at high frequencies within our model. Column (1) shows the unconditional CAPM. Column (2) shows the unconditional CAPM with an analog of Dimson betas. The Dimson beta analogs are estimated as the sum of the coefficients off the multiple regression of an asset's return on all leads and lags of the market return. Columns (3) and (4) show the conditional CAPM, conditioning on the previous systematic factor realization. Column (5) shows a two-factor model composed of the market return factor and a second factor that is long opaque assets (high $\Delta\beta$) and short transparent assets (low $\Delta\beta$). All models reported have 20% opaque assets, three periods, five total assets, and agents with a risk aversion of five. High-frequency alphas and expected returns are "annualized" by multiplying by the number of high-frequency periods.

	(1)	(2)	(3)	(4)	(5)
	CAPM Unconditional	CAPM Dimson	CAPM Conditional $f=0$	$f=1$	2 Factor Unconditional
Transparent Asset					
$E[R_i]$	0.293	0.293	0.293	0.293	0.293
$\beta_{MKT,i}$	1.024	0.967	1.051	0.936	1.000
$\beta_{\Delta\beta,i}$					-0.200
α_i	-0.007	0.010	-0.002	-0.015	0.000
Opaque Asset					
$E[R_i]$	0.293	0.293	0.232	0.476	0.293
$\beta_{MKT,i}$	0.907	1.109	0.799	1.257	1.000
$\beta_{\Delta\beta,i}$					0.800
α_i	0.027	-0.032	0.008	0.061	0.000
Market Factor					
$E[R_{MKT}]$	0.293	0.293	0.281	0.330	0.293
$\Delta\beta$ Factor					
$E[R_{\Delta\beta}]$					0.000

Table 2.9: Conditional Betas

This table shows the empirical unconditional and conditional betas of the portfolios with the highest and lowest $\Delta\beta$, which is the difference between quarterly and daily CAPM β (estimated at the end of the previous year using 60 months of data). The conditional betas are conditioned on the previous month's market return. The previous period returns are divided into halves in Panel A and quartiles in Panel B, and a conditional beta is calculated for each half or top/bottom quartile using monthly returns over the full sample window. The sample period is 1969-2010. Heteroscedasticity-robust White standard errors are in parentheses.

Panel A: CAPM β conditional on the median market return

	Portfolios formed on $\Delta\beta$	
	Port. 1 (Transparent)	Port. 5 (Opaque)
Returns above Median	0.906	1.421
	(0.034)	(0.078)
Unconditional	0.912	1.379
	(0.016)	(0.043)
Returns below Median	0.918	1.350
	(0.018)	(0.051)

Panel B: CAPM β conditional on 25^{th} and 75^{th} percentile market returns

	Portfolios formed on $\Delta\beta$	
	Port. 1 (Transparent)	Port. 5 (Opaque)
Returns above 75^{th} Percentile	0.902	1.483
	(0.038)	(0.111)
Unconditional	0.911	1.379
	(0.016)	(0.042)
Returns below 25^{th} Percentile	0.916	1.308
	(0.027)	(0.073)

Table 2.10: CAPM and the $\Delta\beta$-Factor

This table presents unconditional alphas (measured in basis points) for five value-weighted portfolios formed annually based on the difference between quarterly and daily CAPM β (estimated at the end of the previous year using 60 months of data). The sample period is 1969-2010. α represents the average pricing error relative to either the CAPM in Panel A or a two-factor model in Panels B and C. In Panel B, the two-factor model includes the market factor and $\Delta\beta$-factor. The $\Delta\beta$-factor is the return difference between value- weighted portfolios of stocks in the top and bottom terciles of stocks sorted on the difference between their quarterly and daily CAPM β. In Panel C, the two-factor model includes the market factor and $\Delta\beta$-factor that has been orthoganalized to the SMB factor. All daily α's are compounded to quarterly α's for comparison. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CAPM

