Macro to Micro: Country exposures, firm fundamentals and stock returns

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Abstract

We outline a systematic approach to incorporate macroeconomic information into firm level forecasting from the perspective of an equity investor. Using a global sample of 198,315 firm-years over the 1998-2010 time period, we find that combining firm level exposures to countries (via geographic segment data) with forecasts of country level performance, is able to generate superior forecasts for firm fundamentals. This result is particularly evident for purely domestic firms. We further find that this forecasting benefit is associated with future excess stock returns. These relations are stronger after periods of higher dispersion in expected country level performance.

JEL classification: G12; G14; M41
Key words: macroeconomic exposures, earnings, stock returns, geographic segments.

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1. Introduction

In this paper we examine whether information about a company's geographic (macroeconomic) exposure is useful for forecasting firm fundamentals and stock returns. While the link between firm operating and investing decisions and broader macroeconomic features seems relevant for forecasting, surprisingly little archival, empirical research has examined these relations. Indeed, with an increasingly inter-connected system of economic and financial markets across developed and developing countries, understanding the macroeconomic landscape is important. The rapid change in the relative economic importance of countries around the world suggests that attention to a given company's geographic exposure should be useful to an investor seeking to forecast future cash flows and associated risks for the purpose of security valuation.

The set of potential macroeconomic variables to consider is large, and as such we need to impose structure on the identification of company exposures to these macroeconomic variables. First, we consider how each company is exposed to its home country and other countries. This is a natural choice given that operating and investing choices that span across countries are likely to be a primary mechanism by which macroeconomic factors affect firm performance. We identify country exposures via our own manual coding of the geographic segment sales disclosures in Compustat and FactSet Fundamentals and the geographic sale data collated by FactSet Geographic Revenue Exposures.[1] Second, we rely on information external to the firm via country level forecasts. In our primary analysis, we use forecasts of real GDP growth from Consensus Economics (CE) as a measure of expected country level performance. In

[1] FactSet Geographic Revenue Exposures is a product of FactSet. More details can be found in section 3.1 and at http://www.factset.com/data/factset_data/geo-revenue.

supplementary analyses, we use recent country level stock market returns and aggregate earnings growth forecasts (from I/B/E/S) as alternative measures of expected country level performance.

Country exposures may not be useful in improving forecasts of firm fundamentals for several reasons. First, given our primary measure of country exposures is geographic segment sales data, there is likely to be measurement error due to the subjective manner in which companies disclose disaggregated data across countries and also due to identifying the country exposures primarily by sales data (a data limitation with geographic segment reporting). The cost exposures across countries are missing from our measure, thereby limiting our ability to capture the full set of fundamental exposure.[2] Second, there is a compound forecasting challenge in our empirical exercise. We not only have to measure company to country exposures well, but we must also have a meaningful forecast of relative performance across those countries. While we use multiple measures of expected country level performance, we note that any errors in these forecasts will feed directly into our forecasts of firm fundamentals.

For a sample of 198,315 US and non-US firm-year observations over the 1998-2010 time period, we find that combining country exposures with country level forecasts (we label this measure $MACRO_{i,t}$) improves forecasts of firm fundamentals. The predictive power of $MACRO_{i,t}$ is evident in annual regressions, which suggest that a one percentage point increase in expectations of real GDP growth translates to an additional 27 basis points of return on net operating assets ($RNOA$) over the next year. The predictive power of $MACRO_{i,t}$ is robust to including a wide set of explanatory variables, including sell-side analyst forecasts.

[2] Collins (1976), Silhan (1983) and Roberts (1989) find that the incremental contribution of earnings relative to sales data at the segment level was quite small in terms of improving earnings forecasts, suggesting that revenues is most important for forecasting. In part, the similarity in predictive power from using either sales or earnings based geographic exposures, may be attributable to the subjectivity in cost allocation and transfer pricing for large multi-national companies.

Our sample includes 135,974 ‘domestic’ firm-year observations with exposure only to their home country, and 62,341 ‘non-domestic’ firm-year observations that have exposures to multiple countries. We separately estimate the usefulness of country exposures and country level forecasts to improve forecasts of firm fundamentals for ‘domestic’ and ‘non-domestic’ firms. For domestic firms we find that $MACRO_{i,t}$ is strongly associated with future $RNOA$: a one percentage point increase in expectations of real GDP growth translates to an additional 31 basis points of $RNOA$. For non-domestic firms we find that $MACRO_{i,t}$ is weakly associated with future $RNOA$: a one percentage point increase in expectations of real GDP growth translates to an additional 20 basis points of $RNOA$.

There are two distinct effects driving the positive relation between $MACRO_{i,t}$ and future firm performance. First, we find that forecasts of real GDP growth are useful in forecasting future firm performance for domestic firms. This result does not require the use of potentially noisy geographic segment data. Second, we find that forecasts of real GDP growth are also useful (albeit less strongly) in forecasting future firm performance for non-domestic firms. This result does require the use of potentially noisy geographic segment data. However, additional tests suggest that despite the potential measurement error in the geographic segment disclosure data they are still useful to equity investors interested in forecasting future firm performance. Specifically, we compare our measure of geographic exposure to ‘naïve’ alternatives which ignore the information about the countries from which sales are sourced. We show that these naïve measures have no ability to forecast future firm fundamentals. Thus, despite the measurement error in our geographic exposures based on subjective, and potentially inconsistent, geographic categories by management, they are superior to ignoring the level of disaggregation provided in geographic segment sales disclosures. To the best of our knowledge, the finding that forecasts of real GDP growth are useful in forecasting future firm performance for domestic firms for domestic and non-domestic firms is a new result in the literature.

We also show evidence that stock returns appear to incorporate the information in geographic exposures with a lag. We sort firms into quintiles each month based on $MACRO_{i,t}$ and compute value weighted returns to a dollar neutral hedge portfolio. We obtain statistically significant Sharpe ratios that are not explained by standard risk factors. We note that the economic significance of the stock return predictability is quite strong: annualized excess returns of 16.8 percent using a four factor model. For the sub-sample of purely domestic firms the results are even stronger: annualized excess returns of 22.2 percent using a four factor model. For the sub-sample of non-domestic firms the results are weaker: annualized excess returns of 8.2 percent using a four factor model.

In supplemental analyses, we show that the fundamental and return predictability of information contained in current country exposures and country level forecasts is greater after periods of increased dispersion in real GDP growth forecasts across countries. This suggests that when the information content of $MACRO_{i,t}$ is high ex ante, there is a stronger predictive content. We also show that the return predictability of $MACRO_{i,t}$ is greater when there is greater ex post information content. For this test we split our sample based on the ex post forecast accuracy improvement of including our $MACRO_{i,t}$ measure into forecasts of $RNOA$. Mechanically this partition identifies sub-samples where $MACRO_{i,t}$ is (is not) useful for forecasting $RNOA$. Interestingly, the return predictability is only evident in the sub-sample where there is an ex post improvement in forecasting $RNOA$. This suggests that the return predictability we document is attributable to improved forecasts of firm fundamentals that the market does not price correctly.

A key contribution of this paper is to introduce a simple framework to identify and exploit linkages between firm performance and its potential macroeconomic drivers. Our approach is similar in spirit to recent research exploiting economic linkages across firms, such as Cohen and Frazzini (2008) who show that incorporating information about linkages between firms along the supply chain improves forecasts of firm fundamentals and stock returns, Menzly and Ozbas (2010) who show that incorporating information about linkages across industries, using data from the Bureau of Economic Analysis, improves forecasts of firm and industry level fundamentals and stock returns, and Cohen and Lou (2012) who show that decomposing multi-segment firms into separate 'pure plays' facilitates improved forecasts of fundamentals and stock returns. All of these papers identify linkages between firms and use recent stock returns of relevant linked firms as the 'forecast' for their sample firms. Our paper is different from this stream of research in that we (i) examine a different basis for identification of linkages (geographic location as opposed to industry membership or supply chain links), (ii) use explicit forecasts based on the links we identify (i.e., we focus on forecasts of real GDP growth), and (iii) demonstrate predictive ability for firm fundamentals and stock returns and link these results together.

The rest of the paper is structured as follows. Section 2 lays out a framework for linking country exposures to forecasts of country performance and describes our empirical predictions. Section 3 describes our measures of country exposures and country forecasts. Section 4 presents our empirical analysis, section 5 contains robustness analysis and section 6 concludes.

2. A framework for incorporating macroeconomic information to firm level forecasting

2.1 Linking macroeconomic (country) exposures to firm level profitability

A large literature in accounting and finance has explored the determinants of firm profitability. Penman (1991) and Fama and French (2000) document a strong mean reversion in profitability. This mean reversion is not unexpected as competitive forces will erode firms with above 'normal' profitability and the discipline of the market will remove firms with below 'normal' profitability. A vast literature has expanded the set of determinants of firm profitability to exploit: (i) accruals vs. cash flows (Sloan, 1996 and Xie, 2001), (ii) margins vs. turnover (Fairfield and Yohn, 2001, and Soliman 2008), (iii) earnings volatility (e.g., Dichev and Tang, 2009), (iv) domestic vs. foreign earnings (e.g., Thomas, 2000), and (v) the impact of accounting distortions attributable to conservative accounting practices (e.g., Penman and Zhang 2002).

The majority of past research does not explicitly incorporate information external to the firm itself. While it is possible that disaggregating earnings into components will identify, in a reduced form, links to such external drivers of firm profitability, they are not explicit with respect to these external drivers. Our focus is on first principles to identify potential factors outside the firm's direct control that will have an impact on profitability. As noted in the introduction, this is potentially a very large set of variables. Examples could include: (i) currency movements, (ii) commodity movements, and (iii) financial market variables such as aggregate credit spreads and sovereign yield curves.

We focus our empirical analysis to macroeconomic exposures that are both intuitive and measurable by the researcher. Firms operating across countries are exposed to cross-country differences in a variety of factors (including, but not limited to, those mentioned above) that will, in part, determine their profitability. Not all firms share the same set of exposures across countries at a point in time and not all firms keep their cross country exposures constant through time. For example, Burberry Group PLC specializes in the design, manufacture and distribution of apparel and accessories via retail and wholesale channels. As of December 31, 2011, Burberry has a market capitalization of 5.2 billion pounds and total revenues of 1.5 billion pounds. Burberry's revenue is sourced from around the world as follows: (i) Europe 33.8 percent, (ii) Asia Pacific 30.4 percent, (iii) Americas 25.7 percent, and (iv) other 10.0 percent. In contrast, Mulberry Group PLC designs, manufactures and retails fashion accessories and clothing. It operates a retail and design division and as of December 31, 2011, Mulberry has a market capitalization of 0.9 billion pounds and total revenues of 121 million pounds. Mulberry's revenue is sourced from around the world as follows: (i) Europe 81.5 percent, (ii) Asia 12.7 percent, (iii) North America 4.3 percent, and (iv) other 1.5 percent.

