INATTENTION, LEARNING INCENTIVES, AND FUTURE RETURNS

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ABSTRACT

NICHOLAS P. MARTIN: Inattention, Learning Incentives, and Future Returns
(Under the direction of John R.M. Hand)

I implement an empirical measure of investors' ex-ante learning incentives based on the theoretical learning index described in Van Nieuwerburgh and Veldkamp's (2009) rational inattention theory of investors' learning decisions, which I call the average learning incentive (ALI). I validate ALI by testing three predictions made about it in NV (2009): that it is negatively associated with future returns; positively associated with analyst coverage; and associated with home bias in a quadratic, inverted-U shape. I find support for each prediction. Drawing on accounting theory regarding the cost of capital, I then move beyond the predictions in NV (2009) and test the association between ALI and future factor-adjusted returns in a series of subsamples, and find that while ALI is generally negatively associated with future returns, the reverse relation holds for firms with imperfect equity markets and poor information environments. I also find that the well-established negative association between accrual quality and future returns is mediated by investor learning incentives, and that it only appears when ALI is low, indicating that investors can disentangle poor quality reporting when their motivation to do so is high.

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CHAPTER 1

INTRODUCTION

Rational inattention entered the economics theory literature with Sims (2003, 2006), and has been advanced within the finance literature by Van Nieuwerburgh and Veldkamp (2009, 2010) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2015). Rational inattention models relax the assumption in standard economic models that agents are able to completely and costlessly process all information available to them. Although agents in rational inattention models are rational Bayesians, they face a constraint on the extent to which they can absorb new information and update their prior beliefs. They are endowed with a finite capacity to learn or absorb information, which they then expend to update their beliefs. Prior to learning, the agents are required to choose how they will allocate that capacity, which is generally denoted attention.

Motivated by the rational inattention theory literature, recent empirical work in accounting and finance finds that the market underreacts to information about firms which investors do not pay attention to. This literature generally proceeds either by examining direct measures of investor attention (Ben-Raphael, Da, and Israelsen (2017) and Drake et al. (2018)) or settings where investors are likely to face greater cognitive demands (Hirshleifer et al. (2009)).

My study complements this stream of literature by constructing a theory-driven empirical measure that captures the ex-ante incentive to learn about a firm. This ex-ante incentive differs from realized measure of attention in that realized attention measures are only likely to be observed when investors are ex-post able to successfully find information about a firm and learn from it. In the absence of available and useful information, we will not observe the empirical proxy variables for attention used in the literature. The theory-driven measure I construct, however, is available regardless of the firm's information environment and the available information intermediaries, and it allows me to investigate the effects of investors' desire to learn about firms in settings where such learning is easy and in settings where it is difficult. To do this, I construct an empirical version of the learning index defined in Van Nieuwerburgh and Veldkamp's (2009) rational inattention theory of investors' learning decisions, which I label the Average Learning Incentive (ALI), which measures the extent to which investors desire ex-ante to learn about a firm.

In Van Nieuwerburgh and Veldkamp (2009) (hereafter NV (2009)), domestic and foreign investors attempt to maximize their wealth in a rational expectations framework where there are multiple domestic and foreign assets whose payoffs are determiend by a common set of risk factors. Investors are endowed with prior beliefs about the payoffs of those factors, where the precision of dometstic investors' priors is greater than foreign investors' priors for domestic assets, and vice versa. The model departs from usual rational expectations frameworks in providing investors an opportunity to reduce their uncertainty about the payoff of risk factors in the economy prior to making asset allocation decisions, but limiting the extent to which they can do so - forcing investors to choose how to allocate their scarce attention. In choosing what risk factors to learn about, investors take into account their own prior information, the decisions of other investors, and the information in the current prices of risky assets. In a competitive market with asymmetric information, investors will allocate all of their attention to a single factor. The factor they choose to pay attention to is the one for which their learning index is highest, where the learning index includes the prior Sharpe ratio of the risk factor and the ratio of the precision of the price signal to the precision of the investor's prior information. Intuitively, investors want to learn about factors which have high return-to-risk ratios, and about which they have better prior information than other investors. I base my average learning incentive (ALI) measure on the learning index as defined by NV (2009). When empirically implemented, ALI provides a theory-driven way to measure investors' ex-ante demand for information, whether or not there is information readily available to satisfy that demand.

In addition to the empirical attention literature, my study is related to theoretical and empirical literatures in accounting about the effect that information availability has on firms' costs of capital and future returns. A long stream of theoretical work in accounting has argued that firms have a lower cost of capital when investors are less uncertain about the firms' future performance, and when there is less information asymmetry in the market (Diamond and Verrecchia (1991); Easley and O'Hara (2004); Hughes, Liu, and Liu (2007); Lambert, Leuz, and Verrecchia (2007, 2012); and Lambert and Verrecchia (2015)). Following this line of investigation, an extensive body of empirical research has shown that the supply of information about a firm, and the quality of the information the firm supplies, enables investors to form more precise expectations and decreases information asymmetry, thereby reducing firms' costs of capital and their future returns (e.g., Francis, LaFond, Olsson, and Shipper (2004, 2005); Core, Guey, and Verdi (2008); Francis, Nanda, and Olsson (2008); Armstrong et al. (2011); and Bhattacharya et al. (2012)).

My study also extends the predictions regarding investors' learning incentives and future returns made in NV (2009) by highlighting the ways in which ALI complements the existing investor attention literature by surfacing settings where investor attention measures are unlikely to capture investors' interest in learning about a firm. I further find that long-standing results about the negative association between accounting quality and future returns depends on investors' learning incentives.

I begin my investigation into the effects of investors' learning incentives by testing ALI to confirm that it captures the learning index construct in NV (2009). First, the learning index is expected to negatively predict future returns, as increased demand for information about a firm leads to less uncertainty in the market, driving future returns down. I find that ALI does indeed predict lower subsequent Fama-French adjusted returns, with a one-standard-deviation increase in ALI leading to a 70 basis point reduction in one-year-ahead adjusted returns. This association is present in both the US and the global samples and is consistent with the predictions of NV (2009).

Second, the learning index is expected to positively predict future analyst following, as analysts respond to investors' demand for information by increasing their coverage. I find that lagged ALI is associated with higher current analyst following. This association, while statistically significant in the US, is economically minor and does not appear at all in the global sample. These results, however, may be interpreted cautiously because analyst following could both cause and be caused by investors' learning incentives. Recognizing the potential for endogenous dynamic relations between these variables, I therefore estimate a panel VAR model which allows me to examine these bidirectional effects. In a constant panel of US firms, I find that past increases in ALI are reliably positively associated with future increases in analyst following, and that the reverse holds, leading to feedback-driven and substantial increases in both ALI and analyst coverage following a shock to either variable. I interpret this finding to be consistent with the predictions of NV (2009).

Third, ALI is expected to be quadratically associated with home bias in an inverted-U shaped manner. The intuition for this prediction is that countries with a very low learning index will not attract much attention even from domestic investors; countries with very high learning index values will attract attention from foreigners (despite their information disadvantage); and countries with intermediate learning index values will attract a disproportionate share of home investment. I measure home bias in an investment fund as the difference between the fraction of the fund's holdings in domestic equities and the share of that country's equities in the global public equity market. I then rank the the investment funds in a country-year by their home bias, and select the median fund's home bias as the country-level home bias for that year. To mesure ALI at the country level I take the average ALI of all firms in the country's equity market. The country mean ALI exhibits the expected inverted-U association with median-fund home bias, both in quintile analysis and in regressions containing a quadratic term. Overall, I interpret the results of my set of validation tests as providing affirmative evidence that ALI captures the theoretical learning index construct in NV (2009).

Next, inspired by Lambert, Leuz, and Verrecchia (2012) (hereafter LLV (2012)), I develop a set of theory-based predictions about additional effects of investor learning incentives on future returns. LLV (2012) present a rational expectations model in which two forces affect a firm's cost of capital: the average precision of information about the firm in the market, and the firm's information asymmetry. The first channel lowers firms' cost of equity, and the second increases it. I hypothesize that investors' demand for information (measured by ALI) increases the information about a firm in the market (the information precision channel), producing a lower cost of equity and lower future returns. However, I also hypothesize that investors' demand for information will have an ambiguous effect on information asymmetry. In settings where investors can easily acquire information about a firm, I argue that increased demand for information will lead many investors to do so, resulting in unchanged or reduced information asymmetry. Taken in conjunction with the information precision effect, I predict a reduction in the firm's cost of equity. However, in settings in which investors cannot easily acquire information about a firm, increased demand for information should lead only a subset of investors to successfully acquire information while others do not, thereby increasing information asymmetry and the firm's cost of equity, and yielding higher future returns.

To test these latter hypotheses, I turn to the methods described in Armstrong, Core, Taylor, and Verrecchia (2011) (hereafter ACTV 2011). ACTV (2011) use the number of shareholders of record as a measure of the level of competition in the market for a firm's shares and, based on the models in LLV (2012), assume that information asymmetry will have little to no effect on the cost of capital in highly competitive equity markets. ACTV (2011) find evidence consistent with the theoretical prediction in LLV (2012) that in highly competitive equity markets, where all shareholders are price takers, information asymmetry has no effect on the cost of capital. Like ACTV (2011), I use one-year-ahead Fama-French 3-factor adjusted returns as a measure of firms' costs of capital, and the number of shareholders of record as a measure of the degree of competition in the market for a firm's equity. I find that ALI is negatively associated with adjusted returns for firms in the top two quintiles of number of shareholders but shows no association with returns for firms in the bottom two quintiles. Within the bottom two quintiles, I then examine firms with analyst coverage in the top and bottom quartiles. I find that the insignificant coefficient on ALI in low-equity-market-competition firms is driven by stark differences in the behavior of ALI in different information environments. In low-competition firms with high analyst coverage, ALI is negatively and significantly associated with one-year-ahead adjusted returns. However, in low-competition firms with low analyst coverage, ALI is positively and significantly associated with one-year-ahead adjusted returns. This contrast is consistent with a situation in which (1) the information asymmetry effect and the information precision effect complement each other in rich information settings where investors' demand for information is likely to be satisfied, but (2) the information asymmetry effect overwhelms any information precision effect in poor information environments where investors' information demand is unlikely to be satisfied.

The just mentioned finding contrasts with the result in Fang and Peress (2009) that media coverage, a commmon measure of investor attention, is most negatively associated with future returns in settings with low analsyt coverage. The fact that ALI is positively associated with future returns when analyst coverage is low and investors are most likely to be frustrated in their attempts to learn about a firm suggests that my theory-driven measure of learning incentives can complement existing empirical measures of investor attention by allowing for the possibility that investors might want to learn about a firm with low measures of realized attention, but are unable to do so in a poor information environment.

Lastly, I use ALI to investigate the association between accrual quality and the cost of capital documented in Francis, LaFond, Olsson, and Shipper (2004, 2005) and Francis, Nanda, and Olsson (2008). I hypothesize that high quality accruals may either complement a high incentive to learn, leading to a stronger association between accrual quality and the cost of equity; or alternatively, that a high learning incentive my induce investors to learn enough about a firm to overcome a low quality accounting system, attenuating the association between accrual quality and the cost of equity. I construct a measure of accrual quality following Francis et al (2005) and find that the association between accrual quality and the cost of equity in my sample differs between firms in the top two versus the bottom two quintles of ALI, with only firms in the bottom two quintiles of ALI exhibiting a negative association between high quality accruals and the cost of equity.

