Stock Return Synchronicity and the Informativeness of Stock Prices: Theory and Evidence[1]

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Keywords: Stock return synchronicity; R^2; Firm-specific return variation; Informativeness of stock prices; Transparency; Seasoned equity offering; Cross listing.

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Abstract

This paper argues that, contrary to the conventional wisdom, stock return synchronicity (or R^2) can increase when transparency improves. In a simple model, we show that, in more transparent environments, stock prices should be more informative about future events. Consequently, when the events actually happen in the future, there should be *less* "surprise", i.e., there is less *new* information impounded into the stock price. Thus a more informative stock price today means higher return synchronicity in the future. We find empirical support for our theoretical predictions in three settings, namely firm age, seasoned equity issues, and listing of ADRs**.**

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I. Introduction

Financial economists generally agree that in efficient markets, stock prices change to reflect available information – either firm-specific or market-wide. Recent literature has addressed the question of how a firm's information environment (disclosure policy, analyst following) or its institutional environment (property rights protection, quality of government, legal origin) can affect the relative importance of firm-specific as opposed to market wide factors (Jin and Myers (2006), Piotroski and Roulstone (2003), Chan and Hameed (2006), and Morck, Yeung, and Yu (2000)). This literature has taken the perspective that if the firm's environment causes stock prices to aggregate more *firm-specific information*, market factors should explain a smaller proportion of the variation in stock returns. In other words, the stock return synchronicity or R^2 from a standard market model regression should be lower.

This perspective, while intuitive, is at odds with another equally intuitive implication of market efficiency. In efficient markets, stock prices respond only to announcements that are not already anticipated by the market. When the information environment surrounding a firm improves and more firm-specific information is available, market participants are also able to improve their predictions about the occurrence of future firm-specific events. As a result, prevailing stock prices are likely to already "factor in" the likelihood of occurrence of these events. When the events actually happen in the future, the market will not react to such news, since there is little "surprise". In other words, more informative stock prices today should be associated with less firm-specific variation in stock prices in the future. Therefore, the return synchronicity should be *higher*.

In this paper, we present a simple model to illustrate the point that a more transparent information environment can lead to higher, rather than lower, stock return synchronicity. This is because, for a more transparent firm, there is already more information available to market participants, reducing the “surprise” from future announcements. In our model, we distinguish between two types of firm-specific information. One pertains to time-varying firm characteristics, reflecting the current state of the firm, such as next quarter’s earnings. The other is time-invariant, such as managerial quality. [2] Stock return synchronicity can increase subsequent to an improvement in transparency through disclosure of both types of information. First, greater transparency can lead to early disclosure of time-variant information. This can happen around major events such as seasoned equity issues (SEOs) or cross-listings, during which a big chunk of information about future events is revealed. Thus when future events actually happen, there is less “surprise” and hence less additional information to be incorporated in the stock price, resulting in a higher return synchronicity.[3] While the positive effect of greater transparency on return synchronicity is most significant in the case of a one-time lumpy disclosure, we show that it also holds in the more general setting with regular, early disclosure of information. In particular, we show that in a dynamic setting, if at the beginning of every period, outsiders get to know (one period ahead of time) some of the information that otherwise would come out at the end of the period, the return synchronicity is actually higher.

The second channel through which greater transparency increases stock return synchronicity is due to learning about time-invariant firm-specific characteristics, such as managerial quality. In particular, better disclosure allows market participants to learn about time-invariant firm fundamentals with greater precision (e.g., in the extreme case where the

[2] Strictly speaking all firm characteristics are time varying in the very long run. Here we refer to those characteristics that do not change frequently or do not change much over time (so that they do not affect valuation significantly) as “time-invariant.”

[3] Shiller (1981) notes theoretically that if dividend news arrives in a lumpy and infrequent way, stock price volatility becomes lower. If much of the dividend news reflects firm specific information, one would also expect return synchronicity to become higher.

fundaments are completely known, there is no new learning). Therefore, with more disclosure, the priors about these fundamentals will be revised less drastically as new information comes in. As a result, there will be less firm-specific variation in stock prices, i.e., the return synchronicity will be higher.

We present three pieces of empirical evidence consistent with our model's predictions. We first provide evidence of learning about time-invariant firm-specific information. The idea is that, as a firm becomes older, the market learns more about its time-invariant characteristics, e.g., the firm's intrinsic quality. Therefore, return synchronicity should be higher for older firms, since more of the (time-invariant) firm-specific information is already reflected in the stock price. This prediction is strongly supported by the data.

Second and third, we exploit the fact that the effect of greater transparency on stock return synchronicity is likely to be especially clear when the disclosure is "lumpy", in the sense that the market receives a big chunk of information relevant for future cash flows. Therefore, we focus on seasoned equity offerings (SEOs) and cross-listings in the U.S.[4] It is well known that both events are associated with significant amounts of information disclosure and market scrutiny (see, e.g., Almazan et al. (2002) for SEO, and Lang et al. (2003) for ADR listings). Our model suggests a dynamic response of return synchronicity to an improvement in the information environment. At the time when new information is disclosed and impounded into stock prices, the firm-specific return variation will increase, as suggested by conventional wisdom. However, since a big chunk of relevant information is already reflected in stock prices, we would expect the firm-specific return variation of SEO and cross-listed firms to be subsequently lower. This dynamic response of the firm-specific return variation around seasoned equity issues and cross-

[4] While firms can list their shares in the U.S. exchanges either through ADRs or through direct listings, the literature sometimes uses the two terms "cross listings" and "ADR listings" interchangeably (see, e.g., Lang, Lins, and Miller (2003)). In the rest of this paper, we follow this convention, except when we discuss our sample.

listing events is the main focus of our empirical exercise and we find strong support for it in the data.[5]

Overall, in this paper, we make two contributions to the literature. First, we address the literature on transparency, informativeness of stock prices, and stock return synchronicity by arguing that a more transparent firm can have a higher return synchronicity, contrary to the conventional wisdom. Therefore, our paper highlights that it is important to understand the nature of information disclosure in trying to interpret any particular association (or its absence) between transparency and stock return synchronicity. Second, we add to the growing literature on information disclosure around security issuance events such as SEOs or ADRs by showing that stock price synchronicity changes in a way that is consistent with lumpy information disclosure associated with these events.

The rest of the paper is organized as follows. Section II reviews related literature. Section III presents the model. Section IV reports the empirical findings and Section V concludes.

II. Related Literature

A. Stock Return Synchronicity (R^2)

A recent literature has documented a link between the synchronicity of stock returns and the informativeness of stock prices at the *country level*. Morck, Yeung, and Yu (2000) (MYY (2000) hereafter) first report that, in economies where property rights are not well protected, synchronicity of stock returns – measured by a market model R^2 – is significantly higher. The authors argue that weaker property rights discourage informed arbitrage activity based on private information, and stock prices are driven more by political events and rumors. In a recent paper,

[5] A common concern about the empirical identification of the SEO/ADR effects is the potential self-selection of SEO and ADR listings. We discuss later how our empirical specification addresses this issue.

Jin and Myers (2006) examine the link between measures of corporate transparency and return synchronicity. They argue that in a more transparent environment, proportionately more firm-specific information is revealed to outside investors. As a result, market-wide information explains a smaller proportion of the overall return variation, resulting in a lower return synchronicity.

Others have investigated whether results at the country level carry over to the *firm level*. They find mixed results. On the one hand, Durnev, Morck, Yeung, and Zarowin (2003) find that higher firm-specific stock price variation is associated with higher information content about future earnings. On the other hand, Piotroski and Roulstone (2004) find that return synchronicity increases with analyst coverage. They interpret this as evidence that analysts specialize by industry, and, as a result of greater analyst coverage, more industry-wide and market-wide information gets impounded in stock prices. Using data from emerging markets, Chan and Hameed (2006) report that greater analyst coverage increases return synchronicity. Barberis et al. (2005) find that inclusion in (deletion from) the S&P 500 index, which presumably increases (decreases) firm-level transparency, increases (decreases) a stock's return synchronicity.

Given these inconsistencies, it is useful to review the determinants of the market model return synchronicity. Consider a simple regression of firm return on market return. In this case, $R^2 = \mathrm{SSR/SST} = \beta^2 \mathrm{S_{xx}} / (\beta^2 \mathrm{S_{xx}} + \mathrm{SSE})$. Thus, an increase in return synchronicity can come from three sources: (1) an increase in market-wide return variation ($\mathrm{S_{xx}}$), ceteris paribus; (2) a decrease in the "idiosyncratic return variation (SSE)", ceteris paribus; (3) an increase in beta (β), or the stock's co-movement with the market, ceteris paribus. The results in MYY (2000) for country-level R^2 could be primarily attributable to higher market-wide return volatility associated with weaker property rights protection (which discourages information acquisition and creates more space for noise trading); those in Jin and Myers (2006) are attributable to lower idiosyncratic return variation in countries with poor transparency.

Note that at the country level, as the aggregated beta is exactly 1 by definition, the country level studies have generally associated a lower average R^2 with either a higher firm-specific return variation, or lower aggregate market volatility. This, however, is not the case at the firm level. The mixed results on R^2 at the firm level can be reconciled by this beta effect: S&P additions (Barberis et al. (2005)) or more analyst coverage (Piotroski and Roulstone (2004), Chan and Hameed (2006)) lead to an increased co-movement with market and thus the beta. Barberis et al. (2005), for example, argue that when making portfolio decisions, investors group assets into categories (such as small-cap stocks, value stocks), and allocate funds at the level of these categories. Additions into the S&P 500 may move the stock into a category with more popularity with investors, with a resultant increase in beta and R^2. Likewise, as analysts help to impound more market-wide information into the stock price, the stock return exhibits higher co-movement with the market, resulting in higher beta and return synchronicity. This highlights a need to control for the beta effect in firm-level studies of R^2 when one is primarily interested in how the information environment affects the idiosyncratic return variation.

B. Information Revelation and the Informativeness of Stock Prices

The idea that a more transparent firm has stock prices that are more informative about future events is not new. Fishman and Hagerty (1989), for example, present a model in which firm disclosure increases the informativeness of stock prices about future cash flows, which in turn enhance the resource allocation efficiency. Gelb and Zarowin (2002) empirically find that better disclosure policies are associated with stock prices that are more informative about future earnings changes.[6] In an interesting paper, Bhattacharya et al. (2000) find that shares in the Mexican Stock Exchange react very little to the announcement of company news. This is not because firms listed in the stock exchange in Mexico are more transparent, but rather because, due to insider trading, the superior information of insiders is already incorporated in stock prices, so there is little surprise on announcement.

Several recent papers have made an association between the informativeness of stock prices as measured by stock return synchronicity and the efficiency of resource allocation. For example, Durnev, Morck, and Yeung (2004) and Wurgler (2000) find that higher firm-specific return variation enhances investment efficiency. Chen, Goldstein, and Jiang (2004) use return synchronicity as a measure of private information incorporated in the stock prices and find that investment responds more to stock prices when the stock return synchronicity is lower. Similar to our view, they note that investment does not necessarily respond more strongly to information if the manager was already knowledgeable about the information (and hence has already taken the relevant action). What moves investment-price sensitivity is the information that gets into price through trading by the private speculators (who know something that the manager does not).

III. Disclosure, Transparency and Stock Return Synchronicity: Theory

[6] Lang and Lundholm (1996) examine the relation between firms' disclosure policies, analyst following, and the accuracy of analysts' forecasts. They find that within a particular industry, firms that are more forthcoming in their disclosure policies have larger analyst following, more accurate analyst earning forecasts, less dispersion about individual analyst forecasts, and less volatility of forecast revisions. While they do not directly address the issue of informativeness of stock prices, their results suggest that future outcomes are easier to predict when firms are more transparent.