Clearly, the geographic footprints of these two luxury good specialists are different and this difference in geographic exposures is likely to be a key determinant of the difference in profitability into 2012 and beyond, *conditional* on there being a difference in consumer demand across these geographies. Indeed, as at January 1, 2012 expectations were for lower economic growth in Europe (real GDP growth forecasts of 0.40 percent) relative to Asia (real GDP growth forecasts of 4.41 percent). For the period from January 3, 2012 through to July 2, 2013, Burberry (Mulberry) experienced a reduction in return on assets from 17.9 (28.2) percent to 15.3 (17.4) percent. The cumulative stock return for Burberry (Mulberry) over the same period was 13.4 (-41.4) percent.

Our empirical strategy is to identify for each firm the geographical source of its revenues. In section 3.1, we describe in detail the source of the geographic segment data we use for this purpose, along with the data choices necessary to make these disclosures cross-sectionally comparable.

2.2 Prior research linking macroeconomic (country) exposures to firm level profitability

Prior accounting literature has explored the potential forecasting benefit of industry (line of business) segment disclosure information (see Pacter, 1993, for a summary). Several older papers examined the usefulness of line-of-business segment data to improve forecasts of earnings at the parent company level. These studies typically use very small samples from the early 1970s when the SEC first introduced segment disclosure requirements (e.g., Collins, 1975; Collins, 1976; Kinney, 1971; and Foster, 1975). More recent papers have examined the usefulness of geographic segment disclosures to improve forecasts of earnings at the parent company level (e.g., Balakrishnan, Harris and Sen, 1990; and Roberts, 1989). Again, these papers use very small samples (e.g., 89 firms for Balakrishnan, Harris and Sen, 1990; and 78 firms for Roberts, 1989) making generalizability difficult. Furthermore, prior research finds mixed evidence that segment data at the line-of-business or geographic level improves out-of-sample forecasts of firm profitability. With the exception of Collins (1976), none of these papers examine the speed with which this information is incorporated into security prices or capital market participant investment decisions (e.g., analyst forecasts).

Thomas (2000) shows that decomposing earnings changes into a domestic and foreign component generates superior forecasts of future earnings growth and that the stock market fails to appreciate this in a timely manner. However, this approach does not make any use of information external to the firm. Thomas (2000) uses realizations of domestic and foreign earnings growth without any attempt to forecast the domestic economy relative to foreign economies or to split the foreign exposure into its country level composition.

More recent papers measure firm sensitivities to macroeconomic factors including (i) inflation expectations (e.g., Chordia and Shivakumar, 2005; Basu, Markov and Shivakumar 2010; and Konchitchki, 2011), (ii) foreign currencies (e.g., Bartov and Bodnar, 1994; and Bartram and Bodnar, 2012), and (iii) general macroeconomic state variables (e.g., Cochrane 2000; Cochrane, 2010; Liew and Vassalou, 2000; Vassalou, 2003; and Li, Vassalou and Xing, 2006). A limitation to all of this prior research is that the sensitivities are generally estimated statistically and they do not make any attempt to incorporate forecasts of the respective macroeconomic variables. Our empirical analysis differs from these papers in several key respects. First, we estimate our exposures using 'priors', as opposed to statistical estimation which is known to be an imprecise estimate of latent sensitivities (see e.g., Scholes and Williams, 1977, and Dimson, 1979 for a discussion of estimation errors for 'beta'). Second, we exploit the full set of country exposures provided in the geographical segment disclosures and do not limit our analysis to a comparison of 'foreign' to 'domestic' effects. Third, and perhaps most importantly, we use forecasts of the expected performance of each country that a given company is exposed to. We are thus able to address the question whether knowledge of macroeconomic exposures is helpful in a predictive rather than purely descriptive sense.

In summary, it is an open empirical question as to whether there is information content in the combination of country exposures and forecasts of country level performance for forecasting firm profitability, and whether this information is reflected in analyst forecasts and stock prices in a timely manner.

2.3 Combining country exposures to form a firm level forecast

For each firm-year observation we disaggregate total sales into country level sales based on the geographic segment data in the most recent annual report. We retain companies with a purely domestic footprint (i.e., those companies with zero foreign sales) as this allows us to more cleanly assess the importance of macroeconomic information. For example, if firm A has 50 percent of its sales in Germany and 50 percent of its sales in Greece and Firm B has 100 percent of its sales in Greece, and Greece is expected to outperform Germany, then holding all else equal, the 'best' portfolio exposure to express that view would be via Firm B, the purely domestic firm. As discussed in the introduction, in our full sample we group together the 'domestic' and 'non-domestic' firms. However, we also separately examine the importance of macroeconomic information for these two groups. A potential benefit of examining 'domestic' and 'non-domestic' firms separately is to highlight two related effects. First, investors and analysts may be ignoring macroeconomic information in general. If this is true, then we should see strong predictive ability for the domestic only sample. Second, investors and analysts may be ignoring information in the differential geographic reach of companies. If this is true, then we should also see predictive ability for the 'non-domestic' sample.

After gathering the sales data for firm *i*, for each country *c*, at each point in time *t*, $Sales_{i,t,c}$, we standardize these sales measures so that they sum to one. We then use our forecasts of expected country level performance for each county *c* at each point in time *t*, $E[Performance]_{c,t}$. We use forecasts of real GDP growth from CE as our primary measure of expected country level performance. To generate a company specific fundamental forecast, we take the sum-product of $Sales_{i,t,c}$ and $E[Performance]_{c,t}$, which we label $MACRO_{i,t}$ (i.e., $MACRO_{i,t} = \sum_1^C Sales_{i,t,c} * E[Performance]_{c,t}$). This measure captures both cross sectional and time series variation in firm level sensitivities to macroeconomic (country level) performance drivers. A detailed example of how we compute $MACRO_{i,t}$ for Mulberry Group PLC is contained in Appendix I.

2.4 Empirical tests

We conduct two sets of empirical analyses. First, we assess the performance of forecasts of firm fundamentals (return on net operating assets) that include $MACRO_{i,t}$ relative to those that do not. Second, we assess the ability of $MACRO_{i,t}$ to predict excess stock returns.

2.4.1 Firm fundamentals

Our first empirical prediction can be stated in alternative form as:

P1: Combining country level exposures with expectations of country level performance is useful in forecasting future firm fundamentals.

We test this prediction by examining whether the inclusion of $MACRO_{i,t}$ improves forecasts of firm profitability. The benchmark forecasting model for firm level profitability is a modified random walk that acknowledges profitability is mean reverting, and also exploits various firm characteristics that isolate differences in persistence of profitability (see e.g., Fama and French, 1995; So, 2013; and Hou, van Dijk and Zhang, 2012). Specifically, we run the following regression for each fiscal year (firm subscripts, *i*, dropped for the sake of brevity):

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t + \beta_2 RNOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 DNOA_t + \beta_6 D\_Loss_t + \beta_7 D\_Div_t + \beta_8 Div\_Yield_t + \beta_9 AF\_RNOA_t + e_{t+1} \quad (1)$$

All variable definitions are provided in detail in Appendix II. $RNOA_t$ is computed as operating income divided by average net operating assets. $MACRO_t$ is as defined previously, BTM_t is book-to-price measured as the book value of common equity divided by market capitalization, $Size_t$ is the log of market capitalization (in USD to ensure cross-sectional comparability), $DNOA_t$ is the change in net operating assets as measured in Richardson, Sloan, Soliman and Tuna (2005), D_Loss_t is an indicator variable equal to one for firms reporting a loss in year *t*, and zero otherwise, D_Div_t is an indicator variable equal to one for firms paying a dividend in year t, and zero otherwise, and Div_Yield_t is the dividend yield for year t. AF_RNOA_t is the median consensus forecast of $RNOA_t$ calculated using analysts' forecasts of one year ahead EPS collected from I/B/E/S at the start of year $t+1$. We convert per share earnings to dollar earnings forecasts using the shares outstanding and split adjustment factors reported on I/B/E/S. We then convert the dollar forecasts to profitability forecasts using the most recent value of net operating assets that is publicly available at the time the forecast is made.

We estimate equation (1) using a pooled dataset and compute standard errors clustering for both time and firm effects. We expect profitability to be mean reverting so our priors are for β_2 to be less than one and greater than zero. We expect firms with greater growth opportunities, as measured (inversely) by BTM_t, to have high levels of profitability after controlling for current profitability, so we expect a negative β_3 coefficient. As originally noted in Fama and French (1995), we expect smaller firms to exhibit lower levels of future profitability controlling for current profitability, so we expect a positive β_4 coefficient. We expect β_5 to be negative due to the lower persistence of accruals. We expect loss making firms to have lower profitability (i.e., $\beta_6 < 0$), firms paying dividends to have higher profitability (i.e., $\beta_7 > 0$ and $\beta_8 > 0$), and analysts to have some skill (i.e., $\beta_9 > 0$). By including analyst forecasts directly in equation (1) we can comment on whether analysts fully use the information contained in $MACRO_t$ when making their earnings forecasts. Finally, we expect a positive coefficient for our primary variable of interest, $MACRO_t$. The greater the exposure of a firm to countries that are expected to do well, the greater we expect future profitability to be, controlling for other known determinants of profitability.

To assess the general information content of $MACRO_t$ we estimate equation (1) on the full sample as well as separately for domestic and non-domestic firms. By analyzing domestic firms separately we can assess whether macroeconomic information is useful for forecasting firm fundamentals independent of the use of detailed, and potentially noisy, geographic segment data.

