Available online at www.sciencedirect.com

SCIENCE DIRECT

Journal of Financial Economics 79 (2006) 257–292

JOURNAL OF Financial ECONOMICS

www.elsevier.com/locate/jfec

R^2 around the world: New theory and new tests[☆]

Li Jin[a,*], Stewart C. Myers[b]

[a]*Harvard Business School, USA*
[b]*MIT Sloan School of Management, USA*

Received 9 February 2004; accepted 2 November 2004
Available online 9 September 2005

Abstract

Morck, Yeung and Yu show that R^2 is higher in countries with less developed financial systems and poorer corporate governance. We show how control rights and information affect the division of risk bearing between managers and investors. Lack of transparency increases R^2 by shifting firm-specific risk to managers. Opaque stocks with high R^2s are also more likely to crash, that is, to deliver large negative returns. Using stock returns from 40 stock markets from 1990 to 2001, we find strong positive relations between R^2 and several measures of opaqueness. These measures also explain the frequency of crashes.

JEL classification: G12; G14; G15; G38; N20

Keywords: Corporate control; International financial markets; Firm-specific risks; Information and market efficiency; Crashes

☆We received helpful comments from Campbell Harvey, Simon Johnson, Dong Lee, Randall Morck, Tobias Moskowitz, Jeremy Stein, Rene Stulz, Robert Taggart, Sheridan Titman and seminar participants at the University of Alberta, Boston College, Duke University, Harvard Business School, the University of North Carolina, Tulane University, the 2005 American Finance Association Meetings, the 4th Asian Corporate Governance Conference, the Emerging Market Finance Conference at the University of Virginia and the Conference on Globalization and Financial Services in Emerging Economies at the World Bank. We thank the Research Computing Services Group at Harvard Business School, especially James Zeilter, for help with obtaining and understanding the data used in this paper. Anna Yu and Alvaro Vivanco provided helpful research assistance.
*Corresponding author. Tel.: +1 617 495 5590; fax: +1 617 496 6592.
E-mail address: ljin@hbs.edu (L. Jin).

0304-405X/$ - see front matter
doi:10.1016/j.jfineco.2004.11.003

1. Introduction

Morck, Yeung and Yu (MYY, 2000) show that R^2 and other measures of stock-market synchronicity are higher in countries with relatively low per-capita GDP and less developed financial systems. MYY and Campbell et al. (2001) also find a secular decline in R^2s in the United States from 1960 to 1997. These are intriguing and important results, which suggest that we may be able to learn about corporate finance and governance not just from the level of stock prices, or from short-term event studies, but also from the second or higher moments of stock returns.

Of course there are many possible explanations for the inverse relation between financial development and R^2s, explanations that have nothing to do with corporate finance or governance. The pattern of R^2s could reflect higher macroeconomic risk or lack of diversification across industries in smaller, less-developed countries. MYY control for such effects assiduously. The cross-country pattern in R^2s remains.

MYY propose that differences in protection for investors' property rights could explain the connection between financial development and R^2. MYY are on the right track, but it turns out that imperfect protection for investors does not affect R^2 if the firm is completely transparent. Some degree of opaqueness (lack of transparency) is essential.

We show how limited information affects the division of risk bearing between inside managers and outside investors. Insiders capture part of the firm's operating cash flows. That is, they extract more cash than they would receive if investors' property rights could be completely protected. The limits to capture are based on outside investors' perception of the firm's cash flow and value. This perception is imperfect. Investors can see some changes in cash flow, but not all changes. When cash flows are higher than investors think, insiders' capture increases. When cash flows are lower than investors think, insiders are forced to reduce capture if they want to keep running the firm. Increased capture therefore reduces the amount of firm-specific risk absorbed by outside investors. An increase in opaqueness, combined with capture by insiders, leads to lower firm-specific risk for investors and to higher R^2s.

1.1. Opaqueness and investor protection

In practice opaqueness and imperfect protection of investors' property rights go together and probably are mutually reinforcing. Nevertheless, we draw a distinction between opaqueness and poor protection of investors. That distinction is important to our model and tests.

Poor protection without opaqueness is not enough to explain high R^2s. Consider a simple example. Suppose that poor protection of investors' property rights allows insiders to capture half of the firm's cash flows. Outside investors can see all of the firm's cash flows (complete transparency) but can't prevent capture. Therefore the stock-market value of the firm is half its potential value. Market value still fluctuates as cash flows are realized and the firm's overall value is updated, but by only half of the unexpected change in potential value. The *percentage* changes in market value are *not* affected by the insiders' capture, however. Rate-of-return variance is unchanged. Investors capture half of any value change due to firm-specific information, and also half of any value change due to market risk, that is, market-wide, macroeconomic information. The *proportions* of firm-specific and local market volatility are unaffected by insiders' capture. R^2 is not affected.

The story changes when the firm is not completely transparent. Change the example so that outside investors can observe all market-wide information, but only part of firm-specific information. Insiders still capture half of the firm's cash flows on average, but they capture more when the hidden firm-specific information is positive and less when it is negative. Opaqueness therefore requires insiders to absorb some firm-specific variance. The firm-specific variance absorbed by investors is correspondingly lower. Of course investors absorb all market risk—macroeconomic information is presumably common knowledge. Thus the ratio of market to total risk is increased by opaqueness. Higher R^2s are caused by opaqueness, not by poor investor protection.

The more opaque the firm, the greater the amount of hidden, firm-specific bad news that may arrive in a given span of time. The amount of bad news that insiders are willing to absorb is limited. If a sufficiently long run of bad firm-specific news is encountered, insiders give up and all the bad news comes out at once. Giving up means a large negative outlier in the distribution of returns. Therefore we also predict that stocks in more opaque countries are more likely to "crash," that is, to deliver large negative returns, than stocks in relatively transparent countries.

But why should insiders absorb any firm-specific risk on the downside? Why don't they hide the upside and reveal the downside? The answer, of course, is that insiders would always report bad news even when the true news is good.[1] Bad news is credible only when reported at a cost, for example, the cost of hiring credible auditors and opening up the firm's books to outsiders or the personal costs borne by insiders if they are ejected when bad news is released. These costs set the strike price of the insiders' abandonment option.

We have discussed the case of full transparency but limited protection of investors—the case where insiders can capture cash flow in broad daylight with no impact on R^2. Consider the opposite extreme case. Suppose that investors could enforce their property rights fully and costlessly whenever they receive information about cash flows or firm value. They obtain every dollar of cash flow or value that is apparent to them. Nevertheless, if the firm is not completely transparent, insiders can still capture unexpected cash flows that are not perceived by investors. The insiders will soak up some firm-specific risk. Again, the more opaque the firm, the higher its R^2.

There is only one case in which greater opaqueness does not increase R^2. The case is improbable but worth noting for completeness. Imagine an opaque firm run by a saintly manager who always acts in shareholders' interest, never taking a dollar more

[1]We assume that insiders can't be forced to report completely and truthfully by some mechanism for punishment after the fact. If such a mechanism exists, it is evidently not effective—otherwise firms would be transparent. In real life they are not transparent, especially in developing economies.

or less than deserved. That manager does not have to soak up any firm-specific risk. All firm-specific good or bad news is absorbed by investors sooner or later, even if they cannot see the news as it happens.

The properties of stock market returns in this case depend on how information is finally released. There are three possibilities. First, if the saintly manager reports everything promptly and credibly, opaqueness is eliminated and returns are not affected. Second, suppose that hidden news is revealed after a stable lag. Then the average amount of firm-specific information released in any period is the same as for a transparent firm. Average firm-specific variance and R^2 are not affected by delayed reporting. Third, if a stable lag is implausible, think of good or bad news accumulating within the firm until the difference between intrinsic value and share price reaches a critical value. The news would then be released all at once, like a pressure vessel letting off steam. The releases would not affect average, long-run R^2s, although we would see long tails in the distribution of stock returns. (We will control for kurtosis in our tests.)

1.2. Summary of predictions and results

Our theory makes two basic predictions. (1) Other things equal, R^2s should be higher in countries where firms are more opaque (less transparent) to outside investors. (2) Crashes, that is, large, negative return outliers, should be more common for firms in opaque countries. These are not market-wide crashes, but large, negative, market-adjusted returns on individual stocks.

We test our model's predictions using returns from 40 stock markets from 1990 to 2001. We confirm that R^2 is higher in countries with less developed financial systems, and we find evidence that R^2 has been declining over time internationally. We also find a positive relation between country-average R^2s and several measures of opaqueness. Finally, we show that the frequency of large, negative, firm-specific returns is higher in markets with high R^2 and in countries with less developed financial markets. The frequency of large negative returns is also positively related to our measures of opaqueness.

We do not claim that our model is the exclusive explanation of the differences in R^2s across countries or over time. For example, countries with less developed financial markets are more vulnerable to episodes of political risk, which may translate into increased market risk. Higher market risk obviously generates higher R^2s, other things equal. Our model includes this effect, and we control for cross-country differences in market risk in our tests.

There may be differences in R^2s within countries that could be traced to reasons other than differences in opaqueness. The tests in this paper are limited to differences in country averages, however.

1.3. Prior research

There is not much prior work on our topic. The two leading articles, MYY (2000) and Campbell et al. (2001) are noted above. MYY (2000) suggest that poor protection of investors could make firm-specific information less useful to arbitrageurs, decreasing the number of informed traders relative to noise traders. If the noise traders "herd" and trade the market rather than individual stocks, market risk may be higher in less developed financial markets.[2] Thus poor protection of investors could affect R^2 through two channels. First, poor protection could increase market risk. Second, poor protection could proxy for more opaqueness, which shifts firm-specific risk from outside investors to inside managers. We focus on the second channel, but control for market risk.

Related papers include Wurgler (2000), who finds that capital is more efficiently allocated in countries with better legal protection for minority investors and more firm-specific information in stock returns. Bushman et al. (2003) study two kinds of transparency: financial transparency (the intensity and timeliness of financial disclosures, including interpretation and coverage by analysts and the media) and governance transparency (for example, the identity, remuneration and shareholdings of officers and directors). They find that financial transparency is lower in countries with a high share of state-owned enterprises and in countries where firms are more likely to be harmed by revealing sensitive information to competitors or local governments. Governance transparency is higher in countries with high levels of judicial efficiency and common-law legal origin and in countries where stock markets are active and well developed.

Durnev et al. (2004) find that the magnitude of firm-specific variation in stock returns is positively related to the economic efficiency of corporate investment. This result is consistent with our theory if more transparency encourages efficient investment. Durnev et al. (2003) show that stock returns are better predictors of future earnings changes for firms and industries with lower R^2s. It seems that transparency and low R^2s go together, as we argue in this paper.

Active security analysts should make firms more transparent. Chang et al. (2001) demonstrate that there is a wide variation in security-analyst activity across 47 countries. They suggest that transparency is primarily influenced by countries' legal systems and information infrastructure. The organizational structure of firms—whether they operate as groups or conglomerates, for example—seems to be less important. Our tests will use a measure of transparency based on the dispersion of analysts' forecasts.

Bris et al. (2003) explore international differences in the cost or feasibility of short sales. They find that restrictions on short selling reduce the amount of cross-sectional variation in equity returns. Their results are consistent with our theory if restrictions on short selling make the firm more opaque.

Hong and Stein (2003) and Kirschenheiter and Melamud (2002) work out theories that predict negative skewness (or reduced positive skewness) in returns. They say nothing about R^2, however, and their models address different issues than considered here. Hong and Stein investigate how stock markets work when investors cannot agree. We assume that investors do agree (based on what they can see), but

[2]We see no reason why the effects of noise trading should be confined to market returns, however. De Long et al. (1990), suggest that the risks created by noise traders should be assumed to be market-wide and not firm-specific (p. 707). Their paper only considers a single-asset economy, however.

that their property rights cannot be fully protected. Kirschenheiter and Melamud model financial reporting, showing how managers rationally smooth earnings but occasionally take a big bath of exaggerated losses. We don't model financial reporting. We take transparency, and thus the quality of financial reporting, as given exogenously for each country.