	Portfolios formed on $\Delta\beta$				
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5
Daily Returns α	2.3	29.9**	41.4**	78.8***	68.1*
Monthly Returns α	-7.9	14.2	8.2	38.5	2.6
Quarterly Returns α	-10.0	14.2	5.0	36.6	5.2

Panel B: CAPM + $\Delta\beta$ factor

	Portfolios formed on $\Delta\beta$				
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5
Daily Returns α	19.3	32.6*	33.1*	51.3***	20.2
Monthly Returns α	-5.0	14.5	6.8	34.1**	-6.0
Quarterly Returns α	-6.5	14.0	2.3	29.9**	-6.7

Panel C: CAPM + Orthogonalized $\Delta\beta$ factor

	Portfolios formed on $\Delta\beta$				
	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5
Daily Returns α	17.7	30.7*	32.8	51.9***	24.4
Monthly Returns α	0.2	11.7	1.4	22.9	-19.6
Quarterly Returns α	0.7	13.5	-1.4	16.3	-24.5

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Appendix A
FINANCIAL DATA CONSTRUCTION

Complicating the financial data collection is almost all hospitals have some form of support organization that is legally distinct from the hospital and therefore has a separate Form 990. Support organizations can come in the form of operational support such as record keeping or in the form of financial support such as a foundation. These support organizations can be dedicated support to one hospital or can support multiple hospitals in a hospital system. Support organizations are not independent of the hospital and often have the same managers as the hospital.

In order to obtain a complete financial picture of a hospital I read each Form 990 for each year 2006 through 2010 and created a panel of related organizations. Related organizations and related party transactions are reportable items on Form 990. Complicating the process of mapping a hospital to its support organizations is not all related organizations are support organizations. For example a related organization could be a school. To determine the role of the related organization I read the related organization's Form 990 in order to characterize the relationship between the related organization and the hospital. In order to be classified as a support organization I require a related organization to be an operational support organization or a foundation. I exclude related organizations such as schools, churches, and nursing homes. For the few hospitals that self-insure I do not include the self-insurance trusts.

Patient medical records are tied to the physical hospital where the patient was admitted. The financial data is organized by how the hospital is legally incorporated. There is not necessarily a one to one mapping between a physical hospital and a legal hospital organization. A physical hospital can either be a stand-alone hospital, where the legal entity and the physical identity are the same, or belong to a hospital system. For stand-alone hospitals I aggregate the financial data of the legal hospital and all of its direct support organizations and tie the aggregated financial data to the physical hospital. I treat this aggregated organization as the economic unit of analysis.

Hospital systems come in two main forms. The first type of hospital system is one legal entity directly operating multiple physical hospitals. The parent legal entity can have support organizations. For this type of hospital system I aggregate the financial data in the same manner as a stand-alone hospital. This method of aggregation results in multiple physical hospitals sharing the same financial data. The second type of hospital system is each physical hospital is its own legal entity but multiple legal entities share a support organization that acts as a parent organization. The parent organization is legally distinct from the daughter hospitals, but the parent organization could provide management services or act as the entity that holds public debt for the daughter hospitals. For this type of hospital system I attribute all of the parent's financial data to each daughter hospital. Each legally distinct daughter hospital can have supporting organizations that solely support the daughter hospital. I attribute these support organization's financial data solely to the daughter hospital. This method of aggregation results in multiple physical hospitals having similar, but not identical, financial data.

Appendix B

GEOGRAPHIC CALCULATIONS

The location of each hospital is based on the physical hospital's zip code. The latitude and longitude of the centroid of each zip code is calculated by Zip-Codes.com. Similarly the location of each public firm is based on the zip code of the headquarters as reported by CorpWatch API, which gathers firm location from 10-K reports gathered from EDGAR. The distance between sets of coordinates was calculated according to the haversine formula:

$$d = 2r\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)} \tag{B.1}$$

where ϕ_1, ϕ_2 are the latitudes of point 1 and 2, λ_1, λ_2 are the longitudes of point 1 and 2, and r is the radius of the earth, 6,367 kilometers.