To assess the information content of $MACRO_t$ attributable to foreign country exposures, we estimate regression equation (1), additively decomposing $MACRO_t$ into its domestic, D_MACRO_t, and foreign country, F_MACRO_t, components. This enables us to assess whether the information content of $MACRO_t$ with respect to future fundamentals is attributable to only domestic exposures. To assess whether we benefit from relying on segment disclosures to capture specific geographic exposures, or whether F_MACRO_t simply captures the exposure to growth of all foreign countries, we compute two 'naïve' versions of $MACRO_t$ and its foreign component. First, $Naive\_MACRO\_Home_t$ is measured as the real GDP growth forecast for the home country, assuming all sales are domestic. This measure ignores all potential information content of the geographic segment sales disclosures. For example, for Mulberry Group PLC $Naive\_MACRO\_Home$ is equal to the real GDP growth forecast for the UK in a given year and ignores that some sales are foreign. Second, $Naive\_F\_MACRO_t$ is measured as the product of the ratio of foreign sales to total sales and weighted average real GDP growth forecasts across all foreign countries. This measure includes some, but not all of, the information from the geographic segment sales disclosures. For example, for Mulberry Group PLC, as outlined in Appendix I, 90% of its sales are to Europe, and the relative importance of UK's GDP in Europe is 11.6%. Thus, Mulberry has 10.44% (89.56%) domestic (foreign) sales. We then compute $Naive\_F\_MACRO$ as 89.56% multiplied by the GDP-weighted average of real GDP growth forecasts of all other countries.

2.4.2 Stock returns

Our empirical prediction can be stated in alternative form as:

P2: Stock prices do not efficiently incorporate fundamental information related to country level exposures and expectations of country level performance.

We employ standard time series portfolio tests to assess the relation, if any, between future stock returns and the information contained in company level geographic exposures and country level performance. We sort each cross-section into five quintiles based on $MACRO_t$. We then construct a dollar neutral portfolio which is long (short) the constituents of the top (bottom) quintile of $MACRO_t$. We value weight the constituents of each quintile. We then perform standard time series regressions where the return of the hedge portfolio ($HEDGE$) is projected onto factor-mimicking portfolio returns (e.g., Fama and French, 1992 and 1993). Using the time series of monthly hedge portfolio returns, we estimate the following regression:

$$HEDGE_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + e_t \quad (2)$$

MKT is the return to the global market portfolio (excess of the U.S. 1 month T-Bill rate) as reported from Ken French's website. SMB, HML, and MOM are the factor-mimicking portfolio returns from Ken French's website. As our sample contains global set of securities, we use the global factor returns based on stock level data from 23 developed markets that correspond closely to our sample composition. To the extent that factor-mimicking portfolio returns reflect compensation for risk, we control for time series variation in risk in our analysis by including these variables. The relevant test is whether the intercept in this time series regression is statistically different from zero.

3. Data Issues and Sample Selection

3.1 Geographic exposure data

We extract geographic exposure data from the annual fundamental file created by Compustat for US firms, and the annual fundamental file created by FactSet Fundamentals for non-US firms. We use the geographic sales data because the coverage of geographic earnings data is very limited. We use the disclosures provided by each firm as contained in their annual report. The disclosure practices of firms related to geographic segment disclosures vary considerably, both over time and across firms. There is little homogeneity in how firms choose to describe the geographic regions in which they source their revenues. This creates a challenge for accurately mapping geographic regions to countries. We use a standard tree structure that maps various geographic regions to member countries. For companies that report sales at an aggregated regional level (e.g., 'North America' or 'Europe'), we allocate those sales across the member countries using a GDP weighting for that respective year (consistent with Roberts, 1989). This approach exploits the relative importance of economic activity across countries within that region by allocating more sales to the more important member countries. This choice introduces measurement error into our country level sales exposures for firms that have targeted certain countries within a geographic region. However, absent reliable data we cannot do more than this. Balakrishnan, Harris and Sen (1990) note that for their sample of 89 firms there is a close mapping between actual country specific sales disclosures and implied country specific sales (using a GNP weighting across countries within a particular region), suggesting that the measurement error may not be that large for our sample. We then standardize the country level sales data such that they sum to one for each firm year. A detailed example for Mulberry Group PLC is shown in Appendix I.

In addition to our own extraction of geographic segment sales data, we also use FactSet Geographic Revenue Exposure (FGRE). FGRE uses a proprietary geographic classification structure consisting of more than 320 country and region hierarchy levels. It uses primary sources of information disclosed directly by companies via regulatory filings as well as investor and analyst reports to derive revenues by geographic region. Thus, FGRE has the potential to capture more granular geographic revenue data compared to our analysis which is limited to firm annual reports. Analysts of FGRE are trained to interpret information in a consistent manner and these analysts input the raw data into a data management system. Proprietary algorithms then allocate geographic revenues to regions and countries. The data we have access to from FactSet covers a subset of our cross-section of firms. In our empirical analysis we combine geographic exposures that we manually collect with the geographic exposures from FGRE. When exposures are available from both sources we use the FGRE geographic exposures. For our full sample of 198,315 firm-years we have available data from FGRE to compute $MACRO$ for 21,205 firm-years. The correlation between $MACRO$ using the two different sources of geographic revenue data is 0.947. In supplemental tests, we examine the effect of not using the FGRE data (see section 5.1).

Our final sample covers 198,315 unique firm-years, spanning 45 countries over the 1998 to 2010 period. Panel A of Table 1 provides a breakdown of the country of headquarters for the firms in our sample. We only show unique country locations for 33 countries where there are at least 100 firm-years in a given country. We group the remaining 12 countries into the 'Other' category. The most important countries are Japan (19.5 percent), US (17.2) percent, UK (7.4 percent), China (6.2 percent), and India (5.1 percent). As reported in panel B of Table 1, the average firm in our sample reports \$1.04 billion in annual sales, \$1.89 billion in total assets and has a market capitalization of \$1.01 billion. In contrast, the median firm in our sample has \$129 million in annual sales, \$176 million in total assets and has a market capitalization of \$104 million. All of these amounts are expressed in USD. We have translated balance sheet (income statement) amounts reported in local currency to USD using fiscal year end (average) foreign exchange spot rates. Our sample contains some of the largest multi-national companies in the world, but also contains a large number of the smaller firms. The average (median) firm in our sample has a BTM value of 1.07 (0.76) and reports on average a 6.4 percent return on net operating assets. 57.2 (24.7) percent of sample firms pay dividends (report losses). As reported in panel C of Table 1, the sample covers the main economic sectors with the greatest concentration in money and finance (14.9 percent), manufacturing (14.8 percent), and business equipment (14.3 percent). In some subsequent regression analyses we use subsets of this full sample depending on data requirements specific to each model.

3.2 Country level forecasts

We use country level real GDP forecasts from Consensus Economics (CE) as the basis of our primary measure of expected country level performance. CE was founded in 1989 and they have been collecting survey data from over 700 economists since that time. Each month, CE surveys the economists to collect opinions on a variety of measures across a large set of countries. The surveyed economists typically provide a forecast of real GDP growth (and components) for the next two calendar years. A key benefit of this data source is that it is 'point-in-time': the forecasts of economists that are included in the CE datasets are never changed.

Prior research has shown that, with few exceptions, the CE forecasts are less biased and more accurate in terms of mean absolute error and root mean square error relative to forecasts from the OECD and IMF (Batchelor, 2001). We use the average GDP forecast across the CE survey participants for each country. We create a 12 month ahead real GDP growth forecast by combining the one year ahead and two year ahead GDP growth forecasts by placing less (more) weight on the one (two) year ahead GDP growth forecast as the forecasting month gets closer to the end of the first year. This 12 month-ahead forecast of GDP growth has a natural economic interpretation as it is measured in percentage points of expected growth. We describe alternative measures of expected country level performance in section 5.5.

Panel A of Table 1 reports the distribution of 12 month ahead real GDP growth forecasts by country. Given that our time period spans the 1998 to 2010 period, it is not surprising that the countries with the highest average level are concentrated in the developing markets (e.g., China and India). Across all countries, however, there is significant variation in expected country performance, which is important for our predictive tests to have any power.

As described in section 2.3, we combine the country level forecast with the firm level geographic exposures (from the most recent fiscal year) to compute $MACRO_t$. Panel B of Table 1 notes that the average value of $MACRO_t$ is 2.99 consistent with most countries experiencing real GDP growth during this time period. More important, however, is the large standard deviation in the measure, 2.65, and large inter-quartile range, 2.52, respectively. Thus, ex ante, there should be sufficient power to exploit both time series and cross sectional variation in $MACRO_t$ to help forecast firm fundamentals and future stock returns. Finally, we also decompose $MACRO_t$ into its domestic, D_MACRO_t, and foreign, F_MACRO_t, components. As discussed earlier this is an additive decomposition. Using the case of Mulberry PLC described in Appendix I, D_MACRO_t is based on 11.6% (relative importance of UK's GDP in Europe) of 90% (the fraction of sales Mulberry makes to Europe), or 10.44% of its total sales. F_MACRO_t is then based on the sales to all remaining countries. We do this decomposition only for the 25,266 firm-years with significant foreign sales (greater than 50 percent). Panel B of Table 1 reports considerable variation in both D_MACRO_t and F_MACRO_t. F_MACRO_t is larger in magnitude, due to the fact that foreign sales account for the majority of sales in this sub-sample.

3.3 Fundamental, analyst and market data

All of our fundamental data to compute the measures described in section 2.4 are derived from annual financial statements collected by Compustat for US firms and FactSet Fundamentals for non-US firms. Analyst forecast data are sourced from I/B/E/S for both US and non-US firms. Our market data are obtained from CRSP for US firms and Compustat Global for non-US firms. We include all firms in our analysis with non-missing data to compute $MACRO_t$, and make no exclusions on the basis of industry membership. Our primary sample starts in 1998 due to our inability to obtain geographic segment data from FactSet Fundamentals prior to 1998.

4. Results

4.1 Firm fundamentals

Table 2 reports the regression coefficient estimates of equation (1). We estimate this regression on the pooled sample of firms clustering standard errors for firm and time dependence. Inferences are similar if we instead estimate separate cross-sectional regressions by sector each year. We estimate equation (1) for three different samples: (i) all firm-years (198,315 observations), (ii) only domestic firm-years (135,974 observations), and (iii) only non-domestic firm-years (62,341 observations). In panel A (estimated without AF_RNOA), our variable of interest, $MACRO_t$, is positive and significant for all three samples, but only marginally so for the non-domestic sample.[3] These results are consistent with P1. Focussing on the full sample, the β_1 coefficient is 0.270. This regression coefficient has a clear economic interpretation: a one percentage point change in real GDP growth forecasts is associated with an

[3] When we use two alternative measures of expected country performance in Section 5.5, $MACRO_t$ is strongly significant in the non-domestic sample, as reported in Table 8 Panel A.

additional 27 basis point increase in $RNOA$ in the following year controlling for other known determinants of profitability.