ALI is based on a factor model of firm payoffs which closely follows the definition of the learning index in NV (2009). An alternative and potentially complementary approach to my construction of investors' ex-ante incentive to learn about a firm is to construct a measure based on firm returns that incorporates the intuition from the NV (2009) model but does not follow its formal structure. In NV (2009) investors want to learn about factors which offer good risk-adjusted returns and about which they have a prior information advantage. Applying this idea to firms rather than factors, I construct a firm-by-firm measure which captures firms' recent returns, and the extent to which their returns are explained by contemporaneous macro indicators. The intuition behind the measure is that investors will have an incentive to learn about firms which have recently had good-risk adjusted returns and whose returns are not well explained by readily observable macro indictors. I label this firm-based measure ALI_ALT, and find that when I include both ALI and ALI_ALT in regressions of future abnormal returns both measures are negatively associated with future returns. I then test the association of ALI and ALI_ALT with future returns in each of the subsamples described earlier, and find that while ALI continues to differ accross the subsamples in a theoretically consistent pattern, ALI_ALT is constant accross each subsample. While this indicates that ALI_ALT is not capturing the same construct as the ALI, it is nevertheless interesting that it appears to partially overlap with ALI, and to negatively predict returns in its own right.

Overall, my study contributes to the rational inattention literature by implementing and validating a theory-driven empirical measure of investors' ex-ante incentive to learn about a firm, adding to the evidence that investor learning decisions are characterized by rational allocations of limited attention. The measure I construct also complements the progress being made in the attention literature that instead uses realized attention proxies and attention-intensive settings. Using ALI, I am able to investigate settings where the information environment is poor, and investors may want to learn about firms but be unable to do so, which ex-post measures of attention might classify as being firms which investors are uninterested in. My study also contributes to the literature on information quality and the cost of capital by showing that the relation between accrual quality and the cost of equity depends on how strongly investors' desire to learn about a firm.

The remainder of this paper proceeds as follows. In section 2 I discuss in detail the theoretical motivation behind ALI and explain the empirical construction of ALI (and ALI_ALT). I develop my hypotheses in section 3. I discuss my data and sample selection in section 4. Section 5 presents and discusses the results of my tests, and section 6 concludes.

CHAPTER 2

THEORETICAL MOTIVATION

2.1 The Learning Index

In their study, NV (2009) present a multi-agent, multi-asset, limited attention, rational expectations model of home bias in which there are two classes of investors, home and foreign, and two categories of assets, home and foreign. Investors have negative exponential utility over wealth at the end of the period and are endowed with prior beliefs about the payoffs of assets. The precision of home investors' prior beliefs about home assets is greater than the precision of their prior beliefs about foreign assets, and the reverse is true for foreign investors. Investors have a finite capacity to learn, and they use this capacity to reduce their uncertainty about the payoffs of assets. Learning takes place by decomposing asset payoffs into risk factors, each with its own payoff and uncertainty. Home and foreign investors perceive the same risk factors but have different levels of uncertainty about the payoffs of the factors. Learning consists of reducing uncertainty about the payoff of a risk factor. Prior to making asset allocation decisions, investors choose how to allocate their learning capacity, which amounts to choosing the risk factors about which they want to reduce their uncertainty. After they make their investment decisions, the markets clear, returns are observed, and investors realize their utility.

In equilibrium, the NV (2009) model predicts that investors choose to devote all of their learning capacity to a single risk factor, in order to maximize their information advantage relative to other investors. This result contrasts with models with unlimited learning capacity, where investors who do not face limits on their ability to learn choose to learn about all risks and resolve as much uncertainty as the market environment (rather than their finite capacities) allows. The intuition behind the NV (2009) result is that investors desire to earn high risk-adjusted returns, and that they are best able to do so by investing in assets about which they have superior information, for which they have resolved more uncertainty than the rest of the market through their learning, and whose prices are therefore low relative to the level of uncertainty which the investor possesses.

The single risk factor that a given investor will choose to invest in is the factor for which her learning index is highest, where the learning index is a construct that takes into account the prior precision of her beliefs, the precision of the information that is revealed in prices, the ratio of the precision of the price signal to that of her prior, and the expected return of the factor. Formally, the learning index is

$$\mathcal{L}_i^j \equiv (\rho \hat{\Lambda}_i^a \Gamma_i^\top \bar{x})^2((\Lambda_i^j)^{-1} + \Lambda_{pi}^{-1}) + \frac{\Lambda_{pi}}{\Lambda_i^j}. \tag{1}$$

In equation (1) above, Λ_i^j is the prior uncertainty about factor i of investor j, $\hat{\Lambda}_i^j$ is the posterior uncertainty, ρ is a risk aversion parameter, Γ_i is the vector of asset loadings on the ith risk factor, and $\bar{x}$ is the vector of the supply of the assets in the market. Finally, Λ_{pi} is the uncertainty of the price signal.

It is easier to see the meaning of equation (1) when we consider that $(\rho \hat{\Lambda}_i^a \Gamma_i' \bar{x})$ is the expected return to risk factor i. Thus, equation (1) can be rewritten

$$\mathcal{L}_i^j \equiv E^j[Return_i]((\Lambda_i^j)^{-1} + \Lambda_{pi}^{-1}) + \frac{\Lambda_{pi}}{\Lambda_i^j}. \tag{2}$$

Since Λ_i^j is the uncertainty of investor j about the return of factor i, and Λ_{pi} is the uncertainty in the price signal of factor i's performance, equation (2) can be rewritten

$$\mathcal{L}_i^j \equiv \left(E^j[Return_i] \left(\frac{1}{Uncertainty_i^j} + \frac{1}{Uncertainty_i^{price}} \right) \right) + \frac{Uncertainty_i^{price}}{Uncertainty_i^j}. \tag{3}$$

Thus the learning index $\mathcal{L}_i^j$ reduces to a conceptually simple sum that has two components. The first is a Sharpe ratio based on the uncertainty of the investor and the price signal, and the second is the ratio of uncertainty in prices to uncertainty in investor $j\acute{s}$ prior. $\mathcal{L}_i^j$ therefore captures the sensible intuition that investors prefer to learn about factors that they expect to have high Sharpe ratios, and where the precision of their information is high relative to the precision of the information already revealed in prices.

Having determined how to allocate their learning capacity, investors will place a greater proportion of their wealth into the assets about which they acquire information. This is because they no longer view the risk-return profile of those assets unconditionally, as they did before learning, because they have reduced their uncertainty about a subset of the available assets. The assets about which investors now have reduced uncertainty about have superior conditional risk-return ratios relative to unconditionally similar assets about which they did not learn. This in turn leads investors to rationally invest more (less) in assets they did (did not) choose to learn about, and produces the connection to portfolio bias, which will be most visible in the home-bias predictions about the learning index that I develop in section 2.5.

2.2 An Empirical Version of the Learning Index

NV (2009) outline a multi-step method by which an empirical learning index could be constructed, and I follow their approach.

The first two steps are to undertake a factor analysis [1] of asset payoffs to form risk factor prices and payoffs, and then to divide average factor payoffs by the standard deviation of factor payoffs to form factor level Sharpe ratios. These steps are relatively simple, and they intuitively correspond to the first term in equation (3).

The third step is to regress factor prices at t on a constant and payoffs from t to $t+1$. The ratio of the uncertainty of price information to the uncertainty of the investor's prior - the second term in equation (3) is 1 minus the R^2 from this regression.[2]

[1]The factor analysis NV (2009) describes is a statistical factor analysis rather than an analysis of firms' loadings on economic factors such as the Fama-French factors. In my factor analysis I use the pca command in R to perform a principle components analysis of asset payoffs and construct factors based on those components.

[2]To see how this regression contributes to the construction of the ALI, note that it is adapted from the equation giving equilibrium asset prices in the NV (2009) model: equilibrium asset prices are given as $A+f+Cx$, where A and C are constants defined in terms of other parameters in the model, f is the payoff of the asset in $t+1$, and x is a random supply shock. Moving from assets to risk factors, replacing defined constants with regression parameters, and attributing regression residuals to supply shocks yields the regression of current-period factor prices on a constant and subsequent-period factor payoffs. To see how the R^2 of that regression relates to the relative precision of price information and the investor's prior, note that $R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$. In this setting, SS_{tot} is the uncertainty of the prior expectation of an investor whose prior is based on past observable returns, and SS_{res} is the uncertainty of the regression of current prices on subsequent returns, which can be interpreted as the uncertainty of the price signal. Thus, $1 - R^2 = \frac{SS_{res}}{SS_{tot}}$ is an empirical proxy for $\frac{\Lambda_i^{price}}{\Lambda_i^j}$, the second term in equation (3). NV (2009), n.12, contains a more detailed derivation of this connection.

The final step is to construct the learning index and multiply the vector of factor-level learning indices by the eigenvector matrix defining the risk factors to obtain firm-by-firm learning index values. The basis for any version of the learning index, then, is the factor level learning index:

$$LI_{i,\tau} = \frac{Mean[Return_i]_{\tau-n,\tau-1}}{St.Dev[Return_i]_{\tau-n,\tau-1}} + (1 - R^2)_{\tau-n,\tau-1}, \tag{4}$$

where n is the number of periods in the window used to construct the learning index, i denotes a risk factor, and R^2 is the R^2 from the regression of factor prices in t on factor payoffs from t to $t + 1$ discussed above. The similarities between the empirical learning index in equation (4) and the heuristic presentation of the theoretical learning index in equation (3) become apparent. Each one is the sum of a term representing the Sharpe ratio of the risk factor and a separate term representing the ratio of the uncertainty of a price signal to the uncertainty of an individual investor's prior. However, while the theoretical learning index is defined for each individual investor, the empirical version outlined by NV (2009), and which I create use and test, is defined for the average investor whose prior beliefs are formed on the basis of past returns.

2.3 Construction of the Average Learning Incentive

To empirically construct the ALI I define risk factors based on firm payoffs as suggested by NV (2009). To calculate the $Mean[Return_i]_{\tau-n,\tau-1}$ and $St.Dev[Return_i]_{\tau-n,\tau-1}$ I must calculate risk-factor returns for each year in $[\tau - n, \tau - 1]$. To calculate factor returns for a given year t I therefore first calculate the payoffs for each firm-year in the sample as $f_t = P_{t+1} + D_{t,t+1} - P_t$, where P_t is the first closing share price in calendar year t, P_{t+1} is the last closing share price in t, and $D_{t,t+1}$ is the total dividends paid out over calendar year t. To form the year t risk factors, I then take the sample of firms with non missing payoffs between t and $t - (n - 1)$. For my main ALI construction, I choose $n = 5$, as this provides enough years of data to calculate the firm-by-firm regressions and is consonant with the standard practice of taking five years of data to calculate factor parameters. I then extract the principal components of the payoffs. Prior to the eigen decomposition of the variance-covariance matrix of the payoffs, I normalize the payoffs to have a zero mean and unit standard deviation in order to mitigate the influence of observations with high ideosyncratic volatility. NV (2009) denote the eigenvectors produced by factor analysis Γ. To distinguish my empirical construct from the theoretical definition in NV's model, yet provide some continuity in notation, I refer to the eigenvectors as G. Since I use n years of data to construct these factors, I can extract at most n non-degenerate factors. As the n^{th} factor explains very little variance, I retain $n-1$ factors from the principal components analysis of asset payoffs. Following NV (2009), I then calculate factor returns as the factor payoff minus the price of the factor multiplied by the risk-free rate. The payoff of the $n-1$ factors is defined as $G_t^\top * f_t$, where f_t is a vector of firm payoffs in year t. Factor prices are defined as $G_t^\top * P_t$, where P_t is a vector of firm prices at the beginning of year t. Denoting the risk-free rate in year t as RF_t, the return for factor i in year t can be expressed as

$$Return_{i,t} = G_{i,t}^\top * f_t - G_{i,t}^\top * P_t * RF_t. \tag{5}$$

To construct $\frac{Mean[Return_i]_{\tau-n,\tau-1}}{St.Dev[Return_i]_{\tau-n,\tau-1}}$, I calculate $Return_{i,t}$ for $t \in [\tau-n, \tau-1]$ and then take the mean and standard deviation of that vector.

