Correlated Beliefs, Correlated Returns, and the Cross-Section of Stock Market Volatility*

Joel M. David†   Ina Simonovska‡

USC   UC Davis, NBER

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Abstract

Firm-level stock returns exhibit comovement above that in fundamentals, and the gap tends to be higher in developing countries. We investigate whether correlated beliefs among sophisticated, but imperfectly informed traders can account for the patterns of return correlations across countries. We take a unique approach by turning to direct data on market participants' information - namely, real-time firm-level earnings forecasts made by equity market analysts. The correlations of firm-level forecasts exceed those of fundamentals and are strongly related to return correlations across countries. A calibrated information-based model demonstrates that the correlation of beliefs implied by analyst forecasts leads to return correlations broadly in line with the data, both in levels and across countries - the correlation between predicted and actual is 0.63. Our findings have implications for market-wide volatility - the model-implied correlations alone can explain 44% of the cross-section of aggregate volatility. The results are robust to controlling for a number of alternative factors put forth by the existing literature.

JEL Classification: G15, G12, G10, D8

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†Email: joeldavi@usc.edu.

‡Email: inasimonovska@ucdavis.edu

1 Introduction

Stock prices exhibit 'excess comovement' - that is, comovement, or correlation, above and beyond what can be explained by fundamentals. Moreover, the extent of excess comovement differs across countries, and in a systematic way: emerging markets tend to exhibit higher degrees of comovement than do developed ones. Understanding the determinants of these patterns is important because the correlation of prices is a key driver of aggregate stock market volatility, which has implications for investment incentives on the part of firms, portfolio choice decisions on the part of investors, and ultimately the efficiency of the allocation of capital.

In this paper, we take a new look at the drivers of differences in firm-level stock return correlations across countries. Specifically, we investigate the role of correlated beliefs on the part of sophisticated, but imperfectly informed investors. Quantifying this channel is challenging, since we as the econometricians do not typically observe agents' information sets. We take a novel approach to overcoming this hurdle by turning to direct data on market participants' forecasts of firm fundamentals. We obtain these forecasts from the I/B/E/S Database, which tracks firm-level forecasts made by security analysts across a number of developed and emerging markets. We use these data to document a new fact that sheds light on the role of correlated beliefs: the correlations of analyst forecasts are strongly related to firm-level return correlations across countries, and both exceed the level justified by fundamentals.

To reconcile these findings and to investigate their implications for return correlations and market-wide volatility, we develop a highly parsimonious dynamic model of equity markets under imperfect information. Market participants trade based on their priors and a noisy signal of the current innovation in fundamentals. There is correlation across firms both in fundamentals and in the noise in signals, both of which lead to correlated beliefs. The model makes sharp predictions regarding the correlation in returns and conditions for excess correlation above that in fundamentals - in fact, the simplicity of our setting leads to a sharp characterization of the return correlation as a weighted average of the correlation in fundamentals and signal errors.

We perform a straightforward numerical exercise to assess whether the correlation in beliefs that we measure leads to patterns in return correlations in line with those observed in the data. We calibrate the model using the cross-firm correlations of forecasts from I/B/E/S (and their volatilities) along with readily observable properties of fundamentals. We have several key findings: first, the calibrated model generates return correlations broadly in line with those in the data - the correlation between predicted and actual across countries is 0.63. Moreover, the levels are on par, averaging 0.47 and 0.46, respectively. In other words, the correlation of information suggested by our data leads to cross-sectional patterns as well as levels of excess correlations similar to those in the data. This is a rather striking finding given the simplicity of our setting and empirical approach.

We perform a series of counterfactual experiments to disentangle the various potential drivers of return correlations in the model and find that the non-fundamental component of belief correlation is key - setting the correlation of signal errors to the US level for all countries almost eliminates disparities in return correlations; similar exercises setting overall signal noise and fundamental parameters to their US values make a much smaller difference. This highlights an important and intuitive result from our model: it is not the overall level of firm-specific information, but rather the correlated component of that information, that drives comovement across firms.

We take our analysis one step further and examine an important application of our results mentioned at the outset of the paper - namely, differences in aggregate stock market volatility across countries. Previous work has shown that cross-firm return correlations alone explain a substantial portion of variation in market-wide volatility, and it seems natural to ask if our results have anything to add on this score.[1] We find that the answer is yes: a simple regression shows that our predicted return correlations alone can explain about 44% of the cross-country variation in aggregate volatility in an R^2 sense; for comparison, in our data, the empirical return correlations explain about 64% of the variation in volatility. Our finding here is not surprising once we notice that there is a strong direct relationship between analyst forecast correlations and market volatility. We interpret this result as suggesting that future work investigating the determinants of stock market volatility should take seriously the role of correlated beliefs across presumably sophisticated traders.

Finally, we examine the robustness of our results to controlling for a number of alternative explanations. Specifically, we perform two sets of regression analyses: first, we regress the empirical levels of return correlation directly on analyst forecast correlations (and fundamental corelations) across countries. We find a strong direct relationship. We then control for a variety of plausible alternatives suggested in the literature, including institutional quality and firm-level transparency, capital account openness, and the depth of financial markets. The significance of forecast correlations remains high even after the inclusion of these other factors, confirming the importance of our mechanism. An analogous exercise with aggregate stock market volatility as the regressand gives similar results. Note that this is not to say that other factors play no role; only that the importance of the correlation in beliefs that we measure does not vanish with their inclusion. Lastly, we show that forecast correlations themselves are significantly related to some of these measures, with the interpretation that in some sense, many of these explanations are complementary to ours.

The paper is organized as follows. After reviewing the related literature next, Section 2

[1] We review the related literature at the end of this section.

describes our data sources and documents the motivating facts. Section 3 lays out our model of equity markets with imperfect and correlated information, while Section 4 details our numerical exercise and results. We demonstrate the robustness of our results to controlling for plausible alternatives in Section 5 and conclude in Section 6. For ease of exposition, tables of country-level data are provided in the Appendix. All supplementary empirical results discussed but not reported are available on request from the authors.

Related literature. Our paper relates most closely to the existing literature that examines firm-level stock return comovement. Numerous papers have documented the excess comovement 'puzzle'. Key examples include Pindyck and Rotemberg (1993), who show that return comovement among US firms is too high to be justified by fundamentals, and Morck et al. (2000), who show that excess comovement tends to be higher in poor and emerging markets. Cross-country variation in comovement has been linked to a variety of plausible explanations, including differences in the quality of institutions and the strength of property rights, e.g., Morck et al. (2000), capital account openness, e.g., Li et al. (2004), a lack of firm-level transparency, or 'opaqueness', e.g., Jin and Myers (2006), and limits to arbitrage, e.g., Bris et al. (2007) and Barberis et al. (2005).[2] In contrast to these papers, we focus squarely on an informational theory of comovement - we identify a direct measure of beliefs on the part of market participants and use a simple theoretical framework to quantify the implications of this observable moment for return comovement. Further, we demonstrate that our theory of information-driven comovement is robust to controlling for a number of these alternative explanations, and in fact, is potentially complementary with them. This last point is not surprising, given that a common element in much of this work is uncovering factors that reduce the incentives to gather and trade on firm-specific information.

Particularly relevant is the body of work that specifically investigates correlated information as a potential cause of return comovement. Veldkamp (2006) demonstrates that a noisy rational expectations model featuring endogenous information markets can lead to excess comovement - in equilibrium, investors purchase common information about a subset of assets that they use to price others. Although our model differs on a number of dimensions from hers, we are able to draw some parallels in terms of predictions for excess comovement. Our work builds on hers by directly measuring the correlation in beliefs on the part of informed investors and investigating further the quantitative significance of this channel for return comovement, as well as the implications for the cross-section of countries. Additionally, we can look to her theory as one potential micro-foundation for the belief correlation that we measure in the data.[3]

[2] For an excellent recent survey of the voluminous literature examining the causes and consequences of return comovement, we refer the reader to Morck et al. (2013).

[3] Mondria (2010) proposes an alternative theory in which investors are subject to information processing

Empirically, a number of papers have investigated the role of equity analysts in producing firm-level or aggregate information and influencing trading behavior. Most find that there is a sizable aggregate component in analyst information, consistent with our empirical results. For example, Chan and Hameed (2006) find that firms with greater analyst coverage exhibit more price comovement, as do Piotroski and Roulstone (2004). Israelsen (2015) also highlights the importance of correlated information by showing that US stocks with more common analyst coverage exhibit greater comovement. Relatedly, Hameed et al. (2010) find that analysts tend to cover firms whose fundamentals correlate more with other firms in their industry and that information spills over from these firms to the prices of others.[4] Our analysis is similar in spirit to these and builds on some of their findings. Our innovation is to use our simple theory along with direct data on analyst forecast correlations to quantify the predictions for return comovement across a broad set of countries.

Lastly, by linking our results on comovement to aggregate market volatility, we relate to a broader body of work examining the determinants of differences in volatility across countries. Similar to the connection we make, Harvey (1995) shows that variation in firm-level return correlations accounts for over 50% of the cross-section of market volatilities across a sample of 20 developed and emerging markets. Bekaert and Harvey (1997) find that a series of explanatory variables related to stock market concentration, market development/integration, microstructure effects, and macroeconomic volatility and political risk explain 34% of the cross-sectional variation in market volatility (60% using the panel dimension). In a recent contribution, Hassan and Mertens (2011) demonstrate that small, correlated errors in expectations on the part of investors can lead to high levels of stock market volatility with important consequences for social welfare. We argue similarly, and focus on a measurable piece of this correlation - namely, that stemming from the forecasts of sophisticated information producers (security analysts). Our broader contribution to this literature is to emphasize that, in addition to other factors, informational-driven excess comovement seems to plays an important role in determining the cross-section of market volatility across countries, a finding that should be useful for future researchers in this area.

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constraints and optimally choose to observe combinations of asset payoffs as signals, thus leading to excess comovement. Although the channels in these papers are different, they have similar implications regarding comovement. Our model is quite parsimonious and potentially reflects both of these mechanisms.

[4]It is worth noting that other studies find slightly differently: for example, Crawford et al. (2012) show that firm-level return comovement increases with the first analyst to initiate coverage, but declines upon further coverage. Liu (2011) finds that analyst research contains primarily firm-specific information.

2 Facts

In this section, we describe the various datasets we use for our analysis and establish the stylized facts regarding the cross-section of firm-level correlations - in returns, fundamentals, and beliefs.