Consistent with prior research, we see that profitability, and its components, are mean reverting. For example, column 1 of Table 2 reports the β_2 coefficient as 0.693. As expected, we find that the level of future profitability is generally decreasing in BTM_t, but the statistical significance of that relation is marginal. We find that future $RNOA$ is reliably positively associated with $Size_t$ across all samples. We also document a strong negative (positive) relation between $DNOA_t$ (dividend payment status) and future profitability. Finally, we find a mixed relation between dividend yield and loss making firms and future profitability. These results are generally consistent with recent research (e.g., So, 2013 and Hou, van Dijk and Zhang, 2012).

In panel B of Table 2 we estimate regression equation (1) including AF_RNOA. Consistent with past literature, this reduces our sample size but does not change the significance of other explanatory variables. Thus, for the sake of brevity we only report the $MACRO_t$ and AF_RNOA regression coefficients. For both the full and domestic samples, $MACRO_t$ remains significant. However, for the non-domestic sample $MACRO_t$ is no longer significant.[4] Overall, sell-side analyst forecasts do not incorporate the information content of geographic segment disclosures for domestic firms, but their forecasts assume some of the forecasting power of $MACRO_t$ for future firm profitability for non-domestic firms. Our estimated β_9 regression coefficient is very low in Table 2. While we expect the β_9 regression coefficient to be less than one, due to the well-known optimism in sell side analyst forecasts, we find that it is not different from zero. This is attributable to the inclusion of current $RNOA$ and other explanatory variables

[4] When we use two alternative measures of expected country performance in Section 5.5, $MACRO_t$ is strongly significant in the non-domestic sample, as reported in Table 8 Panel B.

in the regression specification. The correlation between $RNOA$ and AF_RNOA is 0.29. In unreported analyses, we re-estimate equation (1) after excluding $RNOA$ and find significantly positive β_9 regression coefficients. As an example, we find that the β_9 increases to 0.287 for model (2) when $RNOA$ is excluded, and the main effect of $MACRO_t$ is unchanged (β_2 coefficient is 0.384).

To make stronger inferences about the predictive ability of $MACRO_t$, we compare absolute forecast errors using two version of equation (1): with and without $MACRO_t$. Specifically, we estimate equation (1) on an expanding window basis and use estimated regression coefficients starting in 2005 to forecast $RNOA$ for the years 2006 through to 2011. We then compare differences in $RNOA_{t+1}$ forecast errors on a pooled and industry grouping basis. This approach is consistent with the framework of comparing predictive accuracy in Diebold and Mariano (1995). When we include $MACRO_t$ into the forecast, we find that the average and the median absolute forecast errors of $RNOA$ are lower by 2 basis points (significant at the five percent level). While the magnitude of the reduction in forecast error seems small in economic terms, it is consistent with previous research. For example, Fairfield and Yohn (2001) document that a forecasting model for changes in return on net operating assets that includes profit margins and asset turnover relative to a forecasting model that excludes this information, was more accurate by a magnitude of 3 (2) basis points for the average (median) paired difference. Further, Fairfield, Sweeney and Yohn (1996) document that the median improvement in out-of-sample forecast accuracy by separately treating non-recurring items, arguably a more ‘important’ forecasting variable, is between 5 and 10 basis points (relative to book equity) for a large sample of US firms over the 1981-1990 time period.

In Table 3 we further explore the relation between $MACRO_t$ and future firm performance for non-domestic firms. In this table we only examine non-domestic firms with at least 50 percent of total sales sourced from foreign countries. This reduces our sample size from 62,341 non-domestic firm-year observations to 25,266 non-domestic firm-year observations. We focus on this reduced sample as we are now interested in assessing the information content of the detailed geographic segment disclosures we source from annual reports, which are most relevant for the set of firms with material foreign exposures. Specifically, we compare the predictive ability of $MACRO_t$ and F_MACRO_t with that of $Naive\_MACRO\_Home_t$ and $Naive\_F\_MACRO_t$, our naïve versions of $MACRO_t$ and its foreign component as described in section 2.4.1. For the sake of brevity we only report the regression coefficients associated with the various $MACRO_t$ variables.

Panel A in Table 3 shows that the predictive power of $MACRO_t$ for future firm profitability is not attributable to the expected real GDP growth in the firm's home country (i.e., the regression coefficient on $Naive\_MACRO\_Home_t$ is not statistically significant from zero). At the bottom of panel A we report J tests (Davidson and MacKinnon, 1981) and Cox tests (Cox, 1961, 1962) that test the two competing non-nested models against each other (i.e., $MACRO_t$ vs. $Naive\_MACRO\_Home_t$). Both the J test and the Cox test reject model 2 in favor of model 1. When we consider $MACRO_t$ and $Naive\_MACRO\_Home_t$ together, all of the predictive power comes from $MACRO_t$.

Panel B of Table 3 decomposes $MACRO_t$ into D_MACRO_t and F_MACRO_t, which capture the domestic and foreign components of $MACRO_t$, respectively. The objective of this panel is to compare the predictive power of the foreign component, F_MACRO_t, with that of $Naive\_F\_MACRO_t$. We find that F_MACRO_t can predict future profitability, but not

$Naive\_F\_MACRO_t$. This suggests that it is important to pay attention to the specific countries from which the firm sources its foreign sales. The Cox tests reported at the bottom of panel B rejects model 2 in favor of model 1, whereas the J test is equivocal. When we consider F_MACRO_t and $Naive\_F\_MACRO_t$ together, all of the predictive power comes from F_MACRO_t.

In summary, the evidence in tables 2 and 3 show that there are two related effects in our paper. First, knowledge of expected cross-country performance is useful in forecasting future performance of domestic firms. This result does not require the use of detailed, and potentially noisy, geographic segment data. Second, knowledge of expected cross-country performance is useful in forecasting future performance of non-domestic firms. This result does require the use of detailed, and potentially noisy, geographic segment data. The results suggest that despite the potential measurement error in the geographic segment disclosure data, they are still useful to equity investors interested in forecasting future profitability.

4.2 Stock returns

Table 4 reports regression estimates of equation (2) with and without MOM. We report regression results for the full sample as well as for domestic and non-domestic firms separately. For all three samples, we see very significant intercepts which translate into economically and statistically significant conditional Sharpe ratios. These large conditional Sharpe ratios suggest that the portfolio returns are not explained by standard risk factors. Across our time period, portfolio returns for the full, domestic and non-domestic samples sample are positive in 64, 60 and 58 percent of months respectively. The average monthly excess returns are equivalent to annualized returns of 16.8, 22.0 and 8.8 percent respectively across the full, domestic and non-domestic samples. Overall, we interpret the evidence in table 4 as providing support of P2.

In unreported tests, we also examine value weighted dollar neutral portfolio returns using characteristic adjusted returns at the firm level, as per Daniel, Grinblatt, Titman and Wermers (1997). Specifically, we sort all stocks each month into 125 portfolios based on a conditional sorting on the following characteristics: (i) size, (ii) B/P, and (iii) momentum. Value weighted returns are computed for each cell each month. The characteristic adjusted return is then the difference between the security return and the average return for the characteristic portfolio that the security belongs to. The results using this alternative measure are very similar to those reported in Table 4, and for the sake of brevity we do not report them.

Of course, it is always possible there is an unidentified risk factor which time varies with our $HEDGE$ returns. Of the included risk factors, there is evidence that $HEDGE_t$ is positively associated with MKT_t, positively associated with MOM_t (for non-domestic firms only), and negatively associated with HML_t. Specifically, the regression coefficients suggest that the returns to a portfolio exploiting geographic exposures earns positive returns when (i) the overall equity market is doing well, (ii) recent 'winners' have been performing well, and (iii) underperform when 'value' firms outperform. As these portfolios are rebalanced monthly there will be some portfolio turnover each month. Absent clean data on expected transaction costs for an institutional investor in a global context, we are unable to make strong inferences on whether this constitutes a profitable trading strategy. The strategy is implementable in that there is no look-ahead bias in the information necessary to construct the portfolios. Specifically, we ensure that all of the data used in the analysis was publicly available at the start of the relevant forecasting period (i.e., we assume that financial statements are available four full months after the end of the fiscal period). Recent research suggests that round-trip transaction costs for equity trading is about 25 basis points (see e.g., Frazzini, Israel and Moskowitz, 2013). Our monthly portfolio $HEDGE$ returns are 185 (68) basis points for domestic (non-domestic) firms respectively, which appears larger than expected transaction costs (at least on average). Of course, actual transaction costs can be larger and will also depend on the capital invested (as trading costs scale with position sizes).

5. Further analyses

5.1 FactSet Geographic Revenue Exposure (FGRE) data

Our results so far have used a combination of geographic data we source from annual reports and geographic revenue exposures provided by a third party data vendor (FGRE). While we know that the data we are sourcing from annual reports was known at the time the annual reports are released to the market we cannot be certain that the data from FGRE are 'point-in-time'. To address this issue we have re-run our estimates of equations (1) and (2) for our three samples using only the data from annual reports. Table 5 reports the results. For the sake of brevity we only report the $MACRO_t$ regression coefficient from equation (1) and the intercept estimate from equation (2).

In panel A, comparing the regression coefficient for $MACRO_t$ back to Table 2, we see that the full sample result is virtually identical (0.270 in Table 2 compared to 0.269 in Table 5) and a reduction for the non-domestic sample (0.202 in Table 2 compared to 0.178 in Table 5). Similarly, in panel B, we see a small reduction in portfolio returns when we exclude FGRE data. For non-domestic firms the annualized excess return is now 6.8 percent (but remains statistically significant). These results are useful for future researchers as the results we document are not dependent upon access to FGRE data.

5.2 Time series partitions

A necessary condition for $MACRO_t$ to be able to forecast cross-sectional differences in future firm performance and returns is that there is cross-sectional dispersion in the 12 month ahead real GDP forecasts from CE. Table 1 documents considerable variation in these forecasts across countries and time. Our empirical analysis for firm fundamentals thus far has used a panel regression approach. To identify whether there is additional information content in the time series of our country level forecasts, we compute the across country dispersion in the 12 month ahead real GDP forecasts each month. We then associate this measure of dispersion with the predictive ability of $MACRO_t$ for both future firm fundamentals and stock returns. To identify low and high dispersion months, we split the sample into equal halves based on the full sample monthly dispersion in 12 month ahead real GDP growth forecasts from CE.

