Correlated Beliefs, Returns, and Stock Market Volatility*

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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, G17, D8

Keywords: volatility, comovement, emerging markets, forecasting, information frictions

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1 Introduction

Stock returns 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 returns 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 we find that the non-fundamental component of belief correlation is key. In particular, setting the correlation of signal errors to the US level for all countries almost eliminates disparities in return correlations, while setting overall signal noise and fundamental parameters to their US values yields similar return correlations as the baseline calibration. This highlights an important and intuitive result from our model: it is not the overall level of firm-specific information that drives comovement across firms, but rather the correlated component of that information. Our distinction between the commonality of information as opposed to its overall quality helps to reconcile an apparent tension in the recent literature - namely, some studies have found that comovement is higher where stock prices are more informative, some have found the opposite, and others have found the relationship to be non-monotonic.[1] We find a rather weak relationship, in large part because the extent of correlation in information is not strongly related to its overall precision.

We take our analysis one step further and examine the implications of our results for cross-sectional differences in aggregate stock market volatility. 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.[2] 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.

We perform a number of additional exercises geared towards understanding the implications of some important variations on our baseline analysis. First, we demonstrate that excess return correlation is a robust phenomenon across various frequencies - specifically, while our benchmark analysis focuses on annual data, the excess correlation of returns compared to fundamentals features in higher-frequency (quarterly) data as well. Relatedly, we show that excess correlation of forecasts remains present over the forecasting horizon. In particular, while our baseline analysis focuses on forecasts made the month following the release of the prior year's earnings, the cross-firm correlations of forecasts, although generally declining, remain high even up to

[1]See, for some examples, Durnev et al. (2003), Hou et al. (2013), Dasgupta et al. (2010), and Lee and Liu (2011). Dang et al. (2014) contains a useful overview of the state of the literature.

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

one month prior to the end of the period for which the forecast is made. We show that this is the case even though informational quality, measured by the precision of investor information, is generally increasing as the forecast horizon shortens. We also present evidence that analyst information is a plausible, albeit imperfect, proxy for the information of informed traders more generally. In particular, we document that many types of investors purchase information from analysts, that investors react to that information, and lastly, that based on the sources on which analysts rely to form expectations, we might expect a significant degree of overlap between their information sets and those of a broader set of informed investors, whether or not they turn to analysts directly for that information.

Additionally, we address in detail the potential role of aggregate shocks to discount rates in driving excess comovement. First, we show that, in our framework, imperfect information leads to movements in asset prices unrelated to fundamentals - in other words, shocks to beliefs resemble what the literature would typically ascribe to discount rate fluctuations, and so can be interpreted as one mechanism behind them. This is true both at the firm and aggregate level, where the latter depends crucially on the existence of a common component to beliefs. Further, we show that, across countries, the relationship between return correlations and the volatility of macroeconomic factors that typically drive discount factors in structural models is rather weak, suggesting that observable macroeconomic shocks are not a major factor at play. As a last exercise, we control for the effects of a number of additional risk factors that have been shown to be important in asset pricing (as well as for fluctuations in the pure rate of time preference) by regressing firm-level returns on these factors and examining the correlation of the residuals. Although these factors appear to play some role, excess comovement remains, further suggesting that an information-based mechanism deserves scrutiny.

Finally, we examine the robustness of our results to controlling for a number of additional 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 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. In Section 5, we demonstrate the robustness of our findings to a number of variants on our baseline approach and to controlling for plausible alternatives. We 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. 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]

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).[4] 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,

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

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.

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.[5] 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.

[5] It is worth noting that other studies obtain somewhat different findings: 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.[6] 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 and a small number of large outliers, where market volatility is more than 2 standard deviations above the mean.[7] Our final sample is quite broad and consists of a total of 31 countries:[8] 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.[9] 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.[10] We restrict our attention to firm pairs with at least 8 years of overlap - this strikes a reasonable balance between maximizing the number of firms that we are able to include and

[6]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.

[7]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).

[8]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.

[9]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.

[10]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.

ensuring that we have a long enough time-series to obtain robust results.[11] Table 12 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.[12] 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.[13] 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 13 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.

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

[12] 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.

[13] 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 log fundamentals for firm i, a_{it}, follow an AR(1) process. 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., $\mathbb{E}_t\left[a_{it}\right] = \rho a_{it-1}$ or $\mathbb{E}_t\left[a_{it}\right] = a_{it}$ (investors have no information or full information regarding the realization of μ_{it}), we have:[14]

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

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

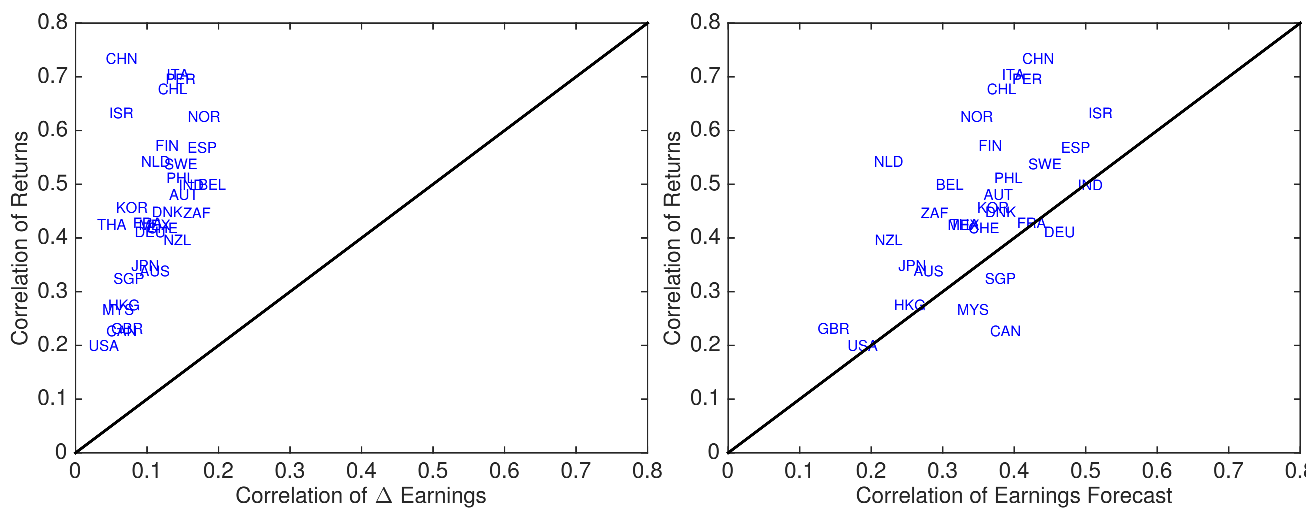

Figure 1: Firm-Level Correlations - Returns, Fundamentals and Forecasts

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:

[14]Full derivations are in Section 3.

return correlations exceed fundamental correlations in every country, generally by a substantial amount. For example, as reported in Table 1, the average return correlation across countries is 0.46 vs only 0.11 for earnings growth, a factor of over 4. Return correlations range from 0.20 to 0.73 across countries; the corresponding values for earnings growth are 0.04 and 0.19. 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 (square the correlation between the two series of 0.51 reported in Table 1), 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 (Table 1 shows the correlation between the two series to be 0.56, higher even than that of returns with earnings) 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).[15]

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. In Section 5, we revisit the stylized facts and demonstrate their robustness to a number of important modifications - specifically, we show that excess comovement is not an artifact of our focus on annual data and remains present at higher frequencies (e.g., quarterly), that excess comovement is not simply a result of aggregate shocks to discount rates that would tend to move all stock

[15]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.

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

	corr(returns)	corr(Δ earnings)	corr(forecasts)
Summary Statistics			
Mean	0.46	0.11	0.36
Max	0.73	0.19	0.52
Min	0.20	0.04	0.15
Std. Dev.	0.15	0.04	0.09
Correlations			
corr(returns)	1.00	0.51***	0.56***
corr(Δ earnings)		1.00	0.23
corr(forecasts)			1.00

Notes: Table reports summary statistics of firm-level correlations of returns, earnings growth, and earnings forecasts across 31 countries. Data on returns and earnings growth are from Compustat. Data on earnings forecasts are from I/B/E/S. *** denotes statistical significance at the 1%-level.

prices simultaneously, and that the high correlation of earnings forecasts persists throughout the forecasting horizon (e.g., for forecasts made one year ahead of the forecast period all the way up to one month ahead).