2.1 Data

Compustat Global. We obtain annual data on firm-level stock returns and earnings per share from Compustat Global. We restrict attention to countries that are classified as either developed or emerging from the MSCI database. Countries included in MSCI tend to have reasonably well-established capital markets that are accessible to international investors so that this seems a reasonable approach to bound our initial set. We focus on the 15 year period spanning 1999-2013 since comprehensive firm-level data across all of our countries are not available earlier.[5] In order to compute meaningful aggregates, we exclude countries where data are available for less than 5 firms in a year or with less than 100 total observations over the 15 year period. We further exclude countries from the former Soviet bloc countries and a small number of large outliers, where market volatility is more than 2 standard deviations above the mean.[6] Our final sample is quite broad and consists of a total of 31 countries:[7] Australia, Austria, Belgium, Canada, Switzerland, Chile, China, Germany, Denmark, Spain, Finland, France, Great Britain, Hong Kong, India, Israel, Italy, Japan, Korea, Mexico, Malaysia, Netherlands, Norway, New Zealand, Peru, Phillipines, Singapore, Sweden, Thailand, United States, and South Africa.

We construct returns as the annual percentage change in the stock price (i.e., ex-dividend), adjusted for splits. This is the notion of returns we will use throughout our analysis.[8] Earnings growth rates are computed analogously. We convert both series into US dollars using exchange rates provided by Compustat and deflate them by the US CPI. We trim the 1% tail of each series to eliminate outliers. We then compute the average pair-wise cross-firm correlation in each series.[9] We restrict our attention to firm pairs with at least 8 years of overlap - this strikes

[5]Since we are examining earnings growth rates, we are using data from 1998 on. For the countries that have data going back further, our results are robust to using data from the unbalanced panel that spans 1993-2013. We do not examine earlier periods as many of our countries did not have well-developed stock markets. For example, 5 of the countries were added to the MSCI database in 1993.

[6]We additionally exclude Taiwan, which imposed unusually strict limits on intraday price movements until 2015 (see, for example, Cho et al. (2003) and http://focustaiwan.tw/news/aeco/201504010008.aspx).

[7]For example, of our 30 non-US countries, 11 are classified as emerging and 19 as developed by MSCI, although there is some debate in the financial world about how to classify several of the countries.

[8]The properties of returns are almost identical cum or ex-dividend. The theoretical analog of returns in the model will be ex-dividend as well.

[9]An alternative measure of comovement is the R^2 from a market-model style regression, i.e., the regression of firm returns on market returns. Our measure is clearly related to that one. Quantitatively, the two line up closely, with a correlation across countries of 0.98.

a reasonable balance between maximizing the number of firms that we are able to include and ensuring that we have a long enough time-series to obtain robust results.[10] Table 4 in the Appendix reports the series for each country, along with the number of observations.

I/B/E/S. We obtain data on earnings forecasts made by security analysts from the I/B/E/S (Institutional Brokers Estimate System) database. From I/B/E/S, we gather consensus forecasts of 1-year ahead annual earnings. For each firm-year cell, we obtain the mean forecast across analysts and the actual realization of earnings.[11] We determine the reporting month of the previous year's earnings, and examine forecasts made in the following month. This ensures that the previous periods' performance is in the analysts' information sets, which will be consistent with our model. For foreign firms, we convert all nominal figures denominated in local currency into US dollars using year-end monthly exchange rates provided by I/B/E/S, and then deflate them by the US CPI. In cases where there are multiple consensus forecasts for a forecast month for a single year (e.g., two consensus forecasts both made in February for December earnings), we keep the observation with a larger number of individual analyst forecasts. We examine data beginning in 1993, since as already noted, many of our countries did not have well-developed markets in earlier periods.[12] To eliminate the effects of outliers, we trim the 1% tails of actual earnings growth and forecast errors, where the latter are computed as (the log of) realized earnings less (the log of) the forecast. Finally, we construct the average cross-firm correlation in forecasts in exactly the same manner as for returns and earnings growth from the Compustat data.

Table 5 in the Appendix reports each of the series and summarizes the extent of analyst coverage for each country - the number of forecasts and the mean number of analysts per firm. The number of forecasts ranges from a minimum of 331 in Peru to over 70,000 in the US, with an average across countries of about 7,200. The average number of analysts ranges from 4 to 13. There is a moderate relationship between analyst coverage and the level of economic development: for example, the correlations of the number of forecasts and mean number of analysts with income (1999 log income per-capita) are about 0.20 and 0.32, respectively. Thus, the degree of analyst coverage is unlikely to be the primary cause of systematic differences in correlations across countries.

[10] Our findings are robust to different cutoffs on the degree of overlap, for example, 10 years.

[11] I/B/E/S also makes available the forecasts on an analyst-by-analyst basis. For the purposes of our analysis, where there is a single forecast per firm, the summary of these forecasts is sufficient, although it would certainly be interesting to explore the role of heterogeneity across analysts in future work.

[12] To maximize the number of observations within each country and the number of countries with sufficient forecast data to include in our analysis, we compute correlations using firm-level observations from a somewhat longer time period than from Compustat (1993 vs. 1998). Our results are not sensitive to this choice.

2.2 Stylized Facts

We combine our two datasets to establish the main fact motivating our analysis - return correlation is strongly related to correlation in analysts' forecasts of fundamentals (which we alternatively refer to as beliefs), and both exceed the correlation in fundamentals by a wide margin.

To fix ideas, consider a simple framework where fundamentals for firm i, a_{it}, follow an AR(1) process in logs. Fundamental innovations μ_{it} are iid through time and independent of a_{it}, and are correlated across firms with correlation coefficient π^f, i.e.:

$$a_{it} = \rho a_{it-1} + \mu_{it}, \quad \mu_{it} \sim \mathcal{N}\left(0, \sigma_\mu^2\right), \quad \text{corr}\left(\mu_{it}, \mu_{jt}\right) = \pi^f \tag{1}$$

If investor beliefs reflect fundamentals, either past or future, i.e., $\mathbb{E}_t\left[a_{it}\right] = a_{it}$ or $\mathbb{E}_t\left[a_{it}\right] = \rho a_{it-1}$ (investors have full information or no information regarding the realization of μ_{it}), we have:[13]

$$\text{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) = \text{corr}\left(\Delta a_{it}, \Delta a_{jt}\right) = \text{corr}\left(\mathbb{E}_t\left[a_{it}\right], \mathbb{E}_t\left[a_{jt}\right]\right) = \pi^f \tag{2}$$

where Δp_{it} denotes stock returns. In other words, the cross-firm correlations of returns, fundamental growth, and beliefs regarding fundamentals are the same.

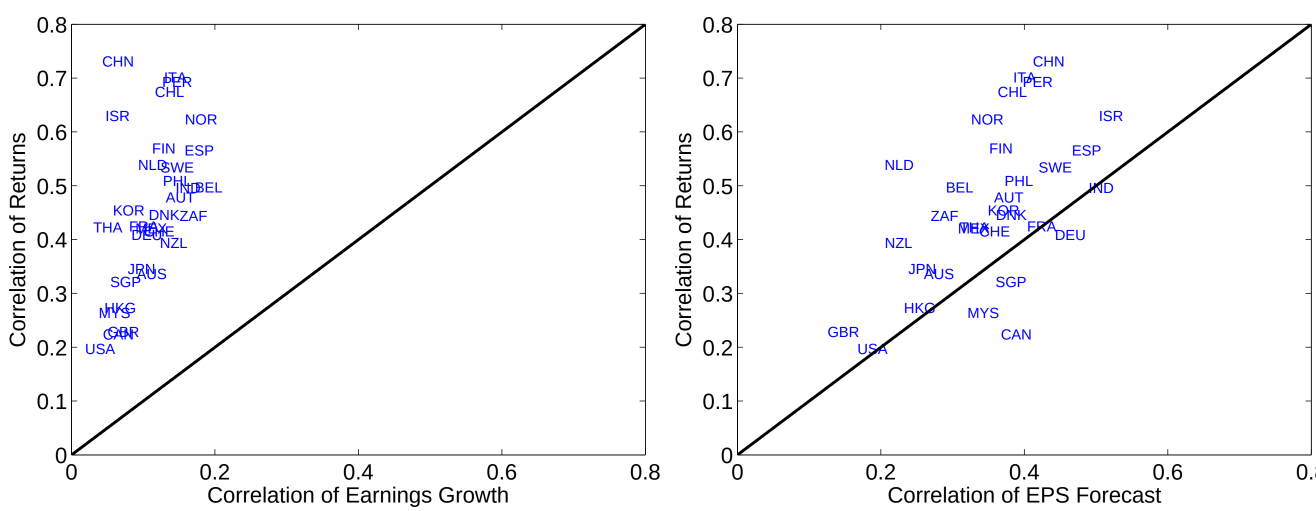

Figure 1: Firm-Level Correlations: Returns, Forecasts and Fundamentals

With that in mind, the left-hand panel of Figure 1 plots firm-level return correlations across the 31 countries in our sample against the correlation of earnings growth rates, along with the 45 degree line. The first equality in expression (2) suggests that the points should lie on the 45 degree line. Two observations are worth pointing out: first, it is clear that (2) fails to hold:

[13] Full derivations are in Section 3.

return correlations exceed fundamental correlations in every country, generally by a substantial amount. For example, the average return correlation across countries is 0.46 vs only 0.11 for earnings growth, a factor of over 4. Second there is a good deal of heterogeneity across countries in return correlations, but the relationship with fundamental correlations, while present, is far from perfect - for example, the regression of return correlations on fundamental correlations shows that variation in the latter explains only about 25% of variation in the former in an R^2 sense, whereas expression (2) implies perfect correlation. In sum, there is simply not enough variation in fundamental correlations to account for the variation in return correlations in a quantitatively meaningful way.

In the right-hand panel of Figure 1, we plot the correlation of returns against the correlation of analysts' forecasts of fundamentals. The two variables are strongly related and are more closely aligned in magnitudes, though return correlations on average exceed forecasts (they average 0.46 and 0.36, respectively). Notice that this implies the second equality in expression (2) fails to hold as well: like returns, the correlation of beliefs exceed the correlation of fundamentals, in this case by a factor of over 3 (0.36 vs 0.11).[14]

To sum up the key insights from Figure 1, we find that the correlations of analyst forecasts are strongly related to firm-level return correlations across countries, and both exceed the level justified by fundamentals. In the next section, we outline a simple theory of imperfectly informed investors trading on correlated information that can reconcile these patterns.