In Table 6 we test whether the ability of $MACRO_t$ in forecasting future firm performance and returns is stronger when there is greater dispersion in expected performance across countries. In panel A of Table 6, we estimate equation (1) annually using firms with the same fiscal year ends (requiring at least 1,000 observations) and calculate the average coefficients of $MACRO_t$ across each of our three samples separately for the low and high dispersion sub-samples. For the full, domestic and non-domestic samples, we find for the high dispersion sub-sample a strong relation between $MACRO_t$ and future firm profitability. Specifically, for the high dispersion group of the domestic (non-domestic) sample we find that a one percentage change in expectations of real GDP growth translates into an additional 69 (42) basis points of $RNOA$. In contrast, there is not a significant relation between $MACRO_t$ and future firm profitability for the low dispersion sub-sample. The formal test of difference across the low and high dispersion sub-samples is significant for the full and domestic samples, but not for the non-domestic sample.

In panel B of Table 6, we examine the difference in value weighted dollar neutral hedge portfolio returns formed on the basis of $MACRO_t$ across low and high dispersion months. We find that for the full, domestic and non-domestic samples the relation between $MACRO_t$ and future stock returns is stronger when there is greater cross-sectional dispersion in real GDP growth forecasts. For example, annualized excess returns are 26.6, 35.3 and 10.3 percent respectively for the full, domestic and non-domestic samples during months with high levels of dispersion in real GDP growth forecasts. In months with low levels of dispersion in real GDP growth forecasts, there is no evidence of portfolio excess returns for any of the three samples. We can reject equality of portfolio returns across low and high dispersion months for the full and domestic samples and marginally so for the non-domestic sample.

Across all three samples, we find consistent evidence that the information content of $MACRO$ for future $RNOA$ and future stock returns is greater during periods when there is greater cross country variation in expected real GDP growth, although the statistical significance of the results is not strong for the non-domestic firm sub-sample.

5.3 Cross-sectional partitions

Table 7 examines whether limited attention and/or institutional impediments can reduce market participants' ability to incorporate information for (i) smaller firms, (ii) less followed firms, (iii) firms not included in broad market indices, and (iv) more complicated firms. We sort each cross-section along each of these dimensions and report (i) value weighted dollar neutral hedge portfolio returns formed on the basis of $MACRO_t$ for firm-months that are within each partition sub-sample, and (ii) regression coefficient β_1 from equation (1) for firm-years that are within each partition sub-sample. We include the regression coefficient across sub-samples for completeness and comparison to previous tables. We do not expect $MACRO_t$ to have differential information content for firm fundamentals across the partitions selected, because our partitions are all with respect to price discovery in secondary markets. We show the full sample results at the top of Table 7 for comparison with the earlier tables, and the fraction of the full sample included in each partition in parentheses beside the partition label. Portfolio returns or regression coefficients that are statistically different across partitions are bolded.

For our size based partitions, we use NYSE breakpoints as suggested in Fama and French (2008). For the size based partitions we retain 100 percent of the full sample as we have this data for all firm-year observations. We find portfolio returns are economically and statistically smaller for the largest sub-sample, for example, large (small) firms have a portfolio hedge return of 85 (200) basis points per month. In unreported tests, we find similar differences if we instead use in-sample break-points for small, medium and large firms. For our analyst following partitions we only have analyst data for 62.9 percent of the full sample. Note that this is larger than the 43.8 percent of the full sample used to estimate equation (1) in Table 2. This difference is due to the fact that for the regression analysis we need an earnings forecast available at the start of the following fiscal period. For the analyst following partition we only use the fact that there was at least one analyst forecasting in any month of the fiscal year. For the analyst partitions, we find portfolio returns are significant across all analyst following sub-groups, and they are statistically greater for the low analyst following sub-group relative to the high analyst following sub-group. Partitions on firm size and analyst following are clearly not independent sorts. In unreported analyses, we have attempted conditional sorts on firm size and analyst following and we find generally similar results: stock return predictability is strongest in smaller firms with less analyst coverage. For example, within the smallest sub-group based on NYSE break points, the low (high) analyst following sub-group has a portfolio hedge return of 230 (122) basis points per month (difference is marginally significant with a test statistic of 1.56).

Our remaining cross-sectional partitions capture the impact of limited attention and institutional impediments specific to the utilization of complex macroeconomic information. First, we examine the effect of security inclusion in the MSCI indices. To the extent that a security is included in the MSCI All Country World Index (ACWI) it will be easier for an informed investor to trade on any macroeconomic view. Partitions based on inclusion in this global index reveal that the monthly portfolio hedge returns to $MACRO_t$ are larger for securities that are not included in the MSCI global index (147 basis points for non-index constituents and 112 basis points for index constituents). However, these differences are not statistically significant at conventional levels. Second, we examine the effect of geographic complexity. Specifically for the sub-sample of non-domestic firms (i.e., 32.6 percent of our full sample with available stock return data), we identify two sub-groups based on the number of geographic segments disclosed in the annual report. Firm-years with more (less) than three segments are classified as complex (simple). We expect the predictive ability of $MACRO_t$ to be greater for firms that are more complex, consistent with the prior literature on limited attention and economic linkages (see e.g., Cohen and Frazzini, 2008 and Cohen and Lou, 2012). We find that monthly portfolio returns are indeed larger for the more geographically complex firms (72 basis points vs. 44 basis points), but we are unable to document statistically significant differences across the simple and complex portfolio returns. As expected, we see no difference in the ability of $MACRO_t$ to forecast future firm fundamentals across the various partitions.

5.4 Linking fundamental predictability to stock return predictability

Our next analysis links the information content of $MACRO_t$ in the context of firm fundamentals to the information content of $MACRO_t$ in the context of stock return predictability. We estimate equation (1) and examine the forecast accuracy improvement of including $MACRO_t$ relative to excluding $MACRO_t$. This provides two forecasts of future firm fundamentals which we then compare with future realizations of firm fundamentals. We compare the absolute values of the resulting forecast errors. We assign firm-year observations into two groups based on the relative size of the two forecast errors. In the first (second) group, which we name "improve" ("not improve"), we place all firm-year observations where the inclusion of $MACRO_t$ generates a lower (higher) forecast error. We then compare the value weighted dollar neutral portfolio hedge returns for $MACRO_t$ across these two groups. The bottom rows labelled 'Improve' and 'Not Improve' in Table 7 summarize these results. Note that we lose 38.8 percent of the full sample as we must first estimate equation (1) and then use the regression coefficients out of sample to forecast $RNOA$, so only 61.2 percent of the full sample is partitioned into these two sub-groups. Where there is an out of sample improvement in forecast accuracy of $RNOA$, there is strong evidence of stock return predictability. For example, a value weighted dollar neutral hedge portfolio formed on the basis of $MACRO_t$, where it is known to improve forecast accuracy of $RNOA$, generates a significant risk-adjusted excess return of 229 basis points per month (using the standard 4-factor Fama-French factors). In contrast, there is no evidence of return predictability for the sub-sample where $MACRO_t$ is known not to improve forecast accuracy of $RNOA$ (a statistically insignificant 64 basis points excess return per month). This difference in monthly portfolio returns is significant at conventional levels. When the information content of

$MACRO_t$ for future firm fundamentals is high ex post, there is strong evidence of greater stock return predictability.

In unreported tests we also attempted to extract ex ante measures of fundamental sensitivity to macro-economic information. Specifically, for each 2 digit SIC industry grouping which has at least 2,000 firm-year observations, we estimate equation (1) using an expanding window approach. This generates 31 regression coefficients of β_1 which we use to sort industry groups into low and high $MACRO$ sensitivity. We examine the differential ex post predictive ability of $MACRO$ across the top and bottom quintiles of industry groupings based on this $MACRO$ sensitivity. We find that the low (high) $MACRO$ sensitivity industry group has a statistically lower (higher) β_1, in future years for predicting future $RNOA$ (0.281 for the high sub-group and 0.142 for the low sub-group). The difference in return results across the two sub-groups is, however, insignificant at conventional levels.

5.5 Alternative measures of expected country level performance

Our primary analysis of the information content in $MACRO_t$ uses one year ahead real GDP growth forecasts from CE. In this section, we examine two alternative measures of $MACRO_t$. Both alternative measures use the same company to country sales exposure matrix, but they differ in the measure of expected country level performance. First, we use the most recent six months country level stock returns as a measure of expected country level performance. We compute country level returns by aggregating firm level returns using value weighting. We have also examined country level returns as reported by MSCI, but this return data is not available for all countries back to the start of our sample, so we focus on our own measures of country level returns. We label this alternative measure as $MACRO_t^{RET}$.

Second, we use changes in expectations of aggregate earnings as a measure of expected country level performance. We label this alternative measure as $MACRO_t^{IBES}$. We measure country level earnings forecasts by aggregating firm level earnings forecasts from the I/B/E/S database (see e.g., Konchitchki and Patatoukas, 2014). We then use the monthly change in aggregate earnings forecasts as our basis for identifying expected country level earnings growth.

We re-estimate equation (1) including each $MACRO_t$ measure separately. To avoid confusion we label our primary measure $MACRO^{CE}$. The sample size in Table 5 is slightly smaller than that reported in Table 2 as we require non-missing data for all three $MACRO_t$ measures. Panel A (B) of Table 5 reports regression coefficients of the respective $MACRO_t$ variables excluding (including) AF_RNOA for our three samples. Across all three measures, with the exception of $MACRO_t^{IBES}$ for the purely domestic sample, there is generally a reliable association with future firm profitability. In panel C of Table 5, we report the value weighted dollar neutral hedge portfolio returns formed on the basis of the three alternative measures of $MACRO_t$. For both $MACRO_t^{CE}$ and $MACRO_t^{RET}$, we see robust positive portfolio returns for all three samples, but we do not see significant portfolio returns for the $MACRO_t^{IBES}$ measure.

6. Conclusion

In this paper we outline an approach to incorporate macroeconomic information into firm level forecasts. Using a large sample of publicly traded firms around the world, we show that combining geographic segment sales disclosures and forecasts of country level performance generates significant improvement in forecasting firm level profitability. This predictive power is particularly strong for domestic firms. We also find that stock prices are slow to incorporate this information.

In an inter-connected global market place, knowledge of how firms are exposed to different geographic locations is increasingly useful for investors. Our focus has been on the geographic revenue exposures of firms to countries. Future research could extend this analysis to explore not only revenue based exposures but also cost based exposures. Current accounting standards under both US GAAP and IFRS both adopt a management approach for the identification of operating segments that may, or may not, be defined on the basis of geography. For those companies that do disclose geographic segment data, it is unusual to obtain a detailed breakdown of revenue and costs across geographic segments. To the extent that such data becomes available, future research could look to exploit differential revenue and cost exposures across countries.