Our results can also be compared to O'Hara (2003), who discusses the effects of public vs. private information on firm value. In that paper, private information gives informed traders an edge in forming optimal portfolios, leaving the uninformed traders with more risk to bear. The uninformed traders demand higher expected returns, thereby decreasing the value of firms that generate less public and more private information. We also distinguish public and private information, but assume that *all* outside investors are imperfectly informed. All private information is held by inside managers, so long as the inside managers do not "give up" and release it.

Our paper also joins a larger number of more general studies of investor protection, corporate governance and the development of financial markets around the world. These include La Porta et al. (1998, 2000), La Porta et al. (2002) and Rajan and Zingales (2001).

The next section presents our theoretical model. Proofs and technical details are located in Appendix A. Section 3 describes the data, explains the setup of the empirical tests and presents our results. Section 4 wraps up the paper and notes several issues open for future research.

2. A model of control and risk-bearing when outside investors have limited information

We extend Myers (2000) to situations where outside investors cannot see what firm value really is. The firm is partly opaque. If good (bad) news arrives that investors cannot see, inside managers capture more (less) cash flow than if the firm were completely transparent.

The information received by investors in a particular firm is a combination of macroeconomic and firm-specific news. But the macroeconomic news can be separated, because it is common to all firms. We therefore assume that outside investors can observe a market factor that drives all stocks' returns, as well as *some* firm-specific information. Lacking a more precise estimate, the outside investors replace the missing firm-specific information with its expected value, conditioned on the information that investors do have.

The firm has an operating asset. For simplicity, we ignore depreciation and reinvestment.[3] The outside equity investors own all the firm's shares[4] and can take

[3]It is easy to introduce depreciation and reinvestment according to a pre-defined schedule. But discretionary investment would introduce complications not modeled here. See Myers (2000, pp. 1030–1033).

[4]None of the following analysis changes if insiders own some of the firm's shares, provided that insiders cannot block outside investors' property rights completely. We can rule that out. Total blockage would mean that the firm has no value to outside investors and that the firm could not go public and enter our sample.

over the operating asset if they are willing to incur a cost of collective action. Define K_t, the intrinsic value of the firm, as the present value of future operating cash flows, where the discount rate is a constant cost of capital r. If future cash flows C_t and firm values are interpreted as certainty equivalents, r is the risk-free rate. Given the information set I_t at date t,

$$K_t(I_t) = PV\{\mathrm{E}(C_{t+1}|I_t), \mathrm{E}(C_{t+2}|I_t), \ldots; r\}. \tag{1}$$

The operating asset's existence and ownership are verifiable. The inside managers cannot take the asset, but they can intercept cash flow, which is not verifiable. Taking part of the cash flow compensates the insiders for their firm-specific human capital. The insiders will take as much cash as possible, however, up to the point where further capture would jeopardize their continued right to manage the firm and capture cash flow in future periods. Any cash flow not captured is paid out as a dividend.[5]

Outsiders can seize the firm and fire its managers. This requires costly collective action. The net value that outsiders can get by taking over the firm is αK_t, where $\alpha < 1$. A high value of α indicates a low cost of collective action. We can interpret α more generally as a parameter that measures how effectively investors' property rights are protected.[6]

The ability of outside investors to take over the firm determines its market value. Outsiders will take over unless they expect future dividends with present value at least equal to $\alpha K_t(I_t)$, their expected payoff from taking over immediately at date t. Insiders will pay the minimum dividend sufficient to forestall takeover, conditional on what outside investors know. If outside investors have full information, and know that the operating asset is worth $K_t(I_t)$, the minimum dividend $Y = r\alpha K_t(I_t)$.[7]

The insiders can leave the firm at any time, taking all the current-period cash flow with them. There is a cost of departing, however, including the lost opportunity to capture future cash flows for at least one future period. Myers (2000) describes the conditions under which the insiders find it optimal to stick to the firm for one more period, rather than departing and setting up their tents elsewhere. We use his results here.

In summary, the insiders must take one of two actions in each period: (1) pay a dividend sufficient to satisfy investors or (2) capture all current-period cash flow, triggering collective action and takeover by outside investors. Action (2), which amounts to exercise of an abandonment option, imposes a cost on the managers, but can relieve them from hiding and absorbing an accumulation of negative, firm-

[5]The model is not restricted to dividend-paying firms. The "dividend" could be an increase in the verifiable value of the operating asset. Investors don't care whether their returns come as cash payouts or as increases in the net value that investors can realize by exercising their control rights.

[6]Jensen and Meckling (1976) would interpret α as the result of outside investors' optimal outlays on monitoring and control. At the optimum, the marginal benefit of monitoring and control equals the marginal cost. Here the marginal benefit is additional cash paid out to investors. Optimal monitoring and control does not force payout of all cash, so the optimal α is less than 1.0.

[7]See Myers (2000, p. 1017).

specific information. Abandonment means a crash, that is, the sudden release of accumulated bad news.

We now give a more formal statement of the model. For simplicity we start by ignoring abandonment and the possibility of crashes. Then we will introduce abandonment and show that our model's basic properties and empirical predictions are unchanged.

2.1. Model setup

The firm's cash-flow generating process is

$$C_t = K_0 X_t, \tag{2}$$

where K_0 is the initial investment, a constant, and X_t captures the random shocks to the cash flow process. X_t is the sum of three independent shocks:

$$X_t = f_t + \theta_{1,t} + \theta_{2,t}, \tag{3}$$

where f_t captures unanticipated changes in a market (macroeconomic) factor that affects all firms and is common knowledge, and $\theta_{1,t}$ and $\theta_{2,t}$ capture firm-specific cash flow innovations. The inside managers observe both $\theta_{1,t}$ and $\theta_{2,t}$, but outsiders only observe $\theta_{1,t}$. Since $\theta_{1,t}$ and $\theta_{2,t}$ are independent, observing one gives no information about the other.[8]

We assume that f_t, $\theta_{1,t}$ and $\theta_{2,t}$ are stationary AR(1). For simplicity we also assume that they all have the same AR(1) parameter:

$$f_{t+1} = f_0 + \varphi f_t + \varepsilon_{t+1}, \tag{4}$$

$$\theta_{1,t+1} = \theta_{1,0} + \varphi\theta_{1,t} + \xi_{1,t+1}, \tag{5}$$

$$\theta_{2,t+1} = \theta_{2,0} + \varphi\theta_{2,t} + \xi_{2,t+1}, \tag{6}$$

where $0<\varphi<1$. The AR(1) assumption makes sense because profitability should mean-revert as industry capacity responds to changes in costs or demand. Stationarity is particularly useful here because it limits the difference between the investors' and the insiders' valuations of the firm. A potentially unbounded difference between these valuations would stretch our model beyond any reasonable economic interpretation.

Our assumptions mean that the distribution of X_t is also stationary AR(1):

$$X_{t+1} = X_0 + \varphi X_t + \lambda_{t+1}, \tag{7}$$

where $X_0 = f_0 + \theta_{1,0} + \theta_{2,0}$, and $\lambda_t = \varepsilon_t + \xi_{1,t} + \xi_{2,t}$.

[8]Think of θ_2 as the forecast error of estimating $\theta_1+\theta_2$ using θ_1 only. Then, by construction, θ_2 is uncorrelated with θ_1.

Define the ratio of firm-specific to market variance in the cash flow generating process as

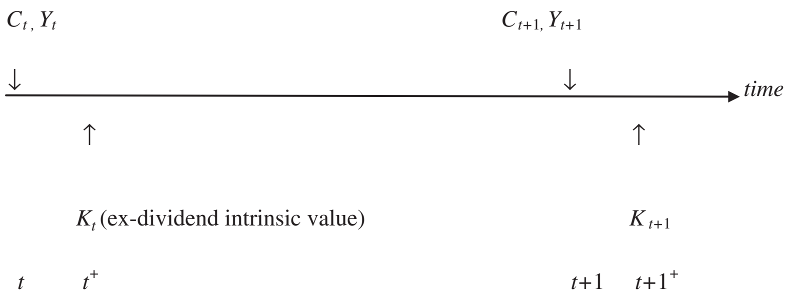
$$\kappa = \frac{Var(\theta_{1,t} + \theta_{2,t})}{Var(f_t)}. \tag{8}$$

Also define the *transparency* of the firm as the ratio of the variance of $\theta_{1,t}$ to the sum of the variances of $\theta_{1,t}$ and $\theta_{2,t}$:

$$\eta = \frac{Var(\theta_{1,t})}{Var(\theta_{1,t} + \theta_{2,t})} = \frac{Var(\theta_{1,t})}{Var(\theta_{1,t}) + Var(\theta_{2,t})}, \tag{9}$$

where the last equality follows from the independence of $\theta_{1,t}$ and $\theta_{2,t}$. For η close to one, most firm-specific information is revealed to outsiders through accounting reports or other channels. For η close to zero, the firm is almost totally opaque.

The time line of the model is:



At time t, a cash flow C_t is realized. The insiders observe C_t (and all three shocks f_t, $\theta_{1,t}$ and $\theta_{2,t}$) and decide on the dividend Y_t. Outside investors observe f_t and $\theta_{1,t}$ and of course the dividend Y_t. Investors use their information to update their expectations of C_t and K_t, and then decide whether to organize to take over the firm. If outsiders decide to not take over, the sequence repeats at $t+1$.

2.2. Investors' estimates of cash flow and value

Now we can write out the conditional and unconditional expectations of the firm's cash flow and value. The first step is to show that both cash flow and the intrinsic value of the firm follow an AR(1) process.

Proposition 1. *C_t and K_t are* AR(1) *with parameter φ:*

$$\begin{aligned} \mathrm{E}(C_{t+1}|C_t) &= K_0X_0 + \varphi C_t = C_0 + \varphi C_t, \\ \mathrm{E}(K_{t+1}|K_t) &= \frac{1}{r}K_0X_0 + \varphi K_t. \end{aligned} \tag{10}$$

The unconditional means of C_t and K_t are

$$\mathrm{E}(C_t) = \frac{K_0 X_0}{1-\varphi},$$
$$\mathrm{E}(K_t) = \frac{1}{r}\frac{K_0 X_0}{1-\varphi}. \tag{11}$$

Proof. See Appendix A.

Proposition 2. *Investors' assessment of the overall value of the firm, conditional on f_t and $\theta_{1,t}$, is*

$$\begin{aligned}\mathrm{E}(K_t|f_t,\theta_{1,t}) &= \frac{1}{r}\frac{K_0X_0}{1-\varphi} - \frac{\varphi}{1+r-\varphi}\frac{K_0X_0}{1-\varphi} + \frac{\varphi}{1+r-\varphi}K_0\left(f_t+\theta_{1,t}+\frac{\theta_{2,0}}{1-\varphi}\right)\\ &= \frac{1}{r}\frac{K_0X_0}{1-\varphi} + \frac{\varphi}{1+r-\varphi}\left[K_0\left(f_t+\theta_{1,t}+\frac{\theta_{2,0}}{1-\varphi}\right) - \frac{K_0X_0}{1-\varphi}\right]. \end{aligned}\tag{12}$$

Proof. See Appendix A.

The conditional value of K_t, given current-period information about f_t and $\theta_{1,t}$, equals the unconditional value $(1/r)K_0X_0/(1-\varphi)$ plus a correction term

$$\frac{\varphi}{1+r-\varphi}\left[K_0\left(f_t+\theta_{1,t}+\frac{\theta_{2,0}}{1-\varphi}\right) - \frac{K_0X_0}{1-\varphi}\right].$$

From the definition of X_t, the bracketed expression in Eq. (12) is just the difference between the expectation of X_t, conditional on observing f_t and $\theta_{1,t}$, and the unconditional expectation of X_t.

2.3. Equilibrium dividend policy

Define V_t^{ex} as the ex-dividend market value of the firm (its value to outside investors), conditional on $\{f_t, \theta_{1,t}\}$.

$$V_t^{\mathrm{ex}}(f_t,\theta_{1,t}) = \frac{\mathrm{E}(Y_{t+1}|f_t,\theta_{1,t}) + \mathrm{E}(V_{t+1}^{\mathrm{ex}}|f_t,\theta_{1,t})}{1+r}, \tag{13}$$

where Y_{t+1} is the dividend to be paid in period $t+1$.