For hospital systems with physical hospitals in multiple zip codes I calculated the average GIndex and average dual CEO-Chairman for each physical hospital as if it were an independent hospital. I then aggregated across physical hospitals within the hospital system by taking the simple average of the physical hospitals in the system.

Appendix C

TESTS OF STATISTICAL SIGNIFICANCE OF β AND α ACROSS FREQUENCIES

C.1 The Null

Our null hypothesis is that CAPM betas are independent of the return frequency used to estimate them. It is well known that, when using logarithmic (additive) returns, beta measurements across frequencies will not differ in the absence of estimation error. Since we use arithmetic (multiplicative) returns throughout our empirical analysis, our statistical tests must account for the difference in betas across frequencies driven by the multiplicative structure of returns, as demonstrated by **?**. In addition, our tests must account for estimation error in betas, such as non-zero realized auto-correlations in returns simply due to chance, which could lead to observed differences in betas across frequencies.

Formally, under our null hypothesis, arithmetic returns are generated by a geometric Brownian motion and are sampled at discrete intervals without measurement error. We assume that both the market return process and the asset return process have constant drift and volatility. The market return process is defined as:

$$\frac{dm_t}{m_t} = \lambda dt + \sigma_m dz_t, \tag{C.1}$$

where λ is the market risk premium, σ_m is the market's volatility, and dz_t is a Brownian shock. The return process of the asset of interest is defined as:

$$\frac{da_t}{a_t} = \beta \frac{dm_t}{m_t} + \sigma_a d\iota_t, \tag{C.2}$$

where β is the asset's true market exposure (systematic risk), σ_a is the asset's volatility, and $d\iota_t$ is an independent Brownian shock (idiosyncratic risk).

We observe the arithmetic returns generated by each geometric Brownian motion at two discrete intervals (sampling frequencies). We then estimate betas at both frequencies and calculate their difference. By comparing the distribution of differences in betas generated by simulations under our null to the actual empirical data, we can then reject or fail to reject the null hypothesis that the data is generated by a geometric Brownian motion. Rejecting the null is akin to stating that an additional effect is driving differences in betas across frequencies in the data beyond the multiplicative structure of returns and estimation error.

C.2 Observations and Estimates

Let us define as T the total length of the sample period for the asset and the market. Assume that the econometrician observes prices only at a series of discrete times and these observation times correspond to two frequencies: a high frequency of length H and a low frequency of length L. For simplicity, assume that H evenly divides L and L evenly divides T. Thus our observations "line up" and completely cover the observation window. We therefore have two sets of nested price observations:

$$\{\{m_0, a_0\}, \{m_L, a_L\}, \{m_{2L}, a_{2L}\}, \ldots, \{m_T, a_T\}\}$$

and its containing set

$$\{\{m_0, a_0\}, \{m_H, a_H\}, \{m_{2H}, a_{2H}\}, \ldots, \{m_T, a_T\}\}.$$

As shown by the above two sets of prices, when estimating the CAPM beta of an asset at two different frequencies, there are fewer observations at the lower frequency, which makes the low-frequency beta estimate noisier. Because the same underlying process generates each beta estimate (only the sampling frequency changes), we must consider their sampling dependence when comparing them, something our procedure explicitly does.

From these observations, the estimates of the mean returns over each frequency for each asset can be written as:

$$\bar{r}_{i,F} = \frac{1}{\frac{T}{F}} \sum_{t \in \{F, 2F, \ldots, T\}} \frac{i_t - i_{t-F}}{i_{t-F}}, \tag{C.3}$$

where F indicates the return frequency (H or L) and i_t indicates the price of individual assets (a_t) or of the market (m_t). As a result, we can form two estimates of β, the asset's market exposure: one from the high-frequency observations and one from the low-frequency observations. Denote these estimates $\hat{\beta}_H$ and $\hat{\beta}_L$, which are given by the following expression:

$$\hat{\beta}_F = \frac{\frac{1}{\frac{T}{F}-1}\sum_{t\in\{F,2F,\ldots,T\}}\left[\left(\frac{a_t-a_{t-F}}{a_{t-F}} - \bar{r}_{a,F}\right)\left(\frac{m_t-m_{t-F}}{m_{t-F}} - \bar{r}_{m,F}\right)\right]}{\frac{1}{\frac{T}{F}-1}\sum_{t\in\{F,2F,\ldots,T\}}\left(\frac{m_t-m_{t-F}}{m_{t-F}} - \bar{r}_{m,F}\right)^2}, \tag{C.4}$$

where F indicates the return frequency (H or L).