To construct the $(1-R^2)_{\tau-n,\tau-1}$ term, I take the same vector of factor prices and payoffs defined above and obtain the R^2 from the following regression:

$$G_{i,t}^\top * P_t = \alpha + \beta(G_{i,t}^\top * f_t) + \epsilon. \tag{6}$$

Using equations (5) and (6) I can then calculate ALI for a particular factor in a particular year τ via the definition in equation (4).

Finally, one of the elements of the learning index in NV (2009) which is not directly captured by the principle components analysis is that the learning index is greater for factors which affect larger portions of the capital market. This too is intuitive - a similarly informative piece of information is more valuable if it pertains to a large fraction of the total equity market than if it pertains to a narrow niche with only a few small firms. To capture this aspect of the NV (2009) learning index I weight the factor-level ALI by the total market cap of its loadings divided by the sum of the total market cap of each factor's loadings.

$$ALI\_FACTORi, \tau = ALI\_FACTOR\_raw_{i,\tau} * \frac{G_{i,\tau}^\top * P_\tau}{\sum_{i=1}^{n-1} G_{i,\tau}^\top * P_\tau} \tag{7}$$

where ALI_FACTOR_raw$_{i,t}$ is the unweighted ALI for factor i formed according to equation (4)

To calculate the ALI for a firm, I take the vector of year τ factor-level ALI values and multiply them by the factor loadings $G_{\tau-1}$ to get the firm-level ALI in year τ:

$$ALI_\tau = G_{\tau-1} * ALI\_FACTOR\tau. \tag{8}$$

where τ denotes the year. When constructing the firm-level ALI, I use the absolute value of the firm's loadings in the eigenvectors, as the sign which they are assigned in the eigen decomposition is arbitrary. The ALI, then, captures each firm's absolute contribution to a factor. Note that G_t is an m by $n-1$ matrix, where m is the number of firms, and $n-1$ is the number of eigenvectors retained from the principal components analysis. Note also that ALI_FACTOR_τ is an $n-1$ by 1 matrix, so that the resulting vector, ALI_τ, is an m by 1 vector, with one observation per firm, where each observation is the sum of the factor learning index values multiplied by the firm's absolute loading on the factor.

2.4 Alternative ALI Construction

While the learning index described in NV (2009) has a complex structure, it also has a relatively simple interpretation. Investors want to learn about firms that offer good risk-adjusted returns, and which do not have prices that precisely forecast future returns, so that learning is rewarded. One the one hand, the factor driven structure is appealing. It captures the intuition that investors learn about concepts which are then applicable to a set of firms, rather than supposing that they learn exclusively about individual firms. However, the the factors extracted in a princple components analsis may not themselves be reliable when the time series of returns they are drawn from is non-stationary, or when there are too few observations to extract reliable factors. An alternative approach to constructing a learning index is to directly identify firms that are likely to posess the intuitive characteristics of the theoretical learning index without implementing the factor structure from the theoretical model. This approach also captures the idea that investors do in fact sometimes learn specific firms.

To match ALI while keeping the alternative, firm-based learning index as similar to ALI as possible, I construct ALI_ALT as a similar sum of two ratios - a firm's Sharpe ratio and one minus the R^2 from a regression of the firm's returns on changes in major macro indicators.[3] ALI_ALT is therefore similar in construction to ALI, and it attempts to capture the same components; a measure of the firm's risk-adjusted returns, and the extent to which investors who attempt to learn about the firm are likely to be rewarded. The Sharpe ratio mesures the first component, just as in the factor-level theoretical learning index, and the R^2 measure captures the second component in a conceptually similar way to the term based on regressing prices on future payoffs described in footnote 2. A high R^2 in that regression would indicate that knowing a small set of major macro indicators would reveal a great deal of information about a firm's returns - and that since such indicators are widely disseminated and freely available, such firms would not likely reward investors for learning about them. $1 - R^2$ from such a regression captures the extent to which a firm's returns are not inferable from major macro news, and would likely reward investors for learning. My alternative firm-based construction of ALI, then, is:

$$ALI\_ALT_{i,t} = \frac{Mean[Return_{i,(t-n,t-1)}]}{St.Dev[Return_{i,(t-n,t-1)}]} + (1 - R^2)_{t-1} \tag{9}$$

where the $(1 - R^2)$ term comes from the R^2 of the following regression:

$$RET_{i,t} = \alpha + \beta_1 \Delta GDP_t + \beta_2 \Delta FedFundsRate_t + \epsilon_{i,t} \tag{10}$$

where in each equation i indexes firms and t indexes quarters, and for each quarter t the regression is run on the preceding twenty quarters.

[3] I am grateful to Jacob Sagi for suggesting this alternative approach.

CHAPTER 3

HYPOTHESIS DEVELOPMENT

NV (2009) make several predictions about the behavior of the empirical learning index as they outline it, and I test these predictions using my ALI to confirm that ALI captures the theoretical construct described in NV's model.

First, NV predict that the empirical learning index will forecast analyst coverage and other information-related measures, the idea being that providers of information will respond to the demand for information on the part of average investors. Accordingly, my first hypothesis is:

H1a: ALI is positively associated with current analyst coverage.

H1b: ALI positively forecasts future analyst coverage.

Second, NV predict that the empirical learning index should negatively forecast CAPM or other factor-adjusted future returns, becasuse as the average investor's demand for information increases, more investors will learn about the firm, reducing the aggregate uncertainty of the market's expectations of its performance and driving down future returns. My second hypothesis, then, is:

H2: ALI is negatively associated with one-year-ahead Fama-French 3-Factor adjusted returns.

Finally, NV (2009) predict that their empirical learning index will be contemporaneously associated with home bias in a quadratic, inverted-U shape. The reasoning behind this non-linear prediction is that countries with very small learning index values will be uninteresting even to local investors, despite their information advantage, while countries with high learning index values will be so desirable to learn about that even foreign investors will learn about them. Since learning about an asset reduces its uncertainty, investors will bias their portfolios towards the assets they have learned about. This produces reduced home bias in countries where either locals choose not to learn about local assets, or foreigners choose to learn about home assets. However, in intermediate learning index countries, home investors will learn about home assets and foreign investors will not learn about home assets, thereby producing a pronounced home bias. Consequently, my third hypothesis is:

> H3: ALI is quadratically associated with home bias, with a positive linear term and a negative quadratic term.

Taken together, the results of my testing these three hypotheses provides evidence on whether ALI adequately captures the theoretical construct of the NV (2009) learning index.

3.1 Additional Subsample Hypotheses

NV (2009) predict that the learning index will be negatively associated with future factor-adjusted returns because the greater demand for information leads to a reduction of uncertainty in the market as a whole. Drawing on the cost of capital literature in accounting, I extend that prediction into a variety of cross sectional cuts, each with its own enriching implication about the association between ALI and future returns. Lambert, Leuz, and Verrecchia (2012) in particular present a rational expectations model which provides some structure that I use to assess the effect of ALI on a firm's cost of capital. LLV (2012) describe two channels through which investors' information about a firm may affect a firm's cost of capital: through the average precision of information in the market, and through the degree of information asymmetry in the market. They find that the average precision of information about a firm unambiguouslys decreases a firm's cost of capital, while the asymmetry in the distribution of that information among market participants increases a firm's cost of capital to the extent that the information is not perfectly revealed in prices. This means that as a firm's equity trades in increasingly perfect markets, the trades of informed investors will fail to move prices, and the cost of capital will be unaffected by information asymmetry. The argument made by NV (2009) is that as a firm's empirical learning index increases, the average investor will learn more about the firm, increasing the average precision of all investors' expectations and driving down the firm's cost of capital. Although this is similar to the information precision channel discussed in LLV (2012), NV (2009) do not make any predictions about how an increase in the empirical learning index might affect information asymmetry, which plays a central role in explaining home bias and other forms of under-diversification.

Despite the differences in the models, the core rational expectations setup is sufficiently similar that I believe it is reasonable to use the model of LLV (2012) to develop hypotheses regarding the association between ALI and future returns based on the effects that increased demand for information might have on the information precision and information asymmetry channels discussed above. First, with respect to the average precision of investors' expectations, I assume that increased demand for information leads to higher average precision. All that is necessary for this to hold is that increased demand for information not lead the market to 'forget' information on average and for at least some investors responding to ALI to be successful in learning about the firm. Following LLV (2012), I aim to isolate the effect of increased average precision in the market by focusing on highly competitive settings, because in such settings changes in information asymmetry induced by changes in ALI should not affect the cost of capital in highly competitive equity markets. Consequently, my fourth hypothesis is:

> H4: Among firms whose equity is traded in a highly competitive market, ALI will be negatively associated with future returns.

Second, with respect to information asymmetry, the effect that an increase in ALI will have on information asymmetry will be mediated by how easy it is to learn about the firm. In settings where it is easy to learn about the firm, I argue that information asymmetry will decrease, as previously less-informed investors choose to learn about the firm. In settings where it is difficult to learn about the firm, information asymmetry will increase if only a relatively small subset of investors are able to learn about the firm when they are incentivized to do so. In this second situation firms with low ALI will have only a few investors who choose to learn about them, and therefore few investors who are informed about the firm relative to other investors, producing low overall information asymmetry. However, a firm with high ALI and a poor information environment will have many investors who attempt to learn about the firm, some of whome will successfully do so, leading to a situation in which there is a greater disparity between the newly endogenously informed investors and the frustrated, still-uninformed investors who tried but failed to learn about the firm. These effects of investor learning incentives on a firm's cost of capital would only be apparent among firms whose equity trades in an environment of imperfect competition. My fifth hypothesis, then, is

H5a: Among firms whose equity trades in less-competitive environments, and that have low-quality information environments, ALI will be positively associated with future returns.

H5b: Among firms whose equity trades in less-competitive environments, and that have high-quality information environments, ALI will be negatively associated with returns.

H5 therefore highlights the complementarity between ALI and other investor attention measures. In most settings, a high incentive to learn about a firm (high ALI) should lead to greater measured investor attention. However, in settings where the information environment is poor, investor attention will be low even in the presence of high learning incentives. Hypothesis 5b therefore presents a setting where ALI is able to capture those features of the relation between investors' learning incentives and future returns that prior literature has been unable to investigate.

3.2 Accrual Quality Hypotheses

The effect of a firm's accounting quality on its cost of capital is a longstanding concern in the academic accounting literature. Francis, LaFond, Olsson, and Shipper (2005), among many others, find that firms which have higher quality accruals face a lower cost of capital, and therefore have lower future returns. I hypothesize that the association between accrual quality and future returns is mediated by the extent to which investors decide to learn about a firm, measured by ALI. This said, I consider two alternative ways in which investors' learning decisions could affect the relation between accrual quality and future returns.

One the one hand, investors' learning may complement a firm's accounting quality, leading to a more precise expectation of future performance and a strong mediating role for ALI. On the other hand, a weaker mediating role might emerge if, when investors have a high incentive to learn about a firm, they are able to disentangle the nuances of its accounting system and successfully use even low quality accruals to form an accurate expectation of the firm's future prospects, weakening the association betwee accrual quality and future returns. My hypothesis then, in two parts, is:

H6a: Among firms with a high ALI, the relation between accrual quality and future returns will be greater than among those with a low ALI.

H6b: Among firms with a high ALI, the relation between accrual quality and future returns will be lower than among those with a low ALI.

