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 324,982 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 out of sample forecasts for firm fundamentals and that this forecasting benefit is not incorporated into sell side analyst earnings forecasts in a timely manner. Finally, we provide some evidence that country exposures are able to improve explanatory power of characteristic regressions of equity returns and this return predictability does not appear to be explained by standard risk factors.

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

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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, the potential role for understanding the macroeconomic landscape is very 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. For example, the International Monetary Fund (IMF) notes that the composition of the top ten countries (in terms of percentage share of global GDP) has changed enormously since 1980. During the 1980s and 1990s, the relative importance of the largest ten countries remained relatively constant (e.g., US 25%, Japan 10%, Germany 6%, France 4%, Italy 4%, UK 4%). However, since the 1990s the relative importance across countries has changed significantly such that the IMF is now forecasting a very different landscape for 2016 (i.e., China 18%, US 17%, India 6%, Japan 5%, Germany 4%, Brazil 3%). These changes in country level economic development, coupled with the rise of integrated international labour, capital and product markets, mean that security valuation is likely to be more sensitive to changing expectations about relative country level performance. The potential usefulness of macroeconomic information from the perspective of security analysis and valuation is the open empirical question that we explore.

The set of possible macroeconomic variables to examine is large. Candidate measures include inflationary expectations, commodity prices, short term interest rates, interest rate term structure, currency movements, purchasing manager surveys, consumer sentiment, as well as traditional market data. Prior literature has attempted to impose some structure on this long list of (non-mutually exclusive) macroeconomic variables, typically via a principal component extraction across a large set of macroeconomic variables (see e.g., Stock and Watson 2004 for a good summary).

We follow in this tradition to reduce the dimensionality of the problem by limiting our focus in two respects. First, we consider only how each company is exposed to other countries. This is a natural choice given that operating and investing choices that span across countries is likely to be a primary mechanism by which macroeconomic factors affect firm performance. If all firms operated in the same country then dispersion in macroeconomic factors across countries would not be relevant. We identify country exposures via the geographic segment disclosures included in annual reports. Second, we rely on information external to the firm via country level forecasts. We use the forecasts of the OECD (Organization for Economic Cooperation and Development) as our primary measure of expected country level performance. The OECD publishes a composite leading indicator (CLI) for its member countries and six non-member countries: Brazil, China, India, Indonesia, Russia and South Africa. We then combine the known country exposures for each company with the OECD forecasts for each country to generate firm specific fundamental forecasts. We also use country level GDP growth forecasts from Consensus Economics in a similar manner and find very similar results.

It is not immediately obvious that country exposures will be useful in improving forecasts of firm fundamentals for several reasons. First, measurement error in the company to country exposure matrix will impede our identification of any information content. Given our primary measure of country exposures is geographic segment data, there is likely to be measurement error due to the subjective manner in which countries are disaggregated across companies and also due to the country exposures being primarily driven 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.[1] 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 same countries. While we use forecasts from the OECD in our primary analyses, and survey forecasts from Consensus Economics in supplementary analysis, we note that any errors in these forecasts will feed directly into our forecasts of firm fundamentals.

It is also not immediately obvious that country exposures will be useful to improve forecasts of sell-side analysts or stock returns for reasons in addition to the measurement error and compounded forecasting challenge described above. Specifically, analysts are likely to utilize macroeconomic information in their earnings forecasts, target prices and stock recommendations. Likewise, stock prices are likely to efficiently incorporate this information on a timely basis. However, the extent of geographic exposures for large multi-national companies and the challenges in systematically incorporating this information into firm specific forecasts, suggest it is an open empirical question as to whether country exposures and country forecasts are useful to improve forecasts of sell-side analysts or directly forecast stock returns.

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[1] It is worth noting that Collins (1976), Silhan (1983) and Roberts (1989) all 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 the exposure of revenues is more important for forecasting.

For a sample of 324,982 firm-years for US and non-US firms over the 1998-2010 time period, we find that combining country exposures with country level forecasts is able to improve forecasts of return on assets (ROA). The predictive power is evident in annual cross-sectional regressions that suggest a one standard deviation increase in relative country performance translates to an additional 40 basis points of ROA over the next four quarters. Further, we show that out of sample forecast accuracy improves when we incorporate information on country exposures. We also find that sell-side analyst earnings forecasts appear to be slow to incorporate this information. Specifically, we find that analyst revisions are associated with information contained in current country exposures and country level forecasts for the next 6 months.

Finally, we show some evidence that stock returns appear to incorporate the information in country exposures with a lag. This is supported in cross-sectional regressions of equity returns where the country exposures combined with country level forecasts are able to explain cross-sectional variation in equity returns for the next 6 months, after controlling for known determinants of equity returns (e.g., momentum, size, beta, earnings-to-price, and book-to-price). Further, time series tests based on portfolios formed using country exposures and country level forecasts achieve statistically significant Sharpe ratios that are not explained by standard risk factors. Our stock return results are concentrated in the smaller firms in our sample, as evidenced by stronger relations in equally-weighted cross-sectional regressions than in value-weighted cross-sectional regressions. The economic significance of the stock return predictability is limited. Portfolios that are formed on the basis of conditional sorts (i.e., first sorting on firm size and then within each size group sorting on the basis of macroeconomic exposures) only show statistically and economically significant Sharpe ratios for the next six months for the bottom three size quintiles.

The primary contribution of this paper is to introduce a simple framework to identify and exploit linkages between firm performance and potential macroeconomic drivers of that performance. Our approach is similar in spirit to Cohen and Frazzini (2008) who exploit explicit linkages between firms along the supply chain to improve forecasts of firm fundamentals and stock returns. The scope for future research in this area is significant. There is a significant body of new research in macroeconomics exploiting a variety of econometric techniques to optimally combine the wide set of macroeconomic variables available to investors (Stock and Watson, 2004). Linking these forecasts to firms via known exposures such as currency, commodity, interest rates and so on is likely to continue to be a fruitful area of research.

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 economic hypotheses. Section 3 describes our measures of country exposures and country forecasts that are used in our empirical tests. Section 4 presents our empirical analysis and section 5 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. Some classic papers include Penman (1991) and Fama and French (2000) where the focus is initially on documenting a strong mean reversion in profitability. Such 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, Whisenant and

Yohn, 2001 and Soliman 2008), (iii) earnings volatility (e.g., Dichev and Tang, 200X), (iv) domestic vs. foreign earnings (e.g., Thomas, 1999), and (v) the impact of accounting distortions attributable to conservative accounting practices (e.g., Penman and Zhang 2002).

A common feature of the majority of past research is that it 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 (a firm that has its operating and investing activity located in another country where transactions are conducted in foreign currencies is exposed to currency movement when translating foreign performance to reporting currency, as well as the risk of end customers changing their consumption behaviour in response to currency movements), (ii) commodity movements (a firm that uses certain commodities in its manufacturing process will have its costs directly affected by commodity price changes, but the net effect on firm profitability is ambiguous as the change in commodity prices itself can be attributable to forward views on aggregate consumption and investment behaviour), (iii) financial market variables such as aggregate credit spreads and sovereign yield curves (a firm that has exposure to 'growth' will generally benefit from low short term rates and low corporate credit spreads, but again the directional link to firm profitability may be hard to identify precisely because of general equilibrium considerations).

Rather than attempt to construct a general equilibrium model linking a set of primitive macroeconomic variables to firm profitability, we have deliberately reduced the focus of our empirical analysis to macroeconomic exposures that are both intuitive and measurable by the researcher. We recognize that 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 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 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 footprint of these two luxury good specialists is 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.

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

There is an old accounting literature exploring the potential forecasting benefit of industry (line of business) segment disclosure information. Pacter (1993) categorizes this literature into papers that explore the effect of industry segment data on (i) investor assessments of expected returns, and (ii) investor assessments of risk and cost of capital. The research linking industry segment data to investor expectations of future cash flows, earnings and dividends is most closely related to our analysis. The classic papers in this area are Collins (1975, 1976), Kinney (1971), and Foster (1975). Kinney (1971) shows that for a sample of 24 multi-segment companies, combining segment level sales and earnings data with simple predictors of industry performance (i.e., industry level shipment data from government surveys and extrapolations of historical industry level sales and earnings) is able to produce earnings forecasts superior to modified random walk models. Collins (1976) extends the work of Kinney (1971) and shows for a sample of 150 multi-segment firms that product-line revenue and profit disclosures combined with industry sales projections published in a variety of government sources provide significantly more accurate estimates of future entity level sales and earnings than do forecasts based solely on entity level data. In addition, Foster (1975) shows for a sample of 58 insurance companies that disaggregating earnings into components across underwriting business, long-term investment business, and short-term investment business is better able to explain contemporaneous changes in stock prices relative to aggregate earnings. Perhaps the most relevant prior paper is Collins (1975), who documents some evidence that segment level sales data is able to generate superior forecasts of future entity level earnings and in turn the resulting 'unexpected' earnings is associated with future stock returns for his sample of 150 multi-segment firms in 1968-1969, but not in 1970.

Balakrishnan, Harris and Sen (1990) extend the work on line-of-business segment data to consider geographic segment data. They examine whether geographic sales data for a sample of 89 firms in the 1979-1985 period helps improve forecasts of firm level profitability. Assuming perfect foresight with respect to foreign currency movements and GNP growth they find evidence of improved forecasting ability from incorporating geographic segment sales data. However, using forecasts of foreign currency movements and GNP growth they are unable to find reliable evidence of improved forecasting of firm fundamentals. Roberts (1989) finds stronger results for a sample of 78 UK companies over the 1981 to 1983 time period. Specifically, combining forecasts of GNP for each country with geographic segment sales data generates superior out of sample earnings forecasts compared to a firm level random walk model.

Collectively, these earlier papers suggest some evidence in support of improved forecasting ability from combining disaggregated sales and earnings information with external sources of macroeconomic data. It is an open empirical question as to whether the results of these earlier papers will hold for a large sample of firms, in more recent years, with a broader set of country level forecasts.

There have also been several recent attempts to link inflationary exposures to future analyst forecast errors and future stock returns (e.g., Chordia and Shivakumar, 2005 and Basu, Markov and Shivakumar 2010). However, a challenge with firm-specific inflationary exposures is measurement. Past research has tended to use either (i) *indirect* measures such as standardized unexpected earnings that are correlated with measures of inflation surprises, or (ii) direct *statistical* measures of sensitivities of firm level earnings changes on contemporaneous inflation surprises. While both measurement approaches have their limitations, Basu, Markov and Shivakumar (2010) provide some evidence that analyst forecast errors and future firm stock returns are predictable, for the next quarter, from combining firm specific estimates of inflation sensitivity and expectations on inflation. An alternative approach to incorporate inflation into forecasts of firm fundamentals and stock returns is described in Konchitchki (2011). He measures firm-specific unrealized inflation gains in the balance sheet due to historical cost accounting and shows that this measure is positively correlated with future profitability and stock returns.

In addition to the accounting literature mentioned above, there has been some research in finance and economics that links macro-economic exposures to firm level profitability. The closest paper we could find exploring the link between 'macro-economic' exposures and the cross section of security returns is Bartram and Bodnar (2011). For a sample of 4,404 firms across 37 countries for the time period 1994 to 2006 they estimate statistical betas (using 60 month rolling regressions) between monthly stock returns and monthly local to foreign currency returns. They then examine unconditional and conditional associations between these estimated betas and future realized returns. Not surprisingly, they find no unconditional relation, but significant conditional correlations. Specifically, they show that when conditioning the sample, *ex post*, on local currency appreciation or depreciation, they are able to explain variation in security returns given the historical stock return to reporting currency appreciation 'beta'. Our empirical analysis is different in three 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, Bartram and Bodnar (2011) examine only local to foreign exposures and make no attempt to incorporate variation in the mix of that foreign exposure. We exploit the full set of country exposures provided in the geographical segment disclosures. Third, and perhaps most importantly, we utilize forecasts of the expected performance of each country that a given company is exposed to. We are thus able to answer the question whether knowledge of macro-economic exposures is helpful in a predictive rather than purely descriptive sense.