C.2.1 Difference in Betas

We are interested in testing whether:

$$\hat{\beta}_H = \hat{\beta}_L. \tag{C.5}$$

Our test statistic therefore is:

$$\Delta\beta = \hat{\beta}_L - \hat{\beta}_H. \tag{C.6}$$

If the null holds, this test statistic should be equal to the difference created by the multiplicative nature of arithmetic returns plus estimation error. If the null fails, this test statistic will be large in magnitude.

C.3 Implementation and Calibration

Practically, we implement the bootstrapping simulation as follows. Consistent with equations (C.1) and (C.2), we generate 10,000 draws of simulated high-frequency return time series of length T for both the market and the asset as:

$$R_{m,t} = \exp\left[\left(\lambda - \frac{\sigma_m^2}{2}\right)\delta t + \sigma_m \delta z_t\right] \tag{C.7}$$

and

$$R_{a,t} = \exp\left[\left(\beta\left(\lambda - \beta\frac{\sigma_m^2}{2}\right) - \frac{\sigma_a^2}{2}\right)\delta t + \beta\sigma_m\delta z_t + \sigma_a\delta\iota_t\right], \tag{C.8}$$

where δ indicates a discrete step of size H: $\delta t = t - (t-H) = H$ and $\delta z_t = z_t - z_{t-H}$, which applies to all Brownian shocks. Separately for each asset we test (e.g., Portfolio 1 in Table 2.3), we calibrate λ, σ_m, β, and σ_a from the actual high-frequency log returns of that asset and the market. As such, we take the beta estimate as the true value to calibrate our data-generating process.

The Brownian shocks are implemented as discrete i.i.d. normal shocks. We use these shocks to generate arithmetic returns as equations (C.7) and (C.8). The net of these returns is used to run CAPM regressions to estimate high-frequency betas ($\hat{\beta}_H$) for each time series. We then aggregate these high-frequency arithmetic returns to obtain low-frequency arithmetic returns, which we use to estimate low-frequency betas ($\hat{\beta}_L$). Finally, we calculate the distribution of the $\Delta\beta$ test statistic and estimate p-values for the differences in betas we observe in the real data.

C.4 Difference in Alphas

Based on the simulated time series of returns, we also estimate the asset's alpha at each frequency from the CAPM regressions. For comparison, we compound the high-frequency alphas into low-frequency ones to match our empirical methodology. We test whether the high-frequency alphas are different from the low-frequency ones for the given asset:

$$\hat{\alpha}_H = \hat{\alpha}_L. \tag{C.9}$$

Our test statistic therefore is:

$$\Delta\alpha = \hat{\alpha}_L - \hat{\alpha}_H. \tag{C.10}$$

If the null holds, this test statistic should be close to zero. If the null fails, this test statistic will be large in magnitude. We use the 10,000 draws to calculate the empirical distribution of this test statistic and estimate p-values for the differences in alphas observed in the data.

C.5 Alternative Asset Pricing Models

We adjust the preceding methodology for the Scholes-Williams (1977) and Dimson (1979) high-frequency betas, and for the Fama-French-Carhart factor model as follows. For the Scholes-Williams correction, also following our empirical approach, we use the formulas provided in Scholes and Williams (1977) to estimate high-frequency betas and alphas for each simulated time series. For the Dimson correction, mirroring our empirical approach, we add two lead returns and two lag returns in the CAPM regression in order to estimate high-frequency betas and alphas for each simulated time series. Finally, for the Fama-French-Carhart factor model, we modify equation (C.8) in order to account for the HML, SMB, and UMD factors and all the factor parameters are calibrated as explained above for the CAPM.