CHAPTER 4

DATA AND SAMPLE SELECTION

The data I use comes primarily from FactSet's Scheduled Data Feeds. I obtain price and return data from FactSet Prices v2, firm-level fundamentals data from FactSet Fundamentals v3, analyst forecast data from FactSet Estimates v4, and fund-level ownership data from FactSet Ownership v5. I choose to use FactSet data rather than the more common Compustat-CRSP-IBES databases for two reasons. First, FactSet seamlessly integrates international data into its databases and has extensive international coverage for each of the data products mentioned above. This is crucial for my home bias tests, which depend on the Ownership data feed, and it is also important for my global sample tests. Second, FactSet's data feeds use common identifiers, dramatically reducing the difficulty of matching firms across different data products. This is especially valuable for international firms and funds, which might otherwise be difficult to match into a unified dataset.

In table 1 I report the results of my sample selection process in Table 1. Panel (a) focuses on distinct firms, and panel (b) on distinct firm-years. My initial sample comprises all publicly traded firms for which data are available in FactSet Prices, FactSet Fundamentals, and FactSet Estimates, beginning in 1984, the first year in which FactSet Prices data exist. From this sample I eliminate firm-years with beginning-of-year prices under USD 2, and restrict the sample to firm-years in which I am able to calculate an ALI[1]. I also eliminate from my sample any firms with missing control variables. Finally, in my detailed cost-of-capital tests I require that the number of shareholders be available. Most of the attrition in this step comes from EU countries, and is likely attributable to EU countries having different reporting requirements for the number of shareholders relative to the US, Japan, and the Asia-Pacific countries. My restrictions reduce the final global sample to 8,130 firms

[1]This calculation requires the availability of a substantial time-series of returns for a firm and results in an analysis sample that begins in 1996, the first year for which I am able to calculate ALI

and 88,624 firm-years, and the final US subsample (which is a strict subsample of the global sample) to 2,726 firms and 34,879 firm-years.

Table 2 panel (a) presents descriptive statistics on the global sample. The average market capitalization is \$5.246 B, the mean ROA is 4.4%, and the mean analyst following is 6.7 analysts. Panel (b) shows the same statistics for the subsample of US firms. US firms tend to be larger, have a higher M/B ratio, and have a lower mean adjusted return. Finally, Table 3 presents Pearson (Spearman) correlations for the variabels I use in my regression tests below (above) the diagonal.

Constructing ALI only requires a time series of past returns. This is a useful feature of the measure, since price and return data are widely available for many firms in many countries and from many sources. However, a fairly long time series is required to calculate ALI. Recall that calculating ALI for year t requires a vector of risk factor returns for five previous years, $[t-5, t-1]$. Moreover, calculating the return for year $t-5$ itself requires an additional $v-1$ years prior to year $t-5$, where v is the number of eigenvectors to be calculated. Since I am extracting 4 vectors, that means that a nine-year time series (including year t) is required to calculate the ALI in my primary tests[2]. The requirement that a firm in year t have an unbroken time series of prices over the previous eight years creates a marked tilt toward larger firms, and I therefore note that am unable to assess whether the ALI is associated with the features or behavior of very young firms.

[2]Depending on how long a rolling window is desired, and how many factors a researcher is interested in, this requirement could of course be relaxed. A two-factor ALI over a 3-year window would require a time series of only five years, for example. Moreover, ALI could be constructed from a series of more frequent returns over a shorter period of time, as I discuss in section 4.7

CHAPTER 5

TEST DESIGN AND RESULTS

5.1 Tests of Hypothesis 1

To test H1, I regress analyst following on ALI and control variables that come from the extant literature. My first specification examines the contemporaneous association between ALI and NUMEST:

$$NUMEST_{i,t} = \alpha + \beta_1 ALI_{i,t} + \sum \gamma CONTROLS_{i,t} + \theta FIXED\_EFFECTS + \epsilon_{i,t}, \quad (11)$$

where $NUMEST$ is the number of analysts included in the FactSet consensus estimate for the most-covered item in the FactSet Estimates Basic Annual Focus table, i denotes firms, and t denotes years. Control variables include the firm's market-to-book and debt-to-equity ratio, and firm size as measured by the natural log of market cap. All variables are defined in appendix A. Year and industry fixed effects are included, with industry fixed effects being defined at the FactSet industry level (approximately 150 distinct industries). A positive coefficient on β_1 is consistent with the hypothesis that analysts shift their coverage promptly in response to investor demand for information measured by ALI (H1a). Separately, because analyst coverage tends to be sticky, I allow for the possibility that analyst coverage only changes in response to sustained investor attention, which the contemporaneous firm-year level ALI will likely do a poor job of capturing. To assess whether sustained high investor attention measured by ALI is associated with analyst following, I also estimate a specification with lagged values of ALI:

$$\begin{aligned} NUMEST_{i,t} = &\alpha + \beta_1 ALI_{i,t} + \beta_2 ALI_{i,t-1} + \beta_3 ALI_{i,t-2} + \sum \gamma CONTROLS_{i,t} \\ &+ \theta FIXED\_EFFECTS + \epsilon_{i,t}. \end{aligned} \quad (12)$$

In equation (12) a positive coefficient on β_2 or β_3 indicates that the lagged ALI was associated with analyst coverage in year t, consistent with analysts responding slowly to investor attention measured by ALI (H1b).

Table 4 reports the results of estimating equations (11) and (12), which test hypotheses 1a and 1b. Hypothesis 1a states that there is a positive contemporaneous association between a firm's ALI and its analyst following. The results in table 4, column (1) offer no support for H1a. The coefficient on ALI is negative but insignificant, indicating that there is no contemporaneous association between ALI and analyst coverage. The second specification (column 2), however, offers some support for H1b. The two-year lag of ALI is associated with year t analyst coverage, while year t ALI is negative and marginally significant.

I consider two possible explanations for these results. The first is that analyst coverage is sticky, so that it takes a sustained, high demand for information to induce analysts to cover a firm. The second is that ALI is lower for firms with more revelatory prices, so the contemporaneous analyst coverage itself may be driving the year t ALI down by increasing the information contained in the price signal. Taken together, these explanations would explain the negative (but insignificant) contemporaneous relation between the ALI and analyst coverage and the lagged positive relation. I repeat the analysis in columns (1) and (2) using the global sample, and present those results in columns (3) and (4). In the global sample, neither the contemporaneous nor the lagged ALI is associated with analyst coverage.

It may, however, be problematic to regress analyst following on ALI because of endogenous relations between ALI and analyst coverage. Analyst coverage is likely to respond to investors' learning incentives, and to shape them by changing the information content of prices. In addition, investor incentives to learn about firms and analyst coverage may be in part simultaneously determined by other factors. While conceptually one could seek to disentangle the relations between the and analyst coverage by using appropriate instruments or exogenous shocks, the factor-based construction of ALI makes it difficult to identify appropriate instruments. Moreover, while exogenous shocks to realized measures of investor attention are available, they do not necessarily capture shocks in investors' ex-ante learning incentives. Therefore, in order to assess the inferential risks to inferences arising from bi-directional relations between ALI and analyst coverage, I employ panel VAR models and the techniques suggested by Holz-Eakin et all (1988), Arellano and Bond (1991), and Blundell and Bond (1998) as implemented in R by Sigmund and Ferstl (2018). Panel VAR techniques combine elements of VAR models, which allow multiple endogenous variables to affect each other over time, and panel data techniques that allow members of the panel to be heterogenous.

In recent years, panel VAR models have started to be used in accounting and finance in situations where the dynamic interplay between two or more possibly endogenous variables is of interest. For example, Desai, Rojgopal, and Yu (2016) emply a panel VAR model to examine the lead-lag relations between short interest, analyst recommendations, and credit ratings and Margolin, Mahlendorf, and Schaffer (2019) uses a panel VAR model to examine the bidirectional relationship between customer satisfaction and firm performance. While panel VAR models cannot establish (econometric) causality, they can usefully describe multi-directional associations over time and demonstrate Granger-causality (Granger (1969)), where a change in one time series reliable produces a change in a future time series. The basic setup of the model that I estimate is:

$$\begin{aligned} ALI_{i,t} &= \sum_{k=1}^{k=n} \gamma_i NUMEST_{i,t-k} + \sum_{k=1}^{k=n} \beta_i ALI_{i,t-k} + \theta_i + \epsilon_{i,t} \\ NUMEST_{i,t} &= \sum_{k=1}^{k=n} \gamma_i NUMEST_{i,t-k} + \sum_{k=1}^{k=n} \beta_i ALI_{i,t-k} + \theta_i + \epsilon_{i,t} \end{aligned} \tag{13}$$

where i indexes firms, t indexes years, the fixed effects are removed through a first-difference transformation, and the equations are estimated through a GMM estimator rather than OLS to avoid Nickell bias (Nickell, 1981) as is standard in this approach[1] Significant coefficients on the non-autocrollative lags indicate Granger-causal relations between the variables, and significant positive values for the betas in the NUMEST equation in particular would be consistent with H1b.

When I examine the time series results from the panel vector autoregression tests it is the case that ALI has significant ability to predict future analyst coverage, and that analyst coverage has significant ability to predict future ALI values. Table 5 presents results for estimating equation (13) with $n = 2$ lags. The number of lags I include in the panel vector autoregressive model is dictated by the Baysian information criterion (BIC) and the Akaike information criterion (AIC) (Andrews and Lu, 2001; Sigmund and Ferstl 2018), and by the number of lags for which the coefficients are

[1]Nickell (1981) shows that in panel data with many groups and relatively short time series estimating equation (13) using OLS produces biased coefficients. Panel VAR methods therefore use GMM approaches to avoid this bias.

significant. I estimate equation (13) with 1, 2, 3, and 4 lags, and find that the AIC and BIC indicate approximately equal model fit for one and two lags with AIC values of -206 and -195 respectively. Model fit declines significantly with the inclusion of more than two lags[2]. Column 1 of Table 5 presents the results for the regression with ALI as the dependent variable, while column 2 presents the results with NUMEST as the dependent variable. The results in column 2 indicate that analyst following is highly persistent, with a coefficient greater than 0.8 on the first lag of NUMEST, and that high learning incentives predict increased future analyst following in the future. While this is not tight evidence of a causal relation, it shows that the time series evolutions of ALI and analyst following are consistent with H1b.

5.2 Tests of Hypothesis 2

To test H2, I regress one-year-ahead Fama-French 3-factor adjusted returns on ALI as well as a set of control variables and fixed effects suggested by prior literature:

$$\begin{aligned} FF\_ADJ\_RETURN_{i,t} = &\alpha + \beta_1 ALI_{i,t} + \sum \gamma CONTROLS \\ &+ \sum \theta FIXED\_EFFECTS + \epsilon_{i,t}. \end{aligned} \tag{14}$$

$FF\_ADJ\_RETURN_{i,t}$ is the realized return for firm i in year t less the return predicted by the Fama-French 3-factor model. I obtain data on the Fama-French factor returns from Ken French's website, and I calculate firms' loadings on the three factors as of January in year t based on the prior 60 months. I then subtract the predicted 3-factor return over year t from the realized return over t to get the 3-factor adjusted return. The remaining controls and fixed effects are similar to the analyst forecast regression specification (12).