There is also an extensive literature in financial economics that studies the link between macroeconomic state variables and equity returns (see e.g., Cochrane 2000 and 2010 for a summary). This literature, however, does not make any explicit attempt to link those macro variables to the firm level and exploit cross-sectional variation in exposures. Most of the asset pricing literature utilizing macroeconomic information does so indirectly by regressing time series returns of test portfolios (e.g., B/P, size etc.) on time series changes in macro variables, rather than forming the test portfolios on the firm level macroeconomic exposures directly. Examples include (i) Liew and Vassalou (2000) who show that the profitability of SMB and HML can be linked to future growth in GDP, (ii) Vassalou (2003) who shows that a news factor extracted from GDP growth can subsume the returns to test portfolios formed on the basis of book-to-price and firm size, and (iii) Li, Vassalou and Xing (2006) who show that sector level investment growth can explain much of the variation in SMB and HML portfolio returns. In contrast to this indirect use of macroeconomic information, our empirical analysis is motivated by a direct interest in the cross-sectional and time-varying exposures to macroeconomic variables, and utilizing forecasts of these macroeconomic variables in order to forecast firm-level fundamentals and stock returns.

2.3 Combining country exposures to form a firm level forecast

Once we have our measure of company to country exposures, we then need to incorporate a forward looking view of relative performance across the identified countries. The example of Burberry and Mulberry discussed above might suggest using a consumer sentiment type measure. However, consumer sentiment is but one part of the broader picture for the fortunes of a country. Our empirical strategy is to be as broad as possible in the selection of variables to identify. As discussed in the introduction, we use the composite leading indicator (CLI) country level forecasts provided by the OECD. In section 3.1, we describe the construction of the CLI measure, and our use of it, in greater detail. Our purpose here is to describe how we combine the company level geographic segment data with the country level OECD forecasts.

For each firm-year observation we disaggregate total sales into country level sales based on the geographic segment data extracted from the most recent annual report. We retain companies with a purely domestic footprint (i.e., those companies with zero foreign sales) because our empirical analysis is based on a global set of firms and retaining domestic firms increases the power of tests to exploit country level variation in expected profitability. 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 one has the strong view that Greece will outperform Germany, then holding all else equal, the 'best' portfolio exposure to express that view would be via Firm B, the purely domestic firm.

After identifying 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 such that they sum to one. We then compute a measure of expected country level performance for each county *c* at each point in time *t*, $E[Performance]_{c,t}$. To generate a company specific fundamental forecast we take the sum-product of $Sales_{i,t,c}$ with $E[Performance]_{c,t}$at each point in time. This results in a measure of expected fundamental performance attributable to changes in macroeconomic conditions which we label $SHOCK_{i,t}$. 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 $SHOCK_{i,t}$ for Mulberry's Group PLC is contained in Appendix I.

2.4 Our empirical tests

We conduct three sets of empirical analyses. First, we assess the relative (out-of-sample) performance of forecasts of firm fundamentals (return on assets) that include $SHOCK_{i,t}$. Second, we assess the ability of $SHOCK_{i,t}$ to forecast sell-side analysts' earnings revisions. To the extent that our measure is able to forecast analyst revisions, it is consistent with analysts failing to incorporate this information in a timely manner. Third, we assess the ability of $SHOCK_{i,t}$to identify relative value equity investment opportunities.

2.4.1 Firm fundamentals

The standard forecasting model for firm level profitability is a modified random walk that acknowledges profitability is mean reverting (at a different rate through time and across industries) and also exploits differences in expected earnings growth using firm size and book-to-price (e.g., Core, Guay and Rusticus, 2006 and Fama and French, 2005). Specifically, we run the following regression for each quarter (firm subscripts, i, dropped for the sake of brevity):

$$ROA_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 ROA_t + \beta_3 BTM_t + \beta_4 Size_t + e_{t+k} \quad (1)$$

Equation (1) is estimated for the next two years (i.e., $k=1$ *or* 2). ROA_{t+k} is return on assets computed as income before extraordinary items divided by average total assets, $SHOCK_t$

is as defined previously, ROA_t is return on assets for the previous twelve months, BTM_t is book-to-price measured as the book value of common equity divided by market capitalization using data available at the start of the period for which we examine future profitability, and $Size_t$ is the log of market capitalization (in USD to ensure cross-sectional comparability). We estimate this regression each year for the 12 sector groupings identified in Fama and French (1997). This ensures that we have sufficient sample size for each sector-year group. 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. Finally, we expect a positive coefficient for our primary variable of interest, $SHOCK_t$. 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.

Our forecasting analysis aims to utilize information contained in annual reports and information outside the annual report. Figure 1 illustrates the timing of our variable measurement for the estimation of equation (1). For simplicity we discuss a December year-end firm, but the timing convention carries over to all fiscal year ends. The timing of variable measurement for a forecast of profitability for the twelve month period ending December 31, 2011 [ROA_{t+12}] is as follows. First, our measure of lagged profitability, ROA_t, is for the twelve month period ended December 31, 2010. Second, our $SHOCK_t$ measure uses the geographic segment data from the *previous* fiscal year (i.e., December 31, 2009) to ensure that this information was known to the market. We then combine these geographic exposures with the

OECD CLI data for the last three months of the December 31, 2010 fiscal year. Third, BTM_t is measured using book equity, B_t, and market capitalization, M_t, as of the year ended December 31, 2010. Fourth, $Size_t$ is measured using market capitalization as at December 31, 2010.

In addition to the descriptive analysis of firm profitability from estimating equation (1), we also evaluate the out-of-sample improvement in forecasts of firm profitability. We do this by estimating equation (1) for each sector grouping every year using an expanding window. This provides a set of sector-year coefficients, β_1 to β_4, which are then combined with the current realizations of the explanatory variables to generate a forecast of future profitability, $E^{with\,SHOCK}[ROA_{t+k}]$. To assess the out-of-sample importance of our primary variable of interest, $SHOCK_t$, we estimate a second forecast of firm level profitability that excludes that variable, $E^{without\,SHOCK}[ROA_{t+k}]$. We then compare the relative accuracy of these two forecasts with the actual future profitability, ROA_{t+k}. The resulting errors are defined as follows:

$$ERROR^{with\,SHOCK} = \left|E^{with\,SHOCK}[ROA_{t+k}] - ROA_{t+k}\right| \qquad (2a)$$

$$ERROR^{without\,SHOCK} = \left|E^{without\,SHOCK}[ROA_{t+k}] - ROA_{t+k}\right| \qquad (2b)$$

We compute standard tests of differences in median across these errors to assess the predictive accuracy of our primary variable, $SHOCK_t$.

2.4.2 Sell-side analyst earnings forecasts

We next examine whether sell-side analysts efficiently incorporate information about company level geographic exposures and country level performance into their firm level earnings forecasts. There are several empirical approaches that could be used. First, we could report associations between our $\mathrm{SHOCK_t}$ measure and future analyst forecast errors as done in Bradshaw, Richardson or Sloan (2001). Second, we could examine directly the speed with which analysts incorporate the information contained in $\mathrm{SHOCK_t}$ into their firm level earnings forecasts. We have adopted this second approach. Specifically, we estimate the following regressions every month (again firm subscripts, i, dropped for the sake of brevity):

$$Revision_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 Revision_{t+k-1} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + e_{t+k} \tag{3a}$$

$$Revision_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 Revision_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + e_{t+k} \tag{3b}$$

Equations (3a) and (3b) are estimated for the next twelve months (i.e., k = 1 to 12). $Revision_{t+k}$ is the monthly revision in consensus sell-side analyst revisions. To ensure cross-sectional comparability of sell-side analyst earnings forecasts across firms with different fiscal year ends, we first take a calendar weighted average of one year ahead, $E[EPS1_{i,t}]$, and two-year ahead earnings forecasts, $E[EPS2_{i,t}]$, where the weight is a linear function of the number of months to the end of the fiscal year, M. We label the resulting twelve month ahead forecast: $E[EPS12M_{i,t}]$. The consequence of this choice is that our resulting earnings forecast is twelve months ahead for *all* firms. Finally, we compute $Revision_{t+k}$ as:

$$Revision_{i,t+k} = \ln \frac{E[EPS12M_{i,t+k}]}{E[EPS12M_{i,t+k-1}]} \tag{4}$$

Given that we use the natural logarithm operator we restrict our firms to those where the calendar weighted forecasts across both months are strictly positive.[2] Prior literature has shown that analyst forecast revisions are highly serially correlated (e.g., Hughes, Liu and Su, 2008). We therefore expect β_2 to be positive. BTM_t is as defined in section 2.4.1, we just update it to use information from the recent fiscal period prior to that month. NI/P_t is the ratio of net income before extraordinary items to market capitalization at the start of the month. We expect both β_3 and β_4 to be negative, as firms with high expectations of earnings growth should, on average, deliver that earnings growth (and changing expectations of growth). $Momentum_t$ is the recent six month stock return. We include this variable as prior research has shown that sell side analyst forecasts reflect expectations embedded in stock price with a lag (e.g., Hughes, Liu and Su, 2008). Consistent with prior research we expect β_5 to be positive. Finally, we expect β_1 to be positive if analysts are slow to incorporate information about company level geographic exposures and country level performance into their firm level earnings forecasts.

The difference between equations (3a) and (3b) is the period over which the lagged analyst revision is measured. In equation (3a) we are looking at the analyst revision in the *(t+k-1)*th month. This is a conservative research design choice to help identify when, or even if at all, sell side analysts incorporate information contained in $SHOCK_t$ into their earnings forecasts. In equation (3b) we do not update the analyst revision control variable as we move the horizon of the regression forward each month. It is also important to note the risk of 'throwing the baby out with the bath water' in equations (3a) and (3b). We have included market price via two variables,

[2] In unreported results we have measured $Revision_{t+k}$ using firms with positive *and* negative twelve month ahead earnings forecasts as follows: $Revision_{i,t+k} = \frac{E[EPS12M_{i,t+k}]-E[EPS12M_{i,t+k-1}]}{(|EPS12M_{i,t+k}|+|EPS12M_{i,t+k-1}|)/2}$. Our inferences are unchanged with this alternative measure.

BTM_t and $Momentum_t$. To the extent that stock prices have efficiently incorporated all information into price, then any predictive content of other information will be reduced.

Figure 2 illustrates the timing of our variable measurement for the estimation of equation (3a) and (3b). The timing of variable measurement for a forecast of analyst revisions six months, $Revision_{t+6}$, starting at June, 2011 (month *t*) is as follows. First, $Revision_{t+6}$ is for December 2011. Second, our measure of lagged revisions is different across equation (3a) and (3b). For equation (3a) our measure of lagged revision, $Revision_{t+5}$, corresponds to November 2011. For equation (3b) our measure of lagged revision, $Revision_t$, corresponds to June 2011. Third, our $SHOCK_t$ measure uses the geographic segment data from the *previous* fiscal year (e.g., December 31, 2010) to ensure that this information was known to the market. We then combine these geographic exposures with the OECD CLI data for three months immediately preceding month t (i.e., April to June 2011). Fourth, BTM_t and NI/P_t are measured using book equity, B_t, and net income before extraordinary items, NI_t, from the most recent fiscal period ended no later than March 31, 2011, and market capitalization is chosen for that respective fiscal period end date. Fifth, $Momentum_t$ is measured for the six month period from December 2010 to May 2011.

2.4.3 Stock returns

Our final set of empirical analyses examines the relation between $SHOCK_t$ and future stock returns. We employ standard cross-sectional characteristic regressions and 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.