3 Model

We consider a parsimonious dynamic model of asset markets under imperfect information. Our setup is designed to provide a simple mapping between the correlation of beliefs on the part of imperfectly informed, but sophisticated investors (equity analysts), and the correlation of stock returns. Indeed, we will show that conditional on a few readily observable moments of

[14]It is important to note that earnings forecasts are computed using I/B/E/S data, while returns are computed using Compustat. I/B/E/S does not include stock prices and there is not a unique firm identifier common to both I/B/E/S and Compustat (in the US, a match is possible using CRSP as an intermediate link; outside the US, firm name would be one possibility, but is notoriously problematic). One concern may be that firms covered by analysts exhibit different fundamental properties than those which are not, and that this selection bias drives some part of our results. For example, Hameed et al. (2010) find that analysts tend to cover firms whose fundamentals correlate more with other firms in their industry. In an important check, we compare the properties of fundamentals, i.e., correlations of earnings growth across the two datasets, since data on earnings are present in both. We find that the average correlation is similar in the two (0.11 in Compustat vs. 0.13 in I/B/E/S) and that they are reasonably correlated across countries at 0.48. The correlation is close to 0.60 without Norway, which is an outlier (for Norway, the correlation is actually higher in Compustat than in I/B/E/S, the reverse of the conjectured bias). Thus, it seems that the properties of Compustat firms line up fairly well with I/B/E/S firms. This may be because both datasets contain large, generally well covered and traded firms.

fundamentals, the correlation of beliefs is a sufficient statistic to predict the correlation of prices and we will derive a sharp analytic expression linking the latter to the former.

The economy consists of a continuum of firms of fixed measure one. For each firm i, there is a unit measure of outstanding stock or equity, representing a claim on the firm's profits. For each firm, these claims are traded by a unit measure of imperfectly informed risk-neutral investors.[15]

Fundamentals. Each firm is characterized by a time-varying fundamental A_{it} and profits (or earnings) are a constant proportion of fundamentals: $\pi_{it} = \Pi A_{it}$. Natural interpretations of A_{it} include the firm's level of productivity or demand.[16] Fundamentals are exogenous from the point of view of the market and evolve stochastically through time according to the AR(1) process in expression (1). As there, a_{it} denotes the (log of the) fundamental of firm i in period t, ρ the persistence of fundamentals, and $\mu_{it} \sim \mathcal{N}\left(0, \sigma_\mu^2\right)$ the innovation in the fundamental. The innovations μ_{it} are independent through time and of a_{it}. Importantly, they are not independent across firms, so that for two firms i and j, $\operatorname{cov}\left(\mu_{it}, \mu_{jt}\right) = \pi^f \sigma_\mu^2$, where $\pi^f \in [0,1]$ for $i \neq j$ is the correlation in fundamental innovations between the firms.

It is straightforward to derive the following properties of fundamentals:

$$\begin{aligned} \operatorname{var}\left(a_{it}\right) &= \frac{\sigma_\mu^2}{1-\rho^2} \\ \operatorname{cov}\left(a_{it}, a_{jt}\right) &= \frac{\pi^f \sigma_\mu^2}{1-\rho^2} \\ \operatorname{corr}\left(a_{it}, a_{jt}\right) &= \pi^f \end{aligned} \tag{3}$$

Information. Investors for each stock observe 2 pieces of information at the beginning of period t that are useful in forecasting fundamentals in that period: first, they perfectly observe the history of fundamental realizations. Because of our assumption of a first-order Markov process, this is equivalent to observing the previous period's realization a_{it-1}. Second, they

[15] The assumption of risk-neutrality is a clear simplification, made primarily to maintain analytic tractability. Veldkamp (2006) shows in a related setting that the presence of risk aversion can generate comovement through portfolio rebalancing effects, but in a quantitative example, finds this channel to be negligible. Risk aversion can also lead to comovement through macroeconomic fluctuations that affect the stochastic discount factor. Interestingly, our results predict correlations on a level similar to those in the data even without these factors, although that does not rule them out as playing a role. One interpretation of our risk-neutral investors is of large investors who take position limits in each stock so that they are never exposed to an individual stock's risk. Think, for example, of large institutional investors or international mutual funds (whose managers may be passed information directly from the research analysts we study). We discuss in more detail the role of various model assumptions Section 4.5.

[16] Standard models of firm dynamics featuring decreasing returns to scale in production or demand lead to exactly this relation.

observe a common noisy signal of the contemporaneous innovation:[17]

$$s_{it} = \mu_{it} + e_{it}$$

where $e_{it} \sim \mathcal{N}\left(0, \sigma_e^2\right)$ is the noise in the signal. The signal noise e_{it} is independent through time and of μ_{it}, but importantly, not across firms, so that $\text{cov}\left(e_{it}, e_{jt}\right) = \pi^e \sigma_e^2$, where $\pi^e \in [0, 1]$ for $i \neq j$ is the correlation in signal errors between the firms.[18]

Using standard Bayesian arguments, investors' expectations of μ_{it} are given by

$$\mathbb{E}_t\left[\mu_{it}\right] = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_e^2} s_{it} = \psi s_{it}$$

where $\psi = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_e^2} \in [0, 1]$ denotes the weight that investors put on the signal s_{it}. If there is no information in the signal, i.e., σ_e^2 grows to infinity, ψ goes to zero, i.e., no weight is put on the signal. If the signal is perfectly informative, $\sigma_e^2 = 0$, the investor puts a weight of 1.

Expectations of the fundamental a_{it} are then:

$$\mathbb{E}_t\left[a_{it}\right] = \rho a_{it-1} + \psi s_{it} = \rho a_{it-1} + \psi\left(\mu_{it} + e_{it}\right) \tag{4}$$

Stock returns. A standard Euler equation implies

$$P_{it} = \mathbb{E}_t\left[\pi_{it} + \beta P_{it+1}\right]$$

and a log-linear approximation around the steady state gives:[19]

$$p_{it} = \xi \mathbb{E}_t\left[a_{it}\right] = \xi \rho a_{it-1} + \xi \psi\left(\mu_{it} + e_{it}\right)$$

where we have suppressed constant terms that do not affect second moments. The stock price is proportional to investors' expectations of firm fundamentals, where the factor of proportionality

[17]Because information is identical across investors for each stock, we can also think of there being a single representative investor for each.

[18]We have assumed a rather stark degree of market segmentation: traders only receive signals about and trade a single asset. Moreover, all traders for each asset receive the same signal, so there is no heterogeneity in information across traders about a particular firm. This keeps the information structure simple: there is no learning from prices, and other than the aggregate component of all signals, traders do not use signals about firm j to update their beliefs about firm i. A related setup would be one where traders all receive a common signal about some aggregate component of fundamentals and a separate signal about an idiosyncratic component. This would preserve the lack of learning from the prices of other stocks. Recent work has shown that prices, even in the US, tend to have a low informational content (see, for example David et al. (2014)). We discuss in more detail the role of various model assumptions Section 4.5.

[19]A Taylor expansion gives $p_{it} \approx \frac{\overline{\pi}}{\overline{P}} \mathbb{E}_t\left[a_{it}\right] + \beta \mathbb{E}_t\left[p_{it+1}\right]$ where bars denote steady state values. Using the fact that $\frac{\overline{\pi}}{\overline{P}} = 1 - \beta$, guessing and verifying that $p_{it} = \xi \mathbb{E}_t\left[a_{it}\right] + \text{constant}$ gives the result.

$\xi = \frac{1-\beta}{1-\beta\rho}$ depends on investors' discount factor β and degree of persistence in fundamentals ρ. Expectations are formed based on the realization of the fundamental from the previous period as well as the realization of the current signal.

From here, it is straightforward to derive the following expression for stock returns:

$$\Delta p_{it} = \xi\rho\left(\rho - 1\right) a_{it-2} + \xi\left(\rho - \psi\right)\mu_{it-1} + \xi\psi\mu_{it} + \xi\psi\left(e_{it} - e_{it-1}\right)$$

Return comovement. We can now derive some properties of returns, specifically, the analogous moments to those of fundamentals in equation (3):

$$\begin{aligned} \operatorname{var}\left(\Delta p_{it}\right) &= \left[\frac{\rho^2}{1+\rho} + \psi\left(\psi - \rho\right)\right] 2\xi^2\sigma_\mu^2 + 2\xi^2\psi^2\sigma_e^2 \qquad (5) \\ \operatorname{cov}\left(\Delta p_{it}, \Delta p_{jt}\right) &= \left[\frac{\rho^2}{1+\rho} + \psi\left(\psi - \rho\right)\right] 2\xi^2\pi^f\sigma_\mu^2 + 2\xi^2\psi^2\pi^e\sigma_e^2 \end{aligned}$$

and putting these together,

$$\operatorname{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) = \frac{\kappa^f\pi^f + \kappa^e\pi^e}{\kappa^f + \kappa^e} \qquad (6)$$

where $\kappa^f = \left[\frac{\rho^2}{1+\rho} + \psi\left(\psi - \rho\right)\right]\sigma_\mu^2$ and $\kappa^e = \psi^2\sigma_e^2$.

Expression (6) is the key prediction of the model: the correlation of stock returns is a weighted average of the correlation of fundamentals and the correlation in beliefs, with weights κ^f and κ^e, respectively. We can characterize the following properties of the return correlation:

1. $\operatorname{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) \leq \max\left(\pi^f, \pi^e\right)$; $\frac{\partial \operatorname{corr}(\Delta p_{it}, \Delta p_{jt})}{\partial \pi^f} > 0$ and $\frac{\partial \operatorname{corr}(\Delta p_{it}, \Delta p_{jt})}{\partial \pi^e} > 0$ so long as $\kappa^e \neq 0$ and $\kappa^f \neq 0$.

2. With full information ($\psi = 1$ and $\sigma_e^2 = 0$) or no information ($\psi = 0$ and $\sigma_e^2 \to \infty$), $\kappa^e = 0$ and so $\operatorname{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) = \pi^f$.

3. In intermediate cases ($\psi \in (0, 1)$), $\operatorname{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) = \pi_f$ if and only if $\pi^e = \pi^f$.

4. $\operatorname{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) > \pi^f$ if and only if $\psi \in (0, 1)$ and $\pi^e > \pi^f$.

First, returns cannot be more correlated than either fundamentals or beliefs and return correlation is monotonically increasing in both. With either full information or no information, the correlation of returns is exactly that of fundamentals.[20] With intermediate information, the return correlation exceeds fundamental correlation when beliefs are more correlated than

[20] This is reminiscent of expression (2).

fundamentals, and equals fundamental correlation only when belief correlation also equals fundamental correlation.

Although the settings are not the same, the properties of return correlations in our model parallel those in Veldkamp (2006). That model is static, features investors with CARA preferences, learning from prices, and takes an explicit stand on the source of common information (the fundamental of a commonly observed asset, which arises endogenously with information markets), whereas our model is dynamic, features risk neutral agents, no learning from prices, and is agnostic regarding the particular source of correlation in beliefs. Despite these differences, our frameworks yield similar conditions for excess comovement: the correlation in beliefs must be higher than the correlation in fundamentals.