In table 6 I present the results of estimating equation (14), which tests the association between ALI and factor-adjusted future returns. NV (2009) predicts that the learning index will be negatively associated with factor-adjusted returns, as investors will increase the precision of information in the market as they learn more about the firm. The results in table 6 panel (a) are broadly consistent with that prediction for the US-only sample. The first specification in panel (a) is a simple linear regression

[2]It is also necessary for each model to satisfy stability requiements. In untabulated analyses I find that each of the candidate models satisfy stability requirements (Sigmund and Ferstl (2018)), and that I can therefore select among them based on model fit.

of one-year-ahead Fama-French 3-factor adjusted returns on ALI. The coefficient on ALI is negative and statistically significant, as predicted. In specification 2 that adds industry and year fixed effects and clusters standard errors by firm, the coefficient on ALI though slightly smaller in magnitude is also negative and significant. Specification 3 keeps the same fixed-effect and clustering structure and adds control variables, and while the coefficient on the ALI becomes slightly less negative it remains negative and significant. The association between ALI and Fama-French adjusted future returns is economically material as well as statistically significant. The average standard deviation of ALI within an industry-year in my sample is .07. In the third specification, then, a one-standard-deviation increase in ALI would imply an approximately 70 basis point lower annual adjusted return.

Panel (b) of table 6 repeats the analysis in specification (3) of panel (a) with a variety of cuts of the global sample of firms. Column (1) includes all firms, column (2) restricts the sample to non-US firms only, and column (3) restricts the sample to non-US developed-economy firms per Fama & French (2012) (The US, Canada, Japan, Singapore, Hong Kong, Australia, New Zealand, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK). The estimated coefficient on ALI remains negative in all specifications, and is significant in all but the developed economies subsample[3]. Although the magnitude of the association between ALI and one-year-ahead adjusted returns weakens for countries outside of the US, this results in table 6 panel (b) reinforce the results in panel table 6 panel (a), and support for hypothesis 2. Overall, I regard the results in table 6 as consistent with hypothesis 2, and with the predictions of NV (2009) regarding the learning index more broadly.

5.3 Tests of Hypothesis 3

The final prediction in NV (2009) regarding the empirical learning index is that it will exhibit an inverted-U shaped association with home bias. The intuition behind the prediction is that in countries whose firms have very low learning index values even domestic investors, with their information advantage, will not find it worthwhile to learn about domestic firms. At the other extreme, in countries whose firms have very high learning index values foreign investors will choose to learn about the

[3] In untabulated results, I find that this result appears to be driven largely by the European firms. Restricting the sample to the non-US developed economies outside of Europe, I find that ALI is negatively and significantly related to Fama-French adjusted returns.

country's firms despite their information disadvantage, thus reducing the level of home bias. On the other hand, investors in countries whose firms have intermediate learning index values will find it substantially more valuable to build on their information advantage and acquire information about local firms, leading to a more pronounced home bias. I calculate the home bias of a fund as the fraction of the fund's equities held in publicly traded domestic firms minus the fund country's share of the global public equity market. I define the home bias of a country as the home bias of its median fund when all funds in a country are ranked by their home bias, and the learning index of a country as the average of the country's firms' ALI values. To test H3 I estimate the following regression:

$$HOMEBIAS_{i,t} = \alpha + \beta_1 ALI_{i,t} + \beta_2 ALI_{i,t}^2 + \theta_i + \epsilon_{i,t}. \tag{15}$$

The combination of a linear term and a squared term aims to assess whether the predicted quadratic form of the association between home bias and ALI is present. The predicted association is an inverted-U shape, viz. $\beta_1 > 0$ and $\beta_2 < 0$.

Figure 1 shows average home bias in countries when grouped into quintiles by their country-level mean ALI. The visual evidence is consistent with hypothesis 3, with median-fund home bias being approximately 5–7 percentage points (or about 12–17 percent) higher for countries in the 3rd ALI quintile than those in the 1st or 5th. In table 7 I provide more statistically rigorous evidence by regressing median-fund home bias on the country's annual ALI and ALI squared. Specification 1 suppresses the intercept, implying an assumption that countries with an ALI of zero would have no home bias. Specification 2 preserves an intercept, allowing linear and quadratic ALI terms to explain variance around it. Finally, specification 3 includes country-level fixed effects rather than a single intercept. The results in each specification show a reliably positive linear coefficient and a reliably negative quadratic coefficient. These results are consistent with hypothesis 3, and together with the visual evidence in Figure 1, provide empirical evidence that ALI is captures the theoretical construct proposed by NV (2009).

5.4 Tests of Hypotheses 4 and 5

To test H4, H5a and H5b, I follow Armstrong, Core, Taylor, and Verrecchia (2011) and use the number of shareholders in a firm as a proxy for the competitiveness of the market for the firm's equity, and the firm's one-year-ahead factor-adjusted returns as a proxy for its cost of equity. LLV (2012) present a theory model in which information asymmetry should not affect a firm's cost of capital in situations of perfect competition. Using the number of shareholders to measure equity-market competitiveness and factor-adjusted one-year-ahead returns to measure a firm's cost of capital, ACTV (2011) find empirical evidence consistent with this. ACTV (2011) construct hedge portfolios long in firms with high information asymmetry and short in firms with low information asymmetry. These hedge portfolios are then grouped by the competitiveness of the equity markets of the firms in the extreme information asymmetry quintiles. After controlling for the market, high-minus-low and small-minus-big factors, the hedge portfolios for firms with less-competitive equity markets (i.e. few shareholders) yield positive returns, while the hedge portfolios for firms with more-competitive equity markets (i.e. many shareholders) yield no abnormal returns. While the number of shareholders in a firm is an imperfect measure of the competitiveness of its equity market, it is readily available for US firms and — through FactSet — for a large number of international firms as well.

I test H4 by estimating equation (11) using only firms in the top two quintiles of NUM_SHRHLDRS, the number of distinct shareholders in a firm. My assumption is that firms in the top two quintiles of the number of shareholders will not be affected by changes that a high ALI might induce in information asymmetry, with the result that any effect on future returns is likely to be attributable to the information precision channel of LLV (2012). I then separately estimate equation (11) using only firms in the bottom two quintiles of NUM_SHRHLDRS. The theory in LLV (2012) does not allow me to make unambiguous predictions as to the sign of the association between ALI and future returns in this sample. As the firms are all in less-competitive equity markets, any effect which ALI has on information asymmetry should be apparent in future returns, along with any effect the ALI has on information precision. Since increased attention could increase or decrease information asymmetry, but should only increase information precision, I expect the most likely outcome to be a more positive (i.e. less negative) association between ALI and future returns than the association found for the high-competition sample.

Table 8 resports the results of estimating equation (11) on the sample cuts just described. Specification 1 in table 8 panel (a) repeats specification 3 in table 6, but with ALI re-computed within the US sample. The results are inferentially similar. Specification 2 then restricts the sample to firms with NUM_SHRHLDRS in the top two quintiles of the US sample, and the coefficient on ALI remains negative and significant. The interpretation of the latter result is that, in a setting where information asymmetry is expected to have no (or little) effect, the association between ALI and a firm's cost of equity remains negative, which is consistent with investors seeking out additional information about high-ALI firms and thereby improving the precision of the market's expectation of those firms' performance. As such, the test aims to isolate the information-precision channel through which ALI might affect future returns.

In Specification 3 I adjust the sample criterion in specification 2 and instead restrict the sample to firms with NUM_SHRHLDRS in the bottom two quintiles of the US sample. In this setting I expect both information asymmetry and the quality of the market's information about a firm to influence future returns. The estimated coefficient on ALI in remains negative but loses significance, which is consistent with an improvement in the quality of information about a firm being offset by increases in information asymmetry due to increases in investors' demand for information about a firm. This increase in information asymmetry is consistent with a setting where all investors have a desire to acquire information about a firm, but only some investors are able to do so.

Taken together, I posit that the results in table 8 panel (a) support hypothesis 4. ALI is negatively associated with the future factor-adjusted returns, but only significantly for firms whose equity is widely held. This indicates that among firms whose equity markets are competitive, ALI is clearly associated with lower future returns, whereas the situation is ambiguous for firms having less-competitive equity markets. I turn to those firms in my test of hypothesis 5 below.

I test H5a by re-estimating equation (11) using firms that are in the bottom two quintiles of market competition and in the top quartile of analyst coverage. I use analyst coverage to measure the quality of a firm's information environment. In testing H5a, I seek to focus on firms where, despite an imperfectly competitive equity market, it is feasible for investors to satisfy an increased demand they may have for information. I assume that analyst coverage is a reasonable proxy for that construct, also but re-estimate equation (11) using the bottom quartile of media coverage in untabulated robusness tests. I test H5b by estimating equation (11) using firms in the same bottom two quintiles of market competition but now also in the bottom quartile of analyst coverage. The idea I have is that firms with poor analyst coverage are likely to be more difficult for investors to learn about, even when there is an increase in demand for information about them.

Table 8 panel (b) reports the results of estimating equation 11 on those two sample cuts. Specification 1 in panel (b) is restricted to firms in the low-competition sample where analyst coverage is in the top quartile of the US sample. Here the estimated coefficient on ALI becomes negative and significant, which is consistent with investors desireing to acquire information about a firm and being able to satisfy their demand. This then increases the amount of information in the market and decreases or leaves unchanged the level of information asymmetry, resulting in lower future returns. Specification 2 in panel (b) restrictes the sample to firms in the low-competition sample that have analyst coverage in the bottom quartile of the US sample. In this sample, the estimated coefficient on ALI is reliably positive, indicating that an increase in the ALI is associated with an increase in future returns, which I interpret as being driven by a higher cost of equity.

The results in table 8, panel (b) are consistent with a situation in which all investors desire to acquire information about a firm but only a subset are able to do so, thus creating an increase in information asymmetry as more (newly) informed traders participate in the market, increasing the risk of trading with a better informed counterpary. This result may seem surprising given Fang and Peress (2009), who find that media coverage is most negatively associated with future returns when analyst coverage is low. However, if media coverage and ALI capture different aspects of the same construct the two findings reconcile with each other — ALI captures investors' ex-ante incentives to learn about a firm while media coverage is only associated with cases where investors both want to and are able to learn about a firm.

In panel (a) of table 9 I repeat the analysis in table 8, panel (a) using the global sample. I find that ALI is reliably negatively associated with future returns in both the high- and low- competition samples (specifications 2 and 3), but the magnitude of the estimated coefficient is smaller in the low-competition setting. In panel (b) of table 9 I split the low-equity-market-competition firms in panel (a) based on analyst coverage. Specification 1 in panel (b) reports the results for the low-competition, high-information-environment sample and shows a significant negative association between ALI and future returns. Specification 2 in panel (b) reports the results for the low-competition, low-information sample, and here the coefficient on ALI remains negative but is statistically indistinguishable from zero. The latter result in table 9, while less striking than the result in table 8 panel (b), nonetheless supports hypotheses 5a and 5b.

Overall, the results in tables 8 and 9 support the predictions made by hypotheses 4, 5a, and 5b. ALI is negatively associated with future returns, both in the US and globally, when firms' equity trades in competitive markets. ALI continues to be negatively associated with future returns, both in the US and globally, when firms' equity trades in imperfectly competitive markets and the firms face a high quality information environment. However, when firms' equity trades in an imperfectly competitive market and the firms face a low quality information environment, ALI is no longer negatively associated with future returns, and in the US setting it is positively associated with future returns. I interpret these findings as being consistent with the proposition that investors' desire to learn about a firm can increase information asymmetry in settings where learning is difficult, and that the increase in information asymmetry can equal or overwhelm any reduction in the cost of equity resulting from reductions in the average uncertainty in the market.