For our cross sectional characteristic tests we run the following regression every month (again firm subscripts, i, dropped for the sake of brevity):

$$RET_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 BTM_t + \beta_3 NI/P_t + \beta_4 Size_t + \beta_5 Beta_t + \beta_6 RET_t + \\ + \beta_7 Momentum_t + e_{t+k} \tag{5}$$

Equation (5) is estimated for the next six months (i.e., k = 1 to 6). To simplify the interpretation of the results, we examine each month separately (i.e., the stock returns, RET_t, are not cumulated across K months, but instead focus on the *Kth* month). The relevant test is whether $\beta_1 = 0$, and finding $\beta_1 > 0$ is consistent with stock returns failing to efficiently incorporate company level geographic exposures and country level performance. Of course, this inference is conditional on our ability to control for known risk attributes in the cross sectional regression model. Building on the work of Penman et al. (2012) we include a set of known attributes that are associated with risky earnings growth: NI/P_t and BTM_t. Given that NI/P_t is an estimate of the forward earnings yield which is a starting point for measuring expected returns, we expect β_3 to be positive (Ball, 1978). Given that BTM_t is known to be *positively* associated with risky future earnings growth, it is also a candidate measure of expected returns, and we therefore expect β_2 to be positive (Penman et al., 2012). We also include measures of firm size, $Size_t$, as defined in Section 2.4.1, and $Beta_t$, measured as the single factor CAPM beta, using monthly data from the last 60 months for each security (minimum of 24 months required). Consistent with Fama and French (1992), and others, we expect β_4 and β_5 to be positive. Finally, we include two measures of recent stock returns. First is Ret_t, which is the return for the most recent month. Given prior research has documented a short term reversal effect (e.g., Jegadeesh,

1990) we expect β_6 to be negative. Second is $Momentum_t$, which is as defined in section 2.4.2. As prior research has shown a continuation in stock returns over the medium term, we expect the coefficient on $Momentum_t$, β_7 to be positive.

We estimate equation (5) three times for each cross-section and then report test statistics using the time series variation in the regression coefficients. Our three estimations cover different cross-sectional weighting schemes. First, we report equally weighted cross sectional regressions. Second, we report value weighted cross sectional regressions. This second approach allows us to assess the strength of any cross sectional relation across firm size. If the return result is attributable to smaller (and potentially less liquid and riskier) securities, this will manifest itself as weaker results in the second approach. Third, we report risk weighted cross-sectional regressions. This weighting scheme is most consistent with the returns experienced by a risk-aware investor. In the standard mean-variance portfolio world, portfolio weights are directly proportional to expected returns and inversely proportional to expected risk. A key driver of 'risk' at the portfolio level is the volatility of idiosyncratic returns of a given security. This is because for these securities it is harder to identify an optimal hedging portfolio (see e.g., Pontiff, 2006). Thus, all else equal, portfolio weights are inversely proportional to idiosyncratic risk. We measure idiosyncratic risk as the standard deviation of historical residual monthly returns (using a single market factor model over the last 24 months). This third weighting scheme allows us to assess the ex-ante impact of risk on the strength of any relation between $SHOCK_t$ and future stock returns.

For our portfolio level analyses we conduct two sets of tests. First, following the suggestion of Fama and French (2008) and Lewellen (2010), we sort each cross-section into five quintiles based on market capitalization, $MCAP$. We then sort firms within each $MCAP$ based on$SHOCK_t$. This allows us to quantify the relation between $SHOCK_t$ and future returns holding firm size constant. A key benefit of this analysis is that allows inferences about economic significance. If a return result is only evident in the smallest securities then the economic significance of the relation is weak. Second, we perform standard time series regressions where the zero-cost hedge portfolio return, $HEDGE$, [a portfolio that is long (short) the securities in the top (bottom) quintile of $SHOCK_t$] is projected onto a set of changes in macro-economic state variables (e.g., Chen, Roll and Ross, 1986) and standard 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:

$$HEDGE_t = \alpha + \beta_1 dRP_t + \beta_2 dTS_t + \beta_3 dIP_t + \beta_4 MKT_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t + e_t \quad (6)$$

SMB, HML, and MOM are the factor-mimicking portfolio returns from Ken French's website. MKT is the excess return to the market portfolio. dRP is the change in corporate risk premium, measured as the change in the default spread (the difference between the Moody's Seasoned BAA Corporate Bond Yield and the 10 year Treasury constant maturity rate). dTS is the change in term structure, measured as the change in the difference between the 10 year Treasury constant maturity rate and the 2 year Treasury constant maturity rate. dIP is the percentage change in Industrial Production for the month. To the extent that factor-mimicking portfolio returns and the changes in our selected macro-economic state variables reflect compensation for changes in risk profile, we control for time series variation in risk in our analysis by including these variables. The relevant test is then whether the intercept in this time series regression is statistically different from zero.

One final point is worth noting: all of our empirical analysis of stock returns uses local currency returns. A consequence of this choice is that an investor who is long the resulting global portfolio is receiving foreign-currency excess returns on their foreign assets plus any return on foreign currencies. As Campbell, Serfaty-De Medeiros and Viceira, (2010) have noted, a risk-averse equity investor may prefer a partial currency hedge for the global portfolio. For the majority of our 1998-2010 time period that we examine there are some currencies, Australian dollar and Canadian dollar, which are *positively* correlated with local-currency equity returns and other currencies, Euro and Swiss Franc, which are *negatively* correlated with local-currency equity returns and other currencies. Therefore, there is a potential currency hedging benefit that could be incorporated into our analysis. In section 4.4.5 we discuss results where all stock returns are measured in USD.

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 capture the geographic exposure data from annual reports for firms with positive sales. We use the geographic sales data because the coverage of geographic earnings data is very limited. SFAS 131 'Disclosures about segments of an enterprise and related information' is the relevant standard in effect for US firms for our sample period. This standard requires companies to disclose detailed segment data using segment definitions based on a 'management approach'. This means that the identification of operating segments for the purpose of external financial reports needs to be consistent with the segment basis used by the firm's key operating decision makers. While this creates considerable flexibility in the identification of operating segments across firms (i.e., some firms may elect to identify operating segments on a product basis or an industry basis, while others may adopt a geographic basis), there is still a clear geographic disclosure requirement for US firms. Paragraph 38a of SFAS 131 states that if a company is not reporting geographic segments, it is required to provide information on revenues from external customers in foreign countries as well as domestic customers, and assets located in the country of domicile and those in foreign countries as a part of its enterprise-wide disclosures, unless it is impractical to do so. If revenues attributable to and assets located in a single foreign country are material, then they need to be reported separately.

In contrast, for non-US firms the relevant accounting standard for the period 1998 to 2008 was IAS14 (to the extent that firms followed international accounting standards). IAS14 required firms to make separate disclosures for geographic segments. A geographic segment is based on either where the enterprise's assets or customers are located (paragraph 13). Materiality thresholds determine the identification of a unique segment (typically 10 percent of the enterprise value). Unique geographies are identified until a 75 percent total threshold is met (paragraph 37), and the smaller segments are typically aggregated together (paragraph 36). Paragraphs 51 to 67 outline in considerable detail the required disclosures for each geographic segment. For fiscal years ending after 2009 IFRS8 is now in effect for firms following international standards (it replaced IAS14 effective January 1, 2009). IFRS8 is virtually identical to FAS131 in its segment disclosure requirements. Thus, for the majority of our sample period (1998 to 2009), it appears that the requirement for geographic disclosures for US firms is less detailed than that for non-US firms, at least for those non-US firms that were following international accounting standards. This suggests that there will be greater measurement error in the identification of geographic exposures for US firms relative to non-US firms, and our empirical results should be weaker for this set of firms. We return to this in section 4.4.2.

We are able to identify 324,982 unique firm-years, spanning 39 countries over the 1998 to 2010 period. Panel A of Table 1 provides a breakdown of the country headquarters for the firms included in our sample. US firms make up 31 percent of our sample. The next most important countries are Japan (15.8 percent), UK (7.5 percent), China (7.2 percent), India (5.4 percent), Australia (3.6 percent), Germany (3.5 percent) and France (3.3 percent). The average firm in our sample reports \$1.15 billion in annual sales, \$2.65 billion in total assets and has a market capitalization of \$1.25 billion. In contrast, the median firm in our sample reports \$109 million in annual sales, \$169 million in total assets and has a market capitalization of \$103 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. Clearly our sample contains some of the largest multi-national companies in the world, but also contains a large number of the smaller firms. In our later empirical analyses, especially for stock returns, we examine the largest firms separately from the smaller firms. The average (median) firm in our sample has a BTM value of 1.03 (0.71) and reports close to zero profitability. The sample covers the main economic sectors with the greatest concentration in money and finance (18.2 percent), business equipment (14.8 percent) and manufacturing (12.9 percent). Our industry groupings are based on Fama and French (1997).

We keep firm-years which do not have any foreign sales (i.e., 'domestic' firms). As reported in panel B of Table 1, our primary sample contains about 75 percent purely domestic firms. We retain these firm-year observations in our primary sample to enhance the power of empirical analysis as described in section 2.3. In later robustness analyses, we exclude the purely domestic firms from our analysis and note that our key inferences remain unchanged (see section 4.4.1).

The disclosure practices of firms related to segment disclosures varies considerably, both across 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 have used a standard tree structure that maps various geographic regions to member countries. For companies that report sales at an aggregated regional level we allocate these 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. Undoubtedly 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.

3.2 Country level forecasts

In our primary empirical analysis we use country level forecasts from the OECD (in supplementary tests reported in section 4.4.4 we use country level forecasts from Consensus

Economics). The OECD system of composite leading indicators (CLI) is designed to predict cycles in economic activity for OECD member countries. There are a large number of potential data series that could be used to predict these business cycles. Admittedly, the OECD CLIs are a 'black box' from our perspective. However a detailed description is provided in OECD (2008). Below we provide a brief overview of the choices the OECD has made to construct the CLI series that we use in our $SHOCK_t$ measure.

The OECD applies a set of pre-selection criteria to their component series where they prefer economic data series that are 'economically relevant' and have broad coverage (i.e., are available through time for most member countries). The OECD then processes the selected economic series to remove seasonal affects, treat outliers, and ensure comparability in periodicity across economic series that are provided at different frequencies. Finally, the OECD aggregates the processed economic series to create a final CLI score for each OECD member country. These CLI scores are updated monthly and are available at the OECD website (http://stats.oecd.org/Index.aspx?querytype=view&queryname=14001).

We have selected the trend restored CLI data series for the 39 member countries listed in Table 2. To ensure that the OECD CLI data was known to the market, we have imposed a 60 day delay when using the OECD data. For example, the OECD releases the August 2011 CLI data for member countries during October 2011. In our predictive regressions we only use the OECD CLI data for August 2011 from November 2011 onwards. To convert the CLI scores to a measure of changing expectations we first difference the trend restored CLI at the monthly frequency and then compute a short term momentum in these first differences as follows:

$$\frac{1}{2}(CLI_t - CLI_{t-1}) + \frac{1}{3}(CLI_{t-1} - CLI_{t-2}) + \frac{1}{6}(CLI_{t-2} - CLI_{t-3}) \quad (7)$$

This measure is thus a moving average of how the CLI for the respective country has changed over the most recent three month period. In unreported tests we have used alternative weighting schemes using monthly changes in the OECD CLI data over the last six and twelve months with very similar results. To ensure cross country comparability in this measure, we scale equation (7) by its own historical volatility using the last 24 months of data. This scaling choice is deliberate given our focus on forecasting future firm performance. If we have less confidence in the direction and magnitude of the forecast for a given country, we should optimally give it less weight in the aggregate forecast across countries. Table 2 reports the distribution of this measure across the 39 OECD member countries. Given that our time period spans the 1998 to 2010 period, it is not surprising to see that the countries with the highest average level are concentrated in the developing markets (e.g., China, India, and Russia). Across all countries, though, there is significant variation in changes in expectations of country performance, a necessary condition for our predictive tests to have any power.

As described in section 2.3, we then combine this volatility scaled country level measure of changing expectations with the firm level geographic exposures (from the most recent fiscal year) to compute $SHOCK_t$. Panel B of table 1 notes that the average (median) value of $SHOCK_t$ is 0.68 (0.39) suggesting that the average firm has been positively exposed to changing expectations about macroeconomic growth over our time period. More importantly, however, is the large standard deviation in this measure (2.09) and large inter-quartile range (1.80). Thus, ex ante, there should be sufficient power to exploit both time series and cross sectional variation in $SHOCK_t$ to help forecast firm fundamentals, analyst revisions and future stock returns.