Appendix D
MODEL DETAILS

This Appendix presents the details of the price, beta, and alpha calculations for our model. We also describe the normalization we choose to make the comparisons across model parameterizations economically meaningful.

D.1 Prices

Agents are identical, so in equilibrium they all hold the same portfolio. Without loss of generality, we normalize the initial wealth of each agent to be that from holding only risky assets. We obtain the standard form for the equilibrium price process of asset i at date t:

$$P_{i,t} = \frac{E_t[-\exp[-\gamma \tilde{W}_T]\tilde{C}_{i,T}]}{E_t[-\exp[-\gamma \tilde{W}_T]]}, \tag{D.1}$$

where $W_T \equiv W_{j,T} = \sum_{i=1}^{N} C_{i,T}$, i.e., terminal wealth is the sum of the cash flows of the individual assets and is the same for all agents.

To compute the expectations in equation (D.1), we take advantage of the discrete nature of the state space, converting the expectations into summations over the state space:

$$P_{i,t} = \frac{\sum_{s \in \mathbb{S}_t} Pr(s)[-\exp[-\gamma W_T(s)]C_{i,T}(s)]}{\sum_{s \in \mathbb{S}_t} Pr(s)[-\exp[-\gamma W_T(s)]]}, \tag{D.2}$$

where $\mathbb{S}_t$ is the set of all possible states conditional on the information present at date t and $Pr(s)$ is the probability of state s, $W_T(s)$ is terminal wealth in state s, and $C_{i,T}(s)$ is the terminal cash flow of stock i in state s.

D.2 CAPM

Using our endogenous price process, we consider the factor pricing structure in this economy. Since we use exponential utility, returns are defined as price differences rather than price ratios:

$$R_{i,\tau \to t} = P_{i,t} - P_{i,\tau}. \tag{D.3}$$

Note that dealing with returns of different frequencies requires us to keep track of the starting date τ and ending date t for the return. Throughout this section let $\mathbb{O}$ denote the set of opaque assets and $\mathbb{T}$ denote the set of transparent assets. We form the market factor as the sum of the returns on the two types of assets:

$$R_{mkt,\tau\to t} = \sum_{i\in\mathbb{T}} R_{i,\tau\to t} + \sum_{i\in\mathbb{O}} R_{i,\tau\to t}. \tag{D.4}$$

We calculate the unconditional market beta of each firm at both the lowest frequency possible (T periods) and the highest frequency possible (1 period). The beta at the lowest frequency is computed in the standard way:

$$\beta^L_{mkt,i} = \frac{\text{cov}(R^L_i, R^L_{mkt})}{\text{var}(R^L_{mkt})}, \tag{D.5}$$

where $R^L_i = R_{i,0\to T}$.

Calculating the highest-frequency unconditional beta is more complicated because there is not a single high-frequency covariance for each asset and the market. Returns in each sub-period have a different distribution, which means that the expected return and covariance structure change across each sub-period. We calculate the unconditional betas as follows:

$$\beta^H_{mkt,i} = \frac{E_0\left[\frac{1}{T}\sum_{t=1}^T \left((R_{i,t-1\to t} - \bar{R}^H_i)(R_{mkt,t-1\to t} - \bar{R}^H_{mkt})\right)\right]}{E_0\left[\frac{1}{T}\sum_{t=1}^T (R_{mkt,t-1\to t} - \bar{R}^H_{mkt})^2\right]}, \tag{D.6}$$

where:

$$\bar{R}^H_i = E_0\left[\frac{1}{T}\sum_{t=1}^T R_{i,t-1\to t}\right] = \frac{1}{T}\sum_{t=1}^T E_0[R_{i,t-1\to t}] \tag{D.7}$$

and

$$\bar{R}^H_{mkt} = E_0\left[\frac{1}{T}\sum_{t=1}^T R_{mkt,t-1\to t}\right] = \frac{1}{T}\sum_{t=1}^T E_0[R_{mkt,t-1\to t}]. \tag{D.8}$$