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 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.[16]

[16]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. We discuss discount rates in more detail in Section 5.2. 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

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.[17] 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, $\text{cov}\left(\mu_{it}, \mu_{jt}\right) = \pi^f \sigma_\mu^2$, 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:

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

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 observe a common noisy signal of the contemporaneous innovation:[18]

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

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.[19]

international mutual funds (whose managers may be passed information directly from the research analysts we study).

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

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

[19]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,

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:[20]

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

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 $\xi = \frac{1-\beta}{1-\beta\rho}$ 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:

$$\Delta p_{it} = \xi\rho\left(\rho - 1\right) a_{it-2} + \xi\left(\rho - \psi\right)\mu_{it-1} + \xi\psi\mu_{it} + \xi\psi\left(e_{it} - e_{it-1}\right) \tag{5}$$

even in the US, tend to have a low informational content (see, for example David et al. (2014b)). We discuss the information structure in more detail in Section 5.3.

[20] 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 $p_{it} = \xi\mathbb{E}_t\left[a_{it}\right] +$ constant gives the result.

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

$$\begin{aligned}\operatorname{var}(\Delta p_{it}) &= \left[\frac{\rho^2}{1+\rho}+\psi(\psi-\rho)\right]2\xi^2\sigma_\mu^2+2\xi^2\psi^2\sigma_e^2 \\ \operatorname{cov}(\Delta p_{it},\Delta p_{jt}) &= \left[\frac{\rho^2}{1+\rho}+\psi(\psi-\rho)\right]2\xi^2\pi^f\sigma_\mu^2+2\xi^2\psi^2\pi^e\sigma_e^2\end{aligned} \tag{6}$$

and putting these together,

$$\operatorname{corr}(\Delta p_{it},\Delta p_{jt})=\frac{\kappa^f\pi^f+\kappa^e\pi^e}{\kappa^f+\kappa^e} \tag{7}$$

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

Expression (7) 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. $\operatorname{corr}(\Delta p_{it},\Delta p_{jt})\le\max(\pi^f,\pi^e)$; $\frac{\partial\operatorname{corr}(\Delta p_{it},\Delta p_{jt})}{\partial\pi^f}>0$ and $\frac{\partial\operatorname{corr}(\Delta p_{it},\Delta p_{jt})}{\partial\pi^e}>0$ so long as $\kappa^e\neq0$ and $\kappa^f\neq0$.

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 $\operatorname{corr}(\Delta p_{it},\Delta p_{jt})=\pi^f$.

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

4. $\operatorname{corr}(\Delta p_{it},\Delta p_{jt})>\pi^f$ 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.[21] With intermediate information, the return correlation exceeds fundamental correlation when beliefs are more correlated than 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,

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

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:

$$\begin{aligned}
\operatorname{var}\left(\mathbb{E}_t\left[a_{it}\right]\right) &= \left(\frac{\rho^2}{1-\rho^2}+\psi\right)\sigma_\mu^2 && (8)\\
\operatorname{cov}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right) &= \left(\frac{\rho^2}{1-\rho^2}+\psi^2\right)\pi^f\sigma_\mu^2+\psi^2\pi^e\sigma_e^2 \\
\operatorname{corr}\left(\mathbb{E}_t\left[a_{it}\right],\mathbb{E}_t\left[a_{jt}\right]\right) &= \frac{\left(\frac{\rho^2}{1-\rho^2}+\psi^2\right)\pi^f\sigma_\mu^2+\psi^2\pi^e\sigma_e^2}{\left(\frac{\rho^2}{1-\rho^2}+\psi\right)\sigma_\mu^2} && (9)
\end{aligned}$$

Rearranging expression (8) gives a relation between the forecast variance and overall information, captured by the noise in the signal, σ_e^2:

$$\sigma_e^2 = \frac{1-\psi}{\psi}\sigma_\mu^2, \quad \text{where} \quad \psi = \frac{\text{var}\left(\mathbb{E}_t\left[a_{it}\right]\right)}{\sigma_\mu^2} - \frac{\rho^2}{1-\rho^2} \tag{10}$$

In other words, given the properties of fundamentals, the variance of forecasts pins down ψ (the weight that investors put on the signal), from which it is straightforward to back out σ_e^2.

Similarly, rearranging (9) gives an expression for π^e as a function of the properties of fundamentals, the signal noise, and the correlation of forecasts:

$$\pi_e = \frac{\left(\frac{\rho^2}{1-\rho^2} + \psi\right)\sigma_\mu^2 \text{corr}\left(\mathbb{E}_t\left[a_{it}\right], \mathbb{E}_t\left[a_{jt}\right]\right) - \left(\frac{\rho^2}{1-\rho^2} + \psi^2\right)\sigma_\mu^2 \pi^f}{\psi^2 \sigma_e^2} \tag{11}$$

Clearly, (10) and (11) 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, $\text{corr}\left(\mathbb{E}_t\left[a_{it}\right], \mathbb{E}_t\left[a_{jt}\right]\right)$, it can be shown that the correlation in returns is equal to:[22]

$$\text{corr}\left(\Delta p_{it}, \Delta p_{jt}\right) = \frac{\text{corr}\left(\mathbb{E}_t\left[a_{it}\right], \mathbb{E}_t\left[a_{jt}\right]\right) - \rho\pi^f}{1-\rho} \tag{12}$$

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 (10) and (11) along with values of σ_μ^2 to infer values of the underlying structural parameters 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.[23] 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

[22]Substitute for $\pi^e\sigma_e^2$ from (11) into (7).

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

Table 14 in the Appendix (many are also included in Tables 12 and 13 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: as reported in Table 2, the correlation between predicted and actual is 0.63. Moreover, the position of the 45 degree line shows 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. Table 2 shows that the properties of predicted returns line up quite closely with the actual on a number of additional dimensions, i.e., the ranges and standard deviations across countries. 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.

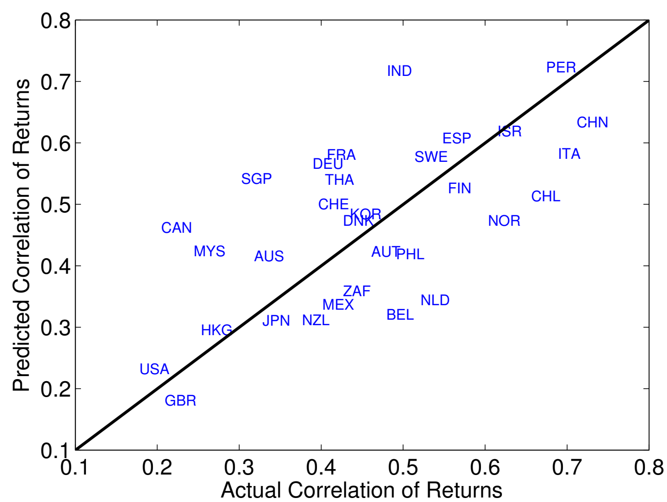

Figure 2: Return Correlations - Predicted vs. Actual

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

Table 2: Predicted Firm-Level Correlations - Returns, Fundamentals and Forecasts

	$\widehat{\text{corr}\,(\Delta p_{it})}$	$\text{corr}\,(\Delta p_{it})$	
Summary Statistics			
Mean	0.47	0.46	
Max	0.72	0.73	
Min	0.18	0.20	
Std. Dev.	0.14	0.15	
	$\text{corr}\,(\Delta p_{it})$	$\text{corr}\,(\Delta a_{it})$ (IBES)	$\text{corr}\,(\mathbb{E}_t\,[a_{it}])$
Correlation with $\widehat{\text{corr}\,(\Delta p_{it})}$	0.63^{***}	-0.09	0.90^{***}

Notes: Table reports summary statistics of model-predicted and actual firm-level correlations of returns across 31 countries. Hats denote variables generated from the calibrated model. Data on returns are from Compustat. Data on earnings growth and forecasts are from I/B/E/S. *** denotes statistical significance at the 1%-level.

of predicted return correlations are close to the actual (as shown in Table 2, they average 0.47 and 0.46, respectively), they both exceed the correlation of fundamentals by a factor of approximately 4.[24]