In order for outside investors to be willing to let the inside managers run the firm for another period, the ex-dividend market value of the firm must at least equal the outside investors' expectation of the net liquidation value of the firm, $\mathrm{E}(\alpha K_t|f_t,\theta_{1,t})$. The insiders will pay a dividend just sufficient to make the investors indifferent between taking over and letting the insiders continue. We assume that investors are satisfied and do not intervene if this condition is met. Thus we have

$$V_t^{\mathrm{ex}} = \mathrm{E}(\alpha K_t|f_t,\theta_{1,t}). \tag{14}$$

Any dividend policy that satisfies the two conditions given by Eqs. (13) and (14) defines an equilibrium. There is only one equilibrium, defined by constant-payout policy, if we rule out equilibria supported by bubbles or empty promises from the manager. Thus we have:

Proposition 3. *The equilibrium dividend is a constant fraction* α *of investors' conditional expectation of cash flow*:

$$Y_t^* = \alpha \mathrm{E}(C_t | f_t, \theta_{1,t}), \quad \forall t. \tag{15}$$

This dividend policy is unique if we rule out bubbles and empty promises.[9]

Given the cost of collective action, outside investors effectively own a fraction α of the firm. Thus they demand payment of the same fraction of the firm's cash flows. Inside managers are willing to pay this dividend to keep investors quiet and satisfied and to keep them from taking over.

But there may be other equilibria if investors can be swayed by empty promises: Managers would like to pay less than the equilibrium dividend today in exchange for a promise to "make it up later." (Note that any dividend shortfall goes directly into the managers' pockets.) But if investors accept such a promise today, they must expect that the managers will play the same game again in the future. In that case, the present value of expected future dividends falls below $\mathrm{E}(\alpha K_t | f_t, \theta_{1,t})$, violating Eq. (14) and triggering collective action by investors. In other words, investors' only rational response to an empty promise is immediate takeover, so in equilibrium empty promises will not be tried.

The cash flow captured by inside managers equals overall cash flow minus the dividend:

$$Z_t = C_t - Y_t = C_t - \alpha \mathrm{E}(C_t | f_t, \theta_{1,t}), \tag{16}$$

where C_t is the firm's actual cash flow, not investors' conditional expectation. When the hidden firm-specific information is bad, inside managers have to make up the difference between the firm's actual performance and investors' estimate of that performance. Thus, Z_t can be small or negative. If it is negative, the insiders have to cut ordinary salaries or come up with other sources of funding. Of course, if the hidden news is bad enough, the insiders will abandon the firm to the outside investors.

2.4. R^2

We can now calculate the rate of return on the firm's shares. Define $\tilde{r}_{i,t+1}$ as the realized return in period $t+1$,

$$\tilde{r}_{i,t+1} = \frac{V_{t+1}^{\mathrm{ex}}(f_{t+1}, \theta_{1,t+1}) + Y_{t+1}(f_{t+1}, \theta_{1,t+1})}{V_t^{\mathrm{ex}}(f_t, \theta_{1,t})} - 1. \tag{17}$$

[9] Using the definition of K_t, we can verify that (15) satisfies the equilibrium conditions. Eq. (15) supports a Nash Equilibrium: As long as the unobserved firm-specific shock is not too bad, the insider will find it optimal to stick to the constant dividend payout. Investors have no incentive to deviate either. In addition, Myers (2000) shows that this solution is efficient, because insiders will take all projects with positive net present values. Thus, this equilibrium will lead to a Pareto-optimal outcome. There may be other equilibria, but it is natural to assume that the actual equilibrium will settle at this one.

Proposition 4. *The return process satisfies*

$$\tilde{r}_{i,t+1} = r + \frac{(1+r)(\tilde{\varepsilon}_{t+1} + \tilde{\xi}_{t+1})}{X_0(1+r)/r + \varphi(f_t + \theta_{1,t})}. \tag{18}$$

Proof. See Appendix A.

The random component in $\tilde{r}_{i,t+1}$ is caused by innovations of both f_{t+1} and $\theta_{1,t+1}$. The conditional expected return is always r, however, regardless of f_t and $\theta_{1,t}$, because the expected values of $\tilde{\varepsilon}_{t+1}$ and $\tilde{\xi}_{t+1}$ are zero. Although the cash flow process is partially predictable (due to the AR(1) processes), there is no return predictability. The market valuation incorporates the predictable component of the cash flows and dividends.

The return on the market portfolio is the same as the return of a stock with no idiosyncratic risk:

$$\tilde{r}_{m,t+1} = r + \frac{(1+r)(\tilde{\varepsilon}_{t+1})}{X_0(1+r)/r + \varphi f_t}. \tag{19}$$

Given stock prices at time t, the $t+1$ rate of return for any particular firm depends on two things: a market factor $\tilde{\varepsilon}_{t+1}$, captured by the market return $r_{m,t+1}$, and a firm-specific factor $\tilde{\xi}_{t+1}$. Conditional on f_t and $\theta_{1,t}$, the proportion of variance explained by the market is fixed:[10]

$$R^2 = \frac{Var(\varepsilon_{t+1})}{Var(\varepsilon_{t+1}) + Var(\xi_{t+1})} = \frac{1}{\kappa\eta + 1}. \tag{20}$$

Eq. (20) shows why stocks could have higher R^2s in countries with less developed financial markets. The stocks could have lower κ, that is, less idiosyncratic cash-flow risk relative to market risk, or lower η, that is, lower *observable* idiosyncratic risk.

Notice that α drops out of the expressions for $\tilde{r}_t$ and R^2. Although α affects the proportion of cash flows paid to investors, and thus the level of stock prices, it does not affect percentage returns. We expect low α's in countries with less-developed financial markets and relatively poor investor protection. That by itself does not explain the high R^2s observed in such countries, however. In our model, R^2s are determined by the ratio of observable to unobservable firm-specific risk, that is, by the degree of transparency.

2.5. Abandonment

The insider has an abandonment option. The option is exercised if the insider is forced to absorb a sufficiently long run of firm-specific bad news. We do not model

[10] The usual market-model regression of a stock's return on the market return is actually misspecified, since the derivative of $\tilde{r}_{i,t+1}$ on $\tilde{r}_{m,t+1}$ depends on the realization of f_t and $\theta_{1,t}$ and therefore is not constant over time. But we will follow previous research and use ordinary least squares (OLS) to fit the market model to individual firms.

this option specifically, but the option clearly will be exercised from time to time. Exercise will release the accumulated bad news all at once. Therefore we predict a greater frequency of large, negative, firm-specific return outliers in countries where firms are less transparent to outside investors.

Abandonment could mean at least three things. (1) Inside managers could just walk away from the firm, leaving it to outside stockholders or creditors. For example, the managers could refuse to pay the dividends called for by public information, thus triggering the outside investors to organize and take over. (2) The managers could stay with the firm, but incur the costs of opening up the firm to outside investors and convincing them that the bad news is true. (Even if the firm pays, these costs still come out of the managers' pockets. The managers can take out more cash if the costs are not incurred.) The managers' cost of abandonment may also include the loss of reputation or private benefits.[11] (3) The costs of keeping outside investors ignorant of poor performance may become so high that insiders can't prevent the discharge of accumulated bad news.[12] Note that in our model the costs of hiding good performance are low, because the upside cash flow that is not seen by outside investors disappears into insiders' pockets.

Although we do not solve for the optimal exercise of the abandonment option, we can write down the conditions for the option to be in the money. Suppose the inside managers incur a fixed cost of abandonment D. Then there is a negative firm-specific shock $\theta_{2,t}$, which is not observed by outside investors. If the inside managers decide to stick with the firm and absorb the cash flow impacts of this negative shock, they will end up paying a total present value of

$$\begin{aligned}&K_0\theta_{2,t} + PV\{K_0\mathrm{E}(\theta_{2,t+1}|\theta_{2,t}), K_0\mathrm{E}(\theta_{2,t+2}|\theta_{2,t}), \ldots; r\}\\ &\quad = K_0\left[\theta_{2,t} + \frac{1}{r}\frac{\theta_{2,0}}{1-\varphi} + \frac{\varphi}{1+r-\varphi}\left(-\frac{\theta_{2,0}}{1-\varphi} + \theta_{2,t}\right)\right]. \qquad (21)\end{aligned}$$

This option is in the money if the value given by Eq. (21) is negative and greater, in absolute value, than D. We know that the option will be exercised if it is far enough in the money. (The optimal exercise boundary could depend on the insiders' wealth, if they are forced to prop up the firm with their own money during a period of hidden bad news.[13])

The cost of abandonment is probably not fixed, but linked to current firm value. In Myers (2000), for example, the defaulting manager takes all of the firm's current-period cash flow, but loses the ability to capture future cash flow by exploiting investors' cost of collective action. The manager is also forced to sit idle for one or more periods before restarting another firm. The loss of captured future cash flow

[11] The managers could run the firm under more stringent control by investors. Once the investors' cost of collective action is sunk, the costs of monitoring and control should fall drastically.

[12] Abandonment does not eliminate investors' costs of collective action, which we capture in the parameter α. In case (1), investors have to intervene. In cases (2) and (3), investors see the firm's true cash flow, but their ability to capture that cash flow is still limited.

[13] Friedman et al. (2003) propose a model in which insiders usually tunnel resources out of the firm, but sometimes prop it up, contributing their own money to keep their future tunneling option alive.

and the opportunity cost of idleness depend on the current cash flow and the current value of the firm.

Suppose that all abandonment costs add up to a constant fraction p of firm value. Then the option is in the money if:

$$K_0\left[\theta_{2,t}+\frac{1}{r}\,\frac{\theta_{2,0}}{1-\varphi}+\frac{\varphi}{1+r-\varphi}\left(-\frac{\theta_{2,0}}{1-\varphi}+\theta_{2,t}\right)\right]$$
$$+p\left\{\frac{1}{r}\,\frac{K_0X_0}{1-\varphi}+\frac{\varphi}{1+r-\varphi}\left[-\frac{K_0X_0}{1-\varphi}+K_0(f_t+\theta_{1,t}+\theta_{2,t})\right]\right\}<0. \tag{22}$$

In this case the decision to abandon is affected by both private information from $\theta_{2,t}$ and public information from $f_t+\theta_{1,t}$. The private information determines the amount of negative shock that the insiders have to soak up if they stay on. The public information affects the value that insiders have to give up by defaulting. A more negative value of $\theta_{2,t}$ makes the insider more likely to give up, while a more positive value of $\theta_{1,t}$ or f_t makes the insider more likely to continue.

Here we encounter some interesting dynamics. If the manager's abandonment costs are positively linked to stock market value, as in Eq. (22), we should find fewer crashes (large, negative, firm-specific return outliers) when market returns are positive and the firm's stock price is doing well. This may be worth testing if future research examines individual firm returns, rather than the country averages used in this paper.

2.6. Abandonment, crashes and R^2

Now we circle back to consider how the possibility of abandonment affects our model and empirical predictions. How does the occurrence of a crash affect (1) the probability of the next crash and (2) the equilibrium dividend payout? Do crashes affect our predictions about the relation between opaqueness and R^2?

The at-the-money calculations in Eqs. (21) and (22) use the steady-state distribution of the unobservable firm-specific information. That is not correct when the manager gives up and the firm starts over again. Abandonment reveals all accumulated information, and the AR(1) process starts afresh. The probability of another crash in the next period after a crash is close to zero, although the probability increases as time passes. Thus time can enter investors' valuations and their assessments of crash probabilities.

Ignoring time and working with the steady-state distribution can nevertheless be an excellent approximation. It typically takes less than ten periods for the variance of the $\theta_{2,t}$ distribution to reach at least 90% of its steady state value. This convergence occurs for a wide range of values of the parameter φ. For example, if $\theta_{2,t}$ is normal, its distribution is completely characterized by its mean and variance, with $\mathrm{E}(\theta_{2,t})=\theta_{2,0}(1-\varphi^{t+1})/(1-\varphi)$ and $Var(\theta_{2,t})=\sigma^2_{2,\xi}(1-\varphi^{2(t+1)})/(1-\varphi^2)$. If we interpret $\theta_{2,t}$ as the forecast error of an unbiased forecast, then it is natural to assume $\theta_{2,0}=0$. Therefore, the mean of the distribution of $\theta_{2,t}$ is always equal to that of the steady state distribution. Furthermore, given that $Var(\theta_{2,t})/Var(\theta_{2,\infty})=1-\varphi^{2(t+1)}$, for φ

not larger than about 0.9, it takes less than ten periods after a crash for the variance of the distribution of $\theta_{2,t}$ to return to at least 90% of the variance of the steady-state distribution. In our empirical tests, a crash is defined to happen at most once in 100 periods. Therefore we believe that the assumption of a steady-state distribution is reasonable.