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 (or interim) 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 $SHOCK_t$, 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 3 reports the regression coefficient estimates of equation (1). We estimate this regression separately each year for each of the twelve industry groups listed in table 1. The reported coefficients are then averaged across years and industry groups. Standard errors are based on the time series and cross sectional variation in industry-year estimates. We estimate equation (1) for the next 12 and 24 months.

Consistent with prior research we see that profitability is mean reverting as evidenced by the β_2 coefficient of 0.608 (0.472) for the one (two) year ahead forecasting equation. As expected, we also see that the level of future profitability is decreasing (increasing) in BTM_t ($Size_t$) for the next year. However, the relation between future profitability and BTM_t is not significant for the two year ahead specification.

The β_1 coefficient of 0.002 for the one year ahead forecast has a clear economic interpretation. A one standard deviation change in $SHOCK_t$ (2.092 from panel B of table 1) translates to a change in $SHOCK_t$ of 0.0042 (2.092 x 0.002). This means that a one standard deviation improvement in the perceived expectations of economic growth across the set of countries that a firm is exposed to is associated with additional profits equivalent to 0.42 percent of average assets. The median ROA for our sample firms is 0.022, thus a one standard deviation change in $SHOCK_t$ translates to an increase of 20 percent in income for the median firm in our sample. The economic importance of $SHOCK_t$ is about twice as large as BTM_t and about one third as large as $Size_t$.

To make stronger inferences about the predictive content of $SHOCK_t$, we compare the absolute forecast errors described in equations (2a) and (2b) in unreported analysis. For each industry-year group we estimate equation (1) with and without the $SHOCK_t$ variable. We re-estimate the equations each year from 2006 to 2011 adding one additional year as we move forward in time. We then compare differences in medians for the ROA_{t+12} forecast errors on a pooled and industry grouping basis. For both the pooled analysis and the industry level analyses we find that the median absolute forecast error is lower by 3 basis points, relative to average total assets, when incorporating $SHOCK_t$ into the forecast. This difference is statistically significant at conventional levels. 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 included profit margins and asset turnover relative to a forecasting model that excluded this information, was more accurate by a magnitude of 0.0003 (0.0002) 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 is between 5 and 10 basis points (relative to book equity) for a large sample of US firms over the 1981-1990 time period. Thus, our finding of improved accuracy of 3 basis points is similar in magnitude to prior research.

4.2 Sell-side analyst earnings forecasts

Table 4 panel A [B] reports the regression coefficient estimates of equation (3a) [(3b)]. We estimate these equations separately for each month and reported coefficients are averaged across months. Standard errors are based on the time series variation in monthly regression coefficients. We estimate both equation (3a) and (3b) for the next 12 months to assess the speed with which information contained in geographic exposures is incorporated into analyst earnings forecasts.

Consistent with prior research we find that analyst revisions are strongly serially correlated. The β_2 coefficient is about 0.2 for the first month and declines to about 0.05 over the following 12 months (see panel B of table 4). Likewise, analyst revisions are also strongly related to past returns (β_5 is strongly significant out to 12 months in panel A and panel B) and market expectations for growth (in particular β_4 is strongly significant out to 12 months in panel A and panel B).

Our primary variable of interest, $SHOCK_t$, is statistically significant out to eight months in both panels of table 4. To assess the economic significance of this relation we note that the standard deviation of $SHOCK_t$ is 2.092 (see panel B of table 1) and that the regression coefficient for β_1 is about 0.0006. This means that a one standard deviation change in $SHOCK_t$ is associated with a change in $Revision_{t+k}$ of about 0.0012. Thus, a one standard deviation change in $SHOCK_t$ is associated with an additional 0.12 percent increase in analyst earnings forecasts. In comparison to the other explanatory variables included in equation (3a) and (3b), $SHOCK_t$ is about half as economically important as BTM_t, NI/P_t, and $Momentum_t$.

4.3 Stock returns

Having established the relative ability of our country shock measure to forecast both firm fundamentals and sell-side analyst earnings revisions, we now turn to assessing whether the country shock measure has any predictive value for equity returns. Table 5 reports regression estimates of equation (5). We estimate equation (5) every month and report averages of estimated regression coefficients. Standard errors are based on the time series variation in estimated regression coefficients. Equation (5) is estimated six times each month to assess the predictive content of our included explanatory variables over the next six months. We report three panels in table 5 to correspond to the three different weighting functions described in section 2.4.3.

Consistent with prior research we see that equity returns are (i) strongly positively associated with BTM_t and NI/P_t, (ii) negatively correlated with the most recent stock returns, RET_t, (iii) positively correlated with $Momentum_t$, and (iv) unrelated with $Beta_t$ and $Size_t$. Our primary variable of interest, $SHOCK_t$, is positively associated with future equity returns out for the next six months using equally weighted regressions in panel A of table 5 and also for risk weighted regressions in panel C of table 5. The strength of the return using the value weighted returns in panel B of table 5 is limited to the first month. Thus, while we are able to document a statistical association between $SHOCK_t$ and future equity returns, the economic significance of that relation is not clear. To help reconcile the difference between the value-weighted and equal-weighted regression results we note that if we remove the largest 20 percent of our sample (based on $MCAP_t$) we find a statistically positive relation between $SHOCK_t$ and future equity returns for the next six months across equal-weighted, value-weighted and risk-weighted regression specifications.

To assess the economic significance of the relation between $SHOCK_t$ and future equity returns, we examine portfolio level returns in table 6. As discussed in section 2.4.3, every month we form 25 portfolios based on a conditional sort, first on $MCAP_t$ and then on $SHOCK_t$. We then compute the *value* weighted return for each of these 25 portfolios over the next six months. We also report a hedge return as the difference in the average portfolio return across the extreme $SHOCK_t$ quintiles. Test statistics are reported based on the time series variation in this hedge return.

The first row of panel A of table 6 reports the average $MCAP_t$ for firms across the five $SHOCK_t$ quintiles. These market values have been adjusted to 2011 dollars using a GDP deflator to allow comparison across time. The smallest quintile contains securities with a market capitalization of about \$18 million and the largest quintile contains securities with a market capitalization of about \$5.48 billion. Clearly there is a very large difference in the economic importance of securities across the five quintiles. Table 6 shows that, across the five $MCAP_t$ quintiles, the value weighted hedge return associated with $SHOCK_t$ is significant for the next month, but the strength of the relation for the largest quintile does not extend beyond the first month. Consistent with the characteristic regressions reported in table 5, the association between $SHOCK_t$ and future equity returns is evident for at least 80 percent of the cross section of equity securities, but it is weak for the largest 20 percent.

The *cumulative* magnitude of the hedge portfolio returns reported in table 6 over the following six months is about 8.6 percent for the smallest quintile and about 3.5 percent for the largest quintile. Remember that we rebalance the portfolio in a given month, *t*, and then look at the returns for the next six months holding that portfolio fixed. A natural question to ask is whether the magnitude of these returns would be sufficient to cover expected transaction costs. In addition, for a long/short portfolio we require (i) estimates of the explicit costs to 'short' a security, and (ii) knowledge of whether it was possible to short a given security. Absent detailed equity lending market data it is not possible to answer these questions for each and every security. However, we can offer some approximations. Saffi and Sigurdsson (2011), using security lending market data from a large participant in the securities lending business, examine lending fees and availability for equity securities over the 2005 to 2008 period. They find that the vast majority of securities are available to be loaned, and that the average fee for their sample of 12,621 securities across 26 countries is 30 basis points.

The total costs associated with constructing the long-short portfolio documented in Table 6 is twice the round trip trading costs (once for the long positions and once for the short positions), plus the explicit shorting costs. We use 30 (100) basis points as an approximation for institutional round trip trading costs on the largest (smallest) securities (see discussion in Richardson, Tuna and Wysocki, 2010). This gives a total cost of between 90 basis points (2 x 30 bps + 30 bps) to 230 bps (2 x 100 bps + 30 bps) for the largest and smallest securities respectively. Comparing these expected transaction cost amounts to the cumulative six month returns discussed earlier, it is possible that the hedge returns are sufficient to cover transaction costs for an institutional investor. However, absent precise data on the liquidity and likely transaction costs across the 39 countries included in our sample, we do not make strong inferences about the implementability of a trading strategy based on macroeconomic exposures.

Finally, in table 7 we report estimates of equation (7). There are three panels corresponding to the different weighting schemes to compute hedge portfolio returns (equal, value and risk weighted). Across all three weighting schemes, we see very significant intercepts which translate into economically and statistically significant conditional Sharpe Ratios (see last row in each panel of table 7). These large conditional Sharpe ratios suggest that the portfolio returns documented in table 7 cannot be explained by the set of seven risk factors. Of course, it is always possible there is an unidentified risk factor which time varies with our hedge portfolio returns. Of the included risk factors, there is some evidence that $HEDGE_t$ is negatively associated with dRP_t, SMB_t, and HML_t, and some evidence of a positive association with MKT_t. Specifically the regression coefficients across the equal-weighted, value-weighted and risk-weighted variants of equation (6) suggest that the returns to a portfolio exploiting geographic exposures tends to underperform when (i) small firms out-perform, (ii) 'value' firms out-perform, and (iii) when the yield on BAA corporate bonds rise relative to 10-year Treasury bonds (at least for the first two months); and outperform when the overall equity market is doing well.

4.4 Limitations and robustness analyses

4.4.1 Removing domestic firms

Our sample of firms includes 75 percent 'domestic' firms. These are firms for which we are unable to locate any geographic segment data from annual reports. These firms will be a combination of pure single segment firms and multi-segment firms that we incorrectly classify as single segment firms (due to incomplete geographic segment data). Thus, removing the firms that we identify as 'domestic' will help mitigate this measurement error in our geographic exposures. However, it is worth noting that the average 'domestic' firm is much smaller than the average ‘non-domestic’ firm. ‘Domestic’ firms have average values of (i) sales: $690 million, (ii) total assets: $1.965 billion, and (iii) market capitalization: $731 million. In comparison, ‘non-domestic’ firms have average values of (i) sales: $2.475 billion, (ii) total assets: $4.596 billion, and (iii) market capitalization: $2.637 billion. These differences are statistically different at conventional levels.

For the reduced sample of ‘non-domestic’ firms we continue to find significant relations between $SHOCK_t$ and future firm performance. Specifically, we find that (i) $SHOCK_t$ is significantly associated with future profitability, (ii) $SHOCK_t$ is significantly associated with future analyst earnings revisions for the next 7 months (in table 4 the primary sample extended to 8 months), but (iii) the relation between $SHOCK_t$ and future stock returns is not robust in the cross-sectional characteristic regressions or time-series portfolio tests. The weaker relation with stock returns for the ‘non-domestic’ sample is consistent with the results presented in tables 5-7, where the relation was weaker for the largest (i.e., ‘non-domestic’) firms.

4.4.2 US firms only

We have re-run all of our regressions limiting the sample to ‘non-domestic’ US firms. As discussed in section 3.1, the segment reporting disclosure requirements over the 1998 to 2010 time period are arguably less detailed for US firms relative to non-US firms who follow international standards. Ideally, we would like to know the precise segment disclosure requirements in each year across each of our 39 countries. We do not have access to this data and instead have chosen to compare US firms to non-US firms, with priors for weaker results with the sample of US firms, because the geographic segment disclosures are less detailed. For the sample of non-domestic US firms over the 1998 to 2010 time period, when FAS 131 was in effect, we find that (i) $SHOCK_t$ is marginally significantly associated with future profitability (t-statistic of 1.57), (ii) $SHOCK_t$ is not significantly associated with future analyst earnings revisions, and (iii) $SHOCK_t$ is not significantly associated with future stock returns. This weakness in the analyst revision and stock return tests is consistent with our priors of less precise geographic segment disclosures for US firms relative to non-US firms. It is, however, also consistent with a view that the US capital market is relatively more efficient and liquid. Thus, a failure to find a robust relation between $SHOCK_t$ and future stock returns in the US is potentially a reflection of that relative efficiency and liquidity.