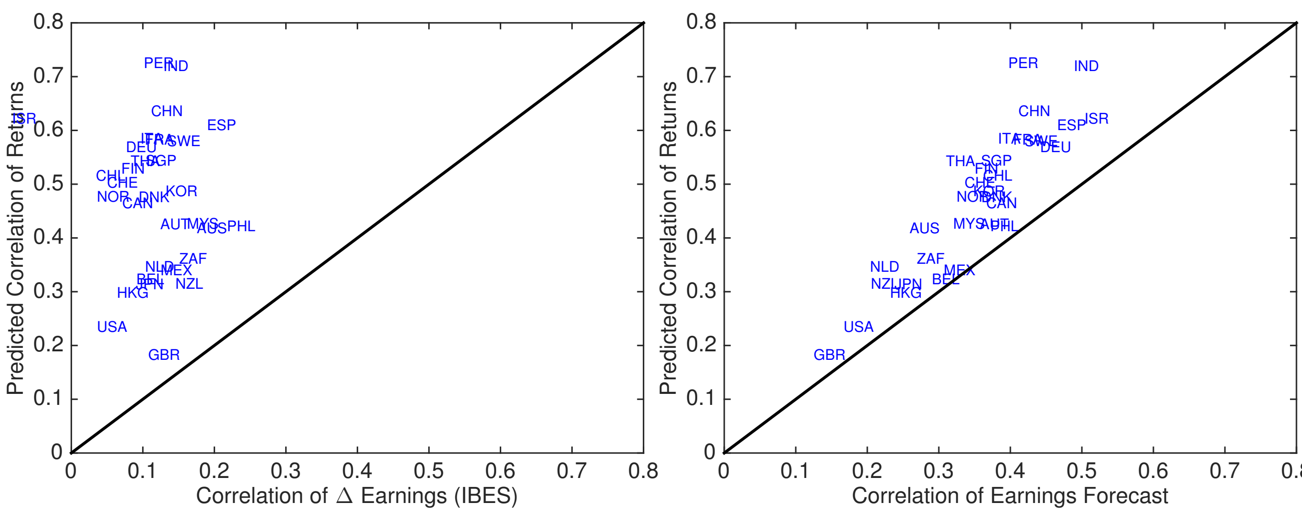

Figure 3: Predicted Firm-Level Correlations - Returns, Fundamentals and Forecasts

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,

[24]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).

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; 0.90 compared to 0.56) 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 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 (10) and (11) 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 15 in the Appendix report the resulting parameter values.[25]

We perform two main exercises geared toward understanding the sources of variation in return correlations. The goal is to understand whether it is the overall level of information or the degree of commonality in that information that accounts for the patterns of return correlations observed in the data. To answer this question, for each exercise, 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 π^e - the correlation in the non-fundamental component of beliefs - and set it to its US value for all countries. We next examine the role of the overall precision of information by setting σ_e^2 - the noise in investors' signals - to its US value. In both exercises we eliminate heterogeneity across countries along one dimension of the signal process. 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. Each plot in the figure displays predicted return correlations against actual. The corresponding values are reported in Table 3. 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 correlations from 0.63 to 0.25 (and is now not significantly different from zero), a fall

[25] 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.

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%. Finally, there is a substantial compression of the cross-sectional variation in correlations - as reported in Table 3, the standard deviation across countries falls from 0.14 in our baseline calibration to only 0.03 in the counterfactual one. 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.

Table 3: Counterfactual Firm-Level Return Correlations

	$\widehat{\text{corr}\,(\Delta p_{it})}$	$\widehat{\text{corr}\,(\Delta p_{it})}$, $\pi^e = \pi^e_{US}$	$\widehat{\text{corr}\,(\Delta p_{it})}$, $\sigma_e^2 = \sigma^2_{e,US}$
Summary Statistics			
Mean	0.47	0.28	0.45
Max	0.72	0.38	0.88
Min	0.18	0.21	0.19
Std. Dev.	0.14	0.03	0.14
Correlation with corr (Δp_{it})	0.63***	0.25	0.51***

Notes: Table reports summary statistics of predicted firm-level correlations of returns under various scenarios. Hats denote variables generated from the calibrated model. Data on returns are from Compustat. *** denotes statistical significance at 1%-level.

In contrast, turning to the overall quality of information and fixing σ_e^2 at its US level results in comparatively small changes in predicted return correlations.[26] The correlation of predicted and actual falls slightly to 0.51. In terms of levels, there is only a small reduction from an average of 0.47 to 0.45. Comparing the plot for this scenario in the top row of Figure 4 to the baseline results in the bottom row shows that there is little difference between the two. This finding is in large part driven by the rather weak relationship between the extent of correlation in information and its overall precision. For example, the posterior variance of investor beliefs is $\left(\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2}\right)^{-1}$. Dividing this by σ_μ^2 and subtracting from 1 gives ψ, the percent of prior variance that is eliminated by the signal. The correlation of ψ with predicted return correlations is negative, but mildly so, at -0.35; the correlation with the empirical return correlation is even lower at -0.19. In other words, overall signal precision does not seem to be the main driver of return correlations, either as predicted by the model or in the data.

In sum, differences in the correlation 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 overall level of information. There is an interesting economic interpretation here - namely, for partially, but imperfectly informed agents, it is not

[26]The exception is India, whose predicted return correlation actually jumps from 0.72 to 0.88.

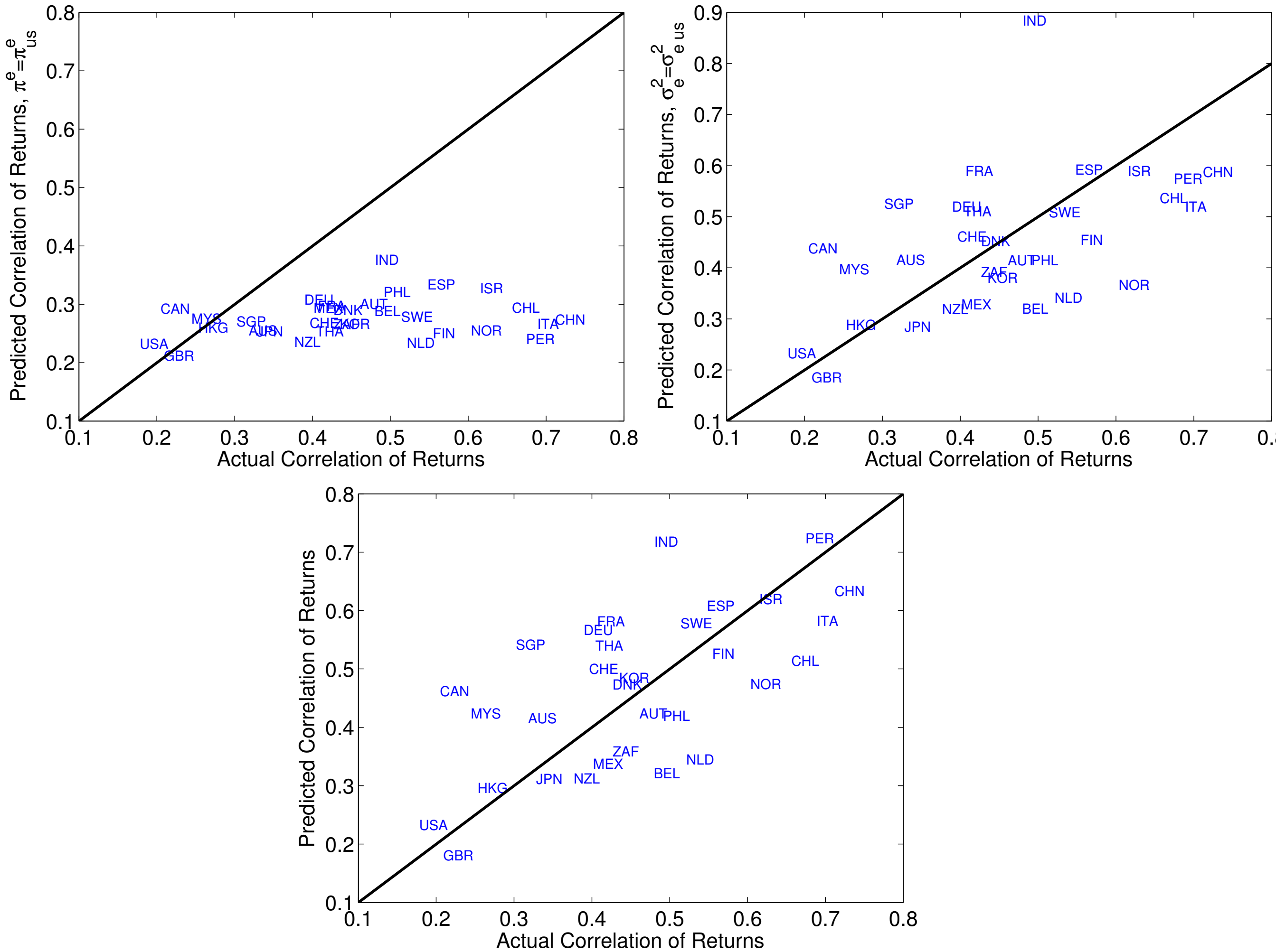

Figure 4: Baseline and Counterfactual Predicted Firm-Level Return Correlations

the overall level of information that matters for return comovement, but rather the extent of its commonality. This insight goes some way towards resolving a seeming tension in the literature, where empirical results regarding the relationship between comovement and information quality have been mixed. As one example, Durnev et al. (2003) find that US firms and industries exhibiting less comovement show a greater association between returns and future earnings, pointing towards higher quality information; in contrast, Hou et al. (2013) find that lower comovement appears to be associated with fluctuations in investor sentiments, and so lesser quality information.[27] Our analysis demonstrates that this relationship depends crucially on both the extent of common information as well as its overall precision. Specifically, where firm-level information is highly correlated - for example, India - increasing its overall accuracy will lead to more comovement, not less, since agents respond more sharply to the correlated