In this section, we present the arguments about how new disclosure and improvement in transparency affect return synchronicity. To facilitate comparison, we frame the arguments in the context of a model developed in a recent paper by Jin and Myers (2006).

As in Jin and Myers (2006), we assume that the firm's cash flow generating process is,

(1) $$C_t = K_0 X_t$$

where K_0 is initial investment, and X_t is the sum of three independent shocks to the firm's cash flow:

(2) $$X_t = f_t + \theta_{1,t} + \theta_{2,t} .$$

Here, f_t captures market factors that are observed by all; $\theta_{1,t}$ and $\theta_{2,t}$ are firm-specific shocks. Outsiders only observe $\theta_{1,t}$, whereas insiders observe both $\theta_{1,t}$ and $\theta_{2,t}$. As in Jin and Myers (2006), we assume that f_t, $\theta_{1,t}$ and $\theta_{2,t}$ are all stationary AR(1) processes with the same AR(1) parameter ϕ, where $1 > \phi > 0$:

(3) $$f_{t+1} = f_0 + \phi f_t + \varepsilon_{t+1}$$

(4) $$\theta_{1,t+1} = \theta_{1,0} + \phi\theta_{1,t} + \xi_{1,t+1}$$

and

(5) $$\theta_{2,t+1} = \theta_{2,0} + \phi\theta_{2,t} + \xi_{2,t+1}.$$

Let $\kappa = \mathrm{Var}(\theta_{1,t} + \theta_{2,t}) / \mathrm{Var}(f_t)$ denote the ratio of firm-specific to market variance in cash flows. Also following Jin and Myers (2006), let $\eta = \mathrm{Var}(\theta_{1,t}) / [\mathrm{Var}(\theta_{1,t}) + \mathrm{Var}(\theta_{2,t})]$, the proportion of the variance of the firm-specific component that is due to the part that is observable to the outsiders. A higher η is associated with better firm transparency.

The "intrinsic value" of the firm from the point of view of investors at any point of time t is the present value of future cash flows conditional on their information set I_t:

(6) $$K_t(I_t) = PV\{E(C_{t+1} \mid I_t), E(C_{t+2} \mid I_t), \ldots, r\}$$

where the discounting is done at the risk-free rate r.

Outside shareholders can seize control of the firm through collective action and manage the firm on their own. The value of the firm under the outsider shareholders' management is αK_t where $\alpha < 1$. This sets the ex-dividend market value of the firm (i.e. its value to outside investors) at

(7) $$V_t^{ex}(I_t) = \alpha \cdot K_t(I_t).$$

We have $V_t^{ex}(I_t) = [E(Y_{t+1} \mid I_t) + E(V^{ex}{}_{t+1} \mid I_t)]/(1+r)$, where Y_{t+1} is the dividend at $t+1$. Jin and Myers (2006) show (Jin and Myers (2006), Proposition 3) that the equilibrium dividend is a constant fraction α of the investor' conditional expectation of cash flow:

(8) $$Y_\tau^* = \alpha E(C_\tau \mid I_t) \ \forall \ \tau \geq t .$$

We now depart from Jin and Myers (2006) by assuming that there is a change in the firm's disclosure policy and the firm becomes more transparent. Specifically, we consider two different types of changes in disclosure policy: one is related to time-variant firm-specific information; the other concerns time-invariant information about firm characteristics.

A. Disclosure of Time-Variant Information

A.1. Lumpy (One-Time) Information Disclosure

During SEOs or ADR listings, the firm becomes more transparent in the sense that a big chunk of information comes out that otherwise would have come out later, or perhaps not at all. To model this type of disclosure, we assume that the market learns, at time t_0, of δ_{t_0+1} where

(9.1) a) $$\xi_{1,t_0+1} = \xi'_{1,t_0+1} + \delta_{t_0+1}$$

(9.2) b) $E(\xi'_{1,t_0+1} \mid \delta_{t_0+1}) = 0$.

The interpretation is as follows. Equations (9.1) and (9.2) imply that the market learns one period ahead of time some information that is relevant for the t_0+1 cash flow innovation. We call this information disclosure "lumpy" because this is a one-time early disclosure of information that reduces the variance of the cash flow shock at t_0+1, so that the quantum of information revealed at t_0 exceeds that at any other subsequent point of time. A major event such as the listing of ADRs is likely to be associated with revelation of information relevant for firm-specific events that could affect future cash flows. This information, however, should be less relevant for events that occur further into the future. For simplicity of exposition, we make the extreme assumption that the information revealed at disclosure affects only the cash flow shock one period later, i.e. it is relevant for events that occur one period later only.

Denote $\sigma = \mathrm{Var}(\xi'_{1,t_0+1}) / \mathrm{Var}(\xi_{1,t_0+1}) < 1$. This parameter measures how much information is revealed early regarding the cash flow shock one period later – the lower is σ, the less is the residual uncertainty regarding the innovation that is revealed at t_0+1, i.e., the greater is the information content of the disclosure at t_0.

We are now ready to compare the effect of the change in disclosure policy at t_0 on stock return synchronicity.

<u>Proposition 1(a)</u>.

(i) *The proportion of the realized variation in period t_0 (i.e. between t_0 and t_0+1) explained by market factors is higher for a firm that experience an improvement in disclosure at t_0 than one that does not.*

(ii) *The proportion of realized variation explained by market factors for period t_0-1 is less for a firm that experiences an improvement in disclosure policy than one that does not.*

Proof: (Appendix A)

Lumpy information disclosure consists of a one-time early disclosure of new information that otherwise would have been revealed later. When the information is revealed and impounded into stock prices, the return synchronicity will decrease. However, the return synchronicity will increase subsequently – there is less information content to later announcements since part of the information is already impounded in the stock price.

A.2. Regular Early Disclosure of Information

One notion of transparency is simply that news is announced in a timely manner, so that the surprise component from future events is lower. To formalize this notion of transparency, we assume that at the beginning of *every period*, there is some disclosure that reduces the variance of the cash flow shock revealed to the public at the end of the period. More formally, we assume

(10.1) a) $\xi_{1,t+1} = \xi'_{1,t+1} + \delta_{t+1}$ for all t

(10.2) b) $E(\xi'_{t+1} \mid \delta_{t+1}) = 0.$

and

(10.3) *c)* $\dfrac{\mathrm{Var}(\xi'_{t+1})}{\mathrm{Var}(\xi_{t+1})} = \sigma < 1.$

We then have the following:

Proposition 1(b). *Suppose the risk-free rate is strictly positive, and the transparency improves in the sense that every period, some* δ_{t+1} *is revealed to outsiders, where* δ_{t+1} *satisfies equations (10.1) - (10.3). Then the stock return synchronicity every period is strictly higher than that of an otherwise identical firm that does not experience an improvement in transparency.*

Proof: (Appendix A).

The result that the return synchronicity actually increases in this case may be somewhat surprising. Each period, some of the information affecting the cash flow innovation is disclosed early and reduces the subsequent "surprise"; however, a new piece of information relevant for the cash flow innovation still one period later is revealed at the end of the period. Why do these two effects not wash each other out completely? The reason is that the information revealed at the end of the period regarding the cash flow innovation still one period later is discounted relative to the information revealed at the beginning of the period, since the former is relevant for a more distant cash flow. Thus, the return synchronicity is higher.[7]

[7] See Peng and Xiong (2006, p.577), for a very similar result illustrating the effect of early arrival of information and discounting.

B. Disclosure of Time-invariant Information about Firm Characteristics

We next show that disclosure that conveys information about time-invariant firm characteristics such as managerial ability can also raise return synchronicity. The intuition is that if managerial ability has to be inferred – for example, on the basis of observable cash flows – then the value of the firm will fluctuate more due to observable cash flow shocks, compared to a situation where managerial quality is already known to the market on account of greater transparency and disclosure. Consequently, the proportion of the overall variation in returns that is explained by market factors will be lower for a less transparent firm.[8] Unlike the case of a one-time early disclosure of information that would have come out later, the effect of this type of disclosure on return synchronicity is likely to be more durable.

To formally demonstrate how the return synchronicity can increase, assume that $\theta_{1,0}$ in equation (4) represents some firm-specific characteristic (such as managerial quality). The true value of $\theta_{1,0}$ is not known to the market , which only knows that it is drawn from some distribution. Moreover, define the information set I_t to include the entire history of the realizations of $(f_t, \theta_{1,t})$. We the have the following:

Proposition 2. *Fix a history* $\langle (f_{t'}, \theta_{1,t'}) : t' \leq t \rangle$ *up to time t. The proportion of the realized variation explained by the market factor in period t will be higher if* $\theta_{1,0}$ *is revealed to the market at any time prior to t than if it is not.*

Proof: (Appendix A).

[8] West (1988) considers a very general framework that has a similar implication. Suppose that I_1 and I_2 are two information sets and I_1 is a subset of I_2. West shows that the forecast of the present discounted value of dividends will be revised more often if the forecast is made on the basis of I_1 rather than I_2.

To summarize, the nature of disclosure associated with an improvement in transparency can take different forms. As in Jin and Myers (2006), it can take the form of more firm-specific information being revealed to outsiders on a regular basis, in which case the return synchronicity will decrease. Alternatively and as we show in this section, it can also be associated with either early disclosure of time-varying firm specific information, or disclosure of time-invariant information about firm characteristics, which may cause return synchronicity to *increase*. In particular, for lumpy information disclosure, return synchronicity will first decrease when new information is impounded in stock prices, but increase subsequently. This dynamic behavior of return synchronicity around lumpy disclosure events is what we attempt to capture in our empirical analysis in the subsequent section.

IV. Empirical Evidence

This section provides evidence consistent with the theory outlined above, in three different settings. The first explores the effect of variation in the information environment as proxied by firm age. The other two correspond to discrete changes in the information environment due to seasoned equity offerings and cross listings.

Since the theory is about return variation that can be explained by the market factors (holding total return variation constant), in our empirical exercises we (inversely) measure stock return synchronicity using log(1- R^2). The advantage of this measure is that it is equivalent to firm-specific return variation or the log of "Sum of Squares of Errors" (SSE) (LSSE hereafter) when log of total return variation (SST) is controlled for.[9] Results based on R^2 as a measure of return synchronicity are qualitatively the same and are not reported for brevity.

A. Stock Return Synchronicity and Firm Age

We now examine the relation between R^2 and firm age to provide evidence of learning about time-invariant firm-specific information. As a firm becomes older, the market learns more about time-invariant firm characteristics, e.g., the firm's intrinsic quality. Thus stock return synchronicity should be higher for older firms.

We first examine the relation between R^2 and firm age by estimating the following basic model:

$$\log(1-R^2)_{i,t} = \alpha + \beta \text{Age}_{i,t} + \gamma \text{Firm Controls}_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t}, \tag{11}$$

where i indexes firms and t indexes years. The dependent variable is based on R^2 estimated from a market model (see Appendix B for details), and, as discussed earlier, is equivalent to firm specific return variation (LSSE). Age is the firm age since IPO. Firm Controls include those commonly used in the literature, namely, firm size (defined as the natural logarithm of assets), Market-to-book (defined as the ratio of market value of equity plus the book value of debt over total assets), leverage (defined as book value of long-term debt over total assets), return on assets (defined as operating income before depreciation over total assets), as well as beta. η_i are firm fixed effects which controls for time-invariant unobserved firm characteristics. δ_t are year fixed effects which control for macro economic changes. In all regressions, we control for the log of

[9] This comes from a direct transformation from R^2 (a ratio variable) to SSE (a level variable). In particular, log $(1-R^2)$ = log(SSE) – log (SST), where SST is total variation.

the total variation of the firm's stock return. Since information disclosed during IPO can still affect R^2 in the years immediately after the IPO year, we require that firm-years in our sample are at least three years after the IPO year.