This is one advantage of using stationary AR(1) processes rather than a random walk or martingale process for the firm's cash flows. In a nonstationary process, the distribution of $\theta_{2,t}$ will always be a function of time.

Once the steady state is reached, investors perceive a constant probability of a crash in each period. To compensate for the potential loss to outsiders during a crash, insiders have to pay a dividend higher than that in Eq. (15), enough to compensate for the losses incurred if a crash occurs. But in the steady state, this higher dividend is proportional to the dividend given in Eq. (15) and the value of the firm remains as in Eq. (14).

A crash does release firm-specific information, however, so the occurrence of a crash in a particular sample period decreases R^2 in that period. Since crashes should be more frequent in more opaque countries, the observed effect of opaqueness on R^2 should be attenuated. The qualitative predictions of our model are unchanged, however.[14]

On the other hand, the effect of opaqueness on crash frequency is clear in our model. We predict a greater frequency of large, negative, firm-specific return outliers in countries where firms are more opaque to outside investors. Of course crash frequency does not depend just on opaqueness. Two firms that are equally opaque can have different crash frequencies if one has more firm-specific risk or if abandonment is more costly for one firm than the other. Crash frequency should always be positively correlated with opaqueness, however.

2.7. Opaqueness and risk-sharing

In our model, the inside managers have no credible way to convey hidden firm-specific information to outside investors. They are always tempted to report a bad firm-specific shock, bad enough that no dividend need be paid to the outsiders. Outside investors, fully aware of the insiders' temptation to under-report, will demand hard proof for any such claim. Hard proof is costly. In some countries, there may be no practical way to convey information credibly.

Absent abandonment, managers are forced to insure outside investors against some of the unobservable, firm-specific cash flow shocks. The managers' inability to convey all the firm-specific information results in inefficient sharing of firm-specific

[14]We run tests on simulated data to confirm that our predictions about opaqueness and R^2 hold up in the presence of crashes. We simulate f_t, $\theta_{1,t}$, $\theta_{2,t}$ and the resulting returns. Crashes are forced when $\theta_{2,t}$ reaches a sufficiently low threshold value. Thresholds are chosen to make crashes rare events, with about the same frequencies as in our COUNT measure, which is described below. We then generate returns, including crashes, by Monte Carlo for different levels of transparency (η). We build up a sample of R^2s and confirm that they decline monotonically as transparency increases. Details of these simulations are available upon request.

risk.[15] A risk-averse insider would like to commit to convey all firm-specific information. Hiring a credible auditing team might be a pre-commitment to convey inside information, for example. The cost of doing so (and also of maintaining the team's credibility ex post) is probably prohibitive in some countries, however.

Credible auditing may also enhance investors' property rights by reducing costs of monitoring and controlling the firm. In our model, this would show up as a higher α, reduced cash flow to insiders, higher dividends and an increase in the amount of outside capital that the firm can raise. New and growing firms that need outside capital have a stronger incentive to establish credibility and transparency. Such firms might end up with lower R^2s for that reason. Even if a credible auditing team is available, the managers may not wish to retain it, however. The managers benefit from a lower α once the firm is up and running.

3. Empirical analysis

MYY examine R^2s for a cross section of 40 countries in 1995.[16] R^2 is higher in countries with low per capita GDP and in countries where investors' property rights are not well protected. MYY measure investor protection by a Good Governance Index, which combines three measures developed by La Porta et al. (1998): measures of government corruption, the risk of government expropriation of private property and the risk of government repudiation of contracts. Low values are taken to mean lack of protection of private property.

There are many other reasons why R^2s could differ across countries. The scope for diversification is limited in smaller markets. Operating cash flows could be more highly correlated if firms in poorer countries are concentrated in relatively few industries. MYY control for these and other possible explanations. Their basic findings do not change. We use the same controls, which are described below.

Our empirical tests are organized as follows. First we replicate MYY's results, using their controls, for stocks in a sample of 40 countries from 1990 to 2001. We also control for kurtosis. Then we test whether R^2 is also positively related to the frequency of crashes, that is, to cross-country differences in the frequency of large negative outliers in firm-specific returns. As predicted, we find a significant positive relation.

This result is consistent with our model, but not a direct test. High R^2 is not caused by a high likelihood of crashes. Both are caused by opaqueness, that is, reduced information available to investors. We therefore introduce five measures of the degree of opaqueness. We find that R^2s are higher in more opaque countries. We also find that crashes are more frequent in more opaque countries. These relations hold even

[15]This raises the intriguing possibility that opaqueness may deter insiders from investments with high firm-specific risks. If so, the direct effect of opaqueness (shifting risk to insiders) could be offset by a bias towards safer investments.

[16]MYY also consider other measures of stock market synchronicity, for example, the average proportion of stocks that move in the same direction (up or down) in a given period. The results for R^2 and these other measures are essentially the same, however. We concentrate on R^2.

when we control for local market volatility. We conclude that our results are driven by opaqueness and firm-specific variance, not just by differences in market risk.

3.1. The sample

We start with returns for all the stocks covered by DataStream from January 1990 to December 2001. We use DataStream's total return index (RI), which includes dividends as well as price changes. We have data for stocks in 30 countries for the entire period and in ten more countries for part of the period. We include stocks in these ten countries for years when sufficient data are available. If a country has less than 25 stocks with valid data in a year, we exclude that country for that year. For example, we always exclude Zambia, which never had more than four listed companies in Datastream.

Following MYY, we exclude stocks that trade for less than 30 weeks during a particular year. We also excluded stocks with American Depository Receipts (ADRs) traded in the U.S. or GDRs (Global Depository Receipts) traded internationally. These stocks could escape the relative opaqueness of their home countries. (Our results are basically the same if these ADRs and GDRs are added back to our sample, however.) We calculate weekly rates of return (Wednesday to Wednesday) for all stocks in our sample. R^2s and residual returns are calculated from an expanded market model regression similar to MYYs:

$$\begin{aligned} r_{it} = \alpha_i &+ \beta_{1,i} r_{m,j,t} + \beta_{2,i}[r_{\mathrm{U.S.},t} + \mathrm{E}X_{jt}] + \beta_{3,i} r_{m,j,t-1} + \beta_{4,i}[r_{\mathrm{U.S.},t-1} + \mathrm{E}X_{j,t-1}] \\ &+ \beta_5 r_{m,j,t-2} + \beta_{6,i}[r_{\mathrm{U.S.},t-2} + \mathrm{E}X_{j,t-2}] + \beta_{7,i} r_{m,j,t+1} + \beta_{8,i}[r_{\mathrm{U.S.},t+1} + \mathrm{E}X_{j,t+1}] \\ &+ \beta_9 r_{m,j,t+2} + \beta_{10,i}[r_{\mathrm{U.S.},t+2} + \mathrm{E}X_{j,t+2}] + e_{it}, \end{aligned} \tag{23}$$

where r_{it} is the return on stock i in week t (in country j), $r_{m,j,t}$ is the local market index, $r_{\mathrm{U.S.},t}$ is the U.S. market index return (a proxy for the global market), and $\mathrm{E}X_{j,t}$ is the change in country j's exchange rate vs. the U.S. dollar. We correct for nonsynchronous trading by including two lead and lag terms for the local and U.S. market indexes, following Dimson (1979).[17] We measure the firm-specific return by the residual return from Eq. (23). This is the return not explained by the local and U.S. markets. We use the kurtosis of the residual return as an additional control variable.

Following MYY, we measure a country's stock market synchronicity by its average R^2 for each year that the country appears in our sample. We use equally weighted averages and also averages weighted by each company's total return variance.[18] We find no clear relations between the R^2 measures and firm size or

[17]We checked this specification by adding continental indexes, e.g. European and Asian index returns for countries in these regions, and then repeating all of our tests. The results are generally the same as reported below. We also add returns on industry indexes, defined globally, not country by country. Again, results are basically unchanged.

[18]MYY use R^2s weighted by each stock's sum of squared total variation of returns. In other words, they used variance weights. We also calculate average R^2s using market-value weights. Our results using this market-weighted measure are similar to the results reported below.

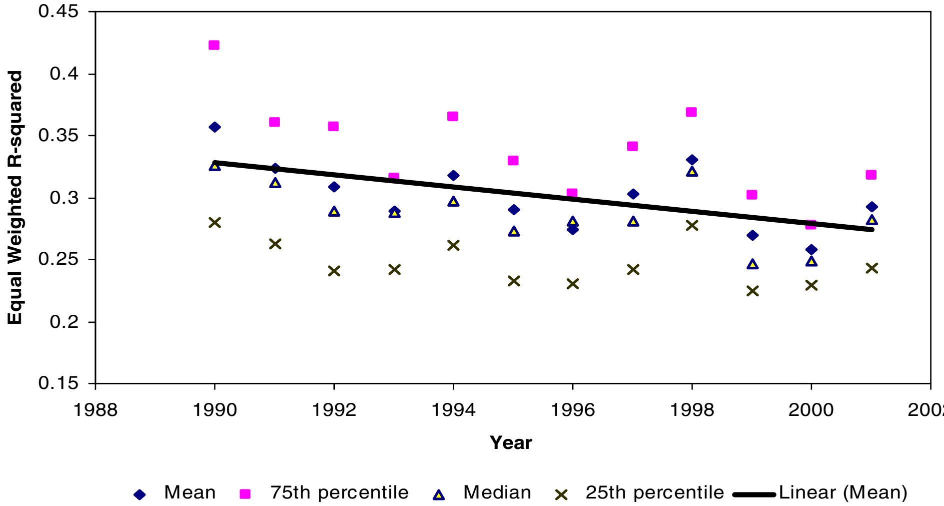


Fig. 1. Equal-weighted R^2's for 30 countries from 1990 to 2001. The trend line for the mean R^2 is Average $R^2 = 0.33-10.00496$ (Year-1990). The t-statistic for the trend is -2.60.

industry, consistent with Roll (1988). Macroeconomic variables for each country are obtained from the IMF International Financial Statistics database and other sources.

We have stock returns for 30 countries for the complete period 1990 to 2001. Fig. 1 plots the mean, median and the 25th and 75th percentiles of R^2 for these countries in each year. Fig. 1 also includes a trend line for the mean R^2. The mean falls by about 0.5% each year, and this decrease is statistically significant. R^2 was clearly decreasing over the 1990s, consistent with the evidence reported in MYY and Campbell et al. (2001). It appears that the ratio of firm-specific to market risk increases as financial markets develop over time.

3.2. Measuring the frequency of crashes

We construct three measures of crash likelihood. The first is the skewness of residual returns. Following Chen et al. (2001), we use the third moment of each stock's residual returns, divided by the cubed standard deviation.[19] We calculate an equally weighted average skewness measure across all stocks in each country for each year.

The second measure, COUNT, is based on the number of residual returns exceeding k standard deviations above and below the mean, with k chosen to generate frequencies of 0.01%, 0.1% or 1% in the lognormal distribution. We

[19]Chen et al. (2001) also use the ratio of upside and downside standard deviations. They note that this measure is less likely to capture the effects of extreme outliers. We are particularly interested in outliers, and therefore reject this alternative measure.

subtract the upside frequencies from the downside frequencies. The difference is averaged across all stocks within each country in each year. A high value of COUNT for a country indicates a high frequency of crashes.