[27]Dang et al. (2014) contains a useful overview of the state of the literature and further citations on this topic.

signal. The opposite is true in environments with more dispersed information about firms - for example, the UK - there, raising signal precision leads to less comovement as agents put more weight on less correlated information. Thus, that empirical results on this score are mixed may not be surprising - our findings suggest that it may be useful to put more emphasis on why agents turn to common sources of information, rather than the overall quality of that information.

In results not reported, we have performed similar experiments for the fundamental parameters, π^f 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 underscores our original observation that properties of fundamentals alone seem difficult to reconcile with measured levels and patterns of return comovement.

4.4 Comovement and Stock Market Volatility

Previous work has shown that return correlations are a key driver of aggregate stock market volatility.[28] 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.[29] The values are reported in Table 12 in the Appendix and summary statistics are presented in Table 4.

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 (to obtain this value, simply square the correlation coefficient between the two series of 0.80 reported in Table 4).[30] 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%

[28] 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.

[29] 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.

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

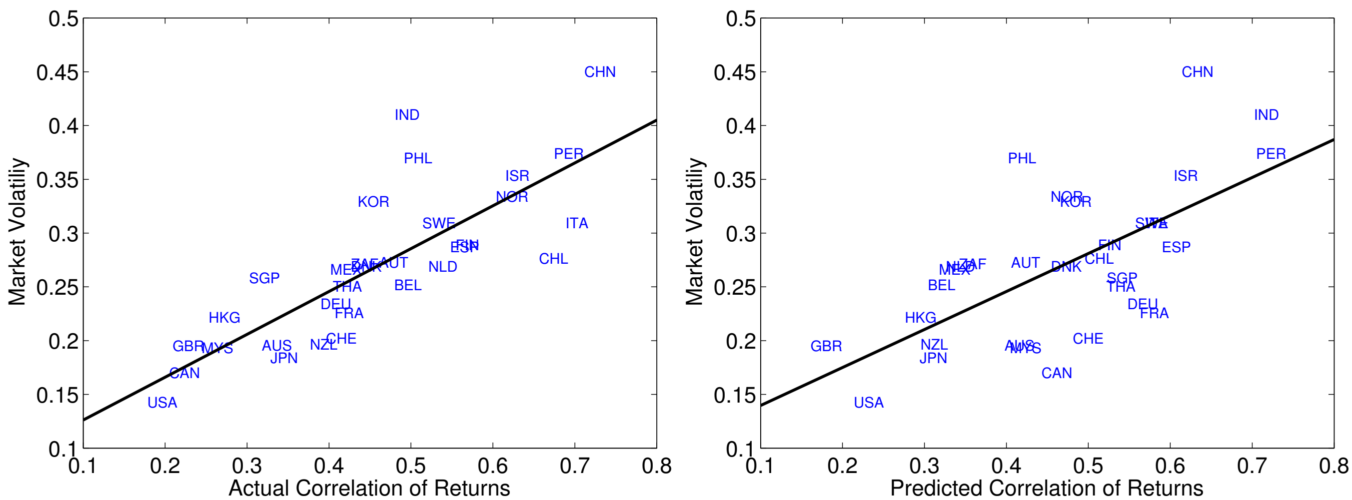

Figure 5: Return Correlations and Aggregate Volatility

of the cross-section of 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 (Table 4 shows the correlation between them to be 0.63), 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.

Table 4: Return Correlations and Aggregate Volatility

	std(market return)		
Summary Statistics			
Mean	0.27		
Max	0.45		
Min	0.14		
Std. Dev.	0.07		
	corr(returns)	corr(predicted returns)	corr(forecasts)
Correlations			
std(market return)	0.80***	0.66***	0.63***

Notes: Table reports summary statistics of the standard deviation of the market return across 31 countries. Market returns for each country are computed as unweighted average returns across all firms within a country. Data on returns are from Compustat. Data on earnings forecasts are from I/B/E/S. Predicted returns are computed from the calibrated model. *** denotes statistical significance at the 1%-level.

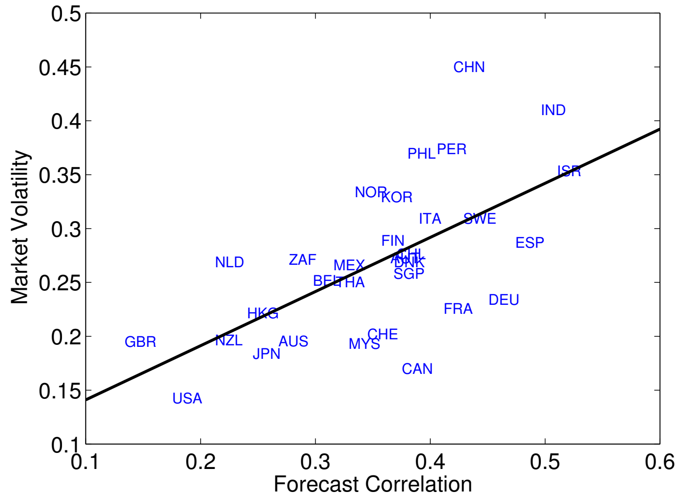

Figure 6: Forecast Correlations and Aggregate Volatility

5 Robustness

In this section, we explore the robustness of our results to some important variations on our baseline approach, as well as the effects of alternative potential drivers of return comovement. All country-level data for this section are reported in Table 16 in the Appendix.

5.1 Timing

Thus far, our analysis has focused on data at the annual frequency. Although this choice is in part driven by data availability (higher frequency earnings and forecast data are not generally available across countries), it is important to note that there is a good deal of evidence that an annual frequency is reasonable and relevant on a number of dimensions. In terms of investor behavior, estimates of typical stock holding periods tend to average somewhat more than a year. Importantly, this is true both for individual as well as institutional investors.[31] In terms of the impact that market movements may have on firm investment decisions, previous work has tended to focus on frequencies that even exceed one year (for example, Morck et al. (1990) and David et al. (2014b) examine three year frequencies), citing the low predictive

[31] For example, a recent report documents that as of 2014, the average stock on the New York Stock Exchange was held for 1.92 years (the lowest level since the 1920s), a figure that includes both individual and institutional investors; the corresponding figure for equity mutual funds is 1.45 years. See "Lengthening the Investment Time Horizon," MFS Investment Management, White Paper Series, February 2015, available at `https://www.mfs.com/`. Similarly, Gaspar et al. (2005) and Gaspar et al. (2012) find that the typical institutional investor (median and average, respectively) holds the average stock in its portfolio for 15 to 27 months. The figures in Barber and Odean (2000) imply a similar horizon of just over 15 months for a sample of individual investors (they report monthly turnover around 6.5% so that the average holding period is $\frac{1}{0.065} = 15.4$). Chien et al. (2012) also document the extent of passiveness on the part of individual investors.

power of investment growth regressions at higher frequencies and the long lags in planning and implementing investment projects.

Despite the relevance of the annual frequency, it is important to understand the sensitivity of our analysis to our baseline assumptions on timing. Here, we explore two modifications: first, we assess whether the excess comovement we document in Section 2.2 is an artifact of our focus on the annual frequency and disappears at higher frequencies; similarly, we investigate the properties of earnings forecasts over the forecasting horizon, i.e., as the period the forecast is made approaches the date the fundamental is realized.