These means ignore the variation in expected returns across sub periods and hence are an average of the expected returns across all the sub periods.[1]

We calculate the alphas under the CAPM at different frequencies as:

$$\alpha^{F,CAPM}_i = \bar{R}^F_i - \beta^F_{i,mkt}\bar{R}^F_{mkt}, \tag{D.9}$$

[1] At the lowest frequency, this collapses back to the traditional β expression of equation (D.5).

where F denotes the frequency of the return measurement (H or L). To facilitate comparison across frequencies, we scale the high-frequency alphas by multiplying them by the number of sub periods T.

D.3 Normalization Used to Compare Across Parameterizations

Changing the number of assets or number of periods in our model alters the amount of risk in the economy. We implement two normalizations designed to mitigate this change, thereby making comparisons across different parameters economically meaningful. The first normalization occurs in equation (2.2). As the number of assets or periods change, we normalize the systematic shock f by $\frac{1}{N\sqrt{T}}$ to keep the size of the economy relatively constant: the division by N provides a normalization as the number of assets grows and the division by $\sqrt{T}$ provides a normalization as the number of periods increases analogous to the one used when defining Brownian motions.[2]

The second normalization affects the way we report alphas and betas. We multiply the alphas and betas by the number of assets to assure we are calculating betas and alphas for a constant sized asset:

$$\beta_{mkt,i}^{F*,\text{model}} = N\beta_{mkt,i}^{F,\text{model}} \quad \text{and} \quad \alpha_{mkt,i}^{F*,\text{model}} = N\alpha_{mkt,i}^{F,\text{model}}, \tag{D.10}$$

where F denotes the frequency of the return measurement (H or L). Without such a normalization, as the number of assets goes to infinity and each asset produces a cash flow of order $\frac{1}{N}$, beta goes to zero because the return movement goes to zero. This normalization is analogous to the division by the previous price in multiplicative returns. This division naturally normalizes asset sizes, ensuring a comparison across constant sized assets, something that is missing when using additive returns.

[2]Loosely speaking, increasing the number of periods is akin to sampling more and more frequently. Despite this normalization, our model ultimately assumes a level of discreteness in the information process and considering the limit as T goes to infinity is not appropriate. The distribution of the terminal cash flow process changes as the number of sub-periods increases, in a way different from that if the underlying process were a Brownian motion.

D.4 Scholes and Williams (1977) and Dimson (1979) Beta Analog

We calculate an analog of the Scholes-Williams (1977) and Dimson (1979) betas by calculating the expected coefficient from the regression of each asset's high-frequency returns on the contemporaneous market return along with all leads and lags of the market. This regression is:

$$R_{i,\tau\to\tau+1} = a_i + b_{i,1} R_{mkt,0\to1} + b_{i,2} R_{mkt,1\to2} + \ldots + b_{i,T} R_{mkt,T-1\to T} + \epsilon_i, \tag{D.11}$$

where the observations are each of the high-frequency returns for asset i matched with all high-frequency market returns. Because we know the true underlying distribution, we calculate these coefficients without sampling error. We define our analog of the Scholes-Williams and Dimson corrected beta for asset i as:

$$\beta_i^D = b_{i,1} + b_{i,2} + \ldots + b_{i,T}. \tag{D.12}$$

Appendix E

TWO-FACTOR MODEL DETAILS

We construct the $\Delta\beta$-factor by forming a zero investment portfolio that is long the opaque assets (high $\Delta\beta$) and short the transparent assets (low $\Delta\beta$):

$$R_{\Delta\beta,\tau\to t} = \frac{1}{1-\omega_{\mathbb{T}}}\sum_{i\in\mathbb{O}} R_{i,\tau\to t} - \frac{1}{\omega_{\mathbb{T}}}\sum_{i\in\mathbb{T}} R_{i,\tau\to t}, \tag{E.1}$$

where $\omega_{\mathbb{T}}$ is the fraction of assets that are transparent. The adjustment to each sum is necessary to have a zero investment long-short portfolio that completely nets out the cash flow effect exposure.