The third measure, COLLAR, accounts for both the frequency and the severity of crashes. COLLAR is defined as the profit or loss from a strategy of buying an out-of-the-money put option on the residual return and shorting a call option on the residual return. We choose the strike price of the put so that it would be in the money with frequencies of 0.01%, 0.1% and 1% in a lognormal distribution. Then we set the call's strike price so that the put-call strategy has zero expected value in a lognormal distribution. In other words, we construct a position that would require zero net investment. Then we calculate the actual profits or losses from the strategy as a percentage of each firm's stock price and average over all stocks within each country and year. High values for COLLAR mean that profits from the downside put outweigh losses from the upside call. A high value of COLLAR for a country-year indicates that crashes in that country were more frequent and/or more severe.

Table 1 contains the sample statistics for the equally weighted (EW) and variance weighted (VW) R^2 measures, the three measures of crash likelihood, kurtosis and local market volatility (annualized variance). Mean R^2s are about 0.30 equally weighted and 0.25 variance weighted. We also show sample statistics for the logistic transformation of R^2, which is the actual dependent variable in MYY's and our regressions.

Residual returns are positively skewed on average and have long tails (excess kurtosis). Both COLLAR and COUNT are on average negative, as expected with positively skewed returns. Extreme positive residual returns generally outnumber and outweigh extreme negative returns in our overall sample. We are not proposing to explain or exploit the average levels of skewness, COLLAR and COUNT, however, but only differences across countries.

Table 2 shows the countries included in our sample. We report each country's equal-weighted and variance-weighted R^2, its average market volatility and its rank on the Good Government Index. We also include country ranks on one measure of transparency, DISCLOSURE, which is described below.

3.3. Replicating MYY's results

The first two columns of Table 3 show results for MYY's specification for a panel of 40 countries from 1990 to 2001. The dependent variable is the logistic transformation of the annual values of country-average R^2s. We fit this and all subsequent specifications using the Fama-MacBeth (1973) method, with an additional correction from Pontiff (1996) for serial correlation of the year-by-year regression coefficients.[20] We believe this procedure generates conservatively low t-

[20]We also checked our results using the clustering method described in Cohen et al. (2003, Appendix B). This method can accommodate both time-series and cross-sectional correlations among error terms. But the clustering gives essentially the same results as reported here, with no material differences in the signs, magnitudes or significance of estimated coefficients.

Table 1
Summary statistics
R^2s for individual stocks are averaged, using equal weights or variance weights, for each country and year. The sample includes 30 countries from 1990 to 2001, plus ten other countries for part of that period. R^2s for each country are then averaged across time. Summary statistics are calculated from the cross-sectional distribution of these country averages. Annual values of kurtosis, skewness (SKEW), COLLAR and COUNT are calculated from each stock's residual returns. Summary statistics for these variables are calculated in the same way as for R^2s, but only as equal-weighted country averages. COUNT is the difference between the numbers of negative and positive residual returns that are k standard deviations below and above the mean. The cutoff return k is set to generate frequencies of 0.01%, 0.1% and 1% in a lognormal distribution. COLLAR is the average payoff from a strategy of buying a put on residual returns, with a strike price chosen to generate payoffs with probabilities of 0.01%, 0.1% and 1% in a lognormal distribution, and selling a call with a strike price that makes the long put-short call portfolio zero NPV.

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Country-average R^2					
Equal weighted	0.3028	0.2873	0.0679	0.1955	0.6920
Variance weighted	0.2470	0.2341	0.0535	0.1566	0.6264
Logistic transformation of R^2					
Equal weighted	−0.8507	−0.9084	0.3097	−1.4149	0.8096
Variance weighted	−1.1321	−1.1855	0.2712	−1.6840	0.5167
Crash likelihood measures					
SKEW	0.4550	0.4542	0.2858	−1.4256	1.3211
COLLAR 0.01%	−0.0002	−0.0002	0.0001	−0.0005	0.0002
COLLAR 0.1%	−0.0003	−0.0003	0.0002	−0.0010	0.0005
COLLAR 1%	−0.0006	−0.0006	0.0003	−0.0017	0.0007
COUNT 0.01%	−0.0026	−0.0026	0.0018	−0.0091	0.0053
COUNT 0.1%	−0.0050	−0.0050	0.0029	−0.0137	0.0070
COUNT 1%	−0.0098	−0.0102	0.0055	−0.0234	0.0113
Control variables					
Kurtosis	4.5121	3.7991	2.6321	0.8866	16.8127
Local market volatility (σ^2)	0.0014	0.0008	0.0018	0.0001	0.0156

statistics, for two reasons. First, the Fama-MacBeth procedure ignores any information about the precision of the coefficients estimated year-by-year in cross-sectional regressions. Second, we assume that any serial correlation observed in the time series of coefficients is "really there," and needs to be corrected for by using higher standard errors to calculate t-statistics. This is probably an over-correction, because some apparent serial correlation is expected in small samples even when the estimation errors in the coefficients are in fact uncorrelated.

The independent variables of most interest to MYY are economic development, measured by the log of per-capita GDP, and protection of investors, measured by the Good Government Index. MYY also include several other variables to control for other factors that might affect a country's average R^2. The number of stocks listed in each country is included, because R^2 should increase as the number of stocks

Table 2
Summary statistics for 40 countries, including equal-weighted and variance-weighted R^2, local market variance and country scores on the Good Government Index and on DISCLOSURE, a measure of transparency

Country name	Time periods	Years in sample	Equal-weighted R^2	Value-weighted R^2	Local market variance (σ^2)	DISCLOSURE	Good Government Index
Argentina	1994–2001	8	0.34	0.27	0.0027	4.9	17.3
Australia		12	0.25	0.22	0.0004	6.3	21.6
Germany		12	0.32	0.24	0.0006	6.0	21.8
Belgium		12	0.29	0.24	0.0004	5.9	20.3
Columbia	1992–2001	10	0.25	0.21	0.0008	4.4	13.0
China	1994–2001	8	0.47	0.38	0.0037	3.8	15.5
Chile		12	0.27	0.22	0.0008	5.8	18.0
Canada		12	0.24	0.21	0.0004	6.3	22.7
Czech Republic	1994–2001	8	0.27	0.23	0.0011	4.2	19.9
Denmark		12	0.24	0.20	0.0005	6.2	23.3
Spain		12	0.34	0.27	0.0007	5.6	19.4
Finland		12	0.29	0.22	0.0020	6.5	23.5
France		12	0.27	0.23	0.0006	5.9	20.2
Hong Kong		12	0.32	0.27	0.0013	5.8	18.4
Hungary	1992–2001	10	0.34	0.24	0.0019	4.8	20.5
India		12	0.36	0.32	0.0021	4.8	13.9
Ireland		12	0.26	0.20	0.0007	5.6	20.6
Japan		12	0.33	0.28	0.0008	5.6	20.5
South Korea		12	0.33	0.28	0.0022	4.7	19.1
Luxembourg	1992–2001	10	0.26	0.22	0.0006	6.0	23.8
Mexico		12	0.31	0.24	0.0014	4.6	16.8
Malaysia		12	0.37	0.29	0.0016	5.1	18.0
Netherlands		12	0.29	0.23	0.0005	6.1	23.6
Norway		12	0.27	0.22	0.0009	5.8	22.6
New Zealand		12	0.27	0.22	0.0005	6.0	22.3
Austria		12	0.29	0.24	0.0007	6.0	21.9
Peru	1994–2001	8	0.27	0.23	0.0011	4.6	15.3
Philippines		12	0.29	0.24	0.0014	4.6	14.8
Poland	1994–2001	8	0.36	0.30	0.0029	4.7	20.1
Portugal		12	0.25	0.20	0.0005	5.1	21.1
Russian Federation	1995–2001	7	0.25	0.23	0.0070	3.8	13.1
South Africa		12	0.27	0.23	0.0008	5.5	17.8
Sweden		12	0.29	0.22	0.0012	6.3	22.8
Singapore		12	0.34	0.27	0.0008	5.9	20.6
Switzerland		12	0.30	0.23	0.0005	5.7	23.0
Taiwan	1999–2001	3	0.33	0.28	0.0024	5.4	17.7
Thailand		12	0.29	0.24	0.0025	4.3	16.1
Turkey		12	0.42	0.34	0.0059	5.1	14.0
United Kingdom		12	0.27	0.21	0.0004	6.3	21.5
Venezuela		12	0.41	0.32	0.0039	3.7	15.7

Of the 40 countries shown, 30 have full data for all years from 1990 to 2002. For the remaining ten countries we show the years in which the countries are included in our regressions.

declines. The log of country size (geographical area) is included as a proxy for limits on within-country diversification. Firm and industry Herfindal indices are included, because countries with relatively few large firms or industries (and relatively low

Table 3
Explaining differences in country-average R^2s across countries and over time.

The dependent variables are logistic transformations of equal-weighted (EW) or variance-weighted (VW) R^2s. The explanatory variables are a Good Government Index based on La Porta et al. (1998), the average skewness and kurtosis of residual returns, the log of GDP per capita, and the variance of the local market return. Additional control variables are defined below the table. The first two columns replicate Morck, Yeung and Yu (MYY, 2000), but for a panel of 40 countries from 1990 to 2001. Coefficients are estimated by the Fama-MacBeth (1973) method and further adjusted for serial correlation of coefficient estimates following Pontiff (1996). *t*-Statistics are reported under each coefficient.

Logistic(R^2)	EW	VW	EW	VW	EW	VW	EW	VW
Variable								
Good Government Index ($\times 10^{-4}$)	−305.76	−323.87	−499.73	−505.83	−535.52	−536.90	−399.55	−430.14
	−(2.62)	−(2.31)	−(2.67)	−(2.01)	−(2.78)	−(2.12)	−(2.10)	−(2.86)
Skewness					−0.45	−0.35	−0.32	−0.23
					−(2.82)	−(1.98)	−(7.54)	−(4.76)
Kurtosis ($\times 10^{-3}$)			−83.84	−79.54	−77.04	−73.91	−66.77	−66.36
			−(6.09)	−(4.25)	−(7.99)	−(5.19)	−(5.90)	−(4.04)
Local market volatility							79.08	58.87
							(4.14)	(3.08)
log(GDP per capita) ($\times 10^{-4}$)	−49.26	−53.91	−20.89	−27.10	−32.61	−35.10	58.89	32.35
	−(1.34)	−(1.17)	−(0.42)	−(0.63)	−(0.62)	−(0.90)	(0.80)	(0.55)
log(number of stocks)	0.01	0.03	−0.04	−0.02	−0.03	−0.01	0.00	0.01
	(0.39)	(1.17)	−(2.43)	−(2.19)	−(1.43)	−(1.13)	(0.06)	(1.79)
log(country size) ($\times 10^{-3}$)	−13.71	−10.43	−5.93	−2.54	−5.30	−2.12	−9.83	−5.95
	−(1.26)	−(1.16)	−(0.81)	−(0.57)	−(0.64)	−(0.42)	−(1.31)	−(1.25)
Variance (GDP growth)	6.60	6.97	2.02	2.29	2.61	2.79	−1.05	0.05
	(0.75)	(0.87)	(0.60)	(1.05)	(0.66)	(1.02)	−(0.33)	(0.03)
Industry Herfindahl Index	0.34	0.08	0.59	0.31	0.45	0.21	0.33	0.10
	(0.94)	(0.25)	(2.55)	(2.11)	(1.30)	(0.82)	(0.75)	(0.34)
Firm Herfindahl Index	2.12	1.15	1.69	0.70	1.92	0.86	1.91	0.77
	(2.55)	(1.67)	(2.38)	(1.06)	(2.41)	(1.22)	(3.09)	(1.33)
Average adjusted R^2	0.20	0.15	0.38	0.32	0.38	0.33	0.54	0.53
Sample size	440	440	440	440	440	440	440	440

Control variables from MYY (2000):
1. The log of the number of stocks traded in each country and year.
2. log(country size). Size means geographical area in square kilometers.
3. The variance of the growth rate of each country's GDP, measured in nominal U.S. dollars, from 1990 to 2001.
4. Herfindal Indices are calculated from the distribution of sales of individual firms or industries within each country and year.

Herfindal indices) are expected to have high R^2s. The variance of GDP growth is included because macroeconomic risk may be higher in poorer countries or in countries where investor rights are not well protected. MYY explain these controls in more detail.[21]

[21]MYY include one further control, an estimate of the co-movement of earnings for firms within each country. Introducing this variable has little effect on our results, but reduces our sample size by more than 30%. We therefore report results estimated without this additional variable.