Higher frequency comovement. One concern is that the relatively low frequency at which we analyze stock market data is responsible for the excess comovement that we document. For example, it might be the case that fundamentals are more highly correlated across firms at higher frequencies, due perhaps to common shocks that are more short-term in nature, or that the connection between returns and fundamentals is stronger. To address this issue, we recompute return and fundamental correlations at the quarterly frequency. Unfortunately, reported measures of quarterly earnings per share are only available for a small set of the countries we examine. However, quarterly data on net income and the number of common shares outstanding are available for all the countries in our sample with the exception of Japan and Korea. Therefore, we proxy earnings per share by net income per share. According to the Compustat manual, these two measures should be essentially equivalent, with differences reflecting preferred dividends and other minor adjustments. To verify that the approximation is a good one, we compute the correlation of income per share and reported earnings per share (both in logs) at the firm-level at the annual frequency for the 29 countries for which data are available. The mean correlation is 0.94, ranging from a low 0.88 in Austria to 0.98 in Finland. In addition, the levels of fundamental correlations computed using the two measures are at par - they are generally quite closely aligned across countries, and both average about 0.12.

We proceed to compute the correlation of returns and fundamentals at the quarterly frequency with the new measure of fundamentals in mind. To maintain consistency with our baseline approach, we consider firm pairs with at least 32 quarters, or 8 years, of overlap. We plot the results in Figure 7, maintaining the same axes as in Figure 1 for comparability, and report the corresponding values in Table 5. The plot shows that the excess comovement puzzle arises with quarterly data as well and, if anything, is somewhat worsened. Just as at the annual frequency, return correlations exceed fundamental correlations in every country by a substantial amount. The average return correlation is 0.47, almost identical to that at the annual frequency, and ranges from 0.20 to 0.62, compared to an average of 0.07 for fundamentals (and a range of 0.00 to 0.23), which are actually lower values than their annual counterparts. In this sense, the gap is even wider at the quarterly frequency, suggesting that the excess comovement 'puzzle' is somewhat heightened.

Table 5: Quarterly Return and Fundamental Correlations

	corr(returns)	corr(Δ earnings)
Summary Statistics		
Mean	0.47	0.07
Max	0.62	0.23
Min	0.20	0.00
Std. Dev.	0.09	0.05
Correlations		
corr(returns)	1.00	0.31*
corr(Δ earnings)		1.00

Notes: Table reports summary statistics of firm-level correlations of returns and earnings growth computed at a quarterly frequency across 29 countries. Data on returns and earnings growth are from Compustat. * denotes statistical significance at the 10%-level.

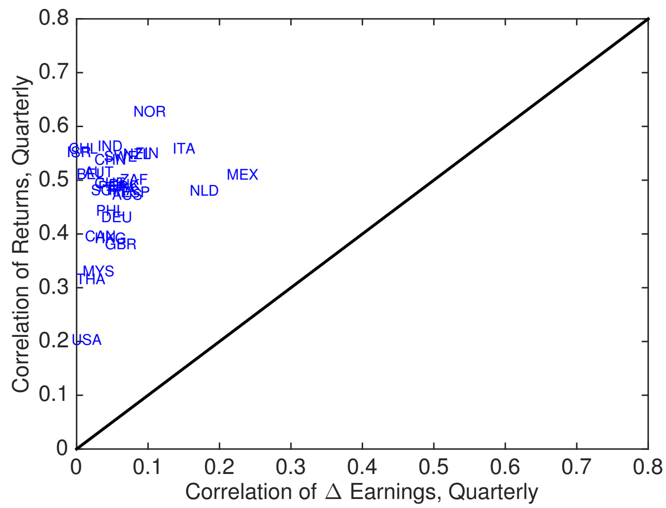

Figure 7: Quarterly Return and Fundamental Correlations

Forecast horizon and revisions. A related concern is that the forecast horizon that we study in our baseline exercise - forecasts issued one month after the previous year's earnings were announced - is responsible for the high forecast correlations that we document, and ultimately, for the close fit between the predicted return correlation and the actual. To address this concern, we recompute the correlations of earnings forecasts using 3 additional forecast horizons - forecasts made 6 months prior to the end of the fiscal year for which the forecast is made, 3 months, and less than 1 month. These periods correspond roughly to the month after the first, second, and third quarter earnings are released, respectively.[32] The idea of the exercise is to understand how informational quality changes as market participants revise their beliefs in response to new information that comes in throughout the year.

For each forecast horizon, we compute the correlation and volatility of forecasts. Two observations emerge: first, as reported in the top panel of Table 6, the correlation of forecasts generally falls as the forecast horizon shortens. For example, the mean correlation of forecasts is 0.36 in our baseline, falls to 0.32 at a 6 month horizon, 0.31 at 3 months, and to 0.28 at 1 month. This pattern is reassuring, as we would expect that as more firm-specific information is revealed throughout the year, beliefs are revised in different directions. However, even at the shortest horizon, forecast correlations remain relatively high, especially as compared to the level of fundamental correlations. Figure 8 plots the correlations of forecasts against those of earnings growth for our baseline horizon and the shortest horizon of one month. As discussed, the levels of forecast correlations generally fall somewhat across the board; however, even at this short horizon, they continue to exceed those in fundamentals.

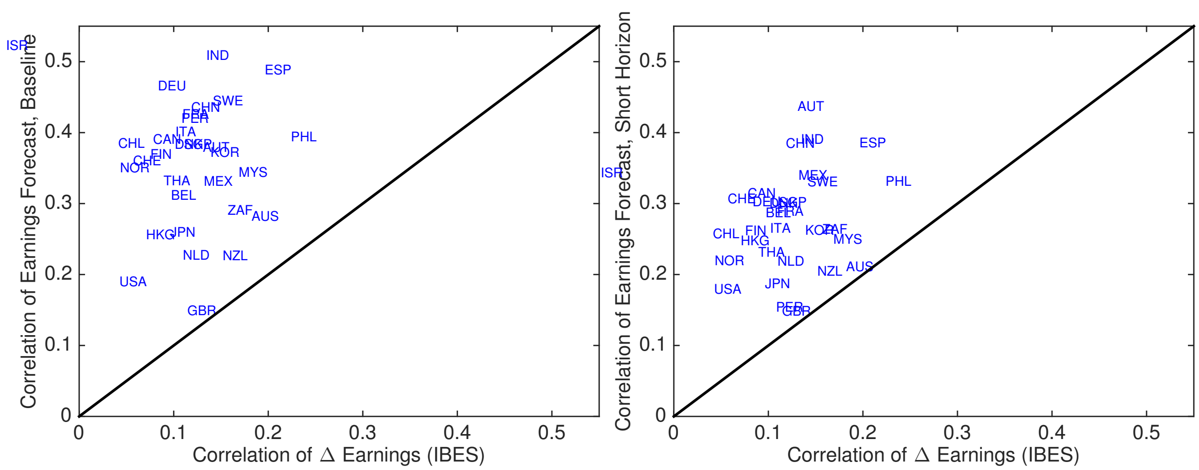

Figure 8: Forecast Correlations - Baseline and Short Horizons

To go one step further, we can use equation (12) to translate these values into predicted return correlations. Table 6 shows that the mean predicted return correlation follows a similar pattern, beginning at 0.47 in our baseline analysis and falling to 0.39, 0.35, and 0.28 at the 6, 3, and 1 month horizons, respectively, always well above the correlation of fundamentals, which averages about 0.11. One caveat here is that due to the differences in timing, with the

[32]As a concrete example, consider a forecast of annual earnings for the fiscal year ending December 31, 2010. Our baseline forecast is likely made sometime between January and March of 2010, following the release of fiscal year 2009 earnings. We then also examine forecasts made in June 2010, roughly the month after first quarter 2010 earnings are released, September 2010, which corresponds to second quarter earnings, and December 2010, third quarter earnings.