Table 1 presents the summary statistics of the main variables. Consistent with learning about time-invariant information, older firms tend to have significantly higher R^2 (lower LSSE) than do younger firms, both in terms of the mean and the median (significant at the 1% levels). Older firms tend to be bigger, more leveraged, and more profitable. They have lower beta and lower Q.

[Insert Table 1 here]

The regression results are reported in column (1) in Panel A of Table 2. Consistent with our univariate analysis, firm age is associated with significantly higher R^2 (and thus lower LSSE), at the 1% levels, reflecting learning about the time-invariant information. Market-to-book and leverage have negative (positive) effects on R^2 (LSSE), whereas higher beta, larger size and higher profitability increases R^2 at the 1% level.

[Insert Table 2 here]

One potential alternative explanation of our results is that the standard market model is not the correct asset pricing model for firm-level returns. For example, our measure of R^2 does not include industry-wide return variation. Thus it is possible that our age effect is driven by a time-varying industry effect. Therefore, we follow Roll (1988), Piotroski and Roulstone (2004), Durnev, Morck, Yeung, and Zarowin (2003), and Durnev, Morck, and Yeung (2004) by adding industry returns in the standard market model regression. The results remain qualitatively unchanged (column (2) in Panel A of Table 2). To further address the concern that our age effects are simply picking up missing risk factors, we estimate R^2 based on Fama-French three-factor model and a four-factor (including momentum) model and include the firm-specific factor loadings as independent variables in our regressions (see Appendix B for details on the construction of these variables). Inclusion of additional risk factors do not change the age effect on return synchronicity (columns (3) and (4) of Panel A in Table 2).

Another alternative interpretation of the age effect is that firm fundamentals are more stable and, therefore, co-move more for older companies. Indeed, if the fundamentals of older firms co-move more either with market or industry, then one would observe a higher R^2 even without "learning." We thus follow MYY (2000) and Durnev et al. (2004) to control for ROA co-movement within three-digit SIC code (see Appendix B for details). The coefficient on idiosyncratic ROA movement is significantly positive, consistent with the conjecture that with greater fundamentals co-movements, stock prices also tends to co-move more (columns (5)-(8) in Panel A of Table 2). However, our age effects remain unchanged.

In Panel B of Table 2, we examine whether some additional firm characteristics, other than those commonly used in the literature, might drive the age effect. One such firm characteristic is diversification. Older firms tend to be larger and more diversified sectorally. Thus they are more like portfolios and it is well known that diversified portfolios are much more correlated than individual stocks with broad market indices. Indeed as shown in columns (1)-(4) in Panel B of Table 1, diversified firms are older and tend to have lower firm-specific return volatility (both differences significant at the 1% level). To ensure that we do not simply pick up a diversification effect, we control for whether or not the firms has multiple segments as reported in COMPUSTAT.[10] As shown in columns (1)-(4) in Panel B of Table 2, Diversification is significantly associated with higher R^2 or low LSSE (at the 5% level).[11] However, diversification does not drive out our age effect.[12] Finally, since diversified firms tend to be more mature and stable, we further add idiosyncratic ROA movement in the estimation (columns (5)-(8) of Panel B in Table 2). Our age effects remain qualitatively unchanged. Both diversification and idiosyncratic ROA movement effects are significant, suggesting that they each have independent influence on return synchronicity.

In addition to our analysis of the age effect on return synchronicity, there is evidence that the information content of news announcements is lower for older firms. Dubinsky and Johannes (2006) develop a numerical method to extract a measure of the "surprise" content from the earnings announcements using options-implied earnings jump volatility. In particular, two options expiring right before and after the announcement dates are used. From the implied volatility of both options one can back out the volatility attributable to the jump on earnings announcement. Based on a sample of firms that have liquid option trading for 1998-2004, one can regress option-implied earnings jump volatility on age and a set of controls. As plotted in Figure 1, the option implied earnings jump volatility is strongly (negatively) related to firm age, implying that the new information content is larger for younger firms.[13]

[Insert Figure 1 here]

[10] The results are robust to some other standard diversification measures in the literature, including the number of segments and Hirfindahl indices based on segment sales and assets, both in terms of the signs of coefficient estimates and their statistical significance (unreported).
[11] We note that adding the diversification measure results in a reduced sample size. This is because our initial sample starts from 1976, whereas COMPUSTAT segment information is available only after 1979.
[12] When we include an interaction term between diversification and age, this interaction is not significant, suggesting that the age effect does not vary across diversified and single-segment firms. In the interest of brevity, this result is not reported but is available upon request.
[13] We thank Wei Jiang and Mike Johannes for providing us the chart based on their project that analyzes the information property of the Dubinsky and Johaness (2006) measure.

B. Stock Return Synchronicity (R^2) and Seasoned Equity Offerings (SEOs)

As discussed earlier, our point about the dynamic effect of the information environment on return synchronicity is best illustrated in cases where the information disclosure is lumpy. One such setting is seasoned equity offerings (SEOs). SEOs are infrequent events that attract market attention and scrutiny, resulting in disclosure of a substantial chunk of new information. Most U.S. equity issuers choose a traditional market offering as a method of issuing seasoned equity.[14] Typically, the issuer goes through a process of book building and road shows much as in an initial public offering. During the road show, the issuing firm explains to potential investors the changes in the company – for example, why it is raising funds now – and thus reveals considerable new firm-specific information.[15] In addition, underwriters are likely to produce information as part of their "due diligence". The information may also be generated by new investors if the process of equity issuance temporarily makes the stock more liquid.

B.1. Empirical Specification

To capture the inter-temporal response of R^2 around SEOs, we pursue a specification that imposes very little structure on the response dynamics. Specifically, we include dummy variables for the year of SEO, for 1 and 2 years after SEO, as well as for the years immediately prior to SEO. These variables should identify the response function of R^2 to the passage of time around

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[14] In the U.S., especially after 1997, many issuers can now also choose to do accelerated offerings rather than traditional marketed offerings. These include accelerated book building (where they only do a one or two day road show or, more often, just a conference call the day before the offering) and block trades, which are similar to sealed bid auctions. However, the traditional method is almost always followed for large offerings.

[15] At the time of information revelation, it is also possible managers may have incentives to increase earnings before and around the time of securities issues (Teoh, Welch, and Wong (1998a) and (1998b)), which may reduce firm-specific return volatility. Thus earnings smoothing would bias against our results, by raising R^2 prior to ADR or SEO events.

SEO. In particular, we estimate the following model on a panel of CRSP firms during 1976-2004 (see Appendix B for details on sample construction):

(12)

$$\log(1-R^2)_{i,t} = \alpha + \sum_k \beta_k \text{ (SEO has occured } k \text{ periods earlier)}_{i,t} + \gamma \text{Firm Controls}_{\text{i,t}} + \eta_i + \delta_t + \varepsilon_{i,t}$$

For the dummy variables indicating SEO has occurred k periods earlier", $k \in \{-1,0,+1\}$, where k = -1 denotes 1-2 years *prior* to SEO, k = 0 denotes the year of SEO, and k = +1 denotes 1-2 years after SEO. Firm controls consist of the same set of variables as in Table 2, namely betas, size, leverage, ROA, and Market-to-book. η_i and δ_t are firm and year fixed effects, respectively.

The β_k's are the coefficients of interest and we test the following hypotheses. Hypothesis 1 derives directly from the first part of Proposition (1a). Hypothesis 2 derives from the second part of Proposition (1a).[16]

Hypothesis 1. To the extent that there is lumpy and early information disclosed at or before the SEO, R^2 should be higher subsequent to the offering. That is, $\beta_k < 0$ for some $k>0$.

Hypothesis 2. To the extent that lumpy information is disclosed prior to or at the SEO, the R^2 would be lower at the time of disclosure. That is, we expect $\beta_k > 0$ for some $k \leq 0$.

[16] We note that in the context of SEOs the relative importance of time-invariant information disclosure may not be significant as in some other contexts such as cross-listings (which will be discussed later) or IPOs. Therefore we do not expect the effect of information disclosure to persist. Indeed, when we experiment with alternative specifications with longer horizons, we do not find any significant effects beyond two years.

One concern about empirical identification of the SEO effects is the potential self-selection of SEOs. That is, SEOs are not randomly assigned; there might be unobserved firm characteristics that simultaneously affect the SEO decisions and return synchronicity. In this paper, we explicitly address this concern in three ways. First, we are not relying on a simple regression of R^2 on an SEO dummy. Rather we focus on a non-monotonic dynamic response of return synchronicity to the SEO. For the self-selection argument to work, it has to be the case that certain SEO-related firm characteristics can influence R^2 in both positive and negative directions *and* that such influences change over time in the exactly same way as our proposed dynamics in SEO effects. This, however, is by no means obvious.

Second, we include firm-fixed effects in all our estimations. This "within-variation" specification effectively tracks the *same* firm before and after its SEO. Thus, to the extent that some time-invariant firm characteristics affect the SEO decisions, these are completely controlled for. Moreover, we include in our regressions (time-varying) firm-level control variables that could potentially affect return synchronicity and SEO decisions, such as size, profitability, Market-to-book, and leverage.

B.2. Results

Panel C of Table 1 presents the summary statistics of our sample. Compared to non-SEO firm-years, SEO firm-years differ in almost all firm characteristics, suggesting that firm characteristics need to be controlled for in our later analysis.

Table 3 reports the regression results. Column (1) in Table 3 is a naïve regression of $1-R^2$ on a dummy variable indicating 1-2 years immediately after a SEO. The coefficient on the post-SEO dummy is significantly negative at the 1% level. That is, contrary to the conventional wisdom, SEO (and presumably greater transparency) is associated with less firm-specific return variation in the years immediately after the offering.

[Insert Table 3 here]

While the above result is consistent with our conjecture that, when the lumpy information is disclosed, there is less surprise afterwards, the specification does not consider the possible inter-temporal effects of lumpy disclosure. Therefore, in columns (2)-(5) of Table 3, we introduce the dynamic response of R^2 as specified in equation (12). Consistent with Hypotheses 1 and 2, R^2 is lower prior to SEO, and increases subsequently (significant at the 10% level or above). The impacts of other firm control variables are similar to those in Table 2.

We plot the R^2 dynamics in Figure 2 (Panel A), which reflects point estimates in column (3) of Table 3 based on industry-augmented market model. We start with the R^2 during "normal" times (non-SEO firm years), which is 0.17. Coefficients β_k translates into R^2 that are about one percentage point lower before an SEO and one percentage point higher during SEO year and one-to-two years afterwards.

[Insert Figure 2 here]

C. Firm-Specific Return Variation and Cross Listings

We now explore the dynamic response to another lumpy information disclosure event, namely ADR listings. We use a very similar specification to the one for SEOs. ADR listings are likely to be bigger information events than SEOs, as the listing firms need to, in addition to the usual disclosure, comply with SEC regulations which typically require more disclosure than exchanges in their home countries. Thus the effects of ADR listings are likely to happen earlier, starting as soon as the firms begin to prepare disclosure and accounts for the listings, and last longer. This is because, first, the lumpier disclosure may remove more uncertainty about time-invariant attributes such as managerial ability, and second, the disclosure environment subsequent to ADR listing may change to one that involves continued early regular disclosure. Then according to our Proposition 1(b) and Proposition 2, the return synchronicity may continue to be higher. However, exactly how long the positive ADR effect lasts is an empirical matter.