More generally, our results speak to the potential benefits to detailed contextual analysis which seeks to identify value drivers that are external to the firm. Combining firm specific exposures to these value drivers with a directional view on the value driver will create improvements in our ability to understand and hopefully forecast future firm fundamentals and associated risks.

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Appendix I: Calculation of $MACRO_t$ for Mulberry Group PLC

In the fiscal year ended on March 2010, Mulberry's sales are from the following regions: (i) Europe 90%, (ii) Asia 5.1%, (iii) North America 3.2%, and (iv) 'Rest of the World' 1.7%. We use this exposure matrix to calculate $MACRO_t$ for each month from August 2010 to July 2011. For example, $Macro_t$ for Mulberry in August 2010 is calculated as:

$$\begin{aligned} MACRO_t = {} & \%\,Sales\ to\ Europe\ \times E_t[Performance\ for\ Europe] + \ \%\,Sales\ to\ Asia \\ & \times E_t[Performance\ for\ Asia] + \ \%\,Sales\ to\ North\ America \\ & \times E_t[Performance\ for\ North\ America] + \ \%\,Sales\ to\ Rest\ of\ the\ World \\ & \times E_t[Performance\ for\ Rest\ of\ the\ World] \end{aligned}$$

To compute our measures of expected performance across the geographic regions we use Consensus Economics (CE) GDP growth forecast data. We calculate the one year ahead GDP growth forecast for each country as the weighted average of the mean forecasts for the first and second years, using *(13-m)/12* as the weight for the first year forecast, where *m* is the forecast month in the calendar year. For example, in October 2010, the mean US GDP growth forecasts for 2010 and 2011 are 2.91% and 2.75%, respectively. The one year ahead GDP growth forecast in October 2010 is calculated as $\frac{3}{12} \times (2.91\%) + \frac{9}{12} \times 2.75\% = 2.79\%$.

For regions that comprise multiple countries, we assume that each company's operations across countries are directly proportional to the relative GDPs across these countries. For example, to compute the expected performance for Europe as of August 2010 (i.e., $E_t[Performance\ for\ Europe]$) we:

1) Calculate the total 2009 GDP of European countries using GDP data from IMF World Economic Outlook Databases (http://www.imf.org/external/ns/cs.aspx?id=28).

2) Calculate the GDP percentage for each of the 28 countries in Europe.

Country	GDP percentage	Country	GDP percentage
Austria	0.020	Lithuania	0.002
Belgium	0.025	Netherlands	0.042
Bulgaria	0.003	Norway	0.020
Czech Republic	0.010	Poland	0.023
Denmark	0.016	Portugal	0.013
Estonia	0.001	Romania	0.009
Finland	0.013	Russian Federation	0.065
France	0.140	Slovakia	0.005
Germany	0.176	Slovenia	0.003
Greece	0.017	Spain	0.078
Hungary	0.007	Sweden	0.022
Ireland	0.012	Switzerland	0.026

Italy	0.113	United Kingdom	0.116
Latvia	0.001	Ukraine	0.007

3) $E_t[Performance\ for\ Europe]$, as of August 2010, is then calculated as the sum of the individual country level one year ahead GDP forecast, as described above, multiplied by the GDP percentages in the above table.

$E_t[Performance\ for\ Asia]$ and $E_t[Performance\ for\ North\ America]$ are calculated similarly. To calculate $E_t[Performance\ for\ rest\ of\ the\ World]$, we assume that the World consists of the 184 countries with GDP data from IMF World Economic Outlook Databases. We first identify the countries included in Rest of the World by removing countries in Europe, Asia, and North America. We then apply the procedure in Step 2) above to calculate $E_t[Performance\ for\ rest\ of\ the\ World]$.

Appendix II: Variable definitions

Variable	Description
AF_RNOA	Analysts' forecast of one year ahead *RNOA*, computed from median EPS forecast at the beginning of the year from I/B/E/S summary file. We first multiply the EPS forecasts with the number of shares outstanding to obtain earnings forecasts. We subtract estimated financial income (net financial assets multiplied with risk free rate) from the forecasted earnings to obtain forecast of operating income. AF_RNOA is then calculated as the forecasted operating income divided by the sum of the closing net operating assets and half of the forecasted operating income.
$Assets$	Total assets as at the end of the fiscal year (in USD millions).
BTM	Book-to-market ratio computed as the ratio of common equity to equity market capitalization, both measured at the fiscal period end date.
D_Div	An indicator variable equal to one for firms that pay dividends and zero otherwise.
Div_Yield	Dividends per share divided by stock prices.
D_Loss	An indicator variable equal to one for firms that have negative earnings before extraordinary items and zero otherwise.
D_MACRO_t	The product of a firm's geographic sales exposure to its home country and the one year ahead Consensus Economics GDP growth forecast of the home country.
$DNOA$	The change of net operating assets, scaled by total assets, where net operating assets are calculated as operating assets (total assets less the sum of cash and investments) minus operating liabilities (total liability minus total debt).
$DOMESTIC$	An indicator variable equal to one for firms that have no foreign sales and zero otherwise.
F_MACRO_t	The sum product of a firm's geographic sales exposure to foreign countries and the one year ahead Consensus Economics GDP growth forecast of the respective foreign countries. In return tests, the geographic sales data are extracted from the most recent annual report prior to month t (ensuring at least a four month gap between the end of the fiscal year and month t).
HML	Monthly mimicking global (developed market) factor portfolio return to the value factor, obtained from Ken French's website.

$MACRO_t$	The sum product of a firm's geographic sales exposure to a country and the one year ahead Consensus Economics GDP growth forecast of the country. In return tests, the geographic sales data are extracted from the most recent annual report prior to month t (ensuring at least a four month gap between the end of the fiscal year and month t). See Section 2.3 for details and Appendix I for an example. $MACRO_t$ = D_MACRO_t + F_MACRO_t .
$MACRO_t^{RET}$	The sum product of a firm's geographic sales exposure to a country and the most recent six month return for that country. We construct country level returns by value weighting returns for all firms domiciled in that country. In return tests, the geographic sales data are extracted from the most recent annual report prior to month t (ensuring at least a four month gap between the end of the fiscal year and month t).
$MACRO_t^{IBES}$	The sum product of a firm's geographic sales exposure to a country and the expected country level earnings growth. Country level earnings growth is computed from firm level earnings forecasts from I/B/E/S. We compute this for each month for each country, and use the monthly change as our basis for identifying expected country level earnings growth. In return tests, the geographic sales data are extracted from the most recent annual report prior to month t (ensuring at least a four month gap between the end of the fiscal year and month t).
$MCAP$	Equity market capitalization (in USD millions).
MKT	Monthly excess (to U.S. 1 month T-Bill rate) global market return, obtained from Ken French's website.
MOM	Average global (developed market) return on the two high prior return portfolios minus the average return on the two low prior return portfolios, obtained from Ken French's website.
$Naive\_MACRO\_Home_t$	One year ahead Consensus Economics real GDP growth forecast for the home country.
$Naive\_F\_MACRO_t$	The product of a firm's geographic sales exposure to all foreign countries and the GDP weighted one year ahead Consensus Economics real GDP growth forecasts across all foreign countries. In return tests, the geographic sales data are extracted from the most recent annual report prior to month t (ensuring at least a four month gap between the end of the fiscal year and month t).
NOA	Net operating assets is the difference between operating assets and operating liabilities. Operating assets is total assets minus cash and investments. Operating liabilities is the difference between total liabilities and the sum of short and long term debt.

$Operating\ Income$	Operating income is measured with income before extraordinary and special items on an after tax basis, excluding interest expense and financial income.
$RNOA$	Return on net operating assets (NOA) is computed as the ratio (in percentage) of operating income to average net operating assets.
$Sales$	Total sales for the fiscal year (in USD millions).
$Size$	Natural logarithm of equity market capitalization (in USD millions).
SMB	Monthly mimicking global (developed market) factor portfolio return to the size factor, obtained from Ken French's website.

Table 1
Summary Statistics

Panel A: GDP Growth Forecast by Country

Country	# Firm-Years	% Sample	Mean	Std. Dev.	Inter-Quartile Range
Australia	7,419	3.74	3.1	0.76	0.53
Austria	785	0.40	1.8	1.03	0.79
Belgium	1,157	0.58	1.71	1.04	0.82
Brazil	2,480	1.25	3.73	1.88	2.36
Canada	6,786	3.42	2.51	0.99	0.66
China	12,256	6.18	8.47	0.98	1.71
Denmark	1,654	0.83	1.68	0.91	0.55
Finland	1,268	0.64	2.4	1.38	0.88
France	6,600	3.33	1.73	1.01	0.66
Germany	6,711	3.38	1.46	1.18	1.03
Greece	2,673	1.35	2.14	2.38	1.37
Hong Kong	7,391	3.73	3.76	1.94	2.35
India	10,100	5.09	6.91	1	1.6
Ireland	456	0.23	3.44	3.14	3.93
Israel	486	0.25	2.99	1.19	1.85
Italy	2,471	1.25	1.15	1.13	0.78
Japan	38,564	19.45	1.03	1.4	1.49
Korea, Republic	8,181	4.13	4.49	1.56	0.79
Malaysia	7,937	4.00	4.75	1.6	1.21
Mexico	1,064	0.54	3.1	1.49	0.87
Netherlands	1,513	0.76	1.68	1.27	1.32
New Zealand	996	0.50	2.41	0.91	0.81
Norway	1,463	0.74	2.18	1.02	1.47
Portugal	505	0.25	1.17	1.57	1.12
Russia	267	0.13	4.12	2.6	2.33
Singapore	4,512	2.28	4.48	2.24	1.91
South Africa	2,745	1.38	3.37	0.98	1.07
Spain	1,416	0.71	2.05	1.59	2.18
Sweden	2,933	1.48	2.45	1.26	1.23
Switzerland	2,302	1.16	1.54	0.82	0.76
Thailand	4,154	2.09	4.14	1.59	1.03
United Kingdom	14,712	7.42	1.85	1.18	0.84
United States	34,109	17.20	2.61	1.28	1.08
Other	217	0.11	3.85	2.15	2.12
Full Sample	**198,315**	**100**	**3.22**	**2.30**	**2.68**