4 Quantitative Exercise

In the preceding section, we laid out a parsimonious model that makes simple and intuitive predictions regarding the determinants of the cross-firm correlation of stock returns, and specifically, the role that correlated beliefs can play in leading to excess correlation above and beyond that of fundamentals. In this section, we perform a simple numerical exercise to ask whether reasonable levels of correlation in beliefs are able to generate realistic levels of return correlation and the cross-sectional pattern across countries. To do so, we first pass our data on beliefs and fundamentals through the model to generate predictions of return correlations; second, we examine whether the predicted correlations line up with the empirical ones on a number of dimensions.

4.1 Calibration

In general, quantifying information-based models is challenging, as information is seldom directly observed. We overcome this hurdle by using our data on the forecasts of informed market participants - in other words, in this instance, we are able to measure agents' information sets directly. Specifically, we use the empirical correlation and volatility of forecasts to place values on the two informational parameters of our model, π^e and σ_e^2.

Expression (4) gives agents' expectation of fundamentals, i.e., the forecast. It is straightforward to derive the following moments of forecasts:

$$\begin{aligned}
\operatorname{var}\left(\mathbb{E}_t\left[a_{it}\right]\right) &= \left(\frac{\rho^2}{1-\rho^2}+\psi\right)\sigma_\mu^2 && (7)\\
\operatorname{cov}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right) &= \left(\frac{\rho^2}{1-\rho^2}+\psi^2\right)\pi^f\sigma_\mu^2+\psi^2\pi^e\sigma_e^2 \\
\operatorname{corr}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right) &= \frac{\left(\frac{\rho^2}{1-\rho^2}+\psi^2\right)\pi^f\sigma_\mu^2+\psi^2\pi^e\sigma_e^2}{\left(\frac{\rho^2}{1-\rho^2}+\psi\right)\sigma_\mu^2} && (8)
\end{aligned}$$

Rearranging expression (7) gives a relation between the forecast variance and overall information, captured by the noise in the signal, σ_e^2:

$$\sigma_e^2=\frac{1-\psi}{\psi}\sigma_\mu^2,\quad \text{where}\quad \psi=\frac{\operatorname{var}\left(\mathbb{E}_t\left[a_{it}\right]\right)}{\sigma_\mu^2}-\frac{\rho^2}{1-\rho^2} \tag{9}$$

In other words, given the properties of fundamentals, the variance of forecasts pins down ψ, from which it is straightforward to back out σ_e^2.

Similarly, rearranging (8) gives an expression for π^e as a function of the properties of fundamentals, the signal noise, and the correlation of forecasts:

$$\pi_e=\frac{\left(\frac{\rho^2}{1-\rho^2}+\psi\right)\sigma_\mu^2\operatorname{corr}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right)-\left(\frac{\rho^2}{1-\rho^2}+\psi^2\right)\sigma_\mu^2\pi^f}{\psi^2\sigma_e^2} \tag{10}$$

Clearly, (9) and (10) pin down the two information parameters of the model. However, as we demonstrate next, it turns out that we do not need to explicitly use these equations to identify the structural parameters so as to generate predictions of return correlations. Specifically, given the correlation of forecasts, $\operatorname{corr}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right)$, it can be shown that the correlation in returns is equal to:[21]

$$\operatorname{corr}\left(\Delta p_{it},\Delta p_{jt}\right)=\frac{\operatorname{corr}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right)-\rho\pi^f}{1-\rho} \tag{11}$$

In other words, given values for ρ and π^f, the correlation of forecasts provides all the information we need to pin down the correlation of returns. This is a particularly attractive feature of our model, since the correlation of forecasts is precisely the moment we examined in Section 2. With this result, we need only calibrate ρ and π^f and use these values in conjunction with forecast correlations to generate predicted correlations of returns. We take this approach to investigate the properties of the model's predicted returns. In the following subsection, we use (9) and (10) along with values of σ_μ^2 to infer values of the underlying structural parameters

[21]Substitute for $\pi^e\sigma_e^2$ from (10) into (6).

and perform counterfactual experiments.

To assign a value to ρ for each country, we perform the autoregression implied by (1) on a firm-by-firm basis and take the average across firms.[22] To pin down π^f, we compute the correlation of fundamentals in the same manner as we did for forecasts - from the last line of expression (3) this is equal to π^f. For both calculations, we use the log of earnings per share to measure log fundamentals, which is consistent with our theory, where log fundamentals are equal to log earnings plus a constant. All data for our exercise comes from the set of I/B/E/S firms for which we have both earnings forecasts and realizations. Moments are reported in Table 6 in the Appendix (many are also included in Tables 4 and 5 also in the Appendix, but we rewrite them for the reader's convenience).

4.2 Results

Return correlations. Figure 2 plots the first main result of our exercise: the predicted return correlations vs. the actual for our sample of 31 countries. Given the simplicity of our model, the relationship is surprisingly strong: the correlation between predicted and actual is 0.63. Moreover, the position of the 45 degree line show that the levels are broadly in line as well: the average correlation in the data is 0.46 compared to 0.47 from the model. Clearly, correlated beliefs are able to lead to both cross-sectional variation as well as levels of return correlations in line with those observed in the data. This is not to say that our mechanism is the only one active in the data; merely that belief correlation seems to play an important role.

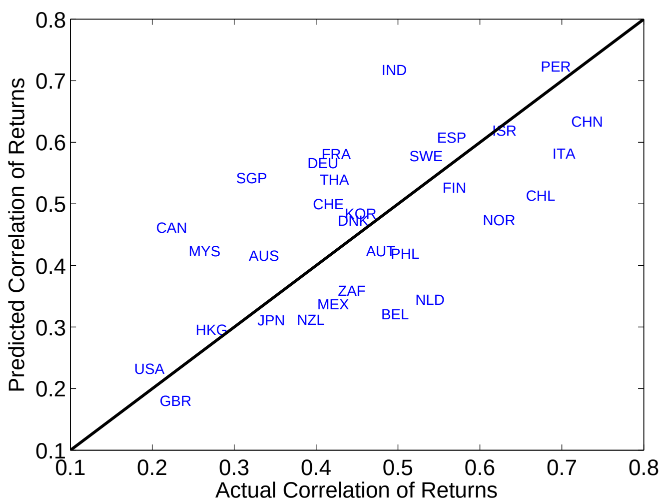

Figure 2: Return Correlations - Predicted vs. Actual

That the model predicts correlations on par with those in the data, despite the much lower

[22]We additionally control for a linear time trend which seems to be present in the data.

correlation of fundamentals, implies that correlated beliefs can lead to realistic levels of excess correlation. The left-hand panel of Figure 3 shows this to be the case. The figure is exactly the analogous one to the left-hand side of Figure 1 and plots the predicted correlation of returns on the vertical axis against the correlation of earnings growth on the horizontal. The plot looks strikingly similar to the empirical one. Across the board, return correlations exceeds fundamental correlations, often by a significant amount, just as in the data. Because the levels of predicted return correlations are close to the actual (0.47 and 0.46, respectively), they both exceed the correlation of fundamentals by a factor of approximately 4.[23]

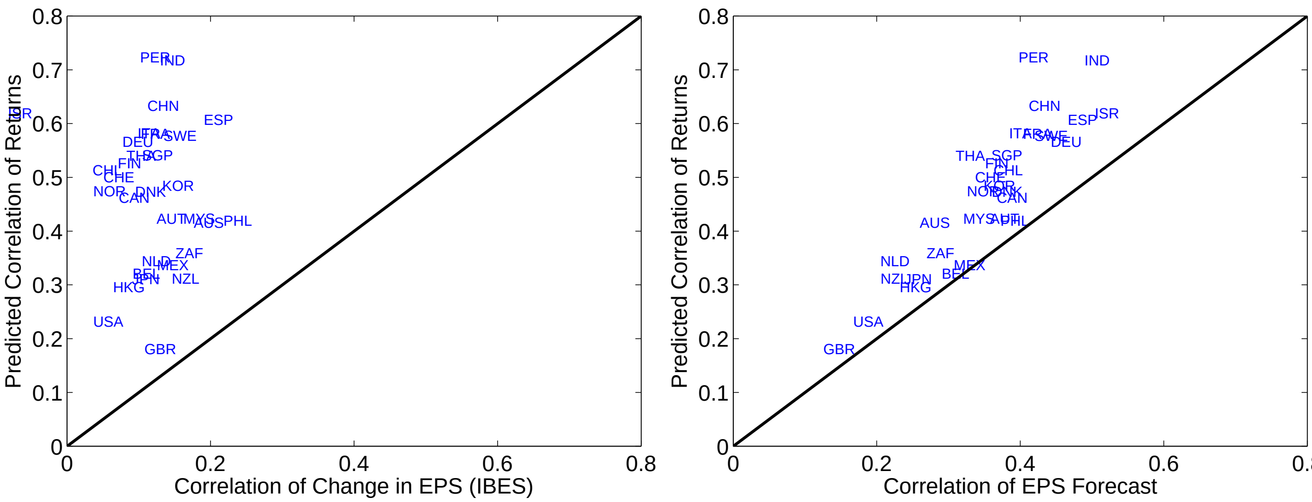

Figure 3: Predicted Firm-Level Correlations - Returns, Forecasts and Fundamentals

The right-hand panel of Figure 3 plots the predicted correlation of returns against the correlation of forecasts. This is exactly analogous to the right-hand side of Figure 1. Again, the figures look broadly similar. The predicted return correlations are strongly related to the correlation of forecasts (a bit more so than in the data) and generally are of a similar magnitude. In sum, our theory is able to reconcile the facts from Section 2: the correlation of returns and forecasts are strongly related, and both exceed the levels justified by fundamentals.