5.5 Test of Hypothesis 6

To test H6 I regress one year ahead adjusted returns on accrual quality and controls, after splitting the sample into the top and bottom two quintiles of ALI. The regression I estimate is:

$$FF\_ADJ\_RETURNS_{i,t} = \alpha+\beta_1 AQ_{i,t}+\sum\gamma CONTROLS_{i,t}+\theta FIXED\_EFFECTS+\epsilon_{i,t}. \tag{16}$$

Accrual Quality AQ is constructed following Francis et al. (2005), with full details of its construction using the FactSet variables provided in Appendix 1. As in Francis et al, I construct AQ such that a high value of AQ indicates low quality accruals, so a negative relation between accrual quality and future returns is indicated by a positive coefficient on β_1. A positive difference between the high ALI and low ALI samples β_1 would support the hypothesis that a high ALI increases the effect of accrual quality on future returns, whereas a negative difference would support the hypothesis that a high ALI leads investors to unravel poor quality accounting, reducing the damaging effect of poor accrual quality on future returns.

Table 10 reports the results of estimating equation (16) in the US sample overall and after applying two cuts of the data. Column one presents findings for the full US sample, column 2 for firms in the top two quintiles of ALI, and column 3 for firms in the bottom two quintiles of ALI. Unlike prior literature, I find no evidence of an association between future returns and accrual quality in the full sample, nor in the high ALI sample. However, in the low ALI sample there is a significantly positive relation. Since the AQ measure is constructed such that a positive association indicates lower future returns for high quality accounting, my results suggest that only firms with low values of ALI have a negative association between high quality accounting and the future returns. Moreover, a formal test of the difference between the coefficient on AQ in the two samples shows them to be significantly different at the 1 percent level. This test then supports Hypothesis 6b that firms with high ALI will exhibit a reduced association between AQ and future returns, since investors will allocate enough attention to them to disentangle even poor quality accounting. It also provides evidence that investors' learning decisions have an important effect on the ways investors process accounting information.

5.6 Performance of the Alternative ALI Construction

All of my analyses thus far have used the main, factor-based version of ALI. As discussed in section 2.4, this measure may be vulnerable to econometric issues particular to factor models, and captures a view of investor learning in which investors learn about factors rather than particular firms. In this section I turn to results obtained using the alternative, firm-based constructi on of the average learning incentive, ALI_ALT. Table 11 presents results for the US sample future returns test with both the ALI and ALI_ALT included on the right hand side of the regression. Column (1) shows results similar to those in table (6) panel (a) specification (3), and shows that both the ALI and ALI_ALT are negatively associated with future returns, with ALI_ALT exhibiting a strikingly more negative association than ALI. Despite the fact that ALI_ALT exhibits a stronger association with future returns than ALI, the factor-based ALI remains reliably negatively associated with future returns at the .05 level for a one-sided test.

In table 11 column (1) it ALI_ALT outperforms ALI in predicting returns; however, when I disaggregate each ALI measure into its component ratios (table 11 column (2)), the results change.

The Sharpe ratio portion of ALI_ALT is strongly negatively associated with future factor adjusted returns, while the R^2 portion is not associated with furture returns at all. Complicting the picture further, the Sharpe ratio portion of ALI is positively associted with future adjusted returns, while the R^2 portion is negatively associated. This makes it clear that the two versons of ALI appear to be picking up different constructs. The factor-based ALI is consistent with a strategic choice by investors to learn about firms where learning is likely to be rewarded, while the effect of the firm-based ALI_ALT is dominated by the Sharpe ratio component.

In Table 12 I repeat the subsample tests from Table 8 panel (b) with both ALI and ALI_ALT on the right hand side of the regression. Interestingly, relation between ALI_ALT and future adjusted returns is essentially constant across the subsamples, while ALI continues to show a negative association with future returns for firms with low equity market competition and high analyst following, and a positive association for firms with low equity market competition and low analyst following.

Taken together it is clear from these results that ALI_ALT appears to predict future returns, and generally does so more strongly and in the same direction as ALI. However, the fact that the R^2 portion of ALI_ALT does not contribute to its predictive ability, and that it appears to exhibit a constant association with returns accross the different subsamples in my analysis indicates that it is not capturing the same construct as the factor-based construction of the ALI. Despite that, it does appear to be a significant predictor of future returns, and presents an interesting finding worth future study in tis own right.[4]

5.7 Robustness Tests

My main construction of ALI uses factors obtained from a five year annual time series. Since the number of observations in this low-observation time series may be too low to reliably allow factors to be extracted, or longer than plausible for the time series to remain stationary, I repeat the analysis in the US sample using factors constructed from weekly prices and payoffs over a rolling two year window, similar to the approach in Gempesaw (2018). Doing so, I find that almost all my results and inferences are unaffected. I also repeat the US and global sample analysis using the main

[4]In untabulated analysis, I find that the ALI_ALT loads negatively and significantly on regressions of one-year-ahead future returns on the Fama-French five factors plus the ALI_ALT, further showing the resliance of the measures' predictive ability

construction of ALI but with Fama-French 5-Factor adjusted returns as the dependent variable. Once again, almost all my results and inferences remain unchanged.

I also expand the information intermediaries in my analyses to media coverage via data from RavenPack. However, I do not find any association between ALI and the count of relevant news events about a firm in a given year. While this does not support a broad form of H1 that encompases information intermediaries other than analysts, I see it as unsurprising given the coarse frequency of my ALI measure compared with the speed with which the media operates. I also use media coverage as a alternative measure of frims' information environment in table 8 panel b. While the requirement to be covered by RavenPack reduces my sample considerably, I do obtain similar results, in that the estimated coefficient on ALI in the high information sub-sample is negative and significant while the estimated coefficient in the low information sub-sample is positive and significant, and the two coefficients differ at the $p < .01$ confidence level.

While both analyst following and media coverage are contemporaneously uncorrelated with ALI, it is possible that they could be determined by past realizations of ALI. Indeed, evidence from the panel VAR in table 5 supports this possibility for analyst coverage. To mitigate the risk that my results in Tables 8 and 9 are driven by partitioning on a potentially pre-determined variable, I repeat the analyses in tables 8 and 9 but instead splitting on the expected level of analyst coverage based on the panel VAR in table 5. In this approach, I interpret firms with higher-than-expected analyst coverage as being in good information environments and those with lower-than-expected analyst coverage as being in poor information environments. I continue to find that ALI is reliably positively associated with future returns in the poor information environment and negatively associated with future returns in the good information environment (and that the two coefficients differ at the $p < .01$ level).

To confirm that my results are not driven by small firms, I repeat the analyses in table 8 omiting firms in the bottom quintile of market cap (approximately less than $90 million). My results in panel a are unchanged, but while my results in panel b are directionally similar, the coefficents on ALI are no longer significant. However, the difference in coefficents across columns remains significant at the (one-sided) $p < .05$ level.

Lastly, I merge in data from WRDS intraday indicators on the bid-ask spread and the adverse selection component of the bid ask spread. I propose that high incentives for investors to learn about a firm will produce different effects on information asymmetry, and thus the cost of capital and future returns, depending on the information environment of the firm. However, using the bid-ask spread and its adverse selection component as measures of information asymmetry, I do not find any significant difference in information asymmetry between firms with low equity market competition and high vs. low quality information environments. While this does not to support my argument that changes in information asymmetry are the mechanism behind the differential association between ALI and future returns in high versus low information environments, the null result could be due to the drastic reduction in sample size which unavoidably occurs when I require that WRDS IID measures be available.

CHAPTER 6

CONCLUSION

In this paper I have developed and tested an empirical implementation of the Van Nieuwerburgh and Veldkamp (2009) learning index, which I call the average learning incentive (ALI). NV (2009) present a rational inattention model of investors' learning behavior, which implies that investors will specialize their learning by focusing on firms which have high learning index values. Using ALI to examine samples comprised of US and global firms in a variety of market and information environmens, I find evidence that firms with high ALI have lower returns. However, in circumstances where investors' demand for information is likely to go unsatisfied, a high demand fails to predict lower returns, or is even associated with higher returns. This finding complements studies of investor attention that employ measures of realized investor attention by focusing on a setting where realized investor attention is unlikely to measure investors' interest in learning about a firm. I also find that the negative association between high-quality accounting and future returns is present only for firms with low ALI values, which I take to be evidence that investors who have a high desire to learn about a firm are often abel to penetrate obscure information systems, and that producing high quality accounting has the greatest effect when investors are not likely to engage in intense learning about a firm.

I confirm that ALI captures the learning index of NV (2009) by testing the explicit predictions made by NV (2009) about the behavior of an empirical learning index. I find weak evidence that a sustained, high ALI predicts increases in analyst coverage in a US sample, but not a global sample. I also find evidence that the home bias of a country exhibits a quadratic, inverted-U shaped association with ALI of its firms, as predicted by NV (2009). Finally, I find that a high ALI is associated with lower one-year-ahead Fama-French 3-factor adjusted returns, which is consistent with the prediction of NV (2009) that a high empirical learning index would drive down abnormal returns as it would lead to more information about a firm coming into the market. Taken together, I believe these results support the argument that ALI captures the learning index described by NV (2009).

Moving beyond the theory of NV (2009), and inspired by the theory of Lambert, Leuz, and Verrecchia (2012), I also test the association of the ALI with future returns in a series of subsamples. I argue that while the heightened attention measured by ALI will unambiguously increase the average precision of information in the market, the effect on information asymmetry will depend on how easy it is for investors to obtain information about a firm. When it is difficult to obtain information about a firm, heightened attention may induce those investors who are able to obtain more information about it to do so, increasing the gap between informed and uninformed investors. When it is easy to do so, however, the gap would shrink, as many investors who had previously learned little about the firm increase the attention they allocate to it.

Drawing on the empirical techniques in Armstrong, Core, Taylor, and Verrecchia (2011), I find evidence consistent with these hypothses. In highly competitive equity markets where information asymmetry is not predicted to affect a firm's future returns, ALI is negatively associated with future returns in both the US and global samples. However, this association becomes insignificant in less-competitive equity markets where information asymmetry is expected to affect a firm's future returns. Within the less-competitive markets, firms with a high analyst following exhibit a strong, negative association between ALI and future returns, while firms with a low analyst following exhibit a strong, positive association between ALI and future returns. I interpret this as evidence that in less competitive markets with poor information availability, increased demand for information about a firm can increase information asymmetry enough to increase a firm's cost of capital, despite bringing more information into the market.

This study contributes to the literature on rational inattention by constructing and validating an empirical version of a theory-driven measure of investors' ex-ante, rational inattention driven, incentive to learn about a firm. The measure can be constructed using only price and return data, and it has predictive power in both domestic and international settings. This research also contributes to the broader literature on investor attention by constructing a mesure that can be used to investigate investors' desire to learn about a firm in setting where learning is difficult, and showing that ex-ante learning incentives can have different effects on future returns than measured investor attention. Finally, it contributes to the literature on the effect of accounting quality by suggesting that when investors have a strong incentive to learn about a firm, they are able to penetrate even poor accounting systems to do so.

APPENDIX A: LIST OF VARIABLES

- ACCRUAL_QUALITY

  The accrual quality of a firm, as constructed in Francis et al. (2005). Accrual Quality is the standard deviation of the residuals of a regression of current accruals on lagged, lead, and current cash from operations; change in sales; and property plant and equipment, with each variable scaled by total assets, all measured over rolling five year windows. I measure total current accruals as $(ff\_assets\_curr_t - ff\_assets\_curr_{t-1}) - (ff\_liabs\_curr_t - ff\_liabs\_curr_{t-1}) - (ff\_cash\_only_t - ff\_cash\_only_{t-1}) + ff\_debt\_st\_cf$, total assets as ff_assets, sales as ff_sales, cash from operations as $ff\_funds\_oper\_gross$, and PPE as ff_ppe_gross.