Panel B: Firm Characteristics

	N	Mean	Std. Dev.	P25	P50	P75
$Sales$	198,315	1,035.40	3,199.12	34.28	128.57	501.61
$Assets$	198,315	1,893.28	6,651.31	54.26	175.74	670.76
$MCAP$	198,315	1,006.87	3247.60	28.20	104.46	447.11
$Size$	198,315	4.783	2.039	3.339	4.649	6.103
BTM	198,315	1.069	1.028	0.414	0.763	1.330
$RNOA$	198,315	6.373	31.295	1.362	7.824	17.142
$DNOA$	198,315	0.052	0.189	-0.030	0.027	0.111
D_Loss	198,315	0.247	0.432	0.000	0.000	0.000
D_Div	198,315	0.572	0.494	0.000	1.000	1.000
$DivYield$	198,315	0.020	0.032	0.000	0.008	0.027
$DOMESTIC$	198,315	0.686	0.464	0.000	1.000	1.000
$MACRO$	198,315	2.994	2.549	1.542	2.653	4.064
AF_RNOA	86,874	14.282	18.489	3.778	9.082	18.135
D_MACRO	25,266	0.445	0.674	0.000	0.183	0.742
F_MACRO	25,266	2.291	1.983	1.180	1.949	2.883

Panel C: Industry Distribution (Fama-French 12 Industries)

	Number of Firm-Year	Percentage
Consumer Non-Durables	18,257	9.21
Consumer Durables	7,128	3.59
Manufacturing	29,385	14.82
Oil, Gas, and Coal Extraction and Products	5,407	2.73
Chemicals and Allied Products	7,773	3.92
Business Equipment	28,326	14.28
Telephone and Television Transmission	4,248	2.14
Utilities	4,369	2.20
Wholesale, Retail, and Some Services	20,223	10.20
Healthcare, Medical Equipment, and Drugs	10,441	5.26
Money and Finance	29,631	14.94
Other	33,127	16.70
Total	198,315	100

This table reports summary statistics for the sample of firm-years used in the fundamental forecast tests in Table 2 for the sample period 1998-2010. Panel A reports the distribution of countries of domicile and the time series distribution of Consensus Economics real GDP growth forecasts for each country. These forecasts are the weighted average of the mean forecast for the first and second years such that the combined forecast always has a twelve month horizon. Panel B reports firm characteristics. All variables are defined in Appendix II. D_MACRO and F_MACRO are reported for firm-years with at least 50% foreign sales, consistent with the tests in Table 3. Panel C presents industry distribution. The industry classification follows the twelve primary industry groupings identified in Fama-French (1997).

Table 2
Macroeconomic Information and Future Firm Performance

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t + \beta_2 RNOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 DNOA_t + \beta_6 D\_Loss_t + \beta_7 D\_Div_t + \beta_8 Div\_Yield_t + \beta_9 AF\_RNOA_t + e_{t+1} \quad (1)$$

Panel A: $MACRO_t$ and Future Firm Performance: Not Controlling for Analyst Forecasts

	Full Sample	Domestic Firms	Non-Domestic Firms
	1	2	3
$Intercept$	-4.623	-4.680	-4.393
	(-3.24)	*(-3.31)*	*(-2.94)*
$MACRO$	0.270	0.313	0.202
	(2.33)	*(2.53)*	*(1.60)*
$RNOA$	0.693	0.693	0.699
	(21.33)	*(20.90)*	*(21.41)*
BTM	-0.255	-0.218	-0.404
	(-1.42)	*(-1.33)*	*(-1.60)*
$Size$	0.554	0.472	0.629
	(8.43)	*(6.23)*	*(8.29)*
$DNOA$	-8.244	-7.301	-10.320
	(-6.89)	*(-5.71)*	*(-6.07)*
D_Loss	1.048	1.002	1.164
	(1.29)	*(1.20)*	*(1.36)*
D_Div	4.318	4.338	4.388
	(10.07)	*(10.06)*	*(8.17)*
Div_Yield	3.803	4.338	-5.147
	(1.17)	*(2.24)*	*(-1.23)*
Adj. R-square	0.503	0.506	0.511
No. of Obs.	198,315	135,974	62,341

Panel B: $MACRO_t$ and Future Firm Performance: Controlling for Analyst Forecasts

	Full Sample	Domestic Firms	Non-Domestic Firms
	1	2	3
$MACRO$	0.228	0.262	0.141
	(2.00)	*(2.35)*	*(0.86)*
AF_RNOA	0.017	0.007	0.030
	(0.57)	*(0.27)*	*(0.77)*
Controls	Yes	Yes	Yes
Adj. R-square	0.611	0.651	0.562
No. of Obs.	86,874	48,594	38,918

This table reports the predictive power of $MACRO$ for one year ahead returns on net operating assets ($RNOA$). The reported numbers are estimated coefficients and t-statistics (in parentheses). We present three samples: the whole sample, domestic firms (no foreign sales), and non-domestic firms (with positive foreign sales). $RNOA$ is operating income scaled by average net operating assets. AF_RNOA is analysts' forecast of one year ahead $RNOA$ which is computed from analysts' forecasts of one year ahead EPS. All regressions are pooled regressions with standard errors clustered at firm and year levels. All variables are defined in Appendix II.

Table 3
Foreign Macroeconomic Information and Future Firm Performance

Panel A: $MACRO_t$ vs. $Naive\_MACRO\_Home_t$

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t + \beta_2 Naive\_MACRO\_Home_t + \beta_3 RNOA_t + \beta_4 BTM_t + \beta_5 Size_t + \beta_6 DNOA_t + \beta_7 D\_Loss_t + \beta_8 D\_Div_t + \beta_9 Div\_Yield_t + e_{t+1} \quad (1)$$

	1	2	3
$MACRO$	0.241		0.264
	(1.88)		*(2.14)*
$Naive\_MACRO\_Home$		0.108	-0.043
		(0.53)	*(-0.19)*
Adj. R-square	0.497	0.496	0.497
No. of Obs.	25,266	25,266	25,266

	J Test		Cox Test	
	t-statistic	p-value	z-statistic	p-value
H0: Model 1, H1: Model 2	-0.48	0.628	0.43	0.333
H0: Model 2, H1: Model 1	3.13	0.002	-8.21	0.000

Panel B: F_MACRO_t vs. $Naive\_F\_MACRO_t$

$$RNOA_{t+1} = \alpha + \beta_1 D\_MACRO_t + \beta_2 F\_MACRO_t + \beta_3 Naive\_F\_MACRO_t + \beta_4 RNOA_t + \beta_5 BTM_t + \beta_6 Size_t + \beta_7 DNOA_t + \beta_8 D\_Loss_t + \beta_9 D\_Div_t + \beta_{10} Div\_Yield_t + e_{t+1} \quad (1)$$

	1	2	3
D_MACRO	0.295	0.246	0.217
	(0.95)	*(0.70)*	*(0.62)*
F_MACRO	0.247		0.391
	(1.92)		*(3.23)*
$Naive\_F\_MACRO$		-0.231	-0.618
		(-0.44)	*(-1.10)*
Adj. R-square	0.495	0.494	0.495
No. of Obs.	25,266	25,266	25,266

	J Test		Cox Test	
	t-statistic	p-value	z-statistic	p-value
H0: Model 1, H1: Model 2	3.49	0.000	0.09	0.465
H0: Model 2, H1: Model 1	4.55	0.000	-8.09	0.000

This table reports the predictive power of foreign country exposures for one year ahead $RNOA$ in the sample of firm-years with significant foreign sales (greater than 50%). In Panel A, the predictive power of $MACRO_t$ is compared to that of $Naive\_MACRO\_Home_t$, which is CE real GDP growth forecast for the home country, ignoring all information in the geographic segment sales disclosures. In Panel B, $MACRO_t$ is decomposed into domestic $MACRO$ (D_MACRO_t) and foreign $MACRO$ (F_MACRO_t). D_MACRO_t is product of the home country sales and CE real GDP growth forecast of the home country; F_MACRO_t is the sum product of individual foreign country sales and CE real GDP growth forecasts of individual foreign countries. The predictive power of F_MACRO_t is then compared to that of $Naive\_F\_MACRO_t$, which is the product of the ratio of foreign sales to total sales and weighted average real GDP growth forecasts across all foreign countries. This measure includes some, but not all of, the information from the geographic segment sales disclosures. $RNOA$ is operating income scaled by average net operating assets. All regressions are pooled regressions with standard errors clustered at firm and year levels. Test statistics of Davidson and Mackinnon's (1981) J test and Cox test (Cox 1961, 1962) for comparing the predictive powers are provided at the bottom of each panel. All variables are defined in Appendix II.

Table 4
Portfolio Return Analyses

$$HEDGE_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + e_t \quad (2)$$

	Full Sample		Domestic Firms		Non-Domestic Firms	
	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor
$Intercept$	0.0142	0.0140	0.0183	0.0185	0.0073	0.0068
	(3.36)	*(3.26)*	*(3.29)*	*(3.27)*	*(2.61)*	*(2.49)*
MKT	0.0025	0.0026	0.0039	0.0039	0.0011	0.0017
	(2.95)	*(2.91)*	*(3.52)*	*(3.23)*	*(2.08)*	*(3.02)*
SMB	0.0001	-0.0002	-0.0009	-0.0007	0.0018	0.0010
	(0.05)	*(-0.09)*	*(-0.37)*	*(-0.29)*	*(1.25)*	*(0.66)*
HML	-0.0029	-0.0027	-0.0047	-0.0048	-0.0047	-0.0045
	(-1.93)	*(-1.76)*	*(-2.41)*	*(-2.38)*	*(-4.41)*	*(-4.40)*
MOM		0.0004		-0.0002		0.0017
		(0.44)		*(-0.20)*		*(2.70)*
Adj. R^2	0.095	0.096	0.112	0.106	0.165	0.202
Sharpe Ratio	0.96	0.93	0.94	0.93	0.74	0.71
Average # of Stocks in Hedge Portfolio	7,770	7,770	5,237	5,237	2,510	2,510
% of Positive Hedge Return	64%	64%	60%	60%	58%	58%

This table reports abnormal returns of hedge portfolios based on $MACRO_t$ for three samples: the whole sample, domestic firms (no foreign sales), and non-domestic firms (with positive foreign sales). For each of the 148 months in the sample period, stocks are sorted into five equal groups based on $MACRO_t$. The portfolio returns are value weighted (where the weights are market capitalization, in USD). The $HEDGE$ return is the difference between the average portfolio returns across extreme quintiles for the following month. The Sharpe ratio is calculated as the ratio of the annualized return (as measured by the intercept) relative to the annualized standard deviation, following Lewellen (2010). The remaining variables are defined in Appendix II.