4.3 Counterfactual Experiments

To hone in on the drivers of high return correlations, we can use our framework to perform a number of revealing counterfactual experiments. Before doing so, we need now put values on the

[23]For this comparison, note that the correlation of fundamentals was computed using Compustat firms to compare to Compustat return correlations in Figure 1, and using I/B/E/S firms to compare to the model predictions. However, as discussed in Section 2, the characteristics of fundamentals look similar across the two datasets. Israel is a clear outlier with a slightly negative correlation in earnings growth in I/B/E/S (-0.07; it is 0.06 in Compustat).

underlying structural parameters of the model. Recall that computing the model's predictions for return correlations did not require this step, once we measured the correlation of beliefs. The remaining parameters to calibrate are π^e, σ_e^2, and σ_μ^2. Expressions (9) and (10) show that using the variance of forecasts as an additional moment (jointly with the correlation of forecasts) allows us to identify π^e and σ_e^2, and this is the approach we take. Finally, we directly follow equation (3) and estimate σ_μ^2 as the average within-firm variance of log earnings multiplied by $1-\rho^2$. The first 3 columns of Table 7 in the Appendix report the resulting parameter values.[24]

We perform two main exercises geared toward understanding the sources of variation in return correlations. For each, we set a parameter of the model equal to its US value for all countries and assess the implications for return correlations. We turn first to the informational parameters and set π^e - the correlation in the non-fundamental component of beliefs - to its US value for all countries. We next perform the analogous exercise for the fundamental component and set π^f to its US value. In both exercises we eliminate heterogeneity across countries in one source of belief correlation. The idea is to see which change goes furthest in eliminating heterogeneity in return correlations.

We plot the results of these exercises in the top row of Figure 4, along with the baseline results in the bottom row for ease of comparison. The figure clearly shows that the non-fundamental component of belief correlation, π^e, is key - setting this to the US level for all countries reduces the correlation of predicted and actual return correlation from 0.63 to 0.24, a fall of about 62%. Moreover, the magnitudes of return correlations fall dramatically as well, from an average of 0.47 to 0.28, a fall of about 41%. Comparing to the baseline results in the bottom row of the figure sums up the results - systematic heterogeneity in return correlations almost vanishes and the magnitudes fall to an average essentially on par with the US. In contrast, turning to the fundamental component of beliefs and fixing π^f at its US level results in comparatively small changes in predicted return correlations. The correlation of predicted and actual actually increases slightly to 0.64. In terms of levels, there is only a small reduction from 0.47 to 0.42. Comparing to the baseline results in the bottom row shows that there is little difference between the two. In sum, differences in the properties of the non-fundamental component of beliefs would seem to be a key determinant of the cross-section of return correlations as well as their magnitudes. There is a much smaller role for the correlation of fundamentals.

In results not reported, we have performed similar experiments for the variance parameters, σ_e^2 and σ_μ^2. We find that fixing these parameters to their US levels across all countries makes very little difference, i.e., predicted return correlations remain quite similar to the baseline case. This

[24]For 2 of the 31 countries, India and Peru, this procedure gives values of π^e that slightly exceed one (1.28 and 1.1, respectively). Rather than exclude these countries, we set π^e equal to 0.99. This makes little difference in our results.

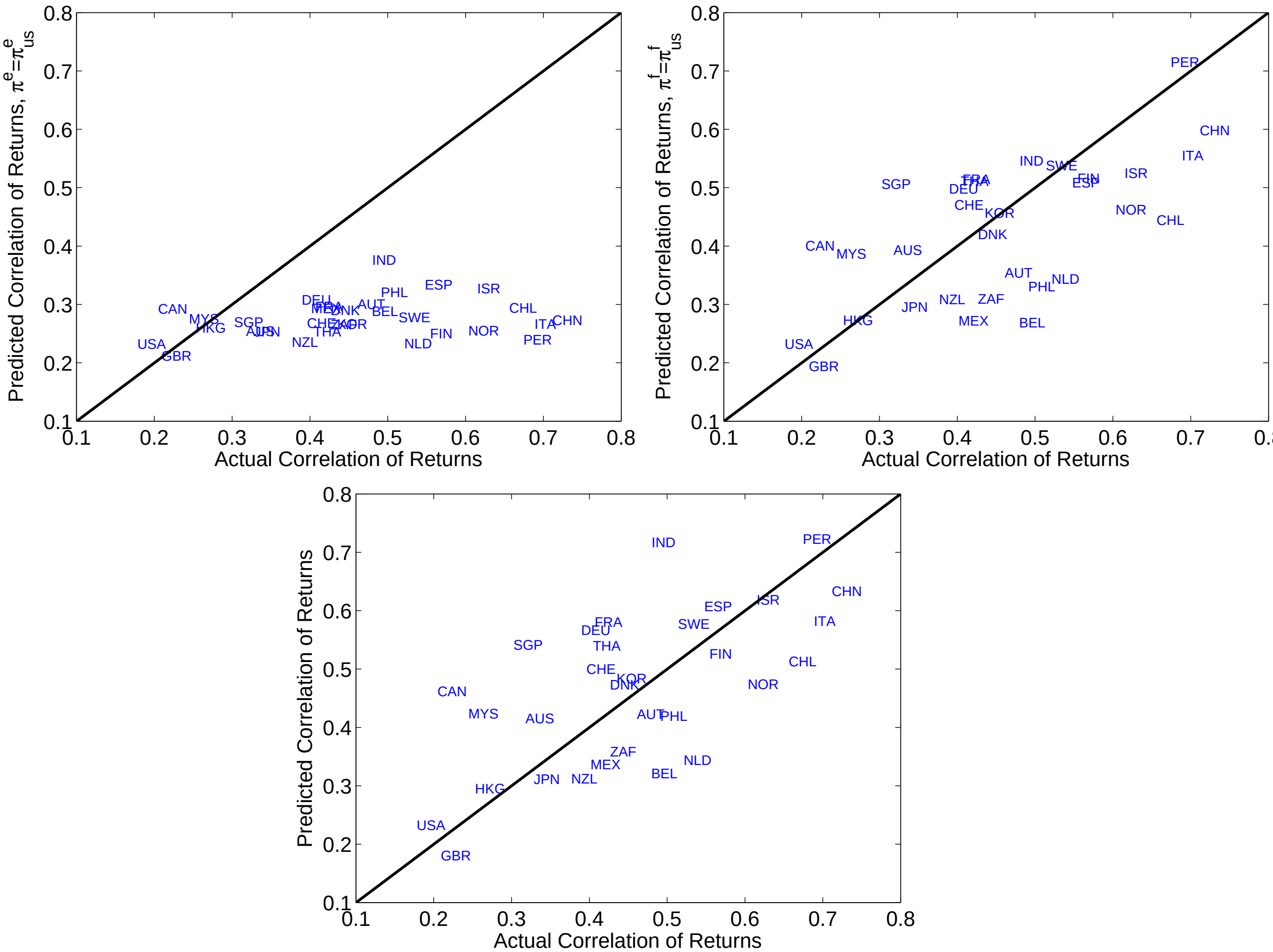

Figure 4: Baseline and Counterfactual Predicted Firm-Level Return Correlations

is not all that surprising of course, since variances appear in the numerator and denominator of the correlation in expression (6). There is an interesting economic interpretation, however, particularly with respect to σ_e^2 - namely, for partially, but imperfectly informed agents, it is not the overall level of information that matters for return comovement, but rather the extent of its commonality.[25]

[25]For example, the posterior variance of investor beliefs is $\left(\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2}\right)^{-1}$ and subtracting this from 1 tells the percent of prior variance that is eliminated by the signal. The correlation of this with predicted return correlation is negative, but mildly so, at -0.35; the correlation with the empirical return correlation is -0.19.

4.4 Comovement and Stock Market Volatility

Previous work has shown that return correlations are a key driver of aggregate stock market volatility.[26] Thus, it seems a natural extension of our main results on return comovement to assess the implications for market-wide volatility. To do so, we construct measures of aggregate volatility as the standard deviation of annual returns from an equal-weighted index for the Compustat firms in our sample.[27] The values are reported in Table 4 in the Appendix.

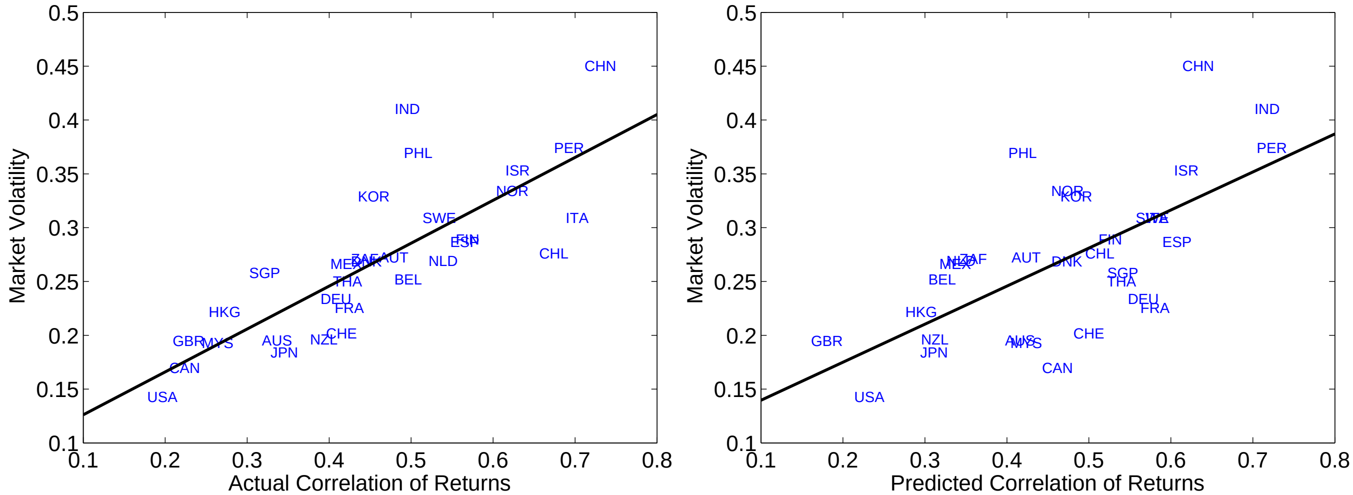

Figure 5: Return Correlations and Aggregate Volatility

The left-hand panel of Figure 5 plots the empirical return correlations against market-wide volatility, along with the line of best fit. Clearly, there is a strong positive relationship: the regression of volatility on correlation yields an R^2 of about 0.64, suggesting that a single statistic, the average cross-firm correlation, explains about 64% of the cross-section of market volatility.[28] The right-hand panel of Figure 5 shows the analogous plot using our predicted correlations. There continues to be a strong positive relationship: a regression of the empirical volatilities on our model-generated return correlation yields an R^2 of 0.44. Thus, our results suggest that realistic levels of correlation in investor beliefs can explain about 44% of the cross-section of

[26]For example, Harvey (1995) finds that variation in the average cross-firm correlation of returns explains over 50% of the variation in market volatility across a number of emerging and developed markets, but that a host of other variables have very little explanatory power, including measures of market size, trading volume, and concentration.

[27]We choose to construct our index using these firms as we have already shown that they exhibit fairly comparable properties of fundamentals to the firms in I/B/E/S. We cannot claim the same for broader market indices. However, it is reassuring that for the set of countries and time window we study (1999-2013), the correlation between our constructed measure of market volatility and that reported by MSCI is reasonably high at 0.64. Going back to 1993, when available, the correlation between our measure and MSCI is even higher, 0.77.