Table 6: Information at Various Forecast Horizons

Forecast Horizon	Baseline	6 Months	3 Months	1 Month
corr(forecasts)				
Mean	0.36	0.32	0.31	0.28
Max	0.52	0.58	0.57	0.44
Min	0.15	−0.09	0.14	0.15
Std. Dev.	0.09	0.13	0.10	0.07
corr(predicted returns)				
Mean	0.47	0.39	0.35	0.28
Max	0.72	0.81	0.80	0.54
Min	0.18	−0.45	0.06	0.11
Std. Dev.	0.14	0.22	0.15	0.09
information precision (ψ)				
Mean	0.45	0.48	0.55	0.64
Max	0.67	1.11	0.85	1.00
Min	0.15	0.14	0.26	0.23
Std. Dev.	0.09	0.17	0.15	0.16

Notes: Table reports summary statistics of (i) firm-level correlations of earnings forecasts, (ii) firm-level correlations of predicted returns, (iii) the information precision parameter, ψ, at various forecast horizons for 31 countries. Data on earnings forecasts are from I/B/E/S. Predicted returns and the information precision ψ are computed from the calibrated model.

exception of our baseline numbers which are essentially annual in nature, these correlations are not really comparable to those we compute from the data.

Next, using the volatility of forecasts in conjunction with the correlation, we infer values for σ_e^2, the noise in investor information, at each forecast horizon, and from this compute $\psi = 1 - \frac{\frac{1}{\sigma_\mu^2}}{\frac{1}{\sigma_\mu^2}+\frac{1}{\sigma_e^2}}$, the fraction of the prior variance that is eliminated by information known at the time of the forecast. We report the results in the bottom panel of Table 6. As we might expect, this fraction increases as the forecast horizon shortens, from an average value of 0.45 in our baseline analysis, to 0.48, 0.55, and 0.64 at the 6 month, 3 month, and 1 month horizons, respectively. Thus, the picture that emerges is one where overall informational quality improves over the forecasting horizon and the firm-specific component becomes more important relative to the common component. On the other hand, even at the shortest horizon, a significant degree of uncertainty remains, along with a substantial component that is common across firms, which continues to imply return correlations that exceed fundamentals.

5.2 Discount Rate Shocks

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). Most notably, our assumption of risk neutrality is a clear simplification. Although this may not be a bad approximation for large, international institutional investors, it comes at a cost: it abstracts from the potential role of aggregate discount rate shocks in driving comovement. It is important to note, however, that our use of direct measures of beliefs about fundamentals means that we are not in danger of misattributing discount rate shocks to informational factors. This is in contrast to an empirical strategy that measures common information using the observed comovement of prices (or even forecasts of them) - in this case, the presence of alternative factors driving comovement would be problematic in the sense of potentially leading to an overstatement of the role of information. We would argue that this a significant, if not the main, beneficial feature of our approach.

Belief shocks as discount rate shocks. Our information-based theory is one potential mechanism behind what the literature typically refers to as discount rate shocks. Specifically, in the spirit of Cochrane (2011), it is well known that cash flow dynamics are not sufficient to account for the behavior of asset prices; therefore, the residual - namely, discount rate shocks - must be the key driver. The precise nature of these shocks, however, is less clear. For example, shocks to expectations about firm cash flows, as in our framework, rather than to earnings themselves, easily map into discount rate shocks. Therefore, the mechanism that we outline in this paper is one potential theory of discount rate shocks themselves. To see this more clearly, consider the expression for stock returns in equation (5) - there, both shocks to fundamentals μ_{it} and shocks to beliefs e_{it} drive variation in prices, and the latter leads to a disconnect between fundamentals and prices.

The same is true of the aggregate market return. To understand this, consider the following representation of our model:

$$\begin{aligned} \mu_{it} &= \mu_t + \tilde{\mu}_{it}, \quad \tilde{\mu}_{it} = \mu_{it} - \mu_t \\ e_{it} &= e_t + \tilde{e}_{it}, \quad \tilde{e}_{it} = e_{it} - e_t \end{aligned} \tag{13}$$

where $\mu_t \sim N\left(0, \pi^f \sigma_\mu^2\right)$ and $e_t \sim N\left(0, \pi^e \sigma_e^2\right)$, i.e., firm-level fundamentals and signals are each composed of an aggregate component and an idiosyncratic one, where the latter is uncorrelated across firms. To highlight the intuition, let's consider for the moment the iid case of our model,

$\rho = 0$ (all the results go through in the general case). Then, from (5), we have

$$\Delta p_{it} = \xi\psi\left(\mu_{it} - \mu_{it-1} + e_{it} - e_{it-1}\right) \tag{14}$$

and integrating across firms, the market return is

$$\int \Delta p_{it} di = \Delta p_{mt} = \xi\psi\left(\mu_{t} - \mu_{t-1} + e_{t} - e_{t-1}\right) \tag{15}$$

Just as in the firm level case, shocks to beliefs show up as discount rate shocks, in the sense of moving market returns in ways that are unrelated to observed fundamentals. If beliefs were uncorrelated, i.e., $\pi^e = 0$, fluctuations in the market return would be purely due to fluctuations in the common element of fundamentals.

Macroeconomic shocks. Of course, a number of additional mechanisms lead to time-varying aggregate discount rates. For example, in any consumption-based asset pricing model, macroeconomics shocks to the stochastic discount factor of investors lead to aggregate movements in asset prices potentially beyond those in fundamentals. While these types of shocks may be responsible for the high variability in asset prices, there is reason to believe that they are not the primary drivers of the cross-sectional differences in excess correlations that we examine in this paper. For example, in the cross section of countries, there does not appear to be a systematic relationship between the correlation of returns and macroeconomic volatility. To reach this conclusion, we obtain data on annual real GDP and consumption per-capita for the 1980-2013 period from the World Bank World Development Indicators (WDI) database for all the countries in our sample.[33] These are factors that are standard in many consumption-based asset pricing models. We then regress return correlations on the standard deviation of the growth rates of these two variables. While the volatility of growth rates is higher in countries where return correlations are higher, the relationship is weak and not statistically significant, as shown in Table 7. Our finding here is in line with those of Pindyck and Rotemberg (1993), who find that macroeconomic variables (observed or latent) cannot account for observed cross-firm correlations in the US, a result that seems to extend to other countries as well.[34]

[33]For Israel, we could only obtain consumption data since 1995.

[34]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.

Table 7: Return Correlations and Macroeconomic Shocks

	(1)	(2)
st.dev(Δ per-capita GDP)	2.795	
	(2.572)	
st.dev(Δ per-capita consumption)		1.806
		(1.889)
R^2	0.04	0.03
# Observations	31	31

Notes: The regressand is the correlation of returns in each country. Regressors and expected signs of coefficients are described in Section 5.2. Standard errors in parentheses.

Empirical risk factors. Next, to further examine the role of discount rate shocks, we follow the empirical finance literature and control for other factors that capture time-varying discount rates and have proven to be important in pricing the cross-section of assets. Now, it is not obvious that these factors are independent of our information-based mechanism. For example, to the extent that investors are learning from news about these factors, they would embed an information element as well. Thus, the ideal experiment would be to find variables that control for these factors independently of information regarding the assets we study - namely, stock prices. One example would be shocks to risk premia on assets other than equity. However, it is not obvious what these variables might be, and whether they would be available across the countries we study. Thus, we include a battery of common factors that at least at first glance are not obviously related to our mechanism. To understand the tension, consider the most common risk factor - namely, the market return. Continuing with the representation of our model in expressions (13)-(15) and the iid case for simplicity, it is straightforward to rewrite firm-level returns as:

$$\Delta p_{it} = \Delta p_{mt} + \xi\psi\left(\tilde{\mu}_{it} - \tilde{\mu}_{it-1} + \tilde{e}_{it} - \tilde{e}_{it-1}\right)$$

that is, firm-level returns consist of an exposure to the market return and an idiosyncratic component. Clearly, controlling for the market return purges the data of our mechanism - specifically, regressing firm returns on the market and examining the residuals would in theory lead to a finding of zero correlation across firms, despite the fact that common information may be playing an important role. Intuitively, as discussed above, correlated beliefs in part drive the market return, and controlling for the latter rids the data of this component.[35]

A similar relationship is not clear for other factors commonly employed in the literature. These include the Fama and French (1993) factors (other than the market return) - the difference

[35]This does not appear to be a bad approximation to the data. Regressing firm-level returns on the market return constructed from our data and correlating the residuals gives an average correlation across countries that is just about 0, ranging from -0.02 to a maximum of only 0.03.

between returns on diversified portfolios of small stocks and big stocks (SMB) and the difference between returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks (HML) - as well as the Carhart (1997) momentum factor, which constitutes the difference between the returns on diversified portfolios of the winners and losers of the past year (WML), and the Pástor and Stambaugh (2003) aggregate liquidity factor. Additionally, controlling for the risk-free rate captures any fluctuations in the pure rate of time-preference, i.e., δ in our framework.