Thus we estimate the following model:

(13)

$$\log(1-R^2)_{i,t} = \alpha + \sum_k \beta_k \text{ ADR listing occured } k \text{ periods ago}_{i,t} + \gamma \text{Firm Controls}_{\text{i,t}} + \eta_i + \delta_t + \varepsilon_{i,t}.$$

For the dummy variables indicating ADR listing had occurred *k* periods earlier, we consider *k* = -2, -1, 0, +1 and +2. In particular, *k* = -2 and *k* = -1 correspond to years 3-4 and 1-2 before listing, *k* = 0 corresponds to the year of listing, and *k* = +1 to +4 correspond to years 1-3, 4-6, 7-9, and more than 10 years after listing. Firm controls consist of the same set of variables as in equation (12), namely betas (home beta and U.S. beta), size, leverage, ROA, and Market-to-book. We address the concern of self-selection of ADR listings in a similar manner to the SEOs. In particular, we focus on the non-monotonic dynamic response of return synchronicity to the ADR listing. η_i are firm-fixed effects which control for time-invariant firm characteristics that might have affected the ADR decisions. δ_t are year fixed effects.

Table 4 provides the descriptive statistics for our sample. Compared to non-ADR firm-years, in ADR firm-years (i.e. a year in which an international firm has an active ADR), firms tend to have significantly higher R^2, larger size, higher Market-to-book, and higher leverage (at the 1% levels).[17] Interestingly, the ADR firm-years tend to have lower profitability measured by ROA in mean but not in median. Since in ADR firm-years, firms on average are more levered, the lower ROA in mean could be due to higher leverage.

[Insert Table 4 here]

Multivariate analysis is presented in Table 5.[18] Again Column (1) of Table 5 is a naïve regression of 1-R^2 on the ADR dummy indicating whether or not the firm has an ADR listing. It shows that ADR listing (and presumably greater transparency) is associated with significantly less firm-specific information in the stock prices (at the 1% level), contrary to the conventional wisdom.[19] Column (2) of Table 5 examines the dynamic responses of R^2. Consistent with our model's predictions, ADRs are associated with a persistent drop in firm specific information in stock prices (i.e., higher R^2) in the years after the listings. The coefficients on dummies indicating years prior to the ADR listings are significantly positive (at the 1% level), implying

[17] We note that LSSE does not differ significantly across the two groups. This is not surprising since meaningful comparison of LSSE can only be made when the total return variation is controlled for.
[18] Here we do not use Fama-French three-factor model or a four-factor model, since there is evidence in the asset pricing literature that the size and book-to-market factors do not work very well for at least some international stocks (e.g., European or Japanese stocks).
[19] We note that this result is quite different from a contemporaneous paper by Fernandes and Ferreira (2008). The differences could be due to methodological differences: Fernandes and Ferreira (2008) measure return synchronicity using $\log[(1-R^2)/R^2]$ (which is $\log[\text{SSE}/(\text{SST}-\text{SSE})]$) and they do not control for total return variation (SST). Thus even if a variable (X) does not affect SSE, it is possible to have a significant coefficient for this variable in the regression due to its correlation with SST. This is because $d\log[\text{SSE}/(\text{SST}-\text{SSE})]/dX = [\text{SST}/\text{SSE}(\text{SST}-\text{SSE})]d\text{SSE}/dX - [1/(\text{SST}-\text{SSE})]d\text{SST}/dX$, which is not zero even if $d\text{SSE}/dX = 0$.

that more firm-specific information is impounded in the stock prices at the time of disclosure. The coefficients on other control variables are similar to those in Table 3. [20]

[Insert Table 5 here]

We now examine how the interplay between institutional factors and improved information disclosure affect the return synchronicity dynamics. For share prices to reflect information, arbitrageurs need to expend resources uncovering proprietary information about the firm (Grossman (1976), and Shleifer and Vishny (1997)). Such arbitrage activity, as argued by MYY (2000), may be economically unattractive in countries with poor protection of property rights due to the influence of unpredictable political events and uncertainty about the arbitrageurs' ability to keep their trading profits. On the other hand, recent literature on international corporate governance finds that firms' incentives to disclose information and improve transparency are weaker without developed institutions. These considerations suggest that the dynamics of return synchronicity surrounding the listing of ADRs are likely to be strongest for firms from countries with strong institutions.

We divide the sample into firms from countries with better institutional development and those without, based on the good-government index constructed by Kaufmann, Kraay, and Mastruzzi (2004) (KKM (2004) hereafter).[21] Specifically, we define countries with a score above

[20] We note that some firms may cross list in countries other than the U.S. Thus our non-ADR sample may contain firms which cross-listed outside the US. To the extent that some of such cross listings are from weak law countries to countries with better disclosure requirements, our results could be weakened. As a robustness check, we drop cross listings outside the U.S. from the control sample. The results (unreported) remain qualitatively the same and are available upon request.

[21] KKM (2004) provide six indicators on institutional environment. Using the alternative indicators does not alter our results, which is not surprising since the correlations between any two indicators are over 70%. The indicators are available after 1996. Since institutional environment changes very slowly, for observations before 1996, we use the value in 1996.

zero, the median of the scores for the good-government index in KKM's (2004) sample, as those with developed institutions, and countries with a score below zero as without. Among 782 cross-listed firms, 685 are from countries with good institutional support. Results in columns (3) and (4) of Table 5 show that, consistent with our conjecture, the dynamic effects of ADR listings in columns (2) are driven by firms in countries with developed institutions. A chow test indicates that the difference between the two groups of countries is significant at the 1% level.

Panel B of Figure 2 shows the R^2 dynamics based on point estimates in column (2) of Table 5. We start with the R^2 during "normal" times (non-ADR firm-years), which is 0.189. R^2 is approximately four percentage points lower before ADR events and four percentage points higher afterwards. Such an effect is larger than in the case of SEO events, reflecting the more "lumpy" nature of information disclosure around ADR listings.

So far the findings correspond well with the implications of our model concerning changes in firm-specific return variation in response to a change in the information environment. We provide three pieces of evidence. First, we find that, consistent with learning about time-invariant information, return synchronicity is strongly positively related to age. Second and third, exploiting settings with lumpy information disclosure during SEO and ADR events, we find a dynamic response of return synchronicity to lumpy information disclosure. In particular, while *at the time* of information disclosure return synchronicity is lower, reflecting greater firm-specific information impounded in the stock prices, return synchronicity *after* the disclosure (and thus with greater transparency) is significantly higher.

One remaining concern is that, since SEO or ADR events can be related to other significant corporate events, it is possible that information disclosures surrounding these events, rather than SEO or ADR events themselves, lead to observed changes in return synchronicity. It is worth noting that while this hypothesis changes the interpretation of our results, it does not refute our main point that there is a dynamic pattern in return synchronicity surrounding information disclosure and that such a dynamic change is inconsistent with the conventional wisdom. Moreover, the timing of these other events has to be exactly the same as SEO/ADR events; otherwise we would not be able to observe the dynamic pattern around the latter. In fact, as we discuss earlier, this is a strength of our empirical design – it is much less likely for a predicted dynamic pattern (i.e., increased pre-event SSE and decreased post-event SSE) to arise spuriously. In an effort to distinguish between changes in return synchronicity due to other corporate events and changes due to SEO/ADR events, we control for large changes in assets, as well as their interactions with the SEO/ADR related dummies, given that significant corporate events are typically associated major changes in asset size. It turns out that these interaction terms are generally not significant and that our main results remain. In the interest of brevity we do not report these results but they are available upon request.

V. Conclusion

Existing literature has taken the perspective that if a firm's information environment causes stock prices to reflect more firm-specific information, market factors should explain a smaller proportion of the variation in stock returns.

This paper broaches, theoretically and empirically, another perspective: that stock prices respond only to announcements that are not already anticipated by the market. When the information environment of a firm improves and more firm-specific information is available, market participants are able to improve their predictions about the occurrence of future firm-specific events. As a result, the surprise components of stock returns will be lower when the events are actually disclosed, and the return synchronicity will be higher.

Our empirical evidence is drawn from three different settings. First, consistent with learning about time-invariant information, return synchronicity is significantly higher for older firms. Second and third, exploiting settings with disclosure of substantial information about the firm, namely seasoned equity issues and ADR listings, we find dynamic responses of return synchronicity that are consistent with lumpy and early disclosure of information relevant for future events, as well as disclosure of information pertinent to time-invariant firm attributes that are relevant for future cash flows. In particular, return synchronicity decreases prior to these events, and increases subsequently.

Overall, we make two contributions to the literature. First, by showing both theoretically and empirically that stock return synchronicity can increase with improved firm transparency, we highlight the importance of understanding the nature of information discovery and the dynamics of response of stock return synchronicity to changes in information environment. Second, our analysis adds to the growing body of literature on information disclosure around security issuance events.

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Appendices

A. Proofs

Proof of Proposition 1(a).

At t_0 , the investors' information set is $I_{t_0} \equiv \{f_{t_0}, \theta_{1,t_0}, \delta_{t_0+1}\}$, whereas for any $t \neq t_{t_0}$, $I_t \equiv \{f_t, \theta_{1,t}\}$

From (2)-(5), we can write

(A-1) $$X_{t+1} = X_0 + \phi X_t + \lambda_{t+1}$$

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

Step 1.

We can write

$C_{t+1} = K_0(X_0 + \phi X_t + \lambda_{t+1}) = K_0 X_0 + K_0 \phi X_t + K_0 \cdot \lambda_{t+1}$, and for arbitrary $k \geq 1$

$C_{t+k} = K_0(1+\phi+\phi^2+...+\phi^{k-1}) \cdot X_0 + K_0 \phi^k X_t + K_0(\lambda_{t+k} + \phi\lambda_{t+k-1} + ... + \phi^{k-1}\lambda_{t+1})$.

Notice that $\lambda_{t+k} = \varepsilon_{t+k} + \xi_{1,t+k} + \xi_{2,t+k}$. For $t = t_0$ and $k = 1$, we have

$$\lambda_{t_0+1} = \varepsilon_{t_0+1} + \xi'_{1,t_0+1} + \delta_{t_0+1} + \xi_{2,t_0+1}.$$

Thus $$E(C_{t_0+k} \mid C_{t_0}, \delta_{t_0+1}) = K_0 \frac{1-\phi^k}{1-\phi} \cdot X_0 + \phi^k K_0 X_{t_0} + K_0 \phi^{k-1} \delta_{t_0+1}$$

and

(A-2) $$E(C_{t_0+k} \mid \theta_{1,t_0}, f_{t_0}, \delta_{t_0+1}) = K_0 \frac{1-\phi^k}{1-\phi} \cdot X_0 + \phi^k K_0 (f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) + K_0 \phi^{k-1} \delta_{t_0+1}$$

where we use the fact that, for any t,

(A-3) $$E(X_t \mid I_t) = f_t + \theta_{1t} + \frac{\theta_{2,0}}{1-\phi}.$$

For any other $t > t_0$,

(A-4) $$E(C_{t+k} \mid \theta_{1,t}, f_t) = K_0 \frac{1-\phi^k}{1-\phi} \cdot X_0 + \phi^k (f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi}) K_0 .$$

<u>Step 2.</u>

The intrinsic value of the firm to the investors at t_0 is:

(A-5) $$\begin{aligned} K_{t_0}(\theta_{1,t_0}, f_{t_0}, \delta_{t_0+1}) &= \sum_{k=1}^{\infty} \frac{E(C_{t_0+k} \mid I_{t_0})}{(1+r)^k} \\ &= \frac{K_0 X_0}{1-\phi} \cdot \frac{1}{r} - \frac{K_0 X_0}{1-\phi} \cdot \frac{\phi}{1+r-\phi} + \frac{K_0 \phi}{1+r-\phi}(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) + \frac{K_0}{1+r-\phi} \delta_{t_0+1} \\ &= \frac{K_0 X_0 (1+r)}{r(1+r-\phi)} + \frac{K_0 \phi}{1+r-\phi}(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) + \frac{K_0}{1+r-\phi} \delta_{t_0+1}. \end{aligned}$$

Similarly, for any $t \neq t_0 - 1$,

(A-6) $$K_{t+1}(I_{t+1}) = \frac{K_0 X_0 (1+r)}{r(1+r-\phi)} + \frac{K_0 \phi}{1+r-\phi}(f_{t+1} + \theta_{1,t+1} + \frac{\theta_{2,0}}{1-\phi}).$$

Thus, for $t \neq t_0 - 1$, using (A-3), we have

(A-7) $$K_{t+1}(I_{t+1}) + E(C_{t+1} \mid I_{t+1}) = \frac{K_0 X_0 (1+r)}{r(1+r-\phi)} + \frac{K_0(1+r)}{1+r-\phi}(f_{t+1} + \theta_{1,t+1} + \frac{\theta_{2,0}}{1-\phi}).$$

<u>Step 3</u>.