[28]This is close to the finding in Harvey (1995).

market volatility (and almost 70% of the 'correlation channel'; 0.44 over 0.64). We view these as important implications of our results that future research into the determinants of aggregate stock market volatility should bear in mind.

As our last point in this section, Figure 6 plots aggregate volatility directly against the correlation of analyst forecasts. Once we see the strength of the relationship between the two, the results in Figure 5 should come as no surprise, since our predicted return correlations generally derive quite closely from forecast correlations. This may be the most direct evidence that correlated beliefs is an important driver of aggregate volatility.

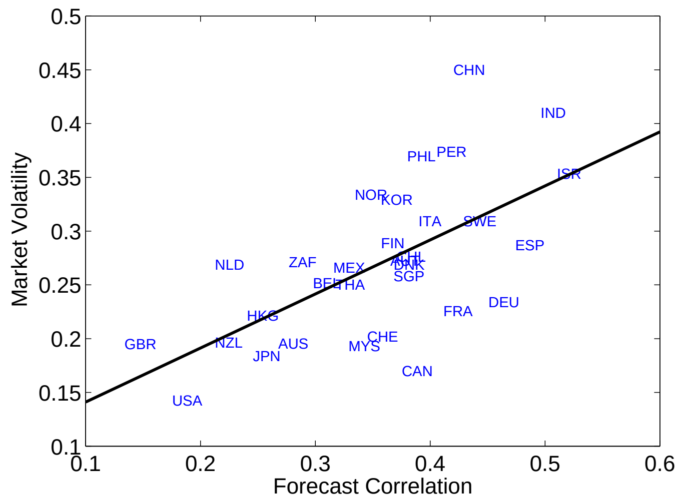

Figure 6: Forecast Correlations and Aggregate Volatility

4.5 Discussion of Model Elements

Our model is highly parsimonious and hones in precisely on the statistic we are after, i.e., the correlation in returns. However, this comes at the cost of abstracting from several factors that likely play a role in driving stock price movements (and the far from perfect fit of our model leaves ample room for these). First, our assumption of risk neutrality is a clear simplification. Although this may not be a bad approximation for large, international institutional investors, it rules out in general the role of aggregate discount rate shocks in driving comovement. However, there is reason to believe that this is not the primary factor behind comovement: for example, Pindyck and Rotemberg (1993) test this hypothesis and reject it - they find that macroeconomic variables (observed or latent) cannot account for observed cross-firm correlations in the US. Barberis et al. (2005) show that when stocks are added to the S&P 500 index, their correlation with the index goes up; they point out that this phenomenon cannot be explained by common macroeconomic factors, such as those that would affect discount rates - these factors should affect all stocks, not just the subset that exhibit the change in comovement.[29] Of course, it is not our goal to a priori rule out aggregate shocks as a potential mechanism, but rather to point out that it has been difficult to measure this phenomenon in the data, and so an information-based theory is worth considering.[30]

Many information-based models of stock prices include heterogeneous information about a single stock across investors, along with noise (or liquidity) traders that prevent the price from being perfectly revealing, elements that we abstract from.[31] Our data suggest that security analysts produce correlated information and supply that information to presumably fairly sophisticated market participants who then act on it. In this sense, we have a direct measure of the correlation of beliefs on the part of 'informed' traders, independent of the actions of noise traders.[32] On the other hand, extending our framework in this direction along with our detailed data may provide further insights on our mechanism, and would certainly broaden the model to match additional features of asset price data.[33] Interestingly, recent work by Hassan and Mertens (2011) show that small correlated errors on the part of near-rational agents with otherwise dispersed information can lead to high stock price volatility, but that small common noise trading shocks do not exhibit the same effects.[34]

[29]Barberis et al. (2005) interpret their findings as pointing to the role of frictions or 'sentiments' among irrational, or completely uninformed, traders. Although similar in spirit to our findings, recall that we are examining the beliefs of what are presumably fairly sophisticated agents. See also the discussion in the following paragraph.

[30]A few additional points: first, recall that our model and calibration strategy control for the correlation in fundamentals; if it were indeed the case that heterogeneity in aggregate discount rate shocks was driving variation in comovement across countries, and if these shocks also affected earnings, we might expect to see a stronger connection between earnings correlations and return correlations. Second, it is not clear that this theory would be independent from ours - for example, correlated news about aggregate factors that affect both discount rates and earnings could be one reason that analysts produce correlated forecasts across firms. Finally, our regression analyses in Section 5 control for additional macroeconomic variables, with little effect on the significance of our mechanism.

[31]Veldkamp (2006) is a closely related example.

[32]It could be the case that the information of our informed traders is in part due to the actions of noise traders if the informed traders learn from the market price, which reflects noise trader demand. On the other hand, as previously pointed out, this channel has been shown in related contexts to be quantitatively small, e.g., David et al. (2014). We revisit the question of exactly why these agents exhibit correlated beliefs in Section 5.2.

[33]For example, it would be fairly straightforward to add noise traders alone, and perform a fitting exercise by calibrating the common component of their demand across stocks to exactly match the correlation of returns. In this case, the interpretation of our findings in this paper is exactly the degree of comovement that would remain in the absence of these traders. The difference between our predicted return correlation and the data is entirely attributable to noise traders, who in this sense, play the role of a residual.

[34]In a related point, we make the rather stark assumption that analyst information is trader information. If only a small piece of the correlated information is actually used by traders, but they act 'near-rationally' as in the model of Hassan and Mertens (2011), the common component we measure could be one potential force behind their mechanism.

5 Alternative Explanations

In this paper, we have argued that differences in the correlation of beliefs about firm fundamentals across countries play an important role in determining the cross-section of excess return comovement and consequently, a portion of the variation in aggregate stock market volatility. Of course, as discussed in Section 1, there are alternative explanations for these patterns, including, for example: differences in the quality of institutions and the strength of property rights, capital account openness, a lack of firm-level transparency or 'opaqueness', and limits to arbitrage.

In light of the large existing literature, it is important to verify whether differences in the correlation of beliefs hold significant explanatory power for return comovement and aggregate market volatility after controlling for variables that pertain to the alternative theories described above. To achieve that task, we begin by regressing the correlation of returns against our main variable of interest: the correlation of earnings forecasts. We expect that the coefficient estimate of this regression is positive. Since returns should reflect news about future earnings, we further add to the regression the correlation of earnings growth and anticipate that the coefficient estimate is positive.[35] We then account for the alternative theories suggested by the existing literature.

First, as suggested by Li et al. (2004), we control for the country's degree of openness using the widely-used openness index from Chinn and Ito (2006), which covers all countries in our dataset throughout the entire period of study.[36] A higher value of this index, which ranges between 0 and 1, implies a higher degree of openness of the capital account, which may be associated with lower comovement and market volatility. Hence, one would hypothesize a negative coefficient estimate in this case. Second, following Morck et al. (2000), we control for the quality of institutions using the average Control of Corruption Index provided by the World Bank's Worldwide Governance Indicators Database for the entire period of study.[37] The index, which is based on surveys, reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of

[35]Notice that including these two factors adheres rather closely to our theoretical framework and empirical approach above. One key difference is that our more structural theory demonstrates that the assumption of a constant coefficient from this regression across countries may be problematic; see, for example, expression (11).

[36]Robustness analysis using the index of openness by Quinn (2003), which spans years until 2004, yields quantitatively similar results. We opt for the Chinn-Ito Index in the baseline analysis due to the longer coverage.

[37]Our results are robust to using a host of alternative measures of the quality of institutions, including indices of the Rule of Law, Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, and Regulatory Quality, all of which are provided by the same database. These variables essentially extend the measures used by Morck et al. (2000) and employed by La Porta et al. (1998) and La Porta et al. (1999) for previous decades. As in those papers, since the measures are highly collinear with each other and since we only have data for 31 countries, we only include one variable at a time so as to not run out of degrees of freedom.

the state by elites and private interests. It ranges between -2.5 and 2.5, with higher values denoting strong governance. Therefore, we hypothesize a negative coefficient estimate. Third, given the findings of Jin and Myers (2006), we control for the degree of firm-level transparency using the average Extent of Director Liability Index provided by the World Bank's Doing Business Database for the 2004-2013 period.[38] The index measures minority shareholders' ability to sue and hold interested directors liable for prejudicial related-party transactions, and in particular, reflects the availability of legal remedies within this context. It ranges between 0 and 10, with higher values denoting stronger governance. Therefore, we hypothesize a negative coefficient estimate. Fourth, in line with Bris et al. (2007), who find that binding short-sale restrictions correlate with return comovement, we control for the average stock market turnover ratio provided by the World Bank World Development Indicators (WDI) database for the 1998-2012 period. The turnover ratio is the total value of shares traded during the period divided by the average market capitalization for the period. Average market capitalization is calculated as the average of the end-of-period values for the current and previous periods. Higher values of turnover typically suggest greater market liquidity and hence fewer trading frictions, or limits to arbitrage. Therefore, we hypothesize a negative coefficient estimate.

Finally, a large body of work has established that return comovement and aggregate volatility are higher in less developed economies. To check whether the degree of development has a direct effect on comovement, conditional on the various measures of market frictions described above which vary systematically across rich and poor countries, we include the average of the log of real gross domestic product (GDP) during the 1998-2013 period to the regression and hypothesize that it earns a negative coefficient.[39]

5.1 Empirical Results

We begin by regressing the correlation of returns against the main variable of interest: the correlation of earnings forecasts. Column (1) in Table 1 shows a highly statistically significant coefficient estimate of 0.897 and an R^2 of 0.31. The strength of the relationship is not surprising in light of the right panel of Figure 1. In column (2) we add the correlation of earnings growth to the regression. The coefficient estimate on the forecast variable falls slightly to 0.749 and maintains its statistical significance at the 1% level. Earnings growth appears important in driving return correlations as well; the coefficient estimate is 1.368 and is statistically significant at the 1% level. Our model predicts that these two variables are key in explaining differences

[38] Our results are robust to using a host of alternative measures of opaqueness, including indices of the Extent of Disclosure, Ease of Shareholder Suits, and Strength of Minority Investor Protection, all of which are provided by the same database.

[39] GDP data in constant US dollars are from the WDI Database. We find similar results using GDP in current US dollars.