4.4.3 Exporters only

Our geographic exposures are based on geographic segment sales data. We do not have a complete set of geographic segment cost data. Thus, a limitation of our geographic exposure matrix is that it will fail to identify the differential importance of country level performance across firms that sell into a country, relative to firms that both sell into and source inputs from that country. To help identify the differential effects across these two types of firms, we have split our sample into two groups based on their exporting status. If we could perfectly identify 'non-domestic' firms who sell their goods and services to foreign locations but have no direct operations in those foreign locations (i.e., pure 'exporters'), the geographic exposures of such firms will be well measured by our geographic sales data. Our proxy for pure exporters is whether reported assets are zero (or missing) for a geographic region that has positive sales. To assess whether the relation between $SHOCK_t$ and future firm performance is different for 'exporters', we re-run all of our regression analysis allowing the linear relations between ROA_{t+k}, $Revision_{t+k}$ and RET_{t+k} to vary across exporters and non-exporters. This analysis is based on the sub-set of firms with foreign sales. Consistent with our priors, we find that the relation between ROA_{t+k} and $SHOCK_t$ is stronger for exporters. The β_1 coefficient from equation (1) is 0.005 for exporters and -0.001 for non-exporters (the difference is statistically significant at conventional levels, and β_1 is only significant for the 'exporter' group). We also find that the relation between $Revision_{t+k}$ and $SHOCK_t$ is stronger for exporters. The β_1 coefficient from equation (3) averages 0.0022 for the next four months for exporters and is only 0.0010 for non-exporters (difference significant at conventional levels). However, we do not find robust differences between RET_{t+k} and $SHOCK_t$ when estimating equation (5) separately for exporters and non-exporters.

4.4.4 Alternative measure of $SHOCK_t$

A potential limitation with our empirical analysis is the reliance on the 'black box' forecasts from the OECD. There is a risk that the CLI data we have extracted from the OECD was not known to capital market participants. This risk is due to the way in which the OECD provides their CLI data. Each month they update their CLI data and at the same time they update their historical data. This means that the set of economic series included in the historical OECD CLI data may include series that are used in the current model used by the OECD but not the model used in the past. Further, there is the issue that many economic series (e.g., GDP growth and its components) are revised and updated, leading to further look-ahead biases in this dataset.

To mitigate the risk of look-ahead biases driving our results, we have sourced country level forecasts from an alternate provider. Consensus Economics (CE) was founded in 1989 and they have been collecting survey data from a set of over 700 economists since that time. Each month, CE surveys a set of economists to collect views on expected growth across a large set of countries. The surveyed economists typically provide a forecast of GDP growth (and components) for the next two calendar years. A key benefit of this alternative data source is that it is 'point-in-time': the forecasts of capital market participants are included in the CE datasets and they are *never* changed. In addition, 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. Similar to our focus on 12-month ahead earnings forecasts from sell side analysts, we combine 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. Thus, unlike the trend restored OECD CLI data, we do not need to difference the forecast to make it cross-sectionally comparable. Another difference with our primary OECD CLI data is the horizon of the forecast and the target attribute being forecasted: the OECD CLI data is designed to forecast business cycle movements over the next 6 months, whereas the CE forecasts are explicit forecasts of GDP growth over the next 12 months. We do not have strong priors as to which attribute, or horizon, is superior, so examining both is informative.

We re-measure $SHOCK_t$ by combining the country level sales data with the CE forecast of GDP growth for the next 12 months. With this alternative measure of $SHOCK_t$ we find that (i) it continues to be significantly associated with future profitability (and even more strongly for the next two to four years), (ii) it continues to be significantly associated with future analyst earnings revisions for the next 4 months, and (iii) it exhibits similar patterns with future stock returns (i.e., the strength of the relation is concentrated in the smallest 60 percent of firms, and the economic significance of the returns as reflected in the joint portfolio sorts is similar to what is reported in table 6).

4.4.5 USD returns

As discussed at the end of section 2.4.3 our stock return analysis is based on local currency returns. This means that foreign currency movements will affect the individual stock level returns. We have repeated all of our analyses converting local currency returns to a common base currency (USD). Given that the correlation between the USD return and local currency return across our large sample of companies is 0.99, it is not surprising to see that none of our inferences change.

5. Conclusion

In this paper we outline an approach to incorporate macroeconomic information into firm level forecasts. Using a large sample of publicly traded firms across the world, we show that combining information in geographic segment disclosures, country level sales, with external forecasts of how those different countries are expected to do, OECD CLIs, is able to generate significant out of sample improvements in forecasting firm level profitability. We also find that sell side analysts are slow to incorporate this information into their forecasts. Finally, we find that stock prices, at least for small to medium sized companies, are also slow to incorporate this information.

Our results suggest the potential for significant benefit 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 should create improvements in our ability to understand and hopefully forecast future firm cash flows and associated risks.

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Appendix I: Calculation of $SHOCK_t$ 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 $SHOCK_t$ for each month from August 2010 to July 2011. For example, $SHOCK_t$ for Mulberry in August 2010 is calculated as:

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

To compute our measures of expected performance across the geographic regions we use OECD CLI data. Starting with the trend restored CLI data we (i) take monthly differences (i.e., $CLI_t - CLI_{t-1}$), (ii) smooth these monthly differences over the most recent three months as follows: $\frac{1}{2}(CLI_t - CLI_{t-1}) + \frac{1}{3}(CLI_{t-1} - CLI_{t-2}) + \frac{1}{6}(CLI_{t-2} - CLI_{t-3})$, and (iii) volatility scale this smoothed difference using the most recent 24 months of data.

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 of each of the 24 OECD countries in Europe.

Country	GDP percentage	Country	GDP percentage
Austria	0.020	Luxembourg	0.003
Belgium	0.025	Netherlands	0.042
Czech Republic	0.010	Norway	0.020
Denmark	0.016	Poland	0.023
Estonia	0.001	Portugal	0.013
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

3) $E_t[Performance\ for\ Europe]$, as of August 2010, is then calculated as the sum of the individual country level differenced, smoothed and volatility scaled OECD CLI data, 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

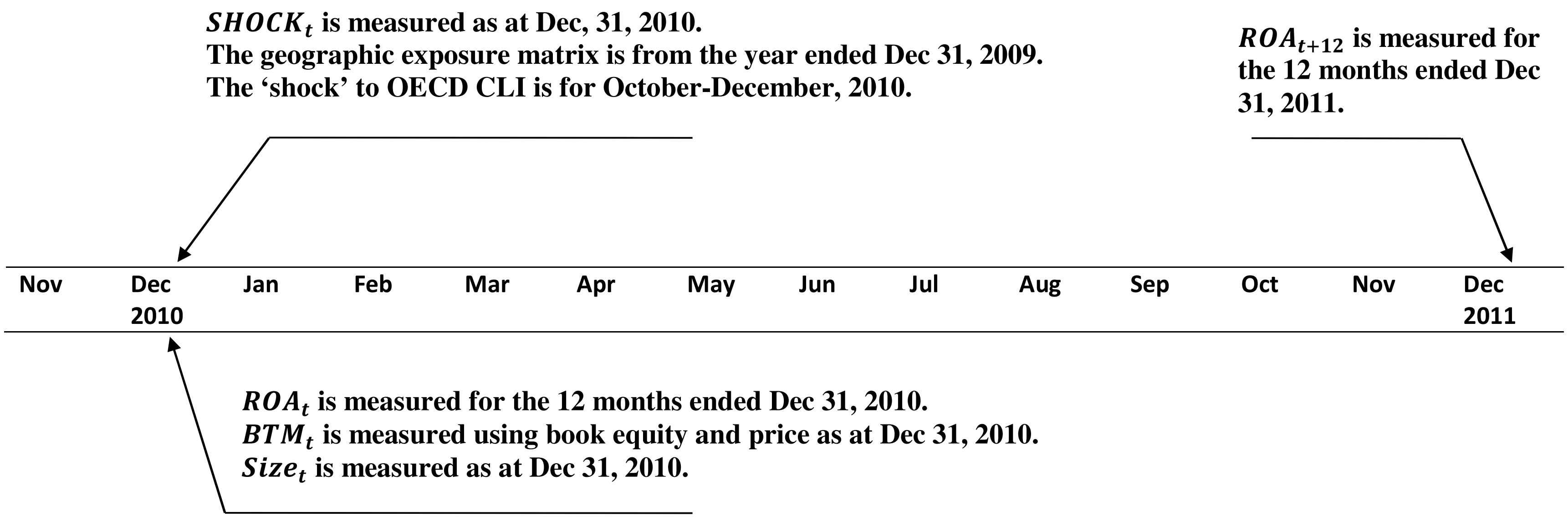
Variable	Description
$SHOCK_t$	The sum product of a firm's geographic sales exposure to a country and the 'shock' that countries expected performance based on the OECD Composite Leading Indicators (CLI_t). The geographic sales data are extracted from the most recent annual report prior to month *t* (ensuring at least a four month gap between the end of the fiscal year and month *t*). The OECD CLI data is obtained from the OECD website (http://www.oecd.org/department/0,3355,en_2649_34349_1_1_1_1_1,00.html). We use the trend restored series for each country, CLI_t, and compute our 'shock' measure as $\frac{1}{2}(CLI_t - CLI_{t-1}) + \frac{1}{3}(CLI_{t-1} - CLI_{t-2}) + \frac{1}{6}(CLI_{t-2} - CLI_{t-3})$. This 'shock' is then scaled by its own historical volatility using the most recent 24 months of data. See the discussion in sections 2.3, and 3.2 for more details.
ROA	Return on assets computed as the ratio of net income before extraordinary items to average total assets.
BTM	Book-to-market ratio computed as the ratio of common equity to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal period prior to month *t*. See Figure 1 for more details.
$Size$	Natural logarithm of equity market capitalization (in USD).
$Sales$	Total sales for the fiscal year (in USD millions).
$Assets$	Total assets as at the end of the fiscal year (in USD millions).
$MCAP$	Equity market capitalization (in USD millions).
$Revision$	This is the monthly revision in median consensus sell-side analyst earnings forecasts. We compute it as $Revision_{i,t+k} = \ln \frac{E[EPS12M_{i,t+k}]}{E[EPS12M_{i,t+k-1}]}$, where $E[EPS12M_{i,t}]$ is a calendar weighted combination of one year ahead, $E[EPS1_{i,t}]$, and two year ahead, $E[EPS2_{i,t}]$, earnings forecasts as at month *t*. The weights across the two earnings forecasts are chosen such that the combined forecast is for twelve months ahead. This ensures cross-sectional comparability across earnings forecast revisions.
$DOMESTIC$	An indicator variable equal to one for firms that have no foreign sales and zero otherwise.
NI/P	Earnings-to-Price ratio computed as the ratio of net income before extraordinary items to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal period prior to month *t*. See Figure 1 for more details.
$Momentum$	The average monthly equity return inclusive of dividends from month *t-6* to month *t-1*.
RET	Monthly equity return inclusive of dividends.
$Beta$	Equity market beta estimated from a rolling regression of 60 months of data requiring at least 36 months of non-missing return data.

Variable	Description
dIP	$\ln\frac{IP_t}{IP_{t-1}}$, where IP is Industrial Production Index at the end of month t from the Board of Governors of the Federal Reserve System (INDPRO), available at the St Louis Fed web site: http://research.stlouisfed.org/fred2/
dRP	Change in risk premium, $RP_t - RP_{t-1}$, where RP is the difference between the Moody's Seasoned BAA Corporate Bond Yield from the Board of Governors of the Federal Reserve System (BAA) and the 10-Year Treasury constant maturity rate from the Board of Governors of the Federal Reserve System (GS10). BAA and GS10 are available at the St Louis Fed web site: http://research.stlouisfed.org/fred2/.
dTS	Change in term structure,$TS_t - TS_{t-1}$, where TS is the difference between the 10-Year Treasury constant maturity rate (GS10) and the 2-Year Treasury constant maturity rate (GS2), both from the Board of Governors of the Federal Reserve System. Both GS10 and GS2 are available at the Louis Fed web site: http://research.stlouisfed.org/fred2/
HML	Monthly mimicking factor portfolio return to the value factor, obtained from Ken French's website.
MOM	Average 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.
MKT	Monthly excess (to risk free rate) market return, obtained from Ken French's website.
SMB	Monthly mimicking factor portfolio return to the size factor, obtained from Ken French's website.