Denote by r_t the realized return in period t. From (7) and (8),

$$r_t = \frac{\alpha K_{t+1}(I_{t+1}) + \alpha E(C_{t+1} \mid I_{t+1})}{\alpha K_t(I_t)} - 1.$$

Substituting from (A-6), and (A-7), for $t \neq t_0$ and $t \neq t_0 - 1$,

(A-8) $$r_t = \frac{\frac{(1+r)K_0}{1+r-\phi}(f_{t+1} + \theta_{1,t+1} + \frac{\theta_{2,0}}{1-\phi}) - \frac{K_0\phi}{1+r-\phi}(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi})}{\frac{K_0 X_0(1+r)}{r(1+r-\phi)} + \frac{K_0\phi}{1+r-\phi}(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi})},$$

whereas for $t = t_0$, using (A-5) and (A-7), we have

(A-9) $$r_t = \frac{\frac{(1+r)K_0}{1+r-\phi}(f_{t_0+1} + \theta_{1,t_0+1} + \frac{\theta_{2,0}}{1-\phi}) - \frac{K_0\phi}{1+r-\phi}(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) - \frac{K_0}{1+r-\phi}\delta_{t_0+1}}{\frac{K_0 X_0(1+r)}{r(1+r-\phi)} + \frac{K_0\phi}{1+r-\phi}(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) + \frac{K_0}{1+r-\phi}\cdot\delta_{t_0+1}}$$

and for $t = t_0 - 1,$ using (A-5) and (A-7), we have

(A-10) $$r_{t_0-1} = \frac{\frac{K_0(1+r)}{1+r-\phi}(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) + \frac{K_0}{1+r-\phi}\cdot\delta_{t_0+1} - \frac{\phi K_0}{1+r-\phi}(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi})}{\frac{K_0 X_0(1+r)}{r(1+r-\phi)} + \frac{\phi K_0}{1+r-\phi}(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi})}.$$

Consider (A-9) first. We can write the right-hand-side as

$$r+\frac{\alpha_0}{\frac{X_0(1+r)}{r}+\phi(f_{t_0}+\theta_{1,t_0}+\frac{\theta_{2,0}}{1-\phi})+\delta_{t_0+1}}$$, where

$$\alpha_0=-X_0(1+r)-r\phi(f_{t_0}+\theta_{1,t_0}+\frac{\theta_{2,0}}{1-\phi})-r\delta_{t_0+1}+(1+r)(f_{t_0+1}+\theta_{1,t_0+1}+\frac{\theta_{2,0}}{1-\phi})$$
$$-\phi(f_{t_0}+\theta_{1,t_0}+\frac{\theta_{2,0}}{1-\phi})-\delta_{t_0+1}$$
$$=-X_0(1+r)+(1+r)(f_{t_0+1}-\phi f_{t_0}+\theta_{1,t_0+1}-\phi\theta_{1,t_0}+\frac{\theta_{2,0}}{1-\phi}-\frac{\phi\theta_{2,0}}{1-\phi})-(1+r)\delta_{t_0+1}$$
$$=-X_0(1+r)+(1+r)(f_0+\varepsilon_{t_0+1}+\theta_{1,0}+\xi_{1,t_0+1}+\theta_{2,0})-(1+r)\delta_{t_0+1}$$
$$=(1+r)(\varepsilon_{t_0+1}+\xi'_{1,t_0+1}).$$

Thus,

$$r_{t_0}=r+\frac{(1+r)(\varepsilon_{t_0+1}+\xi'_{1,t_0+1})}{\frac{X_0(1+r)}{r}+\phi(f_{t_0}+\theta_{1,t_0}+\frac{\theta_{2,0}}{1-\phi})+\delta_{t_0+1}}.$$

Hence, the proportion of the return variation explained by market factor is

$$R^2_{t_0}=\frac{\mathrm{Var}(\varepsilon_{t_0+1})}{\mathrm{Var}(\varepsilon_{t_0+1})+\mathrm{Var}(\xi'_{1.t_0+1})}=\frac{1}{1+\frac{\mathrm{Var}(\xi'_{1,t_0+1})}{\mathrm{Var}(\varepsilon_{t_0+1})}}$$

(A-11)
$$=\frac{1}{1+\frac{\mathrm{Var}(\xi'_{1,t_0+1})}{\mathrm{Var}(\xi_{1,t_0+1})}\cdot\frac{\mathrm{Var}(\xi_{1,t_0+1})}{\mathrm{Var}(\xi_{1,t_0+1})+\mathrm{Var}(\xi_{2,t_0+1})}\cdot\frac{\mathrm{Var}(\xi_{1,t_0+1})+\mathrm{Var}(\xi_{2,t_0+1})}{\mathrm{Var}(\varepsilon_{t_0+1})}}$$
$$=\frac{1}{1+\sigma\cdot\eta\cdot\kappa}>\frac{1}{1+\eta\kappa}.$$

Next, consider (A-10). Proceeding exactly similarly,

$$r_{t_0-1} = r + \frac{\alpha_1}{\frac{X_0(1+r)}{r} + \phi(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi})},$$

where

$$\begin{aligned}
\alpha_1 &= -X_0(1+r) - \phi r(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi}) + (1+r)(f_{t_0} + \theta_{1,t_0} + \frac{\theta_{2,0}}{1-\phi}) \\
&\quad + \delta_{t_0+1} - \phi(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi}) \\
&= -X_0(1+r) + (1+r)(f_{t_0} - \phi f_{t_0-1} + \theta_{1,t_0} - \phi\theta_{1,t_0-1} + \theta_{2,0}) + \delta_{t_0+1} \\
&= (1+r)(\varepsilon_{t_0} + \xi_{1,t_0}) + \delta_{t_0+1}.
\end{aligned}$$

Thus

$$r_{t_0-1} = r + \frac{(1+r)(\varepsilon_{t_0} + \xi_{1,t_0}) + \delta_{t_0+1}}{\frac{X_0(1+r)}{r} + \phi(f_{t_0-1} + \theta_{1,t_0-1} + \frac{\theta_{2,0}}{1-\phi})}.$$

Hence,

$$\begin{aligned}
R^2_{t_0-1} &= \frac{(1+r)^2 \operatorname{Var}(\varepsilon_{t_0})}{(1+r)^2 \operatorname{Var}(\varepsilon_{t_0}) + (1+r)^2 \operatorname{Var}(\xi_{1,t_0}) + \operatorname{Var}(\delta_{t_0+1})} \\
&= \frac{1}{1 + \frac{\operatorname{Var}(\xi_{1,t_0})}{\operatorname{Var}(\varepsilon_{t_0})} + \frac{1}{(1+r)^2} \cdot \frac{\operatorname{Var}(\delta_{t_0+1})}{\operatorname{Var}(\varepsilon_{t_0})}} \qquad \text{(A-12)} \\
&< \frac{1}{1+\eta\kappa}.
\end{aligned}$$

Finally, proceeding as above, for any $t \neq t_0$ or $t \neq t_0 - 1$ – or equivalently, for any t for a firm that does not experience a disclosure event – we have

(A-13) $$r_t = r + \frac{(1+r)(\varepsilon_{t+1} + \xi_{1,t+1})}{\frac{X_0(1+r)}{r} + \phi(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi})}$$

so that

(A-14) $$R_t^2 = \frac{1}{1+\eta \cdot \kappa}.$$

Comparing (A-11), (A-12) and (A-14), the results follow. (Q.E.D)

Proof of Proposition 1(b).

Here, the information set of the outsiders at the beginning of every period t is $I_t = \{f_t, \theta_{1t,} \delta_{t+1}\}$.

Following steps similar to step 1 in the proof of Proposition 1(a), we get

$$E(C_{t+k} \mid \theta_{1,t}, f_t, \delta_{t+1}) = K_0 \frac{1-\phi^k}{1-\phi} \cdot X_0 + \phi^k K_0 (f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi}) + K_0 \phi^{k-1} \delta_{t+1}$$

Hence,

$$K_t(I_t) = \frac{K_0 X_0 (1+r)}{r(1+r-\phi)} + \frac{K_0 \phi}{1+r-\phi}(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi}) + \frac{K_0 \delta_{t+1}}{1+r-\phi}$$

and

$$K_t(I_t)+E(C_t \mid I_t)=\frac{K_0 X_0(1+r)}{r(1+r-\phi)}+\frac{K_0(1+r)}{1+r-\phi}(f_t+\phi_{1,t}+\frac{\theta_{2,0}}{1-\phi})+\frac{K_0\delta_{t+1}}{1+r-\phi}.$$

Proceeding exactly as before, we get

$$r_t = r+\frac{(1+r)(\varepsilon_{t+1}+\xi^{'}_{t+1})+\delta_{t+2}}{\frac{X_0(1+r)}{r}+\phi(f_t+\theta_{1,t}+\frac{\theta_{2,0}}{1-\phi})+\delta_{t+1}}.$$

Hence,

$$R_t^2=\frac{(1+r)^2\,\mathrm{Var}(\varepsilon_{t+1})}{(1+r)^2\left(\mathrm{Var}(\varepsilon_{t+1})+\mathrm{Var}(\xi^{'}_{t+1})\right)+\mathrm{Var}(\delta_{t+2})}$$

$$=\frac{(1+r)^2\,\mathrm{Var}(\varepsilon_{t+1})}{(1+r)^2\,\mathrm{Var}(\varepsilon_{t+1})+(1+r)^2\,\mathrm{Var}(\xi_{t+1})-(1+r)^2\,\mathrm{Var}(\delta_{t+1})+\mathrm{Var}(\delta_{t+2})}.$$

Since $\mathrm{Var}(\delta_{t+1})=\mathrm{Var}(\delta_{t+2})$, it follows that $R_t^2>\frac{\mathrm{Var}(\varepsilon_{t+1})}{\mathrm{Var}(\varepsilon_{t+1})+\mathrm{Var}(\xi_{t+1})}$, which is the return synchronicity for a firm with no early information disclosure.

(Q.E.D)

Proof of Proposition 2.

When the true value of $\theta_{1,0}$ is already revealed, the analysis of Proposition 1(a) applies, and the realized return is given by equation (A-13).

Suppose $\theta_{1,0}$ is not revealed, but the market at each t updates its expectation about $\theta_{1,0}$ from the realized values of $\theta_{1,t}$ for $t' \le t$. Let the posterior mean estimate of $\theta_{1,0}$ at t be $E(\theta_{1,0} \mid I_t) = \theta_{1,0}^t$. Conditional on the information set I_t (which now includes the entire history of the realizations of (f_t, $\theta_{1,t}$)), the expected value of $X_0 = f_0 + \theta_{1,0} + \theta_{2,0}$ computed with respected to the posterior distribution of $\theta_{1,0}$ is $X_0(t) = f_0 + \theta^t{}_{1,0} + \theta_{2,0}$. Proceeding exactly as in the proof of Proposition 1(a), we get:

(A-15)
$$r_t = r + \frac{\frac{(1+r)}{1+r-\phi}(\theta_{1,0}^{t+1} - \theta_{1,0}^t) + (1+r)(\varepsilon_{t+1} + \xi_{1,t+1})}{\frac{X_0(t)(1+r)}{r} + \phi(f_t + \theta_{1,t} + \frac{\theta_{2,0}}{1-\phi})}.$$

The result therefore follows immediately from a comparison of equations (A-13) and (A-15), because conditional on I_t, $\theta_{1,0}^{t+1}$ is a random variable whose value will depend on the realization of $\theta_{1,t+1}$; hence, it has a positive variance. (Q.E.D.)