Table 1: The Cross-Section of Return Correlation

	(1)	(2)	(3)
corr(for)	0.897***	0.749***	0.548**
	(0.248)	(0.229)	(0.246)
corr(Δ EPS)		1.368***	1.191**
		(0.491)	(0.527)
Extent of director liability			-0.018*
			(0.010)
Corruption control			-0.039
			(0.042)
Chinn-Ito openness			0.115
			(0.133)
Turnover ratio			-0.002
			(0.047)
Log per capita GDP			-0.008
			(0.046)
R^2	0.31	0.46	0.57
# Observations	31	31	31

Notes: The regressand is the average cross-firm correlation of stock returns in each country. Regressors and expected signs of coefficients are described in Section 5. *, **, *** indicate significance at 10%, 5%, 1%-levels, respectively. Standard errors in parentheses.

in return comovement, so the R^2 of 0.46 that arises from the regression is somewhat reassuring of our theory.

Column (3) shows that forecast correlations continue to play a key role in explaining differences in return comovement after controlling for the five additional variables described above. The coefficient estimate on forecast correlation again falls slightly to 0.548 and it is statistically significant at the 5% level. In other words, the significant effect of the correlation of information that we measure is robust to the presence of these various factors. Similarly, the coefficient estimate on earnings growth correlation falls to 1.191 and it is statistically significant at the 5% level. Finally, among the variables that aim to measure different frictions across countries, higher accountability is associated with lower return comovement. In particular, the coefficient estimate on the Director Liability Index is negative and statistically significant at the 10% level. The remaining coefficient estimates are not individually statistically different from zero, although they jointly add non-trivial explanatory power to the regression as seen in the R^2's.

A similar picture emerges from the exercises that analyze the determinants of aggregate stock market volatility. The three columns in Table 2 contain the same set of regressions described above, where the regressand now corresponds to the standard deviation of aggregate returns in each country. In this case, the coefficient estimate of the forecast correlation remains highly statistically significant throughout all the exercises; the remaining coefficients are typically not

Table 2: The Cross-Section of Market Volatility

	(1)	(2)	(3)
corr(for)	0.503***	0.466***	0.300***
	(0.115)	(0.117)	(0.105)
corr(Δ EPS)		0.340	0.393*
		(0.250)	(0.224)
Extent of director liability			-0.006
			(0.004)
Corruption control			-0.002
			(0.018)
Chinn-Ito openness			0.026
			(0.056)
Turnover ratio			0.026
			(0.020)
Log per capita GDP			-0.032
			(0.020)
R^2	0.40	0.43	0.69
# Observations	31	31	31

Notes: The regressand is the standard deviation of aggregate stock market returns in each country. Regressors and expected signs of coefficients are described in Section 5. *, **, *** indicate significance at 10%, 5%, 1%-levels, respectively. Standard errors in parentheses.

statistically different from zero, though again, they jointly add significant explanatory power to the regression.

Our empirical results suggest that belief correlations are critical in understanding differences in comovement and aggregate volatility across countries. However, we do not interpret our findings as implying that existing theories emphasizing the roles of institutional quality, opaqueness, capital account openness, limits to arbitrage, or additionally, macroeconomic volatility, fail to explain differences in comovement.[40] In fact, these factors may be captured to some extent by our measures of fundamental and/or belief correlations.

For example, it is clear that macroeconomic volatility should be reflected by the correlation in fundamentals - both point to a more sizable aggregate component in fundamentals. Furthermore, smaller countries may be more specialized in the production of goods and services that span fewer industries. Shocks to these important sectors may therefore have economy-wide implications and result in higher macroeconomic volatility. For example, resource-rich economies find a large fraction of their firms interacting with the resource-producing sector and are therefore exposed to the large shocks this sector encounters. Similarly, if the firms that operate in these sectors dominate the stock market in each country, earnings comovement may be higher.

[40] See Diebold and Yilmaz (2008), among others, for evidence that stock market volatility is higher in countries with more volatile fundamentals.

Finally, fundamentals may be more correlated in countries where stock markets are made up of very few firms, or if a few large firms dominate the market capitalization.

Indeed, in exercises not reported in the paper, we additionally control for each country's standard deviation of real (or nominal) GDP growth rate over the period of study, geographical size (in square kilometers) or population size, Herfindahl index of industry concentration, fraction of rents obtained from natural resources, average number of listed firms, and Herfindahl index of firm concentration in the stock market. The inclusion of these controls renders the coefficient estimate on fundamentals correlation statistically insignificant, which suggests that differences in these variables may be responsible for differences in fundamentals comovement. However, the coefficient estimate of the key indicator of interest - the correlations of forecasts - remains highly statistically significant, which speaks to the robustness of this variable in explaining cross-country differences in return comovement.

5.2 Interpretation: why does belief correlation vary?

Given these results, it makes sense to take a step back and consider why exactly the correlation of beliefs varies across countries. Consider, for example, a micro-foundation for the correlated component of information such as that in Veldkamp (2006): with endogenous information markets characterized by high fixed costs of discovery and low marginal cost of replication, a strategic complementarity is introduced through the market price of information - namely, in equilibrium, information suppliers (analysts) provide the highest value signals (those that are informative for multiple assets) and investors cluster on these signals as they are the most inexpensive. To the extent that the costs of discovery, or the benefits, vary across countries, this may go some way in explaining the patterns we uncover. For example, where firm-level information is costlier to acquire, due perhaps to lower transparency and/or lower reporting requirements, information production may be more concentrated. In countries where macroeconomic instability is high or institutions are weak, the analyst understands that the individual firm's fundamentals are not accurate predictors of the cash flows that investors will obtain from that firm, due, for example, to the high risk of asset expropriation by the government or a lack of incentive on the part of the firm's management to rebate cash flows in the absence of adequate punishment for reneging. In this case, the analyst may not spend her limited resources to acquire individual information about each firm, but may instead spend them to best predict aggregate variables in the country in question. This may generate a higher correlation in beliefs/forecasts.[41]

[41] As one piece of direct evidence of this mechanism, Dang et al. (2014) show that firm-level news comoves more in countries with weaker institutional environments, with the interpretation that institutional quality affects the incentives for firm-specific information production.

These potential mechanisms are clearly related to the measures of institutional quality examined by the literature. In this sense, some of these alternative theories may interact with ours, and are potentially complementary - namely, the varying quality of institutions, firm-level transparency, etc., may be among the underlying forces leading to differences in the commonality of information and beliefs. To explore this relationship in more detail, in Table 3 we directly regress our indicator - forecast correlations - on the measures of institutions already described. The results demonstrate that forecast correlations indeed vary systematically with institutional characteristics. In fact, information seems to be more correlated in countries that are characterized by lower political stability and regulatory quality, both measures of the quality of institutions in a country, as well as in countries where firm behavior is more opaque, i.e., ease of shareholder suit and investor protection are lower. Thus, our results show that there may be a direct link between the quality of institutions, broadly defined, and the specificity of information that we measure. It would be fruitful for future research to focus on understanding the information sets that sophisticated market participants rely on and the factors that they utilize in forecasting future firm-level performance.

Table 3: Institutions and the Correlation of Information

	Political Stability	Regulatory Quality	Shareholder Suit	Investor Protection
Coefficient	-0.040**	-0.049**	-0.018*	-0.020**
(Standard Error)	(0.018)	(0.024)	(0.009)	(0.010)
R^2	0.14	0.13	0.12	0.13
# Observations	31	31	31	31

Notes: The regressand is the average cross-firm correlation of analyst forecasts of earnings per share in each country. Regressors and expected signs of coefficients are described in Section 5.2. *, **, *** indicate significance at 10%, 5%, 1%-levels, respectively. Standard errors in parentheses.

6 Conclusion

In this paper, we have examined the role of correlated beliefs in leading to excess comovement in stock prices, which is particularly stark in poor and emerging markets. Our key innovation is to look directly to agents' information, in the form of equity market analyst forecasts. We use a simple theoretical framework to demonstrate that correlated beliefs on the level of what we observe in the data can lead to realistic patterns in return correlations - both in levels and the cross-section across countries. We explore the consequences of this finding for aggregate stock market volatility.

We have touched on a number of potential directions for future work in the body of the paper. These might include further exploring the I/B/E/S dataset, which contains additional variables that may be useful in a similar vein - namely, to directly measure agents' information, which is typically not observed by the econometrician. Moreover, our theory does not take a stand on the precise source of correlated information or the variation across countries - large fixed costs of information production, similar inputs into the information production process, i.e., relying on common news, or on a common interpretation of that news - these are issues that are worth understanding.

References

Barberis, N., A. Shleifer, and J. Wurgler (2005): "Comovement," *Journal of Financial Economics*, 75, 283–317.

Bekaert, G. and C. R. Harvey (1997): "Emerging Equity Market Volatility," *Journal of Financial Economics*, 43, 29–77.

Bris, A., W. N. Goetzmann, and N. Zhu (2007): "Efficiency and the bear: Short sales and markets around the world," *The Journal of Finance*, 62, 1029–1079.

Chan, K. and A. Hameed (2006): "Stock price synchronicity and analyst coverage in emerging markets," *Journal of Financial Economics*, 80, 115–147.

Chinn, M. D. and H. Ito (2006): "What Matters for Financial Development? Capital Controls, Institutions, and Interactions," *Journal of Development Economics*, 81, 163–192.

Cho, D. D., J. Russell, G. C. Tiao, and R. Tsay (2003): "The Magnet Effect of Price Limits: Evidence from High-Frequency Data on Taiwan Stock Exchange," *Journal of Empirical Finance*, 10, 133–168.

Crawford, S. S., D. T. Roulstone, and E. C. So (2012): "Analyst initiations of coverage and stock return synchronicity," *The Accounting Review*, 87, 1527–1553.

Dang, T. L., F. Moshirian, and B. Zhang (2014): "Commonality in News Around the World," *Journal of Financial Economics*.

David, J., H. A. Hopenhayn, and V. Venkateswaran (2014): "Information, Misallocation and Aggregate Productivity," *NBER Working Paper*.

Diebold, F. X. and K. Yilmaz (2008): "Macroeconomic Volatility and Stock Market Volatility, worldwide," *NBER Working Paper*.

Hameed, A., R. Morck, J. Shen, and B. Yeung (2010): "Information, Analysts, and Stock Return Comovement," Tech. rep., National Bureau of Economic Research.

Harvey, C. (1995): "The Cross-Section of Volatility and Autocorrelation in Emerging Markets," *Finanzmarkt und Portfolio Management*, 9, 12–34.

Hassan, T. A. and T. M. Mertens (2011): "The Social Cost of Near-Rational Investment," Tech. rep., National Bureau of Economic Research.