We define both factor betas in the two-factor model in the standard way for any frequency F (H or L):

$$\beta_i^{F,2Factor} = \Sigma_F^{-1}\Lambda_{F,i}, \tag{E.2}$$

where $\beta_i^{F,2Factor} = [\beta_{mkt,i}^{F,2Factor}, \beta_{\Delta\beta,i}^{F,2Factor}]'$, Σ_F is the covariance matrix of the factors, and Λ_F is the vector of covariances between the factors and asset i. The key complication lies in the calculation of these covariance matrices (and vectors). Similar to our calculations for the CAPM betas, we calculate these unconditional covariances.

The high-frequency (H) covariances in each matrix entry are computed using the following covariance function:

$$cov^H(R_i, R_j) = E_0\left[\frac{1}{T}\sum_{t=1}^{T}(R_{i,t-1\to t} - \bar{R}_i^H)(R_{j,t-1\to t} - \bar{R}_j^H)\right], \tag{E.3}$$

where $\bar{R}_i^H$ is the unconditional mean as defined in the CAPM section. The low-frequency (L) covariances are defined according to the standard covariance function because there is only one mean return at the low frequency. We normalize both the betas and the expected returns we report as explained in Appendix D.

We calculate alphas under the two-factor model at different frequencies F (H or L) as:

$$\alpha_i^{F,2Factor} = \bar{R}_i^F - \beta_{mkt,i}^{F,2Factor}\bar{R}_{mkt}^F - \beta_{\Delta\beta,i}^{F,2Factor}\bar{R}_{\Delta\beta}^F. \tag{E.4}$$

To facilitate comparison across frequencies, we scale the high-frequency alphas by multiplying them by the number of sub periods T.

GLOSSARY

HOSPITAL CHARACTERISTICS:

REVENUE: the total revenue of the hospital system, which includes both service revenue and non-service revenue in millions of dollars.

NET INCOME: the total revenue minus total expenses in millions of dollars.

FIXED ASSETS: the book value of property, plant, and equipment minus accumulated depreciation in millions of dollars.

LEVERAGE: the sum of secured mortgages, notes payable, unsecured loans, and tax-exempt bond liabilities in millions of dollars divided by fixed assets.

CASH: the sum of cash and temporary cash investments.

INVESTMENTS: the sum of investments in publicly traded securities, other securities, and program related investments.

TEACHING HOSPITAL: an indicator if the hospital is designated a teaching hospital by the AHA.

URBAN HOSPITAL: an indicator if the hospital is designated as an urban hospital by the AHA.

PATIENT CHARACTERISTICS:

AGE: the patient's age at admission, which in the regression the analysis age is binned to the following categories: under 55, 55-65, 65-75, 75-85, 85-95, and over 95.

GENDER: a binary indicator equal to one if the patient is female, and zero if the patient is male.

SURVIVED: a binary indicator equal to one if the patient was discharged alive or had a length of stay greater than 3 or 7 days.

LENGTH OF STAY (LOS): the number of days a patient was admitted to the hospital.

AMI TYPE: (0) of anterolateral wall, (1) of other anterior wall, (2) of inferolateral wall, (3) of inferoposterior wall, (4) of other inferior wall, (5) of other lateral wall, (6) true posterior wall infarction, (7) subendocardial infarction, (8) of other specified sites, (9) unspecified site

INCOME QUARTILE: the patient's zip code quartile classification in the distribution of the estimated median household income for a zip code in the state.

AREA CHARACTERISTICS:

GDP: gross domestic product for the county the hospital is located in.

AVERAGE WAGE: first quarter total payroll divided by first quarter total employment for all firms in the MSA the hospital is located in.

UNEMPLOYMENT RATE: unemployment rate for the MSA the hospital is located in.