B. Data Construction

B.1. Computation of R^2 (or LSSE)

R^2 is first computed based on the method proposed in MYY (2000). For the empirical analysis of the U.S. CRSP firms in Sections IV.A. and IV.B., we run the following model using weekly returns for each firm in *each* year:

(B-1) $$r_{it} = a_i + b_i r_{m,t} + \varepsilon_{it}$$

where i, t index firms and weeks, respectively. $r_{m,t}$ is the U.S. market index return defined as the value-weighted returns of all CRSP firms. To mitigate the thin-trading problem, we follow Jin and Myers (2006) and estimate the model using weekly returns (Wednesday close to Wednesday close). LSSE is log of the Sum of Squared Errors from the regressions. Since the regressions are run for each firm in each year, our estimates of market beta and R^2 (or LSSE) are annual variables for each firm.

For each firm in each year, we also estimate its R^2 or LSSE from the Fama-French three factor model and a four factor model with momentum. In particular:

(B-2) $$r_{it} - r_{ft} = a_i + b_{1,i}(r_{m,t} - r_{ft}) + b_{2,i}\text{HML}_t + b_{3,i}\text{SMB}_t + \varepsilon_{it}$$

and

(B-3) $$r_{it} - r_{ft} = a_i + b_{1,i}(r_{m,t} - r_{ft}) + b_{2,i}\text{HML}_t + b_{3,i}\text{SMB}_t + b_{4,i}\text{UMD}_t + \varepsilon_{it}$$

where i, t index firms and weeks, respectively. $r_{m,t}$ is the U.S. market index return defined as the value-weighted returns of all CRSP firms. r_{ft} is the one-month treasury bill rate. We get the daily returns on HLM, SMB and UMD (momentum) from Kenneth French's website and convert them to weekly returns (Wednesday close to Wednesday close). Again the regressions are run for each firm in each year, our estimates of factor loadings, as well as R^2 (and LSSE) are annual variables for each firm.

For the empirical analysis in Section IV.C. involving international firms, we estimate the following model based on weekly returns (again Wednesday close to Wednesday close):

$$r_{it} = a_i + b_{1,i} r_{m,jt} + b_{1,i}[r_{US,t} + e_{j,t}] + \varepsilon_{it} \quad \text{(B-4)}$$

where *i*, *j*, *t* index firms, countries, and weeks, respectively. $r_{m,jt}$ is the local market index return defined as the value-weighted returns of all Datastream companies available for that country. [22] $r_{US,t}$ is the U.S. market return, which is computed from CRSP; $e_{j,t}$ is the rate of change in the exchange rate per U.S. dollar, which is obtained from Datastream and, in cases where it is missing in Datastream, from Reuters. The expression $r_{US,t} + e_{j,t}$ translates U.S. stock market returns into local currency returns.

B.2. Estimating Fundamental Co-movement

Following Durnev et al. (2004), we estimate fundamental (ROA) co-movement using the following model:

$$\mathrm{ROA}_{i,j,t} = a_{i,j} + b_{1,i,j}\mathrm{ROA}_{m,t} + b_{2,i,j}\mathrm{ROA}_{j,t} + e_{i,j,t} \quad \text{(B-5)}$$

i, *j*, *m*, *t* index firm, industry, market and year respectively. We define ROA as net income plus interest expense and depreciation over total assets. Industries are defined based on 3-digit SIC code (2-digit SIC code gives very similar results). Both Market and Industry ROAs are value-

[22] Jin and Myers (2005) require a minimum of 25 stocks. All the countries in our study have over 25 stocks except Zimbabwe, which has 16 stocks.

weighted averages excluding the firm in question. We estimate the regression for each firm in each year using the previous 6 years of data (including the current year). The log of SSE from regression (B-5) is the idiosyncratic ROA movement, which we use as additional control in Table 2.

B.3. The SEO Sample

Our initial SEO sample is retrieved from the SDC Global New Issue database. To ensure significant information disclosure, we require the issue size exceed 10 million and be at least 5% of the issuer's market value of equity. We exclude right issues because they are issued to existing shareholders and the disclosure of information would not be as intense as a public offering. We also exclude Units, shares of beneficial interest, primes and scores, closed-end fund, and REIT's. This procedure gives us 7,523 SEOs in the first instance.

We classify firm-years into SEO firm-years and non-SEO firm-years. To ensure that we do not pick up the informational effects of other confounding events, we further drop from our entire sample firm-years that are within three years before and after another SEO by the same firm, within three years after its IPO, or within three years after it changes the listing stock exchange. The SEO firm-years are defined as those firm-years that are within 2 years before or after an SEO event. The remaining are non-SEO firm-years. Thus our final sample is a panel of 12,015 firms and 89,010 firm-years, of which 2,354 firms have SEO events and 8,377 are SEO firm-years.

B.4. The ADR Sample

We start with all firms covered by the *Worldscope* database for the period 1980-2004. For a firm-year to be included in our sample we require valid information to estimate the market model in equation (B-4). We also require the firm to have relevant accounting information, the shareholders' equity above zero, an asset size more than USD 10 million (to make firms across countries comparable in size – see e.g., Doidge et al. (2004)), and at least 30 weeks of return data in Datastream for a given year (to ensure reliable estimate of return synchronicity – see MYY (2000), and Jin and Myers (2006)). We compute firm age according to the base date provided by Datastream. To avoid potentially contaminating effects of information disclosure at the time of IPO, we require the firm age to be at least four years. Consequently, we have a sample of 20,544 firms with 153,572 firm-years.

To identify cross-listed firm in the U.S., it is useful to recognize that there are two ways for a non-U.S. firm to be listed in the U.S. One is through an ADR program; the other is to directly list shares in the U.S. stock market. There are no readily available databases that provide systematic information on the identity of the cross-listed firms or the starting and ending dates of the listings. Researchers have explored different data sources to identify cross listings (e.g., Reese and Weisbach (2002), and Lang, Lins, and Miller (2003)). In this paper, we follow the approach in these previous studies.

In particular, we identify directly listed non-U.S. firms by first checking, for firms with return data in CRSP, their "countries of incorporation" in COMPUSTAT (COMPUSTAT variable FIC). If the firm is not incorporated in the U.S. and if the company name is not marked with "ADR," it is a direct listing. We then determine the effective listing dates and the termination dates based on the beginning and ending dates of return data in CRSP. We identify 583 directly listed firms, of which 378 have active listings at the end of 2004.

To identify ADR listings, we start with the information provided by major ADR sponsor institutions, namely, Bank of New York, Citibank and JP Morgan that provide a database of ADR listings. Firms may list different types of ADRs which are subject to different levels of disclosure requirement. Level II and level III ADRs are listed in the stock exchanges (NYSE, Nasdaq, AMEX), have the most strict disclosure requirement, and are subject to the closest public scrutiny (Lang, Lins, and Miller (2003), and Doidge et al. (2004)). Therefore, all else equal, the improvement in firm transparency should be more significant for Level II and III ADRs than for lower level ADRs, namely Level I and 144A/Regulation S ADRs. To preserve the power of our tests, we follow Lang, Lins, and Miller (2003) and include only Levels II and III ADRs in our sample. Moreover, as pointed out by Reese and Weisbach (2002) and Lang, Lins, and Miller (2003), the legal and informational implications of these ADRs and direct listings are essentially the same.

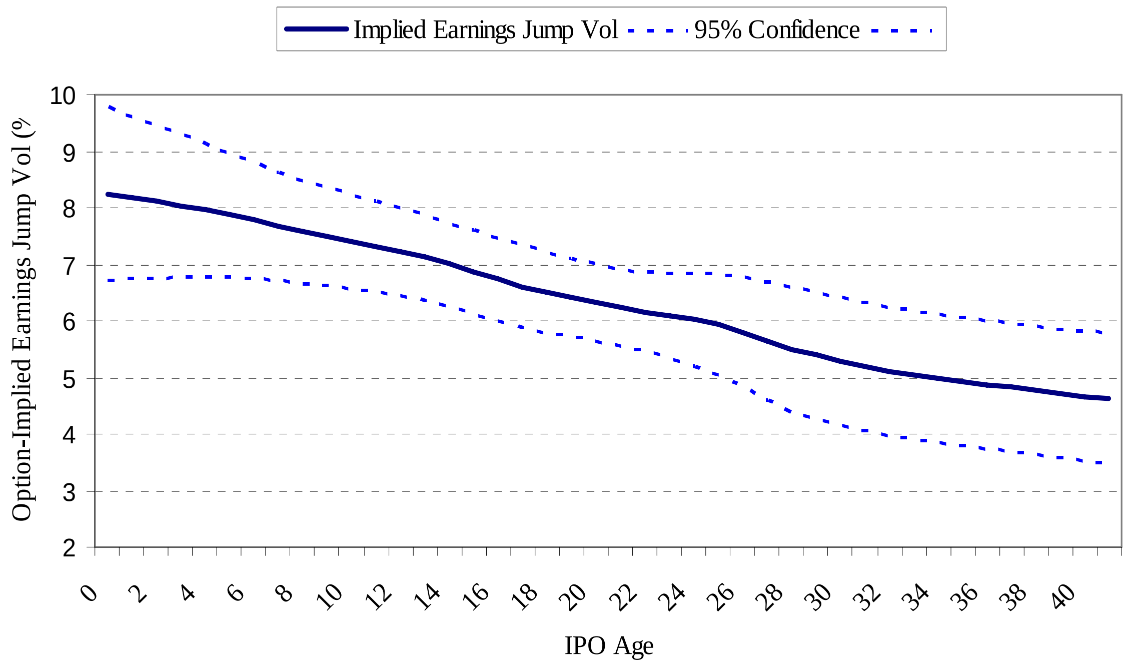
Firms may list multiple ADRs at the same time and terminate their listings. If a firm has multiple ADR programs, we consider the highest level of ADR. When an ADR program is terminated, the ADR sponsor institutions remove these inactive programs from their database. Therefore, there is a survivorship bias in reported ADRs in the sponsoring banks' databases. To correct this bias, we check, for each firm with return data in CRSP, the country of incorporation in COMPUSTAT. ADR firms have countries of incorporation outside the U.S. and are marked with "ADR" at the end of the COMPUSTAT company name. The beginning and ending dates of the return time series in CRSP are then taken as the effective listing and termination dates, respectively. This search yields 102 additional inactive Level II & III ADRs. Thus we have in total 507 firms with active ADRs at the end of year 2004 and 102 inactive ADR firms.

As pointed by Reese and Weisbach (2002), not every cross-listing firm can be matched in Worldscope.[23] Out of our 1192 cross-listed firms, 782 have information in Worldscope. Thus we have 782 cross-listed firms from 41 countries/regions, of which 442 are ADR firms and 340 are directly listing firms.

[23] Indeed, since there is not any reliable (i.e., consistently non-missing) common identifier between CRSP (or COMPUSTAT) and Worldscope, we need to manually merge many of our cross listing firms with Worldscope, based on company name, country of incorporation, and, if necessary, assets or sales.