Israelsen, R. D. (2015): "Does Common Analyst Coverage Explain Excess Comovement?" in *Journal of Financial and Quantitative Analysis, forthcoming.*

Jin, L. and S. C. Myers (2006): "R 2 around the world: New theory and new tests," *Journal of Financial Economics*, 79, 257–292.

La Porta, R., F. L. de Silanes, A. Shleifer, and R. W. Vishny (1998): "Law and Finance," *Journal of Political Economy*, 106, 1113–1155.

La Porta, R., F. Lopez-de Silanes, A. Shleifer, and R. Vishny (1999): "The Quality of Government," *Journal of Law, Economics and Organization*, 15, 222–79.

Li, K., R. Morck, F. Yang, and B. Yeung (2004): "Firm-Specific Variation and Openness in Emerging Markets," *Review of Economics and Statistics*, 86, 658–669.

Liu, M. H. (2011): "Analysts? incentives to produce industry-level versus firm-specific information," *Journal of Financial and Quantitative Analysis*, 46, 757–784.

Mondria, J. (2010): "Portfolio choice, attention allocation, and price comovement," *Journal of Economic Theory*, 145, 1837–1864.

Morck, R., B. Yeung, and W. Yu (2000): "The Information Content of Stock Markets: Why do Emerging Markets Have Synchronous Stock Price Movements?" *Journal of Financial Economics*, 58, 215–260.

——— (2013): "R 2 and the Economy," *Annu. Rev. Financ. Econ.*, 5, 143–166.

Pindyck, R. S. and J. J. Rotemberg (1993): "The Comovement of Stock Prices," *Quarterly Journal of Economics*, 1073–1104.

Piotroski, J. D. and D. T. Roulstone (2004): "The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices," *The Accounting Review*, 79, 1119–1151.

Quinn, D. P. (2003): "Capital Account Liberalization and Financial Globalization, 1890-1999: A Synoptic View," *International Journal of Finance & Economics*, 8, 189–204.

Veldkamp, L. L. (2006): "Information Markets and the Comovement of Asset Prices," *The Review of Economic Studies*, 73, 823–845.

Appendix

Table 4: Compustat - Returns and Earnings

Country	Obs.	corr (Δp_{it})	corr (ΔEPS_{it})	std (r_{mt})
AUS	8144	0.34	0.11	0.20
AUT	711	0.48	0.15	0.27
BEL	1088	0.50	0.19	0.25
CAN	2661	0.22	0.07	0.17
CHE	2342	0.42	0.12	0.20
CHL	1326	0.67	0.14	0.28
CHN	17675	0.73	0.06	0.45
DEU	6049	0.41	0.11	0.23
DNK	1653	0.45	0.13	0.27
ESP	871	0.57	0.18	0.29
FIN	1200	0.57	0.13	0.29
FRA	6317	0.42	0.10	0.23
GBR	15749	0.23	0.07	0.19
HKG	2279	0.27	0.07	0.22
IND	12933	0.50	0.16	0.41
ISR	2102	0.63	0.06	0.35
ITA	1582	0.70	0.14	0.31
JPN	36713	0.35	0.10	0.18
KOR	6571	0.45	0.08	0.33
MEX	845	0.42	0.11	0.27
MYS	9420	0.26	0.06	0.19
NLD	1424	0.54	0.11	0.27
NOR	1560	0.62	0.18	0.33
NZL	945	0.39	0.14	0.20
PER	625	0.69	0.15	0.37
PHL	1784	0.51	0.15	0.37
SGP	5663	0.32	0.08	0.26
SWE	2736	0.53	0.15	0.31
THA	3565	0.42	0.05	0.25
USA	57684	0.20	0.04	0.14
ZAF	3286	0.44	0.17	0.27

Table 5: I/B/E/S - Forecasts and Earnings

Country	Obs.	Analysts/firm	corr (for_{it})	std (for_{it})	corr (EPS_{it})	std (EPS_{it})	corr (ΔEPS_{it})
AUS	6935	6	0.28	0.47	0.22	0.56	0.20
AUT	887	6	0.38	0.48	0.33	0.60	0.14
BEL	1244	8	0.31	0.44	0.30	0.56	0.11
CAN	7540	5	0.39	0.52	0.31	0.66	0.09
CHE	2880	9	0.36	0.47	0.24	0.62	0.07
CHL	813	4	0.38	0.49	0.31	0.56	0.06
CHN	8243	4	0.43	0.45	0.26	0.59	0.13
DEU	6181	9	0.46	0.48	0.36	0.65	0.10
DNK	1536	6	0.38	0.47	0.31	0.61	0.12
ESP	1759	13	0.49	0.50	0.42	0.63	0.21
FIN	1640	8	0.37	0.46	0.19	0.62	0.09
FRA	5504	9	0.42	0.45	0.32	0.55	0.12
GBR	17458	6	0.15	0.48	0.13	0.54	0.13
HKG	6515	9	0.25	0.46	0.22	0.60	0.09
IND	5779	7	0.51	0.50	0.43	0.64	0.15
ISR	368	4	0.52	0.47	0.40	0.60	-0.07
ITA	2574	10	0.40	0.45	0.24	0.63	0.11
JPN	38716	4	0.26	0.52	0.21	0.69	0.11
KOR	8885	6	0.37	0.62	0.24	0.83	0.15
MEX	1251	8	0.33	0.52	0.31	0.69	0.15
MYS	4544	7	0.34	0.46	0.27	0.61	0.18
NLD	2192	13	0.23	0.47	0.16	0.57	0.12
NOR	2032	6	0.35	0.52	0.20	0.75	0.06
NZL	1340	5	0.22	0.40	0.17	0.48	0.17
PER	331	4	0.42	0.66	0.18	0.81	0.12
PHL	1050	7	0.39	0.62	0.38	0.74	0.24
SGP	3478	8	0.38	0.45	0.25	0.56	0.13
SWE	3176	7	0.44	0.47	0.27	0.63	0.16
THA	3719	6	0.33	0.70	0.22	0.80	0.10
USA	72251	7	0.19	0.46	0.16	0.56	0.06
ZAF	3031	5	0.29	0.48	0.25	0.53	0.17

Table 6: Predicted Return Correlations

Country	ρ	π_f	$\text{corr}\left(\mathbb{E}t\left[a_{it}\right], \mathbb{E}_t\left[a_{jt}\right]\right)$	$\widehat{\text{corr}}\left(\Delta p_{it}, \Delta p_{jt}\right)$	$\text{corr}\left(\Delta p_{it}, \Delta p_{jt}\right)$
AUS	0.68	0.22	0.28	0.42	0.34
AUT	0.49	0.33	0.38	0.42	0.48
BEL	0.55	0.30	0.31	0.32	0.50
CAN	0.48	0.31	0.39	0.46	0.22
CHE	0.55	0.24	0.36	0.50	0.42
CHL	0.64	0.31	0.38	0.51	0.67
CHN	0.53	0.26	0.43	0.63	0.73
DEU	0.49	0.36	0.46	0.57	0.41
DNK	0.55	0.31	0.38	0.47	0.45
ESP	0.63	0.42	0.49	0.61	0.57
FIN	0.48	0.19	0.37	0.53	0.57
FRA	0.60	0.32	0.42	0.58	0.42
GBR	0.68	0.13	0.15	0.18	0.23
HKG	0.58	0.22	0.25	0.30	0.27
IND	0.73	0.43	0.51	0.72	0.50
ISR	0.44	0.40	0.52	0.62	0.63
ITA	0.53	0.24	0.40	0.58	0.70
JPN	0.50	0.21	0.26	0.31	0.35
KOR	0.47	0.24	0.37	0.48	0.45
MEX	0.26	0.31	0.33	0.34	0.42
MYS	0.51	0.27	0.34	0.42	0.26
NLD	0.66	0.16	0.23	0.34	0.54
NOR	0.46	0.20	0.35	0.47	0.62
NZL	0.62	0.17	0.22	0.31	0.39
PER	0.56	0.18	0.42	0.72	0.69
PHL	0.69	0.38	0.39	0.42	0.51
SGP	0.55	0.25	0.38	0.54	0.32
SWE	0.44	0.27	0.44	0.58	0.53
THA	0.66	0.22	0.33	0.54	0.42
USA	0.63	0.16	0.19	0.23	0.20
ZAF	0.66	0.25	0.29	0.36	0.44

Table 7: Counterfactual Return Correlations

Country	σ_μ^2	π^e	σ_e^2	$\widehat{\text{corr}}\left(\Delta p_{it}, \Delta p_{jt}\right)$ Baseline	$\pi^e = \pi^e_{US}$	$\pi^f = \pi^f_{US}$
AUS	0.17	0.55	0.20	0.42	0.25	0.39
AUT	0.28	0.49	0.26	0.42	0.30	0.35
BEL	0.22	0.33	0.27	0.32	0.29	0.27
CAN	0.33	0.57	0.30	0.46	0.29	0.40
CHE	0.27	0.64	0.44	0.50	0.27	0.47
CHL	0.19	0.69	0.14	0.51	0.29	0.44
CHN	0.25	0.85	0.34	0.63	0.27	0.60
DEU	0.32	0.68	0.44	0.57	0.31	0.50
DNK	0.26	0.57	0.34	0.47	0.29	0.42
ESP	0.24	0.73	0.40	0.61	0.33	0.51
FIN	0.30	0.70	0.43	0.53	0.25	0.52
FRA	0.19	0.77	0.18	0.58	0.30	0.51
GBR	0.16	0.22	0.12	0.18	0.21	0.19
HKG	0.24	0.34	0.36	0.30	0.26	0.27
IND	0.19	0.99	1.10	0.72	0.38	0.55
ISR	0.29	0.77	0.29	0.62	0.33	0.53
ITA	0.28	0.77	0.59	0.58	0.27	0.56
JPN	0.35	0.37	0.47	0.31	0.25	0.30
KOR	0.54	0.62	0.69	0.48	0.27	0.46
MEX	0.44	0.36	0.39	0.34	0.29	0.27
MYS	0.28	0.51	0.39	0.42	0.28	0.39
NLD	0.19	0.47	0.24	0.34	0.23	0.34
NOR	0.45	0.60	0.84	0.47	0.25	0.46
NZL	0.14	0.41	0.14	0.31	0.24	0.31
PER	0.45	0.99	0.43	0.72	0.24	0.71
PHL	0.29	0.45	0.43	0.42	0.32	0.33
SGP	0.22	0.72	0.26	0.54	0.27	0.51
SWE	0.32	0.75	0.40	0.58	0.28	0.54
THA	0.36	0.82	0.26	0.54	0.25	0.51
USA	0.19	0.28	0.20	0.23	0.23	0.23
ZAF	0.16	0.48	0.08	0.36	0.27	0.31