- ALI

  The average learning incentive. The ALI is defined in section 2.3

- ALI_ALT

  An alternative, returns-based construction of the average learning incentive. The ALI_ALT is defined in section 2.4

- COUNTRY_ALI

  The mean ALI for firms in a country-year

- D/E

  The debt-to-equity ratio for a firm-year, defined as ff_debt / ff_com_eq

- FF_ADJ_RET

  Fama-French 3-factor adjusted returns. Fama-French 3 factor models are estimated for firms based on the previous 60 months, as of January in year t. The parameters for each firm are then multiplied by the realized factor returns over year t and the products added together to arrive at predicted Fama-French returns for each firm. The predicted return is then subtracted from the firm's realized return over year t to arrive at the FF_ADJ_RET. Negative adjusted returns indicate a lower return than predicted by a Fama-French 3-factor model.

- MKTCAP

  The market capitalization of a firm in year t, expressed as ln(1+(ff_price_close_fp*ff_com_shs_out))

- MED_HOME_BIAS

  Median fund home bias for a country-year. The home bias of a fund is calculated as the fraction of the fund's assets under management whicha are invested in domestic equities minus the share of the global equity market attributable to the country in which the fund is located. All funds within a country-year are then ranked by their home bias, and the median level of home bias is slected as the home bias for that country-year.

- M/B

  The market-to-book ratio for a firm-year, defined as ff_com_eq / (ff_price_close_fp*ff_com_shs_out)

- NUMEST

  The number of analysts covering a firm in a given year. This is the *num_est* field in the FactSet Estimates Basic Annual Focus Table with the highest value for a firm-year.

- NUM_SHRHLDRS

  The number of shareholders of record for a firm-year. This is the FF_NUM_SHRHLDRS field from FactSet Fundamentals.

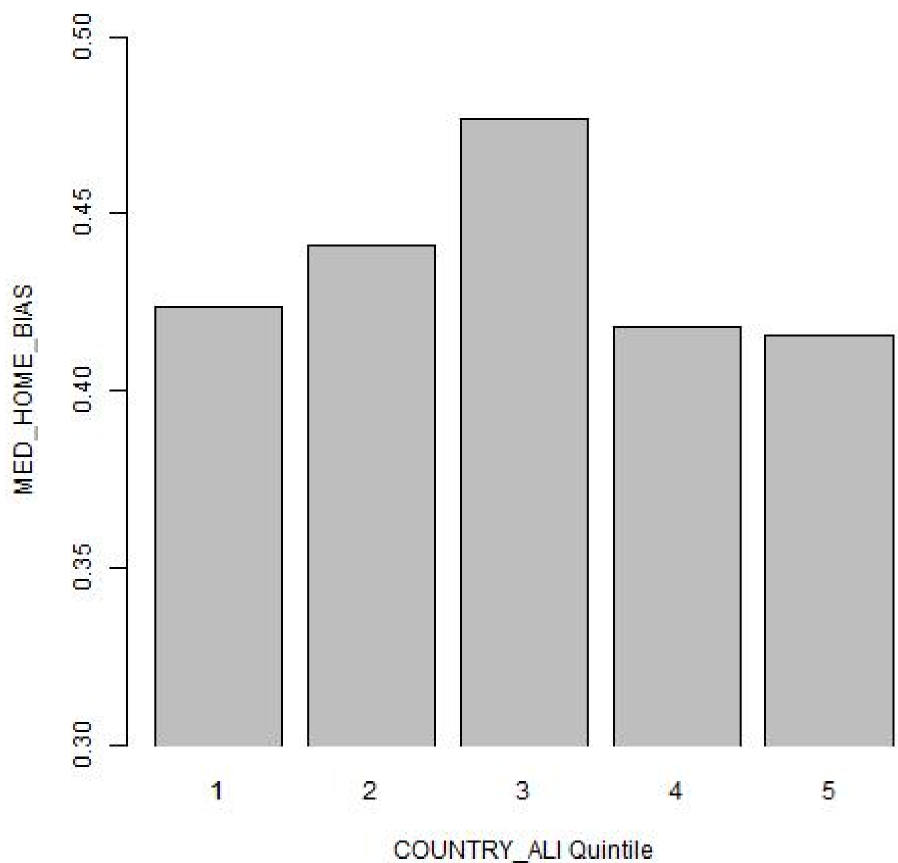
- ROA

  The return on assets for a firm-year, defined as ff_net_income / ff_assets

APPENDIX B: FIGURES

Figure 1: MED_HOME_BIAS by COUNTRY_ALI Quintile.

Median-fund home bias (MED_HOME_BIAS) and COUNTRY_ALI are defined in Appendix A. Home bias is lowest in the extreme quintiles and most pronounced in the middle of the ALI distribution.



APPENDIX C: TABLES

Table 1: Sample Formation

Panel (a) shows the number of distinct firms in each geographical region for each major sample restriction. Panel (b) shows the number of distinct firm-years. The table shows the number of observations remaining after each restriction, moving from left to right.

(a) Number of Distinct Firms

Region	Beginning Sample	Price >$2	Has ALI	Has Control Variables	Has Number of Shareholders
Global	34,841	25,731	12,818	12,719	8,130
North America (includes US)	6,839	5,819	3,310	3,306	2,830
European Union	5,185	4,606	2,791	2,776	772
Japan	3,576	3,559	2,898	2,896	2,890
Asia-Pacific	3,193	758	261	261	218
Other	16,048	10,989	3,558	3,480	1,420
US-Only Sample	5,094	4,789	2,794	2,790	2,726

(b) Number of Distinct Firm-Years

Region	Beginning Sample	Price >$2	Has ALI	Has Control Variables	Has Number of Shareholders
Global Sample	499,528	284,745	129,033	127,653	88,624
North America (includes US)	103,376	78,532	40,774	40,670	35,994
European Union	82,291	62,388	32,008	31,529	9,937
Japan	72,280	62,522	33,156	33,088	33,041
Asia-Pacific	44,705	6,182	2,241	2,231	1,912
Other	196,876	75,121	20,854	20,135	7,740
US-Only Sample	81,142	67,951	35,521	35,441	34,879

Table 2: Descriptive Statistics

Panel (a) presents descriptive statistics for the global sample. Panel (b) presents descriptive statistics for the US sample.

(a) Global Sample

Variable	Mean	Std. Dev.	10%	25%	50%	75%	90%
ALI	0.2	0.1	0.05	0.1	0.2	0.3	0.4
FF Adj. Return	0.04	0.5	-0.4	-0.2	0	0.2	0.5
Market Cap ($ M)	5,246	19,878	42	127	560	2,637	10,547
M/B	3.3	78.2	0.5	0.9	1.5	2.5	4.3
D/E	0.9	41.0	0	0.1	0.4	1.1	2.2
ROA	0.04	1.4	-0.02	0.01	0.03	0.1	0.1
Analyst Following	6.7	8.7	0	0	3	10	19

(b) US Sample

Variable	Mean	Std. Dev.	10%	25%	50%	75%	90%
ALI	0.2	0.1	0.03	0.1	0.2	0.3	0.4
FF Adj. Return	0.02	0.4	-0.4	-0.2	0	0.2	0.4
Market Cap ($ M)	7,979	29,362	68	247	1,032	4,009	15,087
M/B	6.2	127.1	0.8	1.3	1.9	3.2	5.5
D/E	1	44.1	0	0.1	0.5	1.1	2.2
ROA	0.1	2.7	-0.03	0.01	0.03	0.1	0.1
NUMEST	8.0	8.1	0	2	6	12	20

Table 3: Correlation Table

Correlations (Pearson) between Regression Variables

Pearson (Spearman) correlations are below (above) the diagonal.

Variable	ALI	lag1_ALI	lag2_ALI	FF_ADJ_RET	LN(MVE)	M/B	D/E	ROA	NUMEST
ALI	1	0.417	0.071	-0.009	0.052	0.025	-0.01	0.033	0.034
lag_ALI	0.425	1	0.422	-0.029	0.037	-0.013	-0.001	0.016	0.03
lag2_ALI	0.044	0.429	1	-0.059	0.004	-0.075	0.016	-0.024	0.02
FF_ADJ_RET	-0.005	-0.019	-0.054	1	0.061	0.116	-0.031	0.158	-0.005
LN(MVE)	0.057	0.039	0.005	0.030	1	0.471	0.187	0.232	0.807
M/B	-0.005	-0.006	-0.005	0.005	0.007	1	0.075	0.430	0.406
D/E	-0.005	-0.001	0.004	0.004	0.009	0.107	1	-0.325	0.186
ROA	-0.004	-0.002	-0.004	0.006	0.015	0.192	-0.001	1	0.179
NUMEST	0.031	0.027	0.023	-0.028	0.746	-0.004	0.006	-0.002	1

Table 4: Association Between Analyst Following and ALI

Column (1) shows analyst following regressed on the contemporaneous ALI for US firms, Column (2) includes two years of lagged values of the ALI. Columns (3) and (4) repeat the analysis for global firms. Standard errors are clustered by firm in all specifications, and t-statistics are reported in parentheses below the coefficients. The coefficient on M/B is multipled by 100 for ease of presentation. ALI is defined in section 2.3, and all control variables are defined in appendix A.

		Dependent variable:			
		NUMEST			
	H1	(1)	(2)	(3)	(4)
ALI	+	−0.52	−0.80	−0.16	−0.10
		(−1.1)	(−1.8)	(−0.4)	(−0.3)
lag ALI	+		0.29		−0.36
			(0.9)		(−1.4)
lag2 ALI	+		1.45***		−0.033
			(3.2)		(−0.1)
ROA		−0.08***	−0.08***	−0.68**	−0.75
		(−8.4)	(−8.1)	(−2.2)	(−1.6)
M/B		−0.12***	−0.12***	−0.13	−0.28**
		(−8.3)	(−7.9)	(−1.6)	(−2.4)
ln(mve)		2.88***	3.05***	2.95***	3.07***
		(29.3)	(28.9)	(30.6)	(30.6)
Fixed Effects		Ind and Year	Ind and Year	Ind and Year	Ind and Year
Sample		US Firms	US Firms	Global Firms	Global Firms
SE Clusters		Industry	Industry	Industry	Industry
Observations		35,706	29,972	91,964	72,117
Adjusted R^2		0.7	0.7	0.7	0.7

Note: **p<0.05; ***p<0.01

Table 5: Panel VAR of Analyst Following and ALI

t-stats are reported in parentheses below estimated coefficients, and are corrected for heteroskedastisity. The regressions are estimated using the GMM method outlined in Sigmund and Ferstl (2018) to correct for Nickell bias (Nickell (1981)). The data used are from a constant panel of US firms with non-missing observations in 2000-2017.

		Dependent variable:	
	H1	ALI	NUMEST
lag1_ALI	?/+	0.30***	1.69***
		(22.7)	(8.8)
lag1_NUMEST	?/?	0.02***	0.81***
		(19)	(42.6)
lag2_ALI	?/+	0.06***	1.00***
		(4.7)	(5.5)
lag2_NUMEST	?/?	0.004***	-0.06***
		(4)	(−4.4)
n obs		13,305	
n firms		887	
years		2000-2017	
Note:		**p<0.05; ***p<0.01	

Table 6: Association Between Future Returns and ALI

Panel (a) shows regressions of Fama-French 3-factor adjusted returns on ALI and control variables for the US sample. Coefficients on M/B and D/E are multiplied by 100 for ease of presentation. Column (1) shows a univariate regression of adjusted returns on the ALI, column (2) adds industry and year fixed effects, and column (3) adds control variables to the specification in column (2). Standard errors are clustered by firm in all specifications. Panel (b) repeats the analysis from column (3) of panel (a) on a set of different samples. Column (1) uses the entire global sample, column (2) excludes US firms, and column (3) restricts the sample to non-US, developed-economy firms, as defined in Fama & French (2012).