Figure 1. Age and Option-implied Earnings Jump Volatility

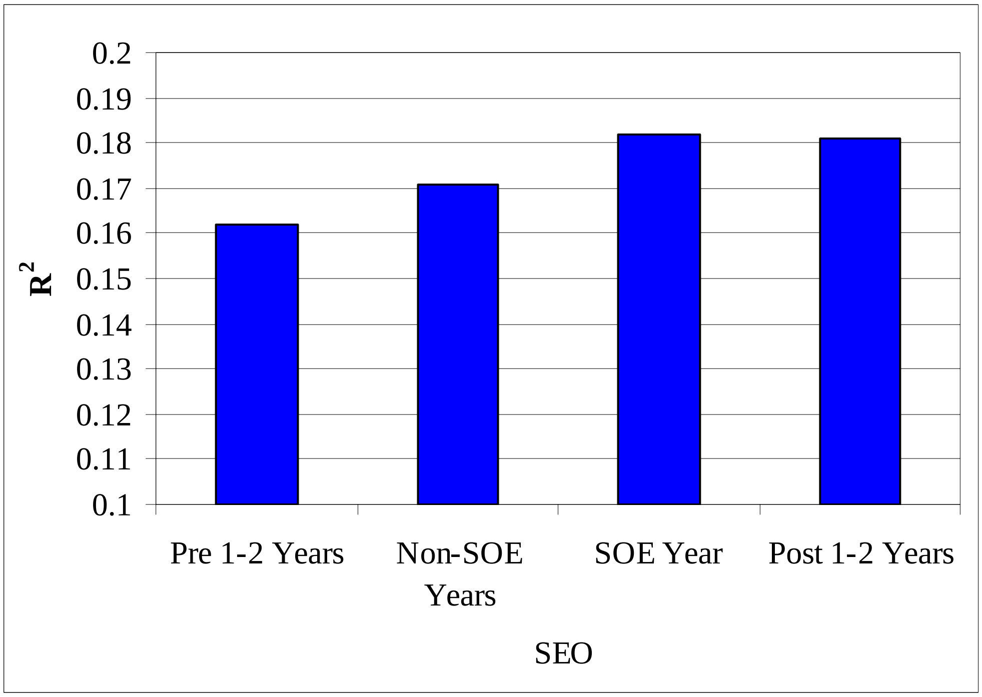
(U.S. Sample)



Sample period: 1998-2004. Control for ln(MV) and M/B, standard errors adjust for clustering at the firm level.

Figure 2. R^2 Dynamics Around SEO and ADR

Panel A. R^2 dynamics around SEO



Panel B. R^2 dynamics around ADR

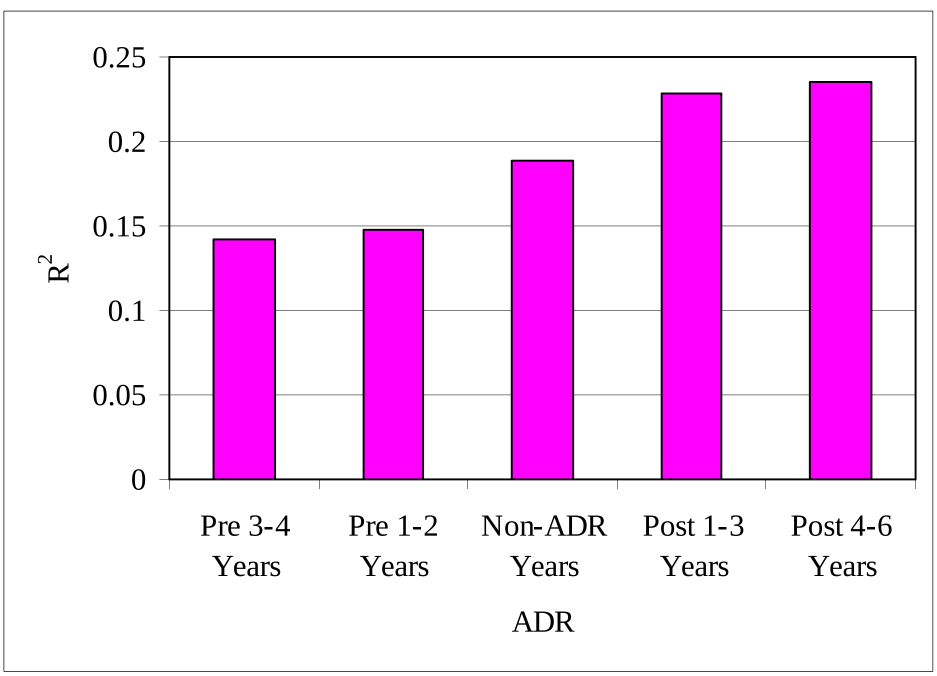


Table 1: Descriptive Statistics

This table reports the descriptive statistics for U.S. firms during the sample period of 1976-2004, with IPO age of at least 4 years. R^2, Firm-specific return variation (SSE), and Beta are estimates from equation (B-1), for each firm-year using weekly data. Age is the number of years since the inclusion in CRSP. Leverage is long-term debt over total assets. Profitability is measured by operating return on assets. Market-to-book is the market value of equity plus the book value of debt over total assets. In Panel B, Diversified Firms are those that have multiple segments reported in COMPUSTAT. In Panel C, the control group, Non-SEO firm-years, contains those firm-years that do not fall into any two-year time period before or after an SEO. Significance of the differences between subsamples are based on two-tailed tests (t test for mean and ranksum test for median). ***,** and * indicate significance at the 1%, 5%, and 10% levels respectively.

	All Firm-Years		Older Firms (IPO Age >= 12 Years)		Younger Firms (IPO Age < 12 Years)		Difference (Older - Younger)	
	mean	median	mean	median	mean	median	mean	median
Panel A: Descriptive Statistics by Firm Age								
Firm-Specific Return Variation (SSE)	0.274	0.125	0.193	0.092	0.361	0.181	-0.168***	-0.089***
R^2	0.130	0.082	0.154	0.105	0.104	0.063	0.050***	0.042***
Age	16.969	12.000	26.038	21.000	7.036	7.000	19.002***	14.000***
Beta	0.830	0.755	0.816	0.765	0.845	0.743	-0.029***	0.023
Total Assets (Mil.)	3718.697	192.110	5335.749	376.548	1947.954	100.380	3,387.795***	276.169***
Market-to-book	1.670	1.145	1.556	1.150	1.794	1.138	-0.238***	0.012***
Leverage	0.351	0.342	0.356	0.350	0.346	0.331	0.010***	0.019***
Profitability	0.098	0.111	0.120	0.121	0.074	0.096	0.046***	0.025***
Number of Observations	89010		46524		42486			

Panel B: Descriptive Statistics by Diversification

	Diversified Firms		Single-Segment Firms		Difference (Diversified - Single-Segment)	
	mean	median	mean	median	mean	median
Firm-Specific Return Variation (SSE)	0.268	0.114	0.397	0.198	-0.129***	-0.084***
R^2	0.148	0.100	0.100	0.054	0.048***	0.046***
Age	21.963	17.000	13.372	10.000	8.591***	7.000***
Beta	0.839	0.785	0.803	0.722	0.036***	0.063***
Total Assets (Mil.)	4192.858	340.881	977.924	66.624	3,214.934***	274.257***
Market-to-book	1.483	1.168	1.912	1.249	-0.429***	-0.081***
Leverage	0.357	0.354	0.292	0.255	0.065***	0.099***
Profitability	0.105	0.118	0.080	0.108	0.025***	0.010***
Number of Observations	34039		43832			

Table 1. Descriptive Statistics (Continued)

Panel C. Descriptive Statistics of the SEO sample vs. the Non-SEO sample

	All Firm-Years		Non-SEO Firm-Years		0-2 Years Before SEO		Difference (Before SEO - Non-SEO)		1-2 Years After SEO		Difference (After SEO - Non-SEO)	
	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median
Firm-Specific Return Variation (SSE)	0.274	0.125	0.278	0.123	0.231	0.138	-0.046*	0.0145***	0.235	0.139	-0.043	0.015***
R^2	0.130	0.082	0.127	0.078	0.156	0.119	0.029***	0.041***	0.175	0.139	0.048***	0.061***
Age	16.969	12.000	16.920	12.000	18.038	12.000	1.118***	0.000***	16.699	12.000	-0.221	0.000***
Beta	0.830	0.755	0.802	0.731	1.054	0.955	0.251***	0.224***	1.146	1.076	0.343***	0.345***
Total Assets (Mil.)	3718.697	192.110	3799.463	177.195	2780	325.504	-1019.789**	148.309***	3138.474	397.202	-660.989	220.007***
Market-to-book	1.670	1.145	1.657	1.134	1.876	1.263	0.218***	0.128***	1.692	1.254	0.034	0.119***
Leverage ratio	0.351	0.342	0.351	0.341	0.368	0.372	0.017***	0.030***	0.339	0.333	-0.011**	-0.008**
Profitability	0.098	0.111	0.098	0.110	0.099	0.120	0.001	0.009***	0.082	0.110	-0.016***	-0.000***
Number of Observations	89010		80633		4604				3773			

Table 2: Age and R^2

This table estimates the effect of firm age on R^2 as follows:

$$\log(1-R^2)_{i,t} = \alpha + \beta \text{Age}_{i,t} + \gamma \text{Firm Controls}_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t},$$

R^2 and Beta are estimated from a market model (equation B-1) in columns (1) and (5); from an industry-augmented market model in columns (2) and (6); and Fama-French (FF) three- factor and a four-factor model with momentum (equations B-2 and B-3) in columns (3), (4), (7), and (8). Age is the number of years since the inclusion in CRSP. Size is the log of market value of assets. Leverage is long-term debt over total assets. Profitability is measured by operating return on assets. Market-to-book is the market value of equity plus book value of debt over total assets. Total volatility is the standard deviation of weekly return over one year. Diversification indicates whether the firm has multiple COMPUSTAT segments reported. Standard errors are clustered at the firm level and are in parenthesis. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

					Controlling for ROA comovement			
	Standard Market Model	Industry-Augmented Market Model	FF Three-Factor Model	FF Three Factors plus Momentum	Standard Market Model	Industry-Augmented Market Model	FF Three-Factor Model	FF Three Factors plus Momentum
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Basic Model								
Log(Age)	-0.040***	-0.018**	-0.026***	-0.029***	-0.044***	-0.023***	-0.023***	-0.025***
	(0.005)	(0.007)	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
Market-to-book	0.003	0	0	0.002**	-0.001	0	-0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Beta (Market factor)	-0.089***	-0.091***	-0.030***	-0.020***	-0.107***	-0.084***	-0.028***	-0.017**
	(0.012)	(0.003)	(0.011)	(0.007)	(0.005)	(0.005)	(0.011)	(0.007)
Beta (Industry return)		-0.152***				-0.119***		
		(0.007)				(0.008)		
Beta (High-minus-low factor)			0.024***	0.021***			0.025***	0.021***
			(0.003)	(0.002)			(0.002)	(0.002)
Beta (Small-minus-big factor)			0.001	-0.001			-0.002	-0.002
			(0.004)	(0.003)			(0.004)	(0.003)
Beta (Momentum factor)				0.004				0.004
				(0.003)				(0.003)
Log of total volatility	0.932***	0.990***	0.872***	0.861***	0.947***	0.923***	0.873***	0.861***
	(0.011)	(0.008)	(0.012)	(0.008)	(0.008)	(0.008)	(0.012)	(0.009)
Log(Assets)	-0.030***	-0.036***	-0.048***	-0.053***	-0.021***	-0.037***	-0.044***	-0.050***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Profitability	-0.018	-0.015	-0.013	-0.023***	-0.003	-0.003	-0.01	-0.022***
	(0.013)	(0.009)	(0.011)	(0.008)	(0.009)	(0.012)	(0.013)	(0.009)
Leverage	0.051***	0.055***	0.067***	0.074***	0.051***	0.070***	0.073***	0.079***
	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)
Idiosyncratic ROA movement					0.003***	0.003***	0.003***	0.003***
					(0.001)	(0.001)	(0.001)	(0.001)
Constant	13.142***	3.944***	3.668***	3.642***	13.188***	3.804***	3.657***	3.624***
	(0.035)	(0.041)	(0.045)	(0.036)	(0.030)	(0.038)	(0.047)	(0.038)
Observations	89010	88133	88979	88968	73156	73094	73146	73137
Number of Firms	12015	11934	12011	12011	9806	9803	9804	9804
R-squared	0.94	0.89	0.91	0.91	0.94	0.90	0.91	0.91