Figure 1

Timeline for ROA Tests

(Dec 31, 2010 fiscal year example)

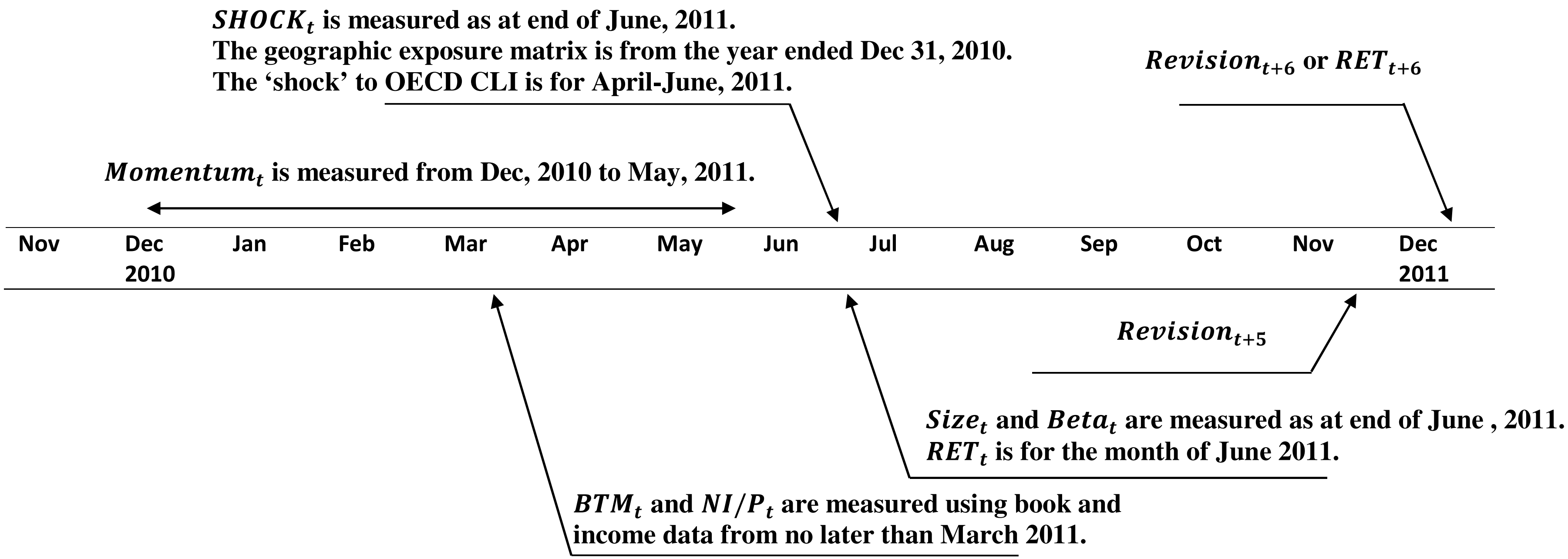


* The regressions reported in table 3 are based on firm-*year* observations. Thus, while we are able to measure $SHOCK_t$ every month we only use $SHOCK_t$ for the period that coincides with the end of the previous year. This is to ensure that all of the explanatory variables are measured prior to the future profitability, ROA_{t+k}, that we are trying to forecast.

Figure 2

Timeline for Return and Analyst Forecast Revision Tests

(June 30, 2011 forecasting period, with k=6)



* The regressions reported in tables 4 and 5 are based on firm-*month* observations. We are careful to ensure that all explanatory variables are known to the analysts and the market at month *t*.

Table 1 Summary Statistics

Panel A: Country Distribution	Number of Firm-Year	Percentage
Australia	11,673	3.59
Austria	1,295	0.40
Belgium	1,872	0.58
Brazil	4,471	1.38
Canada	12,713	3.91
Chile	2,405	0.74
China	23,349	7.18
Czech Republic	386	0.12
Denmark	2,429	0.75
Estonia	86	0.03
Finland	1,763	0.54
France	10,517	3.24
Germany	11,211	3.45
Greece	3,731	1.15
Hungary	507	0.16
India	17,459	5.37
Indonesia	4,368	1.34
Ireland	824	0.25
Israel	2,327	0.72
Italy	3,721	1.14
Japan	51,312	15.79
Korea, Republic	12,228	3.76
Luxembourg	558	0.17
Mexico	1,704	0.52
Netherlands	2,387	0.73
New Zealand	1,461	0.45
Norway	2,466	0.76
Poland	3,002	0.92
Portugal	777	0.24
Russia	1,539	0.47
Slovakia	206	0.06
Slovenia	158	0.05
South Africa	4,548	1.40
Spain	2,034	0.63
Sweden	4,780	1.47
Switzerland	3,413	1.05
Turkey	2,791	0.86
United Kingdom	24,508	7.54
United States	88,003	27.08
Total	324,982	100

Panel B: Firm Characteristics

	N	Mean	Std. Dev.	P25	P50	P75
$Sales$	309,191	1156.56	3881.01	24.26	109.34	488.20
$Assets$	308,044	2654.54	10841.04	41.93	169.27	749.15
$MCAP$	276,905	1251.90	4589.83	24.95	103.06	481.91
BTM	277,580	1.030	1.119	0.381	0.709	1.238
ROA	294,625	-0.001	0.161	-0.008	0.022	0.064
$DOMESTIC$	324,982	0.745	0.436	0.000	1.000	1.000
$SHOCK$	3,703,394	0.678	2.092	-0.388	0.394	1.422

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

	Number of Firm-Year	Percentage
Consumer Non-Durables	25,902	7.97
Consumer Durables	9,972	3.07
Manufacturing	42,010	12.93
Oil, Gas, and Coal Extraction and Products	9,234	2.84
Chemicals and Allied Products	11,567	3.56
Business Equipment	48,003	14.77
Telephone and Television Transmission	8,700	2.68
Utilities	8,668	2.67
Wholesale, Retail, and Some Services	29,561	9.10
Healthcare, Medical Equipment, and Drugs	19,105	5.88
Money and Finance	59,145	18.20
Other	53,115	16.34
Total	324,982	100

This table reports summary statistics for the sample. The sample only includes countries with OECD CLI data. The sample period is 1998-2010. The sample includes 324,982 firm-years and 3,703,394 firm-months. Panel A reports the distribution of countries of domicile. Panel B reports firm characteristics. All variables are defined in Appendix II. Panel C presents industry distribution. The industry classification follows the twelve primary industry groupings identified in Fama-French (1997).

Table 2 Summary Statistics for the Macroeconomic Shocks

Country	Mean	Std. Dev.	P25	P50	P75
Australia	0.91	1.43	0.02	0.80	1.87
Austria	0.99	1.43	0.34	0.99	1.84
Belgium	0.06	1.32	-0.68	0.08	0.99
Brazil	0.60	1.35	-0.29	0.48	1.37
Canada	-0.24	1.32	-0.83	-0.19	0.69
Chile	0.71	1.43	-0.36	0.58	1.55
China	6.01	3.29	3.17	6.02	8.60
Czech Republic	0.94	1.67	-0.12	0.82	1.71
Denmark	0.05	1.52	-0.75	0.10	0.95
Estonia	0.72	1.30	-0.23	0.92	1.64
Finland	0.51	1.45	-0.46	0.49	1.61
France	-0.19	1.44	-0.89	-0.22	0.76
Germany	0.31	1.26	-0.30	0.40	1.10
Greece	-0.11	1.89	-1.68	-0.09	1.03
Hungary	0.72	1.37	0.21	0.80	1.56
India	1.89	1.76	0.69	1.74	3.07
Indonesia	0.53	0.98	-0.24	0.69	1.28
Ireland	2.29	2.62	0.63	1.69	3.84
Israel	0.97	1.68	-0.31	1.00	1.83
Italy	-0.34	1.26	-1.03	-0.40	0.59
Japan	0.14	1.29	-0.65	0.27	0.87
Korea, Republic	0.97	1.26	0.11	0.75	1.89
Luxembourg	0.19	1.27	-0.58	0.28	1.09
Mexico	0.40	1.15	-0.52	0.53	1.33
Netherlands	0.41	1.34	-0.28	0.52	1.28
New Zealand	0.07	1.21	-0.91	0.27	0.97
Norway	0.55	2.15	-0.71	0.36	1.48
Poland	1.35	1.28	0.08	1.72	2.37
Portugal	-0.11	1.42	-1.30	-0.11	0.91
Russia	1.37	1.71	0.39	1.06	2.64
Slovak	0.95	1.35	0.16	1.02	1.97
Slovenia	0.67	1.50	-0.49	0.58	1.70
South Africa	0.61	1.64	-0.46	0.75	1.51
Spain	-0.22	1.55	-1.16	0.08	0.86
Sweden	0.42	1.49	-0.59	0.58	1.43
Switzerland	0.40	1.25	-0.38	0.48	1.37
Turkey	0.80	1.37	0.24	0.76	1.67
United Kingdom	-0.45	1.23	-1.13	-0.36	0.40
United States	0.12	1.28	-0.66	0.12	1.12

This table reports summary statistics for the monthly macroeconomic shock measures calculated from the OECD Trend Restored CLI data. The shock variable is calculated as $\frac{1}{2}(CLI_t - CLI_{t-1}) + \frac{1}{3}(CLI_{t-1} - CLI_{t-2}) + \frac{1}{6}(CLI_{t-2} - CLI_{t-3})$ scaled by its own standard deviation over the previous 24 months.

Table 3 Macroeconomic Shocks and Future Firm Performance

$$\boldsymbol{ROA_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 ROA_t + \beta_3 BTM_t + \beta_4 Size_t + e_{t+k}} \qquad \textbf{(1)}$$

	α	β_1	β_2	β_3	β_4	Adj. R^2
k=12						
Coefficient	-0.026	0.002	0.608	-0.002	0.005	0.415
(t-statistic)	*(-8.14)*	*(3.03)*	*(44.19)*	*(-4.40)*	*(17.09)*	
k=24						
Coefficient	-0.033	0.002	0.472	0.001	0.006	0.273
(t-statistic)	*(-6.10)*	*(2.74)*	*(24.23)*	*(0.53)*	*(7.83)*	

The reported regression coefficients are mean coefficients from regressions, weighting each regression by the square root of sample size for each year-industry. The *t*-statistics (reported in parentheses below coefficient estimates) are based on the standard errors of the coefficient estimates across the year-industry regressions, adjusted for autocorrelation in the annual coefficient estimates based on an assumed AR(1) autocorrelation structure. Standard errors are multiplied by an adjustment factor, $\sqrt{(1+\rho)/(1-\rho) - 2\rho(1-\rho^n)/n(1-\rho)^2}$, where n is the number of years and ρ is the first-order autocorrelation of the annual coefficient estimates. All variables are defined in Appendix II.