(a) US Sample

		Dependent variable:		
		FF_ADJ_RET		
	H2	(1)	(2)	(3)
ALI	-	-0.15^{***}	-0.12^{***}	-0.11^{***}
		(-8.7)	(-3.8)	(-3.3)
M/B				0.002^{***}
				(3.6)
ROA				0.001
				(0.8)
D/E				0.006
				(1.1)
ln(mve)				-0.02^{***}
				(-10.9)
Constant		0.05^{***}		
		(11.6)		
Fixed Effects		None	Industry, Year	Industry, Year
SE Clusters		None	Firm	Firm
Observations		35,787	35,787	35,757
Adjusted R^2		0.002	0.01	0.02
Note:				**p<0.05; ***p<0.01

(b) Global Sample

		Dependent variable:		
		FF_ADJ_RET		
		All Firms	Non-US Firms	Non-US Developed-Economy Firms
	H2	(1)	(2)	(3)
ALI	-	-0.06^{***}	-0.05^{**}	-0.03
		(-3.6)	(-2.2)	(-1.1)
M/B		0.005^{**}	0.01^{***}	0.02^{***}
		(2.2)	(5.3)	(6.7)
ROA		0.003	0.09^{**}	0.06^{**}
		(0.9)	(2.1)	(2.1)
D/E		0.005	0.003	0.006^{**}
		(1.6)	(0.7)	(2.4)
ln(mve)		-0.01^{***}	-0.01^{***}	-0.005^{***}
		(-13.7)	(-8.6)	(-4.6)
Fixed Effects		Industry, Country, Year	Industry, Country, Year	Industry, Country, Year
SE Clusters		Firm	Firm	Firm
Observations		128,750	92,994	72,195
Adjusted R^2		0.02	0.04	0.04
Note:				$^{**}p<0.05$; $^{***}p<0.01$

Table 7: Associaton Between Home Bias and ALI

Column (1) presents the results of an OLS regression of median-fund home bias on average ALI and the average ALI squared with the intercept suppressed. Column (2) presents the same regression without the intercept suppressed, and column (3) presents a test with country-level fixed effects rather than an intercept.

		Dependent variable:		
		MED_HOME_BIAS		
	H3	(1)	(2)	(3)
COUNTRY_ALI	+	3.81***	0.52**	0.29***
		(20.8)	(1.8)	(2.7)
COUNTRY_ALI_SQRD	-	−7.21***	−1.38**	−0.73***
		(−12.5)	(−2.0)	(−3.0)
Constant			0.40***	
			(13.1)	
Fixed Effects		None	None	Country
SE Clusters		None	None	None
Observations		936	936	936
Adjusted R^2		0.5	0.002	0.9
Note:			**p<0.05; ***p<0.01	

Table 8: Association Between Futrure Returns and ALI, split by Equity Market Competition

Column (1) repeats the analysis in table 6, panel (b), column (1), with ALI re-estimated within the US sample. Column (2) restricts the sample to firms in the top two quintiles of equity market competition, where the degree of equity market competition is measured by the number of shareholders of record. Column (3) restricts the sample to firms in the bottom two quintiles of equity market competition. Variables are defined in appendix A, and standard errors are clustered by firm in all specifications. Coefficients for M/B and D/E are multiplied by 100 for ease of presentation. Panel (b), column (1) takes the sample from panel (a) column (3), and requires that firms have high-quality information environments, measured by being in the top quartile of analyst coverage (NUMEST). Column (2) of panel (b) requires that firms be in low-quality information environments, measured as being in the bottom quartile of analyst coverage. The remainder of the analysis is the same.

(a) US Sample

		Dependent variable:		
			FF_ADJ_RET	
		Full Sample	High Competition	Low Competition
	H4	(1)	(2)	(3)
ALI	-/-/0	−0.06***	−0.05**	−0.05
		(−2.9)	(−2.0)	(−1.1)
M/B		0.003***	−0.01	0.004
		(4.4)	(−0.5)	(0.6)
ROA		0.001	0.04	0.001
		(0.8)	(0.9)	(0.7)
D/E		−0.02	−0.01	−0.002
		(−1.7)	(−0.4)	(−0.1)
ln(mve)		−0.01***	−0.02***	−0.02***
		(−9.6)	(−9.3)	(−5.1)
Fixed Effects		Industry, Year	Industry, Year	Industry, Year
SE Clusters		Firm	Firm	Firm
Observations		33,228	15,204	10,339
Adjusted R^2		0.02	0.03	0.01
Note:				**p<0.05; ***p<0.01

(b) US Sample, Low Equity Market Competition

		Dependent variable:	
		FF_ADJ_RET	
		High Analyst Following	Low Analyst Following
	H5	(1)	(2)
ALI	-/+	-0.16^{**}	0.26^{***}
		(-2.2)	(2.7)
M/B		0.06	-0.007
		(1.2)	(-0.3)
ROA		0.63^{***}	0.001
		(9.5)	(0.4)
D/E		0.04	-0.02^{**}
		(0.5)	(-2.2)
ln(mve)		-0.03^{***}	-0.02^{*}
		(-4.6)	(-1.9)
Fixed Effects		Industry, Year	Industry, Year
SE Clusters		Firm	Firm
Observations		3,650	2,249
Adjusted R^2		0.1	0.05
Note:			**p<0.05; ***p<0.01

Table 9: Association Between Future Returns and ALI, split by Equity Market Competition, Global Sample

Table 9 repeats the analysis in table 8 in the global sample. Column specifications and split criteria are unchanged, but the sample is the global sample of firms. Coefficients on M/B and D/E are multiplied by 100 for ease of presentation.

(a) Global Sample

		Dependent variable:		
			FF_ADJ_RET	
		Full Sample	High Competition	Low Competiton
	H4	(1)	(2)	(3)
ALI	-/-/0	-0.07^{***}	-0.13^{***}	-0.11^{***}
		(-3.6)	(-4.1)	(-3.1)
M/B		0.005^{**}	-0.001	0.003^{***}
		(2.2)	(-0.1)	(3.6)
ROA		0.003	0.1	0.001
		(0.9)	(1.1)	(0.9)
D/E		0.005	-0.07^{**}	0.008^{***}
		(1.6)	(-2.2)	(5.2)
ln(mve)		-0.01^{***}	-0.01^{***}	-0.02^{***}
		(-13.7)	(-3.2)	(-11.1)
Fixed Effects		Ind, Yr Country	Ind, Yr Country	Ind, Yr Country
SE Clusters		Firm	Firm	Firm
Observations		128,750	33,261	36,392
Adjusted R^2		0.02	0.04	0.03
Note:				$^{**}p<0.05$; $^{***}p<0.01$

(b) Global Sample, Low Equity Market Competition

		Dependent variable:	
		FF_ADJ_RET	
		High Analyst Following	Low Analyst Following
	H5	(1)	(2)
ALI	-/+	-0.19^{***}	-0.04
		(-3.2)	(-0.7)
M/B		0.06^{***}	0.002
		(3.4)	(1.4)
ROA		0.1	0.000
		(1.9)	(0.1)
D/E		-0.05	0.006^{***}
		(-1.8)	(3.3)
ln(mve)		-0.03^{***}	-0.02^{***}
		(-5.6)	(-5.1)
Fixed Effects		Industry, Year Country	Industry, Year Country
SE Clusters		Firm	Firm
Observations		11,651	13,648
Adjusted R^2		0.03	0.1
Note:			$^{**}p<0.05$; $^{***}p<0.01$

Table 10: Association Between Future Returns and Accrual Quality, split by ALI Level, US Sample

Column (1) shows the relation between accrual quality and future returns in the full US sample. Column (2) restricts the sample to firms in the top two quintiles of ALI, and Column (3) restricts the sample to firms in the bottom two quintiles of ALI. Coefficients on M/B and D/E are multiplied by 100 for ease of presentation.

		Dependent variable:		
			FF_ADJ_RET	
		Full Sample	High ALI	Low ALI
	H6	(1)	(2)	(3)
AQ	-/?/?	0.001	−0.04	0.07**
		(0.06)	(−1.2)	(2.0)
M/B		0.02	−0.01	0.04***
		(0.9)	(−0.2)	(2.8)
ROA		0.42***	0.54***	0.42***
		(8.2)	(7.9)	(5.8)
D/E		−0.02	−0.01	−0.03
		(−1.6)	(−0.5)	(−0.8)
ln(mve)		−0.02***	−0.02***	−0.02***
		(−6.8)	(−5.8)	(−3.6)
Fixed Effects		Industry, Year	Industry, Year	Industry, Year
SE Clusters		Firm	Firm	Firm
Observations		14,247	6,253	4,965
Adjusted R^2		0.045	0.061	0.048
Note:				**p<0.05; ***p<0.01

Table 11: Association between Future Returns and ALI, including ALI_ALT, US Sample

This table repeats the analysis in specification 3 of table 6, but includes both the factor-based ALI and the firm-based alternative construction, ALI_ALT in the analysis. Specification (1) includes both versions of ALI in their aggregated form, while specification (2) disaggregates them into the ratios from which they are constructed. 'sr' denotes the Sharpe ratio portion of each ALI version, and 'r2' denotes the portion of each ALI version based on the r-squared from the regressions outlined in Section 2. Coefficients on M/B and D/E are multiplied by 100 for ease of presentation.

		Dependent variable:	
		FF3F Adjusted Returns	
		Aggregate ALI	Disaggregated ALI
	H2	(1)	(2)
ALI_ALT	-	-0.02^{***}	
		(-8.240)	
ALI	-	-0.04^{**}	
		(-1.905)	
ALI_ALT.sr	-		-0.12^{***}
			(-9.914)
ALI_ALT.r2	-		0.001
			(0.054)
ALI.sr	-		0.02^{***}
			(2.648)
ALI.r2	-		-0.03^{***}
			(-2.685)
M/B		0.003^{***}	0.004^{***}
		(4.962)	(5.072)
ROA		0.001	0.001
		(0.856)	(0.880)
D/E		-0.01	-0.01
		(-0.939)	(-0.958)
ln(mve)		-0.01^{***}	-0.01^{***}
		(-8.663)	(-8.436)
Fixed Effects		Ind, Year	Ind, Year
SE Clusters		Firm	Firm
Observations		33,226	33,226
Adjusted R^2		0.025	0.027
Note:			**p<0.05; ***p<0.01

Table 12: Association Between Future Returns and ALI, Including ALI_ALT, split by Equity Market Competition, US Sample

This table presents the results of repeating the analysis from table 8, panel b with both versions of ALI included in the analysis. Both columns are restricted to firms in the bottom two quintles of NUM_SHRHLDRS; column (1) shows the results when the sample is further restricted to firms with NUMEST in the top quartile, and column (2) shows the results for firms with NUMEST in the bottom quartile. Coefficients on M/B and D/E are multiplied by 100 for ease of presentation.

		Dependent variable:	
		FF_ADJ_RET	
		High Info Quality	Low Info Quality
	H5	(1)	(2)
ALI_ALT	-/+	-0.03^{***}	-0.03^{**}
		(-4.144)	(-2.351)
ALI	-/+	-0.14^{**}	0.29^{***}
		(-1.967)	(2.925)
M/B		0.1	0.00
		(0.969)	(0.006)
ROA		0.65^{***}	0.0002
		(9.323)	(0.058)
D/E		0.1	-0.01
		(0.850)	(-1.477)
ln(mve)		-0.03^{***}	-0.01
		(-3.831)	(-1.035)
Fixed Effects		Ind, Year	Ind, Year
SE Clusters		Firm	Firm
Observations		3,650	2,248
Adjusted R^2		0.083	0.032
Note:			$^{**}p<0.05$; $^{***}p<0.01$

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