The results in the first two columns of Table 3 are by and large consistent with MYY. Countries with high per capita GDP or high scores on the Good Government Index have low R^2s, although the coefficients for GDP are not significant. None of the control variables is significant individually except the firm Herfindahl index in the equally weighted regressions.

The industry Herfindahl index is also significant in columns 3 and 4, where we control for kurtosis in residual returns. The t-statistics for kurtosis are negative and highly significant. Countries with high kurtosis (long tails in residual return distributions) have low R^2s. We retain kurtosis as a control in all subsequent tests.

3.4. Crash frequency as a predictor of R^2

Columns 5 and 6 of Table 3 add skewness as a measure of crash likelihood. The coefficient is negative and significant in the equally weighted regressions, and just shy of significance ($t = -1.98$) with value weights. This is just as we predicted. Lower skewness means relatively more negative outliers in the distribution of residual returns. Thus, lower skewness is associated with higher R^2, controlling for kurtosis and all of MYY's explanatory variables. Correcting for kurtosis and skewness does not change sign or significance for the Good Government Index. Log(GDP per capita) remains insignificant.

The final columns of Table 3 add local market volatility, measured as the variance of each country's market return, as an additional independent variable. MYY do not include this variable. They interpret high local market volatility and high R^2s as results of poor investor protection and the concentration of noise trading on the market portfolio rather than on individual stocks. Our theory concentrates on firm-specific risk and says nothing about local market volatility. We therefore include local market volatility as a control to make sure that the variables of interest in our theory are not just proxies for differences in market risk.

Local market volatility is of course positively related to R^2, as shown in columns 7 and 8 of Table 3. The addition of local market volatility increases the t-statistics for skewness dramatically, to -7.54 in the equally weighted regressions. Kurtosis and the Good Government Index play the same role as before. The coefficient for log(GDP per capita) switches to a positive sign but is not significant.

Skewness is one measure of the frequency of crashes in firm-specific returns. We have two other measures, COLLAR and COUNT. The relations between these measures and R^2 are summarized in Table 4. For each measure there are three critical values, corresponding to lognormal crash frequencies of 0.01%, 0.1% and 1%. For each frequency we run regressions with both equally weighted and value-weighted R^2s as dependent variables. Results for COLLAR and COUNT are in Panels A and B, respectively. The coefficients on these variables are positive, as predicted, and significant in all regressions. Average R^2s are higher in countries where the frequency and severity of crashes are high. We use the same controls as in Table 3, although to save space we report coefficients only for the Good

Table 4
Effects of crash frequency on R^2.

Independent variables are a Good Government Index based on La Porta et al. (1998), the log of GDP per capita, and COUNT and COLLAR. COUNT is the difference between the number of negative and positive outliers, defined as residual returns exceeding k standard deviations below and above the mean. The cutoff return k is set to generate critical values of 0.01%, 0.1% and 1% in a lognormal distribution. COLLAR is the average payoff from a strategy of buying a put on residual returns, with a strike price chosen to generate payoffs with probabilities of 0.01%, 0.1% and 1% in a lognormal distribution, and selling a call that would generate payoffs with the same probabilities. Controls included but not reported include kurtosis, local market volatility, log of the number of stocks in each country, log of country size, variance of GDP growth, and industry and firm Herfindahl indices. Coefficients are estimated by the Fama-MacBeth (1973) method and adjusted for serial correlation of coefficient estimates following Pontiff (1996). t-Statistics are reported under each coefficient.

Independent variables	Critical value, equal weights			Critical value, variance weights		
	0.01%	0.10%	1%	0.01%	0.10%	1%
Panel A: Tests with COLLAR as measure of crash frequency						
COLLAR	1004.91	468.64	225.43	671.42	433.32	123.23
	(3.21)	(3.00)	(4.55)	(2.65)	(2.60)	(4.69)
Good Government Index ($\times 10^{-4}$)	−376.05	−374.68	−386.59	−410.58	−412.37	−416.14
	−(2.47)	−(2.69)	−(2.06)	−(2.29)	−(2.57)	−(2.43)
log(GDP per capita) ($\times 10^{-4}$)	71.40	62.45	64.85	40.62	32.86	39.03
	(0.97)	(0.91)	(0.88)	(0.68)	(0.59)	(0.66)
Panel B: Tests with COUNT as measure of crash frequency						
COUNT	31.03	22.48	11.31	17.40	13.07	7.29
	(3.41)	(4.14)	(4.73)	(3.93)	(4.13)	(6.27)
Good Government Index ($\times 10^{-4}$)	−377.31	−387.99	−414.89	−412.21	−414.95	−432.85
	−(2.69)	−(2.90)	−(2.66)	−(2.94)	−(2.74)	−(2.98)
log(GDP per capita) ($\times 10^{-4}$)	75.75	64.94	54.13	43.88	38.69	32.03
	(1.04)	(0.89)	(0.79)	(0.74)	(0.67)	(0.54)

Government Index and GDP per capita. These coefficients are about the same as in the final right-hand columns of Table 3. There were no surprises in the coefficients for the control variables.

3.5. Measures of opaqueness

The positive relation between R^2 and our measures of crash likelihood does not imply causality in either direction. Our theory says that they are both determined by opaqueness. We have two hypotheses: Countries where firms are more opaque to investors have (1) higher average R^2s and (2) more frequent crashes in firm-specific returns. We now test these hypotheses directly.

Opaqueness means the lack of information that would enable investors to observe operating cash flow and income and determine firm value. We are concerned with value-relevant information, which may not be the same thing as accounting detail. Accounting numbers can be meaningless or misleading, even in the U.S., as recent scandals illustrate. Therefore we cast a wider net and look for a range of proxies for opaqueness or transparency. We end up with five measures: (1) A survey-based measure from the Global Competitiveness Report, (2) a measure of auditing activity, (3) a measure of how many key accounting variables are included in financial statements, from La Porta et al. (1998), (4) an opaqueness measure from PricewaterhouseCoopers and (5) an opaqueness measure based on the diversity of analysts' forecasts.

We consider and reject one further measure from Global Advantage (2000). The measure is based on the proportion of firms adopting an international or U.S. accounting standard. This measure is constructed for relatively few countries, and for relatively few firms in the countries covered. More important, the measure seemed disconnected from other plausible measures of economic development or opaqueness. For example, China ranks very high on the proportion of firms that adopt an international standard, but countries such as the U.K., Singapore and Canada, which other measures rank as highly transparent, have hardly any firms adopting international standards.

3.5.1. A transparency measure from the Global Competitiveness Report

The Global Competitiveness Reports for 1999 and 2000 include results from surveys about the level and effectiveness of financial disclosure in different countries.[22] Survey respondents were asked to assess the statement "The level of financial disclosure required is extensive and detailed" on a scale from 1 (strongly disagree) to 7 (strongly agree). Respondents were also asked to assess the "availability of information" on the same scale. For each country, we take the average response for each question in 1999 and 2000, and average again over these two years. The result is a disclosure score (DISCLOSURE) for each of the 40 countries in our sample. Note that high values for DISCLOSURE measure transparency, not opaqueness. High DISCLOSURE scores should predict low R^2s.

[22] Gelos and Wei (2002) suggest use of the Global Competitiveness Report to measure transparency.

3.5.2. Auditing

Bhattacharya et al. (2003) use the number of professional auditors as a proxy for transparency. They report the number of auditors per 100,000 people for 38 different countries, based on data from Saudagaran and Diga (1997). Our variable, AUDITOR, is the number of auditors relative to each country's stock-market capitalization in 1996, measured in billions of U.S. dollars. AUDITOR is again a measure of transparency, not opaqueness.

3.5.3. Accounting standards

La Porta et al. (1998) create an index of accounting standards (STANDARDS) for 36 countries. They base the index on 1990 annual reports for a sample of companies in each country. They check against a list of 90 specific accounting items that could be reported on income statements, balance sheets, etc. The more items actually reported, the higher the STANDARDS score. A perfect STANDARDS score equals 90.

3.5.4. Opacity

PricewaterhouseCoopers (2001) reports a Global Opacity Index for 2000, with an opacity factor (OPACITY) for each of 35 countries. OPACITY reflects a survey of CFOs, bankers, equity analysts and local PricewaterhouseCoopers consultants. The survey covers corruption in government, legal protection of property and contracts, macroeconomic policies, accounting standards and business regulation. Poor scores on these dimensions are converted to high opacity factors.

3.5.5. Diversity of analyst forecasts

DIVERSITY is the standard deviation of analysts' forecasts of the firm's earnings in the following year, normalized by the mean forecast, and then divided by the square root of the number of analysts following that firm:

$$\text{DIVERSITY} = \frac{\hat{\sigma}_{\text{S}}/\hat{\mu}_{\text{s}}}{\sqrt{N}}. \tag{24}$$

Appendix B shows that this measure is proportional to the standard deviation of hidden firm-specific information. If analysts receive noisy signals about a firm's income, then part of each period's change in residual cash flow is revealed to the market. The part that is not revealed remains opaque to investors.

We construct DIVERSITY from analysts' earnings forecasts reported in I/B/E/S international editions from 1990 to 2001. We have such forecasts only for a subset of the firms in our main sample. Only 26 countries have I/B/E/S data for the full sample period, and the number of firms covered by I/B/E/S is about half the number in Datastream. In addition, we exclude firms in years for which the firm's DIVERSITY equals zero, i.e., where all analysts agree. Complete agreement could reflect full information, but it could also imply total ignorance.

Although use of DIVERSITY cuts our sample size, it does vary over time. Each of the previous measures is estimated at one time only.

3.6. Opaqueness, R^2 and the frequency of crashes

Table 5 shows the relations between R^2 and these five measures of opaqueness or transparency. For example, the first two columns show results for DISCLOSURE, which is a measure of transparency. High scores should mean *low* R^2s. We rank countries on their DISCLOSURE scores and use this rank as the independent variable. Again we include the Good Government Index, GDP per capita, kurtosis and local market volatility. The rest of MYY's control variables are also included in the regressions but not reported in the table. As predicted, the coefficients on DISCLOSURE are negative. The t-statistic is nearly significant at conventional levels (-1.85) for the variance-weighted regressions and solidly significant ($t = -4.45$) for the equally weighted regressions. It appears that effective disclosure means more transparency and lower R^2. Coefficients for the Good Government Index, kurtosis and local market volatility have about the same magnitudes and t-statistics as in Table 3.

Our tests for AUDITOR, STANDARDS, OPACITY and DIVERSITY are carried out in exactly the same way as for DISCLOSURE. We predict negative coefficients for AUDITOR and STANDARDS, which measure transparency, and positive coefficients for OPACITY and DIVERSITY, which measure opaqueness. These predictions are confirmed in Table 5, with t-statistics above 2.0 in all cases, except for OPACITY in the equally weighted regressions. The coefficient for the Good Government Index remains negative and significant in all regressions. The controls for local market volatility and kurtosis play their usual roles. Log(GDP per capita) seems to have a positive effect on R^2 once opaqueness or transparency and the other controls are accounted for, although the t-statistics for this variable manage to exceed 2.0 in only one regression.

Table 6 tests whether the five opaqueness or transparency measures explain crash likelihoods, measured by skewness, COLLAR and COUNT. R^2 is no longer the dependent variable, so we can eliminate local market volatility and several variables introduced by MYY to control for other determinants of R^2. We retain the Good Government Index, log(GDP per capita) and kurtosis as controls, although to save space we do not report the coefficients for these variables[23] and we present the COLLAR and COUNT results only for the lognormal frequency of 0.1%. (The results for frequencies of 0.01% and 1% are similar.)

The top panel of Table 6 (based on weekly returns) thus shows 15 coefficients and 15 t-statistics, three for each of the five opaqueness or transparency measures. DISCLOSURE, AUDITOR and STANDARDS are transparency measures, so we predict positive signs for skewness (SKEW) and negative signs for COLLAR and COUNT. OPACITY and DIVERSITY measure opaqueness, so the predicted signs reverse. These predictions are borne out in all cases, with t-statistics above 2.0 in all cases except for the COUNT regressions for DISCLOSURE ($t = -1.72$) and OPACITY ($t = 1.77$) and in the COLLAR regression for AUDITOR ($t = 1.88$).