Table 4A : Macroeconomic Shocks and Future Analyst Forecast Revisions

$$\boldsymbol{Revision_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 Revision_{t+k-1} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + e_{t+k}} \quad \textbf{(3a)}$$

	k	α	β_1	β_2	β_3	β_4	β_5	Adj. R^2
Coefficient	1	0.0114	0.0006	0.1907	-0.0019	-0.0373	0.0770	0.066
(t-statistic)		*(29.53)*	*(4.93)*	*(35.58)*	*(-6.55)*	*(-21.96)*	*(21.82)*	
Coefficient	2	0.0111	0.0005	0.1973	-0.0016	-0.0361	0.0628	0.064
(t-statistic)		*(27.97)*	*(4.69)*	*(36.80)*	*(-5.60)*	*(-22.34)*	*(19.40)*	
Coefficient	3	0.0107	0.0005	0.2002	-0.0011	-0.0366	0.0509	0.062
(t-statistic)		*(24.27)*	*(4.15)*	*(37.18)*	*(-4.17)*	*(-24.91)*	*(16.90)*	
Coefficient	4	0.0106	0.0004	0.2015	-0.0009	-0.0350	0.0418	0.061
(t-statistic)		*(22.42)*	*(3.23)*	*(36.86)*	*(-3.54)*	*(-23.70)*	*(15.53)*	
Coefficient	5	0.0102	0.0004	0.2031	-0.0007	-0.0328	0.0384	0.060
(t-statistic)		*(20.88)*	*(2.76)*	*(37.25)*	*(-2.77)*	*(-24.37)*	*(15.19)*	
Coefficient	6	0.0099	0.0004	0.2028	-0.0004	-0.0321	0.0340	0.058
(t-statistic)		*(19.95)*	*(2.70)*	*(37.05)*	*(-1.50)*	*(-24.32)*	*(14.71)*	
Coefficient	7	0.0096	0.0003	0.2021	-0.0002	-0.0301	0.0346	0.057
(t-statistic)		*(19.38)*	*(2.30)*	*(37.04)*	*(-0.84)*	*(-24.00)*	*(13.92)*	
Coefficient	8	0.0095	0.0002	0.2041	-0.0002	-0.0290	0.0268	0.056
(t-statistic)		*(18.63)*	*(1.43)*	*(36.71)*	*(-0.70)*	*(-23.41)*	*(11.77)*	
Coefficient	9	0.0093	0.0001	0.2046	0.0000	-0.0280	0.0219	0.055
(t-statistic)		*(17.70)*	*(0.81)*	*(36.36)*	*(0.18)*	*(-21.59)*	*(9.70)*	
Coefficient	10	0.0093	0.0001	0.2038	0.0001	-0.0274	0.0170	0.054
(t-statistic)		*(17.52)*	*(0.56)*	*(36.14)*	*(0.39)*	*(-21.44)*	*(7.72)*	
Coefficient	11	0.0094	0.0001	0.2038	0.0002	-0.0267	0.0129	0.053
(t-statistic)		*(17.74)*	*(0.55)*	*(36.01)*	*(0.73)*	*(-21.62)*	*(6.41)*	
Coefficient	12	0.0094	0.0000	0.2035	0.0004	-0.0258	0.0093	0.052
(t-statistic)		*(17.38)*	*(0.33)*	*(36.12)*	*(1.30)*	*(-20.17)*	*(4.55)*	

Table 4B : Macroeconomic Shocks and Future Analyst Forecast Revisions

$$Revision_{t+k} = \alpha + \beta_1 SHOCK_t + \beta_2 Revision_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + e_{t+k} \quad \textbf{(3b)}$$

	k	α	β_1	β_2	β_3	β_4	β_5	Adj. R^2
Coefficient	1	0.0114	0.0006	0.1907	-0.0019	-0.0373	0.0770	0.066
(t-statistic)		*(29.53)*	*(4.93)*	*(35.58)*	*(-6.55)*	*(-21.96)*	*(21.82)*	
Coefficient	2	0.0106	0.0006	0.1749	-0.0019	-0.0357	0.0628	0.051
(t-statistic)		*(23.30)*	*(4.18)*	*(35.32)*	*(-5.77)*	*(-22.64)*	*(16.80)*	
Coefficient	3	0.0095	0.0004	0.1813	-0.0009	-0.0385	0.0385	0.052
(t-statistic)		*(19.50)*	*(2.87)*	*(47.36)*	*(-3.27)*	*(-23.61)*	*(13.77)*	
Coefficient	4	0.0101	0.0005	0.1077	-0.0013	-0.0393	0.0398	0.029
(t-statistic)		*(17.95)*	*(2.83)*	*(27.04)*	*(-3.96)*	*(-21.70)*	*(12.73)*	
Coefficient	5	0.0101	0.0005	0.0945	-0.0013	-0.0381	0.0412	0.024
(t-statistic)		*(16.48)*	*(2.94)*	*(21.31)*	*(-4.09)*	*(-20.95)*	*(13.01)*	
Coefficient	6	0.0101	0.0004	0.1037	-0.0003	-0.0385	0.0258	0.027
(t-statistic)		*(18.51)*	*(2.75)*	*(32.23)*	*(-0.93)*	*(-22.13)*	*(10.20)*	
Coefficient	7	0.0108	0.0003	0.0577	-0.0005	-0.0373	0.0309	0.019
(t-statistic)		*(20.21)*	*(2.14)*	*(17.65)*	*(-1.55)*	*(-22.53)*	*(12.73)*	
Coefficient	8	0.0112	0.0002	0.0480	-0.0006	-0.0360	0.0316	0.016
(t-statistic)		*(21.43)*	*(1.53)*	*(15.12)*	*(-1.85)*	*(-20.51)*	*(12.64)*	
Coefficient	9	0.0113	0.0001	0.0660	-0.0000	-0.0336	0.0214	0.018
(t-statistic)		*(23.83)*	*(0.39)*	*(17.89)*	*(-0.15)*	*(-19.98)*	*(8.18)*	
Coefficient	10	0.0116	0.0001	0.0437	-0.0001	-0.0312	0.0174	0.012
(t-statistic)		*(24.10)*	*(0.80)*	*(14.06)*	*(-0.44)*	*(-20.78)*	*(6.45)*	
Coefficient	11	0.0107	0.0001	0.0387	-0.0000	-0.0309	0.0162	0.010
(t-statistic)		*(17.83)*	*(0.71)*	*(13.06)*	*(-0.05)*	*(-19.48)*	*(7.03)*	
Coefficient	12	0.0102	0.0002	0.0612	0.0006	-0.0299	0.0030	0.013
(t-statistic)		*(17.07)*	*(1.35)*	*(20.21)*	*(2.15)*	*(20.40)*	*(1.29)*	

The reported regression coefficients are mean coefficients from monthly regressions, weighting each regression by the square root of sample size for each month. All variables are defined in Appendix II. Panel A (B) reports the results from the estimation of equation 3a (3b) where $Revision_{t+k-1}$ ($Revision_t$) is used as an explanatory variable.

Table 5 Macroeconomic Shocks and Future Stock Returns

$$RET_{t+k} = \alpha + \beta_1 Shock_t + \beta_2 BTM_t + \beta_3 NI/P_t + \beta_4 Size_t + \beta_5 Beta_t + \beta_6 RET_t + \beta_7 Momentum_t + e_{t+k} \quad (5)$$

Panel A: Equal-weighted

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
k=1									
Coefficient	-0.0051	0.0035	0.0041	0.0094	0.0003	-0.0002	-0.0257	0.0316	0.061
(t-statistic)	*(-0.83)*	*(2.62)*	*(5.52)*	*(7.04)*	*(0.82)*	*(-0.16)*	*(-4.16)*	*(1.92)*	
k=2									
Coefficient	-0.0041	0.0028	0.0036	0.0081	0.0003	-0.0002	0.0016	0.030	0.057
(t-statistic)	*(-0.66)*	*(2.21)*	*(4.84)*	*(6.02)*	*(0.64)*	*(-0.19)*	*(0.29)*	*(1.96)*	
k=3									
Coefficient	-0.0043	0.0026	0.0038	0.0079	0.0003	-0.0002	0.0147	0.0249	0.057
(t-statistic)	*(-0.71)*	*(2.07)*	*(5.05)*	*(5.88)*	*(0.70)*	*(-0.14)*	*(2.58)*	*(1.71)*	
k=4									
Coefficient	-0.0050	0.0025	0.0040	0.0076	0.0003	-0.0002	0.0046	0.0245	0.055
(t-statistic)	*(-0.81)*	*(2.21)*	*(4.93)*	*(5.60)*	*(0.84)*	*(-0.17)*	*(1.02)*	*(1.67)*	
k=5									
Coefficient	-0.0036	0.0025	0.0041	0.0071	0.0003	0.0000	0.0044	0.0327	0.054
(t-statistic)	*(-0.59)*	*(2.38)*	*(5.10)*	*(5.04)*	*(0.66)*	*(0.00)*	*(0.95)*	*(2.40)*	
k=6									
Coefficient	-0.0011	0.0024	0.0040	0.0066	0.0001	0.0000	0.0078	0.0445	0.053
(t-statistic)	*(-0.19)*	*(2.27)*	*(4.97)*	*(4.64)*	*(0.27)*	*(0.00)*	*(1.67)*	*(3.52)*	

Panel B: Value-weighted									
	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
k=1									
Coefficient	-0.0026	0.0025	0.0032	0.0114	0.0002	-0.0000	-0.0139	0.0311	0.082
(t-statistic)	*(-0.39)*	*(1.84)*	*(3.58)*	*(6.78)*	*(0.47)*	*(-0.03)*	*(-1.93)*	*(1.49)*	
k=2									
Coefficient	-0.0022	0.0019	0.0028	0.0097	0.0002	-0.0002	0.0002	0.0261	0.078
(t-statistic)	*(-0.33)*	*(1.46)*	*(3.09)*	*(5.69)*	*(0.40)*	*(-0.14)*	*(0.03)*	*(1.37)*	
k=3									
Coefficient	-0.0035	0.0016	0.0031	0.0097	0.0003	0.0000	0.0132	0.0167	0.075
(t-statistic)	*(-0.54)*	*(1.32)*	*(3.47)*	*(5.84)*	*(0.69)*	*(0.01)*	*(1.94)*	*(0.93)*	
k=4									
Coefficient	-0.0025	0.0015	0.0032	0.0099	0.0002	-0.0002	0.0032	0.0178	0.074
(t-statistic)	*(-0.39)*	*(1.31)*	*(3.36)*	*(5.99)*	*(0.57)*	*(-0.13)*	*(0.55)*	*(0.98)*	
k=5									
Coefficient	-0.0017	0.0016	0.0034	0.0088	0.0002	-0.0000	0.0007	0.0270	0.072
(t-statistic)	*(-0.27)*	*(1.44)*	*(3.63)*	*(5.15)*	*(0.50)*	*(-0.03)*	*(0.12)*	*(1.59)*	
k=6									
Coefficient	0.0000	0.0012	0.0034	0.0085	0.0001	0.0001	0.0085	0.0317	0.071
(t-statistic)	*(0.01)*	*(1.13)*	*(3.56)*	*(4.86)*	*(0.18)*	*(0.04)*	*(1.42)*	*(1.95)*	

Panel C: Risk-weighted									
	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
k=1									
Coefficient	0.0039	0.0027	0.0020	0.0092	-0.0003	0.0016	-0.0235	0.0780	0.060
(t-statistic)	*(0.86)*	*(2.97)*	*(3.28)*	*(7.63)*	*(-0.86)*	*(0.77)*	*(-3.53)*	*(4.13)*	
k=2									
Coefficient	0.0037	0.0022	0.0017	0.0076	-0.0002	0.0012	0.0105	0.0678	0.056
(t-statistic)	*(0.80)*	*(2.44)*	*(2.71)*	*(6.19)*	*(-0.69)*	*(0.64)*	*(1.86)*	*(3.91)*	
k=3									
Coefficient	0.0029	0.0019	0.0018	0.0074	-0.0002	0.0012	0.0218	0.0611	0.055
(t-statistic)	*(0.63)*	*(2.09)*	*(2.97)*	*(5.71)*	*(-0.49)*	*(0.63)*	*(3.75)*	*(3.63)*	
k=4									
Coefficient	0.0022	0.0018	0.0020	0.0069	-0.0001	0.0007	0.0037	0.0635	0.054
(t-statistic)	*(0.48)*	*(2.07)*	*(3.06)*	*(5.20)*	*(-0.22)*	*(0.37)*	*(0.76)*	*(3.69)*	
k=5									
Coefficient	0.0024	0.0016	0.0023	0.0065	-0.0001	0.0009	0.0097	0.0711	0.054
(t-statistic)	*(0.52)*	*(2.02)*	*(3.55)*	*(4.66)*	*(0.23)*	*(0.48)*	*(2.00)*	*(4.22)*	
k=6									
Coefficient	0.0046	0.0014	0.0023	0.0057	-0.0002	0.0012	0.0181	0.0847	0.054
(t-statistic)	*(1.01)*	*(1.81)*	*(3.49)*	*(3.99)*	*(-0.70)*	*(0.63)*	*(3.45)*	*(5.22)*	

The reported regression coefficients are mean coefficients from monthly regressions. In computing averages and standard errors each cross section is weighted by the square root of sample size given more weight to the largest cross sections. Within each cross section security level returns are (i) equally weighted in panel A, (ii) value weighted in panel B (where the weights are the square root of the securities market capitalization, in USD), and (iii) risk weighted in panel C (where the weights are inversely proportional to the historical volatility of idiosyncratic returns). All other variables are defined in Appendix II.