To account for the common variation in discount rates captured by these factors, we project firm-level returns on them and compute the cross-firm correlation of the residuals. To the extent that our information-based mechanism interacts with these factors, our strategy here is likely conservative, in the sense that we may understate the role of informational forces. Thus, it is somewhat difficult to interpret the results in the absence of a deeper understanding of what underlying risk factors these variables capture. However, our more limited goal here is simply to assess the degree of excess return correlation that remains after controlling for them. Following the arguments in Fama and French (2012) for the importance of local factors, for each country in our dataset, we use region-specific factors provided by those authors.[36] These include the risk free rate, SMB, HML, and WML. The authors consider four regions: North America, Europe, Asia Pacific, and Japan (where the last is a standalone). We assign the countries in our sample to each of these regions.[37] As regional data for the liquidity factor is not available, we use the US liquidity factor throughout.[38] We convert all factors into real US dollars using the US CPI.

For each firm, we run monthly regressions of returns on these factors for the entire period of study and compute the residual at the monthly level. For comparability to our baseline results, we then aggregate the residuals to an annual level and compute cross-firm correlations using firm-pairs for which we have at least eight years of overlap. Figure 9 reproduces the plots from Figure 1 using these 'risk-adjusted' return correlations. Table 8 compares the properties of the adjusted correlations to the baseline and computes the correlation of the former with fundamentals and forecasts. As is apparent from the figure, the excess comovement puzzle remains. Risk-adjusted returns continue to exhibit excess correlation relative to fundamentals and remain systematically related to the correlations in earnings forecasts. For example, Table 8 shows that the average risk-adjusted return correlation across the 31 countries is 0.33, somewhat lower than the baseline of 0.46, but well in excess of the average correlation in fundamentals (0.11). Moreover, countries that exhibit high return correlations are also characterized by

[36]Obtained from Kenneth French's website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

[37]We group Peru and Chile with North America and Israel and South Africa with Europe. All reported results are unaffected if we drop these four countries from the analysis.

[38]Obtained from Lubos Pastor's website at `http://faculty.chicagobooth.edu/lubos.pastor/research/`.

high adjusted correlations; the correlation of the two series is 0.67.[39] Further, there remains a strong relationship with the correlation of forecasts - Table 8 shows the correlation between the two series to be 0.42 and statistically different from zero. Therefore, it seems reasonable to conclude that discount rate shocks explain a part of the excess comovement puzzle, but ample room remains for the information mechanism that we study in this paper.

Table 8: Firm-Level Correlations in Risk-Adjusted Returns

	Risk Adjusted corr(returns)	Baseline corr(returns)	
Summary Statistics			
Mean	0.33	0.46	
Max	0.59	0.73	
Min	0.10	0.20	
Std. Dev.	0.10	0.15	
	Baseline corr(returns)	corr(Δ earnings)	corr(forecasts)
Correlations			
Risk Adjusted corr(returns)	0.67***	0.44**	0.42**

Notes: Table reports summary statistics of firm-level correlations of returns across 31 countries. Risk-adjusted returns are computed as the residuals from factor regressions as described in Section 5.2. Data on returns and earnings growth are from Compustat. Data on earnings forecasts are from I/B/E/S. ***, ** denote statistical significance at the 1% and 5%-levels, respectively.

Our findings in this section are perhaps not overly surprising in light of the existing empirical literature. For example, as previously discussed, Pindyck and Rotemberg (1993) find a small role for observable macroeconomic factors in driving comovement 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.[40] 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

[39]For a small number of mostly developed countries (15 in total, with China and India being the least developed), we were able to obtain country-level estimates of the factors from `http://homepage.sns.it/marmi/Data_Library.html` for the same period of study (with the exception of China for which data becomes available in July 2000). Using these, the qualitative picture remains similar. Although the average correlation falls a bit further from 0.31 to 0.21 for this set of countries, it remains well above that in fundamentals. Notably, this is particularly the case in the two emerging markets, China and India, where the adjusted return correlations are 0.65 and 0.27, respectively. Further, for the 15 countries, the correlation between their adjusted values and the baseline is quite high at 0.67.

[40]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.

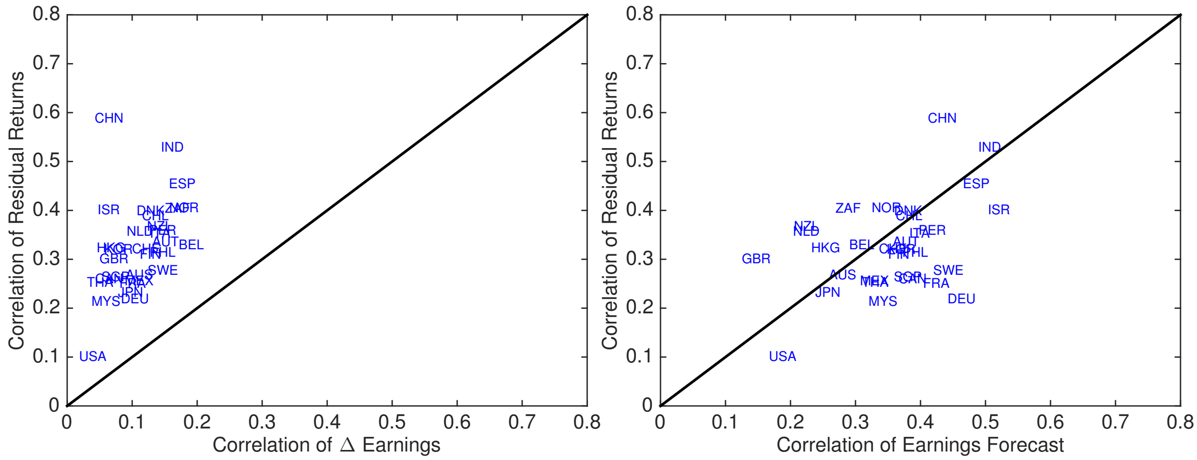

Figure 9: Firm-Level Correlations in Risk-Adjusted Returns, Earnings, and Forecasts

has been difficult to measure this phenomenon in the data, and so an information-based theory is worth considering. Our findings in this section suggest that modeling the two in tandem may well be necessary for a comprehensive explanation of excess comovement and asset price behavior more generally.

5.3 Informed Traders and Analysts

Throughout our analysis, we have used analyst information to proxy for the information sets of informed investors. A potential concern may be the degree to which analyst forecasts actually reflect the information set of a typical informed investor. Notice that for our mechanism to be at work, it is not necessarily the case that investors need to purchase this information directly from analysts. Investors, like analysts, forecast firms' earnings based on available information. To the extent that various types of sophisticated market participants use similar sources of information to form beliefs, the relevant information sets will contain considerable overlap. Unfortunately, we don't have direct data on a broader set of investor beliefs and so rely on analyst data as what we hope is a useful proxy. We would argue that this represents some progress, since we are able to directly measure beliefs for an important subset of investors across a large set of firms and countries.

That being said, we note that many investors of all types turn to analysts as a source of information. For example, institutional investors routinely purchase analyst reports and in fact annually rank analyst team performances (see, e.g., `www.institutionalinvestor.com`). These investors include mutual, hedge, pension, sovereign wealth, and endowment funds, as well as securities firms, private equity, insurance companies and commercial banks. Similarly, retail (individual) investors acquire analyst information via standard websites such as finance.yahoo.com, bloomberg.com, and seekingalpha.com. Thus, the evidence suggests that even sophisticated investors benefit from acquiring detailed information from analysts and incorporate this information into their beliefs. For example, Asquith et al. (2005) find that investors react to news that they obtain from analysts, and in particular, to information that is contained in the analysts' detailed reports over the summary statistics. Similarly, Green (2006) finds that early access to analyst recommendation changes enables profitable trades for brokerage firm clients.

Given that our analysis builds centrally on analyst forecasts, it is useful to understand how analysts arrive at these forecasts. Ramnath et al. (2008) offer a comprehensive review of the analyst literature and a number of insights from the analyst sphere. The authors argue that analysts rely on the following sources to arrive at earning forecasts at different horizons, recommended stock prices and buy/sell recommendations: (i) past earnings, (ii) other information from SEC filings, (iii) industry information, (iv) macroeconomic information, and (v) direct communication with management. In addition to directly purchasing analyst information, given that many of these categories are publicly available, it seems plausible that there is overlap in the information of analysts and other sophisticated investors, so that the analyst forecasts on which we rely contain valuable insights into a broader set of investor information.