Table 5
Results without Using FGRE data

Panel A: Future Firm Profitability

	Full Sample	Domestic Firms	Non-Domestic Firms
	1	2	
$MACRO$	0.269	0.313	0.178
	(2.33)	*(2.53)*	*(1.26)*
Adj. R-square	0.503	0.506	0.511
No. of Obs.	198,315	135,974	62,341

Panel B: Future Stock Returns

	Full Sample		Domestic Firms		Non-Domestic Firms	
	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor
$Intercept$	0.0135	0.0133	0.0183	0.0185	0.0061	0.0057
	(3.19)	*(3.10)*	*(3.29)*	*(3.27)*	*(2.12)*	*(2.00)*
Adj. R^2	0.080	0.075	0.112	0.106	0.159	0.184
Sharpe Ratio	0.91	0.88	0.94	0.93	0.60	0.57
Average # of Stocks in Hedge Portfolio	7,770	7,770	5,237	5,237	2,510	2,510
% of Positive Hedge Return	62%	62%	60%	60%	55%	55%

This table replicates the results in Table 2, Panel A and Table 4 using the geographic segment data from Compustat and FactSet, without using the data from FactSet Geographic Revenue Exposure (FGRE). To conserve table space, we only report the regression coefficient of $MACRO$ from estimating equation (1) in Panel A and the intercept from estimating regression equation (2) in Panel B.

Table 6
Macroeconomic Information and Future Firm Performance: Time Series Partitions

Panel A: Future Firm Profitability

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t + \beta_2 RNOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 DNOA_t + \beta_6 D\_Loss_t + \beta_7 D\_Div_t + \beta_8 Div\_Yield_t + \beta_9 AF\_RNOA_t + e_{t+1} \quad (1)$$

	Mean of β_1		
	Full Sample	Domestic Firms	Non-Domestic Firms
Low Dispersion	0.184	0.254	0.106
	(1.22)	*(1.61)*	*(0.62)*
High Dispersion	0.574	0.693	0.423
	(5.14)	*(5.82)*	*(3.12)*
Difference	-0.390	-0.439	-0.318
	(-2.09)	*(-2.24)*	*(-1.47))*

Panel B: Future Stock Returns

	4-factor α		
	Full Sample	Domestic Firms	Non-Domestic Firms
Low Dispersion	-0.0004	-0.0004	-0.0006
	(-0.08)	*(-0.06)*	*(-0.17)*
High Dispersion	0.0222	0.0294	0.0086
	(3.30)	*(3.34)*	*(2.33)*
Difference	-0.0226	-0.0298	-0.0092
	(-2.66)	*(-2.65)*	*(-1.74)*

This table presents the results of the predictive powers of $MACRO_t$ with respect to future firm profitability and stock returns by partitioning the sample based on the cross-country dispersion in 12 month ahead GDP growth forecast. We present the results for three samples: the whole sample, domestic firms (no foreign sales), and non-domestic firms (with positive foreign sales). For each month, we compute the standard deviation of the country level GDP growth forecasts. In Panel A, β_1 is estimated annually across the low and high dispersion year groups separately, and we report the average values of β_1 across the two sub-periods. We estimate equation (1) annually using firms with the same fiscal year ends, requiring at least 1,000 observations in each regression. Because of this data requirement, we lose 18% (17%, 17%) of observations in the full sample (domestic firms sample, non-domestic firms sample). In Panel B, we calculate the 4-factor α as in Table 4 using months with low and high dispersions in GDP growth forecast. For the tests in Panel B, we use all observations in the full sample, domestic firms sample, and non-domestic firms sample. Numbers in parentheses are t-statistics.

Table 7
Macroeconomic Information and Future Performance: Cross Sectional Partitions

	Hedge Return	**Future Profitability**
	4-factor α	**Coefficient of $MACRO$**
Full Sample:	0.0140	0.270
	(3.26)	*(2.33)*
Firm Size (NYSE breakpoints)		
Small (71.3%)	**0.0200**	0.263
	(3.44)	*(1.90)*
Medium (17.9%)	0.0137	0.218
	(2.30)	*(2.45)*
Large (10.9%)	**0.0085**	0.217
	(2.20)	*(1.74)*
Analyst Following		
Low (26.0%)	**0.0169**	0.122
	(2.63)	(0.774)
Medium (17.3%)	0.0135	0.183
	(2.08)	(1.41)
High (19.6%)	**0.0083**	0.223
	(2.41)	*(2.06)*
MSCI Index Inclusion		
Constituents (8.0%)	0.0112	0.410
	(2.97)	*(3.21)*
Non-Constituents (92.0%)	0.0147	0.267
	(2.86)	*(2.23)*
Firm Complexity		
Complex (11.5%)	0.0072	0.177
	(2.03)	*(0.80)*
Simple (21.1%)	0.0044	0.151
	(1.32)	*(1.26)*
RNOA Forecast Improvement		
Improve (31.3%)	**0.0229**	**1.528**
	(4.07)	*(2.47)*
Not Improve (29.9%)	**0.0064**	**-0.975**
	(1.20)	*(-1.58)*

This table presents the results of the predictive powers of $MACRO_t$ with respect to future firm profitability and stock returns by partitioning the sample based on various firm characteristics. The percentage right after each subsample indicate the sample size relative to the full sample. The partition on analyst following is based on 62.9% of firm-months with analyst following. The partition on firm complexity is based on 32.6% firm-months with positive foreign sales. The partition on $RNOA$ forecast improvement is based on 61.2% of firm-months used in the out-of-sample forecasts. Sections 5.3 and 5.4 provide detailed descriptions of these sub-samples. In the first column we report the 4-factor α as in Table 4 using firm-months in the respective cross-sectional sub-sample for a given characteristic. In the second column we report β_1 from equation (1) estimated annually using firm-years in the respective cross-sectional sub-sample for a given characteristic. Numbers in parentheses are t-statistics. Bolded numbers indicate significant within partition differences.

Table 8
Macroeconomic Information and Future Firm Performance: Alternative $MACRO$ measures

Panel A: $MACRO_t$ and Future Profitability: Not Controlling for Analyst Forecasts

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t^{CE}(MACRO_t^{RET},\ MACRO_t^{IBES}) + \beta_2 RNOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 DNOA_t + \beta_6 D\_Loss_t + \beta_7 D\_Div_t + \beta_8 Div\_Yield_t + e_{t+1} \quad (1)$$

	Full Sample			Domestic Firms			Non-Domestic Firms		
	1	2	3	4	5	6	7	8	9
$MACRO^{CE}$	0.269			0.313			0.200		
	(2.33)			*(2.53)*			*(1.59)*		
$MACRO^{RET}$		0.227			0.193			0.364	
		(2.32)			*(2.12)*			*(2.65)*	
$MACRO^{IBES}$			0.074			0.042			0.239
			(1.66)			*(0.99)*			*(3.12)*
Adj. R^2	0.504	0.504	0.503	0.506	0.506	0.506	0.511	0.511	0.511
No. Obs.	198,286	198,286	198,286	135,965	135,965	135,965	62,326	62,326	62,326

Panel B: $MACRO_t$ and Future Profitability: Controlling Analyst Forecasts

$$RNOA_{t+1} = \alpha + \beta_1 MACRO_t^{CE}(MACRO_t^{RET},\ MACRO_t^{IBES}) + \beta_2 RNOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 DNOA_t + \beta_6 D\_Loss_t + \beta_7 D\_Div_t + \beta_8 Div\_Yield_t + \beta_9 AF\_RNOA_t + e_{t+1} \quad (1)$$

	Full Sample			Domestic Firms			Non-Domestic Firms		
	1	2	3	4	5	6	7	8	9
$MACRO^{CE}$	0.228			0.262			0.141		
	(2.00)			*(2.35)*			*(0.86)*		
$MACRO^{RET}$		0.227			0.153			0.380	
		(1.93)			*(1.45)*			*(2.46)*	
$MACRO^{IBES}$			0.092			0.005			0.303
			(1.96)			*(0.13)*			*(3.75)*
AF_RNOA	0.017	0.020	0.021	0.007	0.012	0.013	0.030	0.032	0.033
	(0.57)	*(0.65)*	*(0.704)*	*(0.27)*	*(0.27)*	*(0.50)*	*(0.77)*	*(0.81)*	*(0.85)*
Adj. R^2	0.611	0.611	0.611	0.651	0.651	0.651	0.562	0.562	0.562
No. Obs.	86,874	86,874	86,874	48,594	48,594	48,594	38,918	38,918	38,918

Panel C: $MACRO_t$ and Future Stock Returns

	4-factor α		
	Full Sample	Domestic Firms	Non-Domestic Firms
$MACRO^{CE}$	0.0131	0.0176	0.0068
	(2.99)	*(3.02)*	*(2.49)*
$MACRO^{RET}$	0.0087	0.0118	0.0063
	(2.33)	*(2.26)*	*(2.29)*
$MACRO^{IBES}$	0.0029	0.0083	-0.0010
	(0.65)	*(1.39)*	*(-0.23)*

This table presents the results of the predictive powers of alternative measures of macroeconomic information with respect to future firm profitability and stock returns in three samples: the whole sample, domestic firms (no foreign sales), and non-domestic firms (with positive foreign sales). $MACRO_t^{CE}$ is $MACRO_t$ in Tables 2-4. $MACRO_t^{RET}$ and $MACRO_t^{IBES}$ are alternative measures of $MACRO_t$. We compute $MACRO_t^{RET}$ as the sum product of a firm's geographic sales exposure to a country and the weighted average of the most recent six month stock returns for that country. We construct country level returns by value weighting returns for all firms domiciled in that country. We compute $MACRO_t^{IBES}$ as the sum product of a firm's geographic sales exposure to a country and the expected country level earnings growth. For each month we compute country level earnings forecasts from firm level earnings forecasts from I/B/E/S for each country, and use the monthly change to measure expected country level earnings growth. For the stock return tests we sort all stocks into five equal sized groups each month based on the respective measure of $MACRO_t$. The portfolio returns are value weighted (the weights are market capitalization, in USD). The $HEDGE$ return is the difference in total returns between the average portfolio returns across extreme quintiles for the following month. The 4-factor α is the intercept from the 4-factor model used in equation (2). Numbers in parentheses are t-statistics. The sample sizes in this table are slightly smaller than those reported in tables 2 and 4 as we require all three measures of expected county level performance to be available in this table.