Table 2: Age and R^2 (Continued)

	Standard Market Model	Industry-Augmented Market Model	FF Three-Factor Model	FF Three Factors plus Momentum	Standard Market Model	Industry-Augmented Market Model	FF Three-Factor Model	FF Three Factors plus Momentum
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: The Effect of Diversification								
Log(Age)	-0.040***	-0.026***	-0.018***	-0.024***	-0.043***	-0.028***	-0.020***	-0.025***
	(0.005)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)
Market-to-book	0.001	0.001	0.001	0.001	0	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Beta (Market factor)	-0.073***	-0.071***	-0.020**	-0.011*		-0.074***		
	(0.011)	(0.004)	(0.009)	(0.006)		(0.015)		
Beta (Industry return)		-0.134***			-0.074***	-0.054***	-0.019**	-0.010*
		(0.007)			(0.012)	(0.010)	(0.009)	(0.006)
Beta (High-minus-low factor)			0.020***	0.017***			0.021***	0.016***
			(0.003)	(0.003)			(0.003)	(0.003)
Beta (Small-minus-big factor)			-0.003	-0.005			-0.005	-0.004
			(0.004)	(0.003)			(0.004)	(0.003)
Beta (Momentum factor)				0.004				0.004
				(0.003)				(0.003)
Log of total volatility	0.832***	0.974***	0.790***	0.781***	0.822***	0.810***	0.778***	0.767***
	(0.087)	(0.008)	(0.082)	(0.081)	(0.098)	(0.095)	(0.092)	(0.091)
Log(Assets)	-0.028***	-0.032***	-0.045***	-0.049***	-0.027***	-0.041***	-0.044***	-0.047***
	(0.007)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Profitability	-0.006	-0.012*	-0.01	-0.009	-0.003	-0.006	-0.01	-0.009
	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Leverage	0.085**	0.057***	0.101***	0.105***	0.089**	0.102***	0.105***	0.109***
	(0.035)	(0.010)	(0.033)	(0.032)	(0.037)	(0.036)	(0.035)	(0.034)
Diversification	-0.007*	-0.005	-0.008*	-0.008*	-0.007**	-0.006	-0.007*	-0.007*
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Idiosyncratic ROA movement					0.005**	0.005**	0.004**	0.005**
					(0.002)	(0.002)	(0.002)	(0.002)
Constant	12.817***	3.871***	3.373***	3.355***	12.805***	3.468***	3.354***	3.328***
	(0.244)	(0.044)	(0.229)	(0.226)	(0.265)	(0.261)	(0.249)	(0.245)
Observations	77871	77061	77853	77845	70265	70205	70253	70247
Number of Firms	10802	10727	10801	10801	9803	9801	9803	9803
R-squared	0.91	0.89	0.89	0.88	0.91	0.88	0.89	0.88

Table 3. The Dynamic Response of R^2 to SEOs

This table reports the dynamics of R^2 in response to SEOs from the model below:

$$\log(1-R^2)_{i,t} = \alpha + \sum_k \beta_k \text{ (SEO has occured } k \text{ periods earlier)}_{i,t} + \gamma \text{Firm Controls}_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t}$$

R^2 and Beta are estimated from a market model (equation B-1) in columns (1) and (2); from an industry-augmented market model in column (3); from Fama and French (FF) three-factor and a four-factor model with momentum (equations B-2 and B-3) in columns (4) and (5). Age is the number of years since the inclusion in CRSP. Size is the log of market assets. Leverage is long-term debt over total assets. Profitability is measured by the return on assets. Market-to-book is the market value of equity plus book value of debt over total assets. Total Volatility is the standard deviation of weekly return over a year. Standard error are clustered at the firm level and are in the parenthesis. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Standard Market Model		Industry augmented market model	FF Three-Factor Model	FF Three Factors plus Momentum
	(1)	(2)	(3)	(4)	(5)
1-2 years prior to SEO		0.006	0.011**	0.012***	0.009**
		(0.004)	(0.005)	(0.004)	(0.005)
Year of SEO	0.002	0.003	-0.013*	-0.007	-0.005
	(0.004)	(0.005)	(0.008)	(0.005)	(0.006)
1-2 years subsequent to SEO	-0.011***	-0.010***	-0.012**	-0.012***	-0.016***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Beta (Market factor)	-0.089***	-0.089***	-0.091***	-0.030***	-0.020***
	(0.012)	(0.012)	(0.003)	(0.011)	(0.007)
Beta (High-minus-low factor)				0.024***	0.021***
				(0.003)	(0.002)
Beta (Small-minus-big factor)				0.001	-0.001
				(0.004)	(0.003)
Beta (Momentum factor)					0.004
					(0.003)
Beta (Industry return)			-0.152***		
			(0.007)		
Log of total volatility	0.932***	0.932***	0.991***	0.873***	0.862***
	(0.010)	(0.010)	(0.008)	(0.012)	(0.008)
Market-to-book	0.002	0.002	0	0	0.002**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Log(Age)	-0.040***	-0.040***	-0.018***	-0.027***	-0.030***
	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)
Log(Assets)	-0.029***	-0.029***	-0.035***	-0.047***	-0.052***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Profitability	-0.019	-0.019	-0.015	-0.013	-0.023***
	(0.013)	(0.013)	(0.009)	(0.011)	(0.008)
Leverage	0.050***	0.050***	0.053***	0.066***	0.073***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)
Constant	13.141***	13.141***	3.942***	3.666***	3.641***
	(0.035)	(0.035)	(0.042)	(0.045)	(0.036)
Observations	89010	89010	88133	88979	88968
Number of permno	12015	12015	11934	12011	12011
R-squared	0.94	0.94	0.89	0.91	0.91

Table 4: Descriptive Statistics of the ADR sample

This table reports the descriptive statics for the ADR sample. The sample contains international firm-years from Datastream and Worldscope during 1980-2004. An ADR firm-year is a year in which the international firm has an active ADR. Otherwise, a firm-year is a non-ADR firm-year. R^2, SSE, Home Beta and U.S. Beta are estimated for each firm-year from an augmented market model (equation B-4). Leverage is long-term debt over total assets. Profitability is measured by the return on assets. Market-to-book is the market value of equity plus book value of debt over total assets. Significance of the differences between the ADR firm-years and non-ADR firm-years are based on two-tailed tests (t test for mean and ranksum test for median). ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	All Firm-Years		ADR Firm-Years		Non-ADR Firm-Years		Difference (ADR - Non-ADR)	
	mean	median	mean	median	mean	median	mean	median
Firm-Specific Return Variation (SSE)	0.192	0.097	0.198	0.094	0.192	0.097	0.006	-0.003
R^2	0.190	0.128	0.260	0.212	0.187	0.126	0.072***	0.086***
Home Beta	0.946	0.722	1.329	1.084	0.933	0.711	0.395***	0.372***
US Beta	-0.009	0.000	0.058	0.021	-0.012	0.000	0.069***	0.021***
Total Assets(Mil.)	3891.104	267.560	20497.430	1986.104	3347	257	17150.068***	1729.061***
Market-to-book	1.987	1.338	2.663	1.868	1.965	1.320	0.698***	0.547***
Leverage ratio	0.130	0.085	0.178	0.150	0.128	0.083	0.049***	0.066***
Profitability	0.017	0.022	0.007	0.027	0.017	0.022	-0.009***	0.005***
Number of Observations	153572		4869		148703			

Table 5: The Dynamics of ADR Effects on R^2

This table reports the dynamics of R^2 in response to ADR listings as in the following model:

$$\log(1-R^2)_{i,t} = \alpha + \sum_k \beta_k \text{ ADR listing occured } k \text{ periods ago}_{i,t} + \gamma \text{Firm Controls}_{\text{i,t}} + \eta_i + \delta_t + \varepsilon_{i,t}.$$

R^2, Home Beta and U.S. Beta are estimated for each firm-year from an augmented market model (equation B-4). The sample contains international firm-years from Datastream and Worldscope during 1980-2004. Countries with good (weak) institutional environments are classified based on the good-government index from Kaufmann, Kraay and Mastruzzi (2004). ADR Listing is a dummy variable indicating the firm-years with active ADRs. "3-4 years prior to ADR" and "1-2 years prior to ADR" are dummy variables indicating the number of years prior to the ADR. "Year of ADR" is a dummy variable indicating the year in which ADR is listed. Likewise, "1-3 (" 4-6, "7-9 and "10) years subsequent to ADR" are dummy variables indicating the number of years after the ADR. Firm size is the log of market assets. Leverage is long-term debt over total assets. Profitability is measured by the return on assets. Market-to-book is the marke value of equity plus book value of debt over total assets. Total Volatility is the standard deviation of weekly return over a year. Standard errors are clustered at the firm level and are in parenthesis. ***, ** and * indicate the significance at 1%, 5%, and 10% levels, respectively.

	Overall Sample		Good Institutions	Weak Institutions
	(1)	(2)	(3)	(4)
ADR Listing	-0.069***			
	(0.020)			
3-4 years prior to ADR		0.056**	0.063***	-0.079
		(0.022)	(0.022)	(0.171)
1-2 years prior to ADR		0.049**	0.055**	-0.085
		(0.024)	(0.024)	(0.179)
Year of ADR		-0.027	-0.015	-0.051
		(0.024)	(0.024)	(0.216)
1-3 years subsequent to ADR		-0.050**	-0.052**	0.017
		(0.023)	(0.023)	(0.178)
4-6 years subsequent to ADR		-0.058**	-0.058**	-0.047
		(0.029)	(0.029)	(0.207)
7-9 years subsequent to ADR		-0.009	-0.01	0.015
		(0.031)	(0.031)	(0.209)
10- Years subsequent to ADR		-0.037	-0.034	-0.015
		(0.037)	(0.037)	(0.297)
Log of total volatility	0.033***	0.033***	0.023***	0.134***
	(0.003)	(0.003)	(0.003)	(0.020)
Home beta	-0.026***	-0.026***	-0.025***	-0.044
	(0.002)	(0.002)	(0.002)	(0.057)
U.S. beta	-0.014***	-0.014***	-0.013***	-0.025
	(0.004)	(0.004)	(0.004)	(0.018)
Log(Assets)	-0.042***	-0.042***	-0.044***	-0.022
	(0.003)	(0.003)	(0.003)	(0.014)
Leverage	0.050***	0.050***	0.068***	-0.023
	(0.014)	(0.014)	(0.015)	(0.028)
Profitability	-0.047***	-0.046***	-0.054***	-0.012
	(0.016)	(0.016)	(0.016)	(0.058)
Market-to-book	-0.001	-0.001	0.000	-0.030***
	(0.001)	(0.001)	(0.000)	(0.009)
Constant	13.325***	13.325***	13.281***	13.485***
	(0.026)	(0.026)	(0.025)	(0.176)
Observations	153572	153572	140351	13221
Number of firms	20544	20544	17876	2668
R-squared	0.88	0.88	0.89	0.83