Another avenue would be to include traders with orthogonal information sets in our theory. For example, 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.[41] 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.[42] 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.[43] Interestingly, recent work by Hassan and Mertens (2011) shows that small correlated errors on the part of near-rational agents with otherwise dispersed information can lead to high stock price volatility, but that

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

[42]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. (2014b). We revisit the question of exactly why these agents exhibit correlated beliefs in Section 5.4.2.

[43]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.

small common noise trading shocks do not exhibit the same effects.[44]

5.4 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.[45] 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.[46] 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.[47] The index,

[44]In a related point, as just discussed, we assume that analyst information is trader information, or at least that the former is a reasonable proxy for the latter. 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.

[45]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 (12).

[46]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.

[47]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

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 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.[48] 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 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.[49]

5.4.1 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 9 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

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.

[48]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.

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

Table 9: The Cross-Section of Return Correlation

	(1)	(2)	(3)
corr(forecasts)	0.897***	0.749***	0.548**
	(0.248)	(0.229)	(0.246)
corr(Δ earnings)		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 5.4. *, **, *** denote significance at the 10%, 5%, and 1%-levels, respectively. Standard errors in parentheses.

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 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.

Table 10: The Cross-Section of Market Volatility

	(1)	(2)	(3)
corr(forecasts)	0.503***	0.466***	0.300***
	(0.115)	(0.117)	(0.105)
corr(Δ earnings)		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 5.4. *, **, *** denote significance at the 10%, 5%, and 1%-levels, respectively. Standard errors in parentheses.

A similar picture emerges from the exercises that analyze the determinants of aggregate stock market volatility. The three columns in Table 10 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 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 or stock market volatility.[50] 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

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

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. 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.

5.4.2 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.[51]

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 11 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 11: 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 5.4.2. *, **, *** denote significance at the 10%, 5%, and 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

[51]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.

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. A more comprehensive modeling of discount rates and a strict accounting of their role versus the information channel we focus on would be fruitful, if challenging, as would further investigating the implications of our findings on market volatility for investment decisions and the international allocation of capital. For example, David et al. (2014a) show that differences in return volatility across countries plays a role in leading to differences in the real return to capital. Finally, 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.

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Appendix

Table 12: Compustat - Returns and Earnings

Country	Obs.	corr(returns)	corr(Δ earnings)	std(market returns)
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 13: I/B/E/S - Forecasts and Earnings

Country	Obs.	Analysts/firm	corr(forecasts)	std(forecasts)	corr(earnings)	std(earnings)	corr(Δ earnings)
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 14: Predicted Return Correlations

Country	ρ	π_f	corr $(\mathbb{E}_t[a_{it}])$	$\widehat{\text{corr}(\Delta p_{it})}$	corr (Δp_{it})
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 15: Counterfactual Return Correlations

Country	σ_μ^2	π^e	σ_e^2	$\widehat{\text{corr}\,(\Delta p_{it})}$ Baseline	$\pi^e = \pi_{US}^e$	$\sigma_e^2 = \sigma_{e,US}^2$
AUS	0.17	0.55	0.20	0.42	0.25	0.42
AUT	0.28	0.49	0.26	0.42	0.30	0.41
BEL	0.22	0.33	0.27	0.32	0.29	0.32
CAN	0.33	0.57	0.30	0.46	0.29	0.44
CHE	0.27	0.64	0.44	0.50	0.27	0.46
CHL	0.19	0.69	0.14	0.51	0.29	0.54
CHN	0.25	0.85	0.34	0.63	0.27	0.59
DEU	0.32	0.68	0.44	0.57	0.31	0.52
DNK	0.26	0.57	0.34	0.47	0.29	0.45
ESP	0.24	0.73	0.40	0.61	0.33	0.59
FIN	0.30	0.70	0.43	0.53	0.25	0.45
FRA	0.19	0.77	0.18	0.58	0.30	0.59
GBR	0.16	0.22	0.12	0.18	0.21	0.19
HKG	0.24	0.34	0.36	0.30	0.26	0.29
IND	0.19	0.99	1.10	0.72	0.38	0.88
ISR	0.29	0.77	0.29	0.62	0.33	0.59
ITA	0.28	0.77	0.59	0.58	0.27	0.52
JPN	0.35	0.37	0.47	0.31	0.25	0.28
KOR	0.54	0.62	0.69	0.48	0.27	0.38
MEX	0.44	0.36	0.39	0.34	0.29	0.33
MYS	0.28	0.51	0.39	0.42	0.28	0.40
NLD	0.19	0.47	0.24	0.34	0.23	0.34
NOR	0.45	0.60	0.84	0.47	0.25	0.37
NZL	0.14	0.41	0.14	0.31	0.24	0.32
PER	0.45	0.99	0.43	0.72	0.24	0.57
PHL	0.29	0.45	0.43	0.42	0.32	0.41
SGP	0.22	0.72	0.26	0.54	0.27	0.52
SWE	0.32	0.75	0.40	0.58	0.28	0.51
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	0.39

Table 16: Country-Level Data for Robustness Exercises

	Quarterly Frequency		Risk-Adjusted	Horizon					
	corr(returns)	corr(Δ earnings)	corr(returns)	corr(forecasts)			std(forecasts)		
				6 Month	3 Month	1 Month	6 Month	3 Month	1 Month
AUS	0.47	0.07	0.27	0.25	0.25	0.21	0.47	0.50	0.50
AUT	0.51	0.03	0.33	0.58	0.57	0.44	0.55	0.52	0.54
BEL	0.51	0.02	0.33	0.32	0.30	0.29	0.58	0.52	0.56
CAN	0.39	0.03	0.26	0.36	0.33	0.31	0.54	0.56	0.61
CHE	0.49	0.05	0.32	0.36	0.34	0.31	0.49	0.50	0.53
CHL	0.56	0.01	0.39	0.17	0.22	0.26	0.45	0.47	0.47
CHN	0.54	0.05	0.59	0.41	0.44	0.38	0.43	0.44	0.47
DEU	0.43	0.06	0.22	0.47	0.37	0.30	0.51	0.50	0.55
DNK	0.49	0.07	0.40	0.44	0.37	0.30	0.49	0.52	0.56
ESP	0.48	0.08	0.45	0.46	0.41	0.38	0.51	0.51	0.58
FIN	0.55	0.10	0.31	0.32	0.29	0.26	0.48	0.51	0.52
FRA	0.48	0.06	0.25	0.38	0.34	0.29	0.44	0.44	0.47
GBR	0.38	0.06	0.30	0.14	0.14	0.15	0.46	0.47	0.49
HKG	0.39	0.05	0.32	0.27	0.26	0.25	0.49	0.49	0.50
IND	0.56	0.05	0.53	0.45	0.43	0.39	0.50	0.54	0.55
ISR	0.55	0.00	0.40	0.45	0.39	0.34	0.49	0.57	0.51
ITA	0.56	0.15	0.35	0.35	0.28	0.26	0.45	0.46	0.54
JPN	NaN	NaN	0.23	0.28	0.19	0.19	0.52	0.57	0.60
KOR	NaN	NaN	0.32	0.33	0.29	0.26	0.62	0.61	0.64
MEX	0.51	0.23	0.25	0.31	0.32	0.34	0.51	0.61	0.62
MYS	0.33	0.03	0.21	0.34	0.29	0.25	0.48	0.47	0.50
NLD	0.48	0.18	0.35	0.21	0.17	0.22	0.46	0.50	0.51
NOR	0.62	0.10	0.40	0.31	0.27	0.22	0.52	0.54	0.60
NZL	0.55	0.08	0.36	0.21	0.21	0.20	0.42	0.45	0.46
PER	0.49	0.05	0.36	−0.09	0.15	0.15	0.52	0.57	0.63
PHL	0.44	0.05	0.31	0.45	0.43	0.33	0.60	0.65	0.57
SGP	0.48	0.04	0.26	0.39	0.35	0.30	0.45	0.46	0.51
SWE	0.54	0.06	0.28	0.39	0.36	0.33	0.50	0.51	0.59
THA	0.31	0.02	0.25	0.29	0.27	0.23	0.69	0.68	0.67
USA	0.20	0.01	0.10	0.19	0.18	0.18	0.48	0.50	0.53
ZAF	0.50	0.08	0.40	0.28	0.28	0.26	0.47	0.50	0.51