Table 6 Future Stock Returns related to $SHOCK_t$ Across Size Quintiles

Panel A: Returns of One Month Ahead

		Size Quintile				
		Small	**2**	**3**	**4**	**Large**
	$MCAP$	17.58	64.27	173.75	516.01	5,477.72
Shock Quintile	**Low**	0.0151	0.0048	0.0054	0.0049	0.0053
	2	0.0251	0.0108	0.0099	0.0078	0.0102
	3	0.0220	0.0173	0.0140	0.0115	0.0067
	4	0.0227	0.0139	0.0169	0.0168	0.0057
	High	0.0413	0.0314	0.0294	0.0164	0.0178
	Hedge	0.0254	0.0262	0.0240	0.0143	0.0116
	t-statistic	3.86	3.92	3.74	2.16	2.3
	Sharpe ratio	1.10	1.11	1.06	0.66	0.66

Panel B: Returns of Two Months Ahead

		Size Quintile				
		Small	**2**	**3**	**4**	**Large**
Shock Quintile	**Low**	0.0086	0.0022	0.0028	0.0031	0.0035
	2	0.0137	0.0065	0.0073	0.0051	0.0052
	3	0.0177	0.0094	0.0072	0.0069	0.0054
	4	0.0193	0.0118	0.0089	0.0071	0.0024
	High	0.0208	0.0167	0.0170	0.0100	0.0099
	Hedge	0.0123	0.0145	0.0141	0.0118	0.0063
	t-statistic	1.96	2.83	2.45	1.89	1.58
	Sharpe ratio	0.56	0.80	0.70	0.57	0.46

Panel C: Returns of Three Months Ahead

		Size Quintile				
		Small	**2**	**3**	**4**	**Large**
Shock Quintile	**Low**	0.0086	0.0029	0.0025	0.0028	0.0026
	2	0.0136	0.0086	0.0080	0.0047	0.0031
	3	0.0170	0.0097	0.0072	0.0058	0.0047
	4	0.0190	0.0088	0.0075	0.0056	0.0027
	High	0.0170	0.0154	0.0167	0.0116	0.0096
	Hedge	0.0083	0.0125	0.0142	0.0125	0.0070
	t-statistic	1.50	2.40	2.43	2.05	1.74
	Sharpe ratio	0.43	0.68	0.69	0.62	0.50

Panel D: Returns of Four Months Ahead						
				Size Quintile		
		Small	**2**	**3**	**4**	**Large**
Shock Quintile	**Low**	0.0086	0.0028	0.0038	0.0039	0.0039
	2	0.0159	0.0060	0.0034	0.0007	0.0016
	3	0.0168	0.0078	0.0055	0.0067	0.0063
	4	0.0190	0.0104	0.0103	0.0072	0.0039
	High	0.0196	0.0153	0.0137	0.0119	0.0065
	Hedge	0.0111	0.0125	0.0099	0.0094	0.0026
	t-statistic	2.04	2.38	1.71	1.52	0.65
	Sharpe ratio	0.58	0.68	0.49	0.46	0.19

Panel E: Returns of Five Months Ahead						
				Size Quintile		
		Small	**2**	**3**	**4**	**Large**
Shock Quintile	**Low**	0.0094	0.0020	0.0013	0.0028	0.0035
	2	0.0126	0.0077	0.0096	0.0030	0.0011
	3	0.0135	0.0059	0.0074	0.0055	0.0054
	4	0.0202	0.0146	0.0095	0.0081	0.0043
	High	0.0232	0.0168	0.0164	0.0107	0.0071
	Hedge	0.0138	0.0148	0.0151	0.0083	0.0033
	t-statistic	2.85	2.96	2.64	1.44	0.84
	Sharpe ratio	0.81	0.85	0.75	0.44	0.25

Panel F: Returns of Six Months Ahead						
				Size Quintile		
		Small	2	3	4	Large
Shock Quintile	**Low**	0.0111	0.0019	0.0020	0.0028	0.0025
	2	0.0098	0.0083	0.0051	0.0046	0.0048
	3	0.0131	0.0064	0.0073	0.0068	0.0054
	4	0.0227	0.0124	0.0069	0.0047	0.0058
	High	0.0261	0.0161	0.0179	0.0114	0.0065
	Hedge	0.0151	0.0143	0.0159	0.0088	0.0039
	t-statistic	2.97	2.71	2.75	1.46	1.00
	Sharpe ratio	0.85	0.78	0.79	0.45	0.29

For each month, stocks are first sorted into five equal groups based on market capitalization (in USD). Then, within each size group, stocks are further sorted based on $SHOCK_t$. Panels A-F report the average returns for 25 (5×5) portfolios for the six months following portfolio formation. The portfolio returns are value weighted (where the weights are computed as market capitalization, in USD). The 'Hedge' return is the difference between the average portfolio returns across extreme quintiles. The Sharpe ratio is calculated following Lewellen (2010). Returns are reported in decimal units (i.e., 0.01 is 1%).

Table 7 Ex Post Return Analysis

$$HEDGE_t = \alpha + \beta_1 dRP_t + \beta_2 dTS_t + \beta_3 dIP_t + \beta_4 MKT_t + \beta_5 SMB_t + \beta_6 HML_t + \beta_7 MOM_t + e_t \quad (6)$$

Panel A: Equal-weighted						
	Hedge1	***Hedge2***	***Hedget3***	***Hedge4***	***Hedge5***	***Hedge6***
α	0.0244	0.0146	0.0134	0.0120	0.0133	0.0157
	(4.61)	*(3.08)*	*(2.95)*	*(2.67)*	*(2.99)*	*(3.46)*
β_1	-0.0264	-0.0342	-0.0002	0.0052	0.0109	-0.0026
	(-1.47)	*(-1.56)*	*(-0.01)*	*(0.25)*	*(0.53)*	*(-0.13)*
β_2	0.0008	-0.0175	-0.0321	-0.0233	0.0027	0.0182
	(0.03)	*(-0.64)*	*(-1.21)*	*(-0.90)*	*(0.11)*	*(0.70)*
β_3	-0.5706	-0.5368	-0.3184	-0.2235	-0.0153	-0.4793
	(-0.81)	*(-0.85)*	*(-0.52)*	*(-0.37)*	*(-0.03)*	*(-0.80)*
β_4	0.0016	0.0019	0.0022	0.0021	0.0018	0.0021
	(1.29)	*(1.70)*	*(2.02)*	*(1.94)*	*(1.67)*	*(1.95)*
β_5	-0.0028	-0.0039	-0.0032	-0.0030	-0.0020	-0.0029
	(-1.80)	*(-2.77)*	*(-2.40)*	*(-2.28)*	*(-1.53)*	*(-2.12)*
β_6	-0.0017	-0.0014	-0.0022	-0.0026	-0.0028	-0.0041
	(-1.13)	*(-1.00)*	*(-1.68)*	*(-1.99)*	*(-2.21)*	*(-3.18)*
β_7	0.0027	0.0024	0.0025	0.0022	0.0007	-0.0001
	(2.91)	*(2.85)*	*(3.07)*	*(2.82)*	*(0.96)*	*(-0.18)*
Adj. R^2	0.038	0.056	0.071	0.065	0.016	0.069
Sharpe ratio	1.31	0.87	0.84	0.76	0.86	1.00

Panel B: Value-weighted

	Hedge1	*Hedge2*	*Hedget3*	*Hedge4*	*Hedge5*	*Hedge6*
α	0.0224	0.0147	0.0139	0.0100	0.0095	0.0120
	(4.46)	*(3.52)*	*(3.19)*	*(2.37)*	*(2.22)*	*(2.75)*
β_1	-0.0431	-0.0417	-0.0187	0.0001	0.0009	-0.0069
	(-1.84)	*(-2.15)*	*(-0.92)*	*(0.01)*	*(0.04)*	*(-0.34)*
β_2	-0.0053	-0.0032	-0.0031	-0.0012	0.0099	0.0157
	(-0.18)	*(-0.13)*	*(-0.12)*	*(-0.05)*	*(0.40)*	*(0.63)*
β_3	-0.5654	-0.6738	-0.5086	-0.4290	-0.1720	-0.3433
	(-0.84)	*(-1.21)*	*(-0.87)*	*(-0.76)*	*(-0.30)*	*(-0.53)*
β_4	0.0001	0.0012	0.0014	0.0019	0.0018	0.0018
	(0.12)	*(1.18)*	*(1.30)*	*(1.85)*	*(1.80)*	*(1.71)*
β_5	-0.0018	-0.0024	-0.0017	-0.0012	-0.0010	-0.0019
	(-1.21)	*(-1.91)*	*(-1.35)*	*(-1.00)*	*(-0.82)*	*(-1.42)*
β_6	-0.0022	-0.0029	-0.0032	-0.0033	-0.0027	-0.0036
	(-1.49)	*(-2.40)*	*(-2.57)*	*(-2.75)*	*(-2.20)*	*(-2.91)*
β_7	0.0014	0.0014	0.0014	0.0014	0.0009	0.0050
	(1.55)	*(1.86)*	*(1.77)*	*(1.87)*	*(1.20)*	*(0.65)*
Adj. R^2	0.007	0.057	0.040	0.057	0.024	0.044
Sharpe ratio	1.26	1.00	0.91	0.68	0.64	0.79

Panel C: Risk-weighted

	Hedge1	*Hedge2*	*Hedget3*	*Hedge4*	*Hedge5*	*Hedge6*
α	0.0149	0.0135	0.0123	0.0105	0.0098	0.0121
	(4.42)	*(4.07)*	*(3.92)*	*(3.43)*	*(3.18)*	*(3.62)*
β_1	-0.0451	-0.0399	-0.0076	0.0066	0.0115	-0.0087
	(-2.86)	*(-2.59)*	*(-0.52)*	*(0.46)*	*(0.81)*	*(-0.57)*
β_2	-0.0026	-0.0072	-0.0141	-0.0076	0.0044	0.0181
	(-0.13)	*(-0.38)*	*(-0.77)*	*(-0.43)*	*(0.25)*	*(0.94)*
β_3	-0.6952	-0.4714	-0.1001	0.1032	0.3780	-0.0635
	(-1.54)	*(-1.07)*	*(-0.24)*	*(0.25)*	*(0.93)*	*(-0.14)*
β_4	0.0019	0.0017	0.0017	0.0019	0.0021	0.0022
	(2.37)	*(2.18)*	*(2.24)*	*(2.60)*	*(2.82)*	*(2.71)*
β_5	-0.0026	-0.0024	-0.0014	-0.0012	-0.0009	-0.0019
	(-2.60)	*(-2.50)*	*(-1.46)*	*(-1.29)*	*(-0.99)*	*(-1.84)*
β_6	-0.0025	-0.0023	-0.0022	-0.0019	-0.0019	-0.0024
	(-2.57)	*(-2.38)*	*(-2.39)*	*(-2.22)*	*(-2.15)*	*(-2.45)*
β_7	0.0010	0.0006	0.0007	0.0007	0.0004	-0.0003
	(1.63)	*(1.03)*	*(1.20)*	*(1.26)*	*(0.68)*	*(-0.43)*
Adj. R^2	0.120	0.096	0.038	0.050	0.061	0.084
Sharpe ratio	1.25	1.16	1.12	0.98	0.91	1.04

For each month, stocks are sorted into five equal groups based on $SHOCK_t$. The portfolio returns are (i) equally weighted in panel A, (ii) value weighted in Panel B (where the weights are market capitalization, in USD), and (iii) risk weighted in panel C (where the weights are inversely proportional to the historical volatility of idiosyncratic returns). The 'Hedge' return is the difference between the average portfolio returns across extreme quintiles. The 'Hedge' return is for the six months following portfolio formation. These returns are not cumulative. 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.