[23]The coefficients for these controls vary from regression to regression. The only significant coefficients are for the kurtosis in the regressions for COUNT, where t-statistics ranged from -1.89 to -6.32.

Table 5
Summary of regressions of R^2 on opaqueness

The five opaqueness measures are ranks of disclosure, auditing activity, inclusion of key accounting information in financial statements, the opacity factor reported by PriceWaterhouseCoopers, and dispersion of analyst forecasts. The dependent variables are logistic transformations of equal-weighted or value-weighted country-average R^2s. Control variables included but not reported are log(country size), variance(GDP growth) and industry and firm Herfindahl indices. Coefficients are estimated by the Fama-MacBeth (1973) method and are further adjusted for serial correlation of coefficient estimates using Pontiff (1996). t-Statistics are reported under each coefficient

	DISCLOSURE		AUDITOR		STANDARDS		OPACITY		DIVERSITY	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Rank of opaqueness/transparency ($\times 10^{-5}$)	−83.31	−82.33	−82.48	−68.57	−37.24	−62.85	184.31	176.05	129.32	120.17
	−(4.45)	−(1.85)	−(2.70)	−(5.09)	−(5.61)	−(2.57)	(1.79)	(4.57)	(3.50)	(3.36)
Good Government Index ($\times 10^{-4}$)	−344.57	−369.99	−356.73	−404.53	−365.13	−471.45	−271.75	−441.18	−406.66	−421.12
	−(2.36)	−(2.39)	−(2.81)	−(2.23)	−(2.81)	−(2.93)	−(2.81)	−(2.60)	−(2.21)	−(2.67)
log(GDP per capita) ($\times 10^{-4}$)	56.61	27.87	48.34	29.91	71.74	60.57	58.70	102.70	80.05	56.96
	(0.86)	(0.49)	(0.76)	(0.58)	(1.24)	(1.80)	(0.98)	(2.08)	(1.13)	(0.90)
Local market volatility	69.83	52.17	78.48	54.06	70.58	35.66	45.06	37.49	70.89	48.18
	(4.25)	(3.07)	(4.25)	(3.65)	(5.75)	(5.64)	(1.65)	(3.05)	(4.08)	(3.64)
Kurtosis ($\times 10^{-3}$)	−71.15	−70.03	−71.60	−70.34	−70.33	−74.47	−66.91	−66.34	−77.06	−72.74
	−(5.79)	−(3.98)	−(4.56)	1−(3.67)	−(5.25)	−(3.95)	−(5.34)	−(3.63)	−(4.44)	−(3.59)
Average adjusted R^2	0.52	0.51	0.57	0.57	0.58	0.54	0.52	0.52	0.56	0.56
Sample size	440	440	421	421	377	377	187	187	418	418

Table 6
Summary of regression results for crash frequency on opaqueness

The five opaqueness measures are ranks of disclosure, auditing activity, inclusion of key accounting information in financial statements, an opacity factor reported by PriceWaterhouseCoopers and dispersion of analyst forecasts. Crash likelihood is measured by the skewness of residual returns, COLLAR and COUNT. COUNT is the difference between the number of negative and positive outliers, defined as residual returns exceeding k standard deviations below and above the mean. The cutoff return k is set to generate critical values of 0.01%, 0.1% and 1% in a lognormal distribution. COLLAR is the average payoff from a strategy of buying a put on residual returns, with a strike price chosen to generate payoffs with probabilities of 0.01%, 0.1% and 1% in a lognormal distribution, and selling a call that would generate payoffs with the same probabilities. Control variables included but not reported are the Good Government Index, log(GDP per capita) and kurtosis. Coefficients were estimated by the Fama-MacBeth (1973) method and further adjusted for serial correlation of coefficient estimates using Pontiff (1996). t-Statistics are reported under each coefficient

Measure of crash likelihood	Opaqueness measures				
	DISCLOSURE	AUDITOR	STANDARDS	OPACITY	DIVERSITY
Weekly returns					
SKEW	146.39	276.38	238.85	−235.34	−268.39
	(2.83)	(2.26)	(3.89)	−(2.24)	−(2.72)
COLLAR at 0.1%	−0.06	−0.14	−0.10	0.16	0.14
	−(3.57)	−(1.88)	−(2.67)	(2.33)	(2.55)
COUNT at 0.1%	−0.99	−2.45	−2.65	2.06	2.40
	−(1.72)	−(2.71)	−(4.09)	(1.77)	(3.67)
Monthly returns					
SKEW	225.15	214.74	192.46	−347.75	−287.75
	(6.33)	(4.10)	(5.27)	−(7.10)	−(7.79)
COLLAR at 0.1%	−0.18	−0.18	−0.16	0.31	0.24
	−(6.05)	−(4.97)	−(6.58)	(7.48)	(7.61)
COUNT at 0.1%	−2.83	−2.80	−2.37	4.34	3.67
	−(6.36)	−(4.66)	−(4.78)	(6.62)	(5.01)

3.7. Tests based on monthly returns

We use weekly returns to estimate R^2s from the regression set out in Eq. (23). Using short-horizon returns is an advantage in estimating variance and R^2s. In addition, we are able to obtain a time series of 12 annual average R^2s for each country in our sample. We then estimate 12 coefficients for each variable in the Fama-MacBeth cross-sectional regressions and correct for possible serial correlation in the 12 coefficients.

But we also check our results using monthly returns. Monthly returns are common for corporate finance applications. In the present context, one might worry whether use of high frequency, weekly returns could introduce noise or oddly shaped residual-return distributions. One might also worry about defining a crash as an event confined to a single week. A large, negative, firm-specific return in a particular week might reverse in the next week, for example, and not really be a crash of the type that the theory predicts. Or a crash that occupied a whole week could affect two weekly returns, unless by chance the crash started on a Wednesday. Thus tests based on monthly returns are particularly useful as a check on our results about the frequency of crashes.

We split our sample into four nonoverlapping three-year periods. For each period we generate monthly returns,[24] estimate equally weighted and variance-weighted R^2s for each country and repeat our tests for the five measures of transparency and opaqueness. We again follow Fama-MacBeth, but with only four cross-sectional regressions we do not attempt to correct for possible serial correlation.

The results for R^2 regressions are basically as in Table 5. The signs of the coefficients for the five opaqueness or transparency measures are unchanged. The t-statistics are higher, in some cases dramatically so.[25]

The bottom panel of Table 6 checks the relation between opaqueness or transparency and crash frequency using monthly returns. Again, the signs of the coefficients are unchanged, but significance levels go up across the board. These results suggest that monthly intervals make more sense when investigating crashes.

3.8. Summary of empirical results

Each of our five measures of opaqueness or transparency doubtless has flaws. But the measures yield consistent performance in a variety of tests, with conservatively estimated t-statistics above 2.0 in almost all regressions, and all signs are as predicted. Taken together, our tests show that countries where firms are more opaque to outside investors have (1) higher R^2s and (2) higher frequencies of crashes.

Conclusion (1) is perhaps not surprising, given MYY's results. We would expect firms to be less transparent in poorer countries with less developed financial markets and poor protection of investors' property rights. Our model draws a logical distinction between the effects of opaqueness and poor protection of investors, but these two factors are probably positively correlated in practice. Conclusion (2) is new, however. As far as we know, no prior theory has made a specific prediction about how the far-left tail of the distribution of residual returns varies across countries, and no such prediction has been tested previously. Thus the significance of our results about crashes is a nice return on our investment in theoretical model building.

[24]We actually use 4-week returns, which yield about 39 returns for each three-year period. Stocks with less than 26 returns in a three-year period are excluded. We estimate Eq. (23) without the leading and lagged returns, because nonsynchronous trading should be much less important over four-week vs. one-week intervals. MYY use two-week returns, without leads and lags.

[25]Of course we are applying Fama-MacBeth with only four cross-sectional regressions and only four coefficients to estimate standard errors from. But the four coefficients for each opaqueness or transparency measure are reasonably stable over time. There is only one sign change, which occurs between the first and second periods for the variance-weighted DISCLOSURE regressions. The coefficients for the control variables bounce around more than in Table 5, however.

Of course statistical and economic significance do not always cohabit, but in this case we believe they do. For example, moving from the 10th to 90th percentile rank on the opaqueness or transparency measures, using the specification in Table 5, shifts the logistic transformation of equally weighted R^2s up by 4% for STANDARDS, 7.5–8% for DISCLOSURE and AUDITOR, 11.5% for DIVERSITY and 21% for OPACITY. The effects on crash frequency are larger. Take one measure of crash frequency, COUNT at a lognormal frequency of 0.01%. Moving from the 10th to 90th percentile rank, using the specification in Table 6, increases the frequency of crashes by 16% for DISCLOSURE, 34–36% for AUDITOR and STANDARDS, 47% for OPACITY and 57% for DIVERSITY. We believe that these changes demonstrate significant economic effects.

Our tests extend MYY's results. For example, all of our tests control for MYY's chief variable of interest, the Good Governance Index. MYY argue that market risk is higher in less developed countries with ineffective governance and poor protection of investors. That is no doubt true, but we control for local market risk directly in order to make sure that our measures of opaqueness are not just proxies for the effects that MYY are interested in. The explanatory power of the Good Government Index sometimes degrades when we introduce local market volatility and our measures of opaqueness. That does not prove that MYY are wrong, only that opaqueness also matters, even when market volatility and a measure of investor protection are also included.

4. Conclusion

We set out to explain MYY's finding that stock market R^2s are higher in countries with less developed financial systems and poorer corporate governance. The key to our explanation is the effect of opaqueness on the division of risk bearing between inside managers and outside investors. Opaqueness is both good news and bad news for insiders. The good news is that more opaqueness allows insiders to capture more cash flow when the firm is doing well. The bad news is that insiders have to hold a residual claim and absorb downside risk. They can abandon the residual claim and reveal downside news to outside investors, but this abandonment option is costly and not frequently exercised. Exercise of this option causes a crash, that is, a large, negative residual return.

We replicate MYY's results for a much larger sample, and show that higher crash frequencies are associated with higher R^2s. We also deploy five measures of opaqueness and show that these measures help explain both R^2 and the frequency of crashes. These latter results are, of course, more direct tests of our theory. All of our results hold when local market volatility is used as a control.

There is plenty more to do. For example, we use kurtosis only as a control variable. Our theory makes no predictions about kurtosis, and we do not explain how or why it affects R^2s so significantly. Also, we only investigate country-average R^2s (following MYY) and country-average crash frequencies, as they vary across countries and over time. There ought to be differences in opaqueness within countries. For example, firms in some industries may be naturally more opaque. Large, actively traded firms may be more transparent than small, thinly traded firms, for example. Conglomerates may be relatively opaque. Growth companies, which have greater appetites for capital, could choose to become more transparent in order to reassure investors and facilitate financing.

The nature and determinants of crashes also deserve further investigation. A crash is defined as a remote, negative outlier in a firm's residual return. We are confident that crashes release firm-specific bad news. The nature of that news is not investigated here. We interpret bad news as abandonment by insiders, but there may be other sources of extreme bad news that are firm-specific. Crashes are rare enough that it may be possible to examine them one by one, at least for a subsample of countries. That would require a deeper investigation of return distributions for individual companies, which will have to wait for another paper.

Appendix A

Proof of Proposition 1. Given the assumptions set out in Section 2,

$$C_{t+1} = K_0 X_{t+1} = K_0(X_0 + \varphi X_t + \lambda_{t+1}) = K_0 X_0 + \varphi C_t + K_0 \lambda_{t+1}. \tag{A.1}$$

Derive the expected cash flow k periods ahead:

$$\begin{aligned} \mathrm{E}(C_{t+k}|C_t) &= \mathrm{E}[K_0(X_0 + \varphi X_{t+k-1} + \lambda_{t+k-1})] \\ &= \sum_{i=0}^{k-1} K_0 X_0 \varphi^i + \varphi^k K_0 X_t = K_0 X_0 \frac{1-\varphi^k}{1-\varphi} + \varphi^k C_t. \end{aligned} \tag{A.2}$$

Combining these results with Eq. (1) gives K_t as a function of C_t:

$$\begin{aligned} K_t(C_t) &= PV\{\mathrm{E}(C_{t+1}|C_t), \mathrm{E}(C_{t+2}|C_t), \ldots; r\} \\ &= \sum_{j=1}^{+\infty} \frac{K_0 X_0 (1-\varphi^j)/(1-\varphi) + \varphi^j C_t}{(1+r)^j}, \end{aligned}$$

$$K_t(C_t) = \frac{1}{r}\frac{K_0 X_0}{1-\varphi} + \frac{\varphi}{1+r-\varphi}\left(-\frac{K_0 X_0}{1-\varphi} + C_t\right). \tag{A.3}$$

We can also plug in the unconditional expected value of C_t into Eq. (A.3) to obtain the unconditional expected value of K_t:

$$\mathrm{E}(K_t) = \frac{1}{r}\frac{K_0 X_0}{1-\varphi} = \frac{1}{r}\mathrm{E}(C_t). \tag{A.4}$$

Eq. (A.3) also gives K_t as a linear function of C_t:

$$K_t(C_t) = a + bC_t, \tag{A.5}$$

where

$$a = \frac{K_0 X_0}{1-\varphi}\left(\frac{1}{r} - \frac{\varphi}{1+r-\varphi}\right) \quad \text{and} \quad b = \frac{\varphi}{1+r-\varphi}.$$

Therefore,

$$\begin{aligned} \mathrm{E}(K_{t+1}|C_t) &= \mathrm{E}(a + bC_{t+1}|C_t) = a + b\mathrm{E}(C_{t+1}|C_t) \\ &= a + b(K_0X_0 + \varphi C_t) = a + bK_0X_0 + b\varphi C_t. \end{aligned}$$

Now verify that

$$a(1-\varphi) + bK_0X_0 = \frac{1}{r}K_0X_0. \tag{A.6}$$

From Eq. (A.3), there is a one-to-one relation between C_t and K_t, so

$$\begin{aligned} \mathrm{E}(K_{t+1}|K_t) &= \mathrm{E}(K_{t+1}|C_t) = a + bK_0X_0 + b\varphi(K_t - a)/b \\ &= a(1-\varphi) + bK_0X_0 + \varphi K_t, \\ \mathrm{E}(K_{t+1}|K_t) &= \frac{1}{r}K_0X_0 + \varphi K_t. \end{aligned} \tag{A.7}$$

That is, K_t follows an AR(1) process with parameter φ. Eq. (11) follows. $\square$

Proof of Proposition 2. The outside investors' estimates of r_t, C_t and K_t are as follows:

$$\mathrm{E}(r_t|f_t, \theta_{1,t}) = f_t + \theta_{1,t} + \mathrm{E}(\theta_{2,t}),$$

so

$$\mathrm{E}(r_t|f_t, \theta_{1,t}) = f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\varphi}. \tag{A.8}$$

$$\mathrm{E}(C_t|f_t, \theta_{1,t}) = \mathrm{E}(K_0 r_t|f_t + \theta_{1,t}),$$

so

$$\mathrm{E}(C_t|f_t, \theta_{1,t}) = K_0\left(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\varphi}\right). \tag{A.9}$$

$$\mathrm{E}(C_{t+k}|f_t, \theta_{1,t}) = \mathrm{E}[\mathrm{E}(C_{t+k}|C_t)|f_t, \theta_{1,t}] = \frac{K_0R_0(1-\varphi^k)}{1-\varphi} + \varphi^k \mathrm{E}(C_t|f_t, \theta_{1,t}),$$

so

$$\mathrm{E}(C_{t+k}|f_t, \theta_{1,t}) = \frac{K_0X_0(1-\varphi^k)}{1-\varphi} + \varphi^k K_0\left(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\varphi}\right). \tag{A.10}$$

$$\begin{aligned}\mathrm{E}(K_t|f_t,\theta_{1,t}) &= \mathrm{E}[K_t(C_t)|f_t,\theta_{1,t}]\\ &= \frac{1}{r}\frac{K_0X_0}{1-\varphi}-\frac{\varphi}{1+r-\varphi}\frac{K_0X_0}{1-\varphi}+\frac{\varphi}{1+r-\varphi}\,\mathrm{E}(C_t|f_t,\theta_{1,t}),\end{aligned}$$

so

$$\begin{aligned}\mathrm{E}(K_t|f_t,\theta_{1,t}) = &\ \frac{1}{r}\frac{K_0X_0}{1-\varphi}-\frac{\varphi}{1+r-\varphi}\frac{K_0X_0}{1-\varphi}\\ &+\frac{\varphi}{1+r-\varphi}K_0\left(f_t+\theta_{1,t}+\frac{\theta_{2,0}}{1-\varphi}\right). \qquad \square \end{aligned} \tag{A.11}$$

Proof of Proposition 4. From Eq. (17) and the definition of V_t^{ex},

$$r_{\mathrm{total},t+1}=\frac{\mathrm{E}(\alpha K_{t+1}|f_{t+1},\theta_{1,t+1})+\alpha\mathrm{E}(C_{t+1}|f_{t+1},\theta_{1,t+1})}{\mathrm{E}(\alpha K_t|f_t,\theta_{1,t})}-1. \tag{A.12}$$

From Eqs. (A.10) and (12)

$$r_{i,t+1}=\frac{\dfrac{1}{r}\dfrac{K_0X_0}{1-\varphi}-\dfrac{\varphi}{1+r-\varphi}\dfrac{K_0X_0}{1-\varphi}+\dfrac{1+r}{1+r-\varphi}\,K_0(f_{t+1}+\theta_{1,t+1})}{\dfrac{1}{r}\dfrac{K_0X_0}{1-\varphi}-\dfrac{\varphi}{1+r-\varphi}\dfrac{K_0X_0}{1-\varphi}+\dfrac{\varphi}{1+r-\varphi}\,K_0(f_{t+1}+\theta_{1,t})}-1. \tag{A.13}$$

The denominator can be simplified to

$$\frac{K_0X_0}{1-\varphi}\frac{(1+r)(1-\varphi)}{r(1+r-\varphi)}+\frac{\varphi}{1+r-\varphi}\,K_0(f_t+\theta_{1,t}). \tag{A.14}$$

After some reorganization, we can write

$$r_{i,t+1}=r+\frac{-r\dfrac{K_0X_0}{1-\varphi}\dfrac{(1+r)(1-\varphi)}{r(1+r-\varphi)}+K_0\,\dfrac{1+r}{1+r-\varphi}[f_{t+1}+\theta_{1,t+1}-\varphi f_t-\varphi\theta_{1,t}]}{\dfrac{K_0X_0}{1-\varphi}\dfrac{(1+r)(1-\varphi)}{r(1+r-\varphi)}+\dfrac{\varphi}{1+r-\varphi}\,K_0(f_t+\theta_{1,t})}. \tag{A.15}$$

Using Eqs. (4) and (5), the numerator becomes $[K_0(1+r)/(1+r-\varphi)](\varepsilon_{t+1}+\xi_{t+1})$, and

$$r_{i,t+1}=r+\frac{(1+r)(\varepsilon_{t+1}+\xi_{t+1})}{X_0(1+r)/r+\varphi(f_t+\theta_{1,t})}. \tag{A.16}$$

Appendix B. Diversity of analyst opinion as a measure opaqueness

In our model, cash flows are generated by $C_{t+1}=K_0X_{t+1}$. Analysts would collect information about X_t. Assume that analyst i generates an independent observation, S_{it}, such that $S_{it}=X_t+\gamma_{it}$, where $\gamma_{it}\sim\mathrm{N}(0,\sigma_s^2)$ and is distributed IID over all i. Assume also that investors observe all S_{it}, either directly or by way of analysts. Then, the market's ex post estimate of X_t is $\hat{X}_t=(1/N)\sum_{i=1}^{N}S_{it}$. Define $\theta_{1,t}=\hat{X}_t-f_t$, recalling that f_t is the market-wide information, and $\theta_{2,t} = X_t - \hat{X}_t$. Thus we have $X_t = f_t + \theta_{1,t} + \theta_{2,t}$, where f_t is the market component, $\theta_{1,t}$ is the observable firm-specific component, and $\theta_{2,t}$ is the unobservable firm-specific component, after the market observes all signals S_{it}. In addition, $\theta_{2,t} \sim \mathrm{N}(0, \sigma_s^2/N)$.

In practice, we estimate σ_s^2 by its sample analogue, $\hat{\sigma}_s^2$, and we define our measure of remaining uncertainty by

$$\text{DIVERSITY} = \frac{\hat{\sigma}_S/\hat{\mu}_s}{\sqrt{N}}.$$

The normalization by $\hat{\mu}_s$ is often used to address the heterogeneity of the size of the forecasts across firms. This proxy for remaining opaqueness can be put in the framework of Barry and Jennings (1992, pp. 172–175), who analyze the informativeness of signals using a Bayesian approach.

References

Barry, C., Jennings, R., 1992. Information and diversity of analyst opinion. Journal of Financial and Quantitative Analysis 27, 169–183.

Bhattacharya, U., Daouk, H., Welker, M., 2003. The world price of earnings opacity. Accounting Review 78, 641–678.

Bris, A., Goetzmann, W., Zhu, N., 2003. Efficiency and the bear: Short sales and markets around the world. NBER Working Paper No. 9466.

Bushman, R., Piotroski, R., Smith, A., 2003. What determines corporate transparency? Working paper, University of Chicago.

Campbell, J., Lettau, M., Malkiel, B., Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. Journal of Finance 56, 1–43.

Chang, J., Khanna, T., Palepu, K., 2001. Analyst activity around the world. Harvard Business School Working Paper No. 01-061.

Chen, J., Hong, H., Stein, J., 2001. Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. Journal of Financial Economics 61, 345–381.

Cohen, R., Polk, C., Vuolteenaho, T., 2003. The value spread. Journal of Finance 58, 609–641.

De Long, B., Shleifer, A., Summers, L., Waldmann, R., 1990. Noise trader risk in financial markets. Journal of Political Economy 98, 703–738.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197–226.

Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797–836.

Durnev, A., Morck, R., Yeung, B., 2004. Value-enhancing capital budgeting and firm-specific stock return variation. Journal of Finance 59, 65–105.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Friedman, E., Johnson, S., Mitton, T., 2003. Tunneling and propping. Journal of Comparative Economics 31, 732–750.

Gelos, R., Wei, S., 2002. Transparency and international investor behavior. Journal of Finance, forthcoming.

Global Advantage, 2000. Available at http://www.globalvantageltd.com/.

Hong, H., Stein, J., 2003. Differences of opinion, short-sales constraints, and market crashes. Review of Financial Studies 16, 487–525.

Jensen, M., Meckling, W., 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. Journal of Financial Economics 3, 305–360.

Kirschenheiter, M., Melumad, N., 2002. Can ‘‘big bath’’ and earnings smoothing co-exist as equilibrium financial reporting strategies? Journal of Accounting Research 40, 761–796.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. Journal of Political Economy 106, 1113–1155.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 2000. Investor protection and corporate governance. Journal of Financial Economics 58, 3–27.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., 2002. Government ownership of banks. Journal of Finance 57, 265–301.
Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58, 215–260.
Myers, S., 2000. Outside equity. Journal of Finance 55, 1005–1037.
O'Hara, M., 2003. Liquidity and price discovery. Journal of Finance 58, 1335–1354.
Pontiff, J., 1996. Costly arbitrage: evidence from closed-end funds. Quarterly Journal of Economics 111, 1135–1151.
PriceWaterhouseCoopers, 2001. The opacity index. Available at http://www.opacity-index.com/.
Rajan, R., Zingales, L., 2001. Financial systems, industrial structure, and growth. Oxford Review of Economic Policy 17, 467–482.
Roll, R., 1988. R-squared. Journal of Finance 43, 541–566.
Saudagaran, S., Diga, J., 1997. Financial reporting in emerging capital markets: characteristics and policy issues. Accounting Horizons 11, 41–64.
Wurgler, J., 2000. Financial markets and the allocation of capital. Journal of Financial Economics 58, 187–214.