The Information Content of Commodity Futures Markets*

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Abstract

We find that commodity futures returns contain information relevant to stock market returns and macroeconomic fundamentals for a large number of countries. Commodity futures returns predict stock market returns in 59 out of 70 countries and macroeconomic fundamentals in 62 countries. This predictability is not concentrated in the Energy and Industrial Metals sectors, as it is economically and statistically significant across all sectors. Surprisingly, we find that the role of countries' dependence on commodity trade is limited in its ability to account for this predictability. This holds true even when considering new measures that take into account indirect exposures through financial and trade linkages between countries. We find much stronger evidence of predictability being related to the ability of commodities to forecast inflation rates. Overall, our evidence is consistent with commodity markets having a truly global information discovery role in relation to financial markets and the real economy.

JEL classification: G11, G12, G13

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We study the information content of commodity futures returns with respect to stock market returns around the world, using an extensive dataset covering 70 countries and six commodity sectors over the course of a sample period between 1979 and 2016. To the best of our knowledge, we are the first to show that the information flow from commodity to stock markets is a pervasive global phenomenon and that the information content of commodity sector returns extends well beyond countries' dependence on commodity trade. Overall, our findings are consistent with the idea that commodity markets play an important role in aggregating dispersed global information.

Commodities are a major source of income for many countries around the world. Proceeds from trading in primary commodities amount to about 7% of the world GDP (van der Ploeg and Venables, 2012). Though this dependence is more acute in emerging countries, developed countries are also highly exposed to commodities. For instance, up to 30% of the GDP in countries like Australia, Canada and Norway is tied to the trade of primary commodities.[1]

In spite of this, very little is known about the relation between various commodity sectors and stock markets around the world. Previous literature has tended to focus on individual commodities, in particular oil, and on developed countries.[2] We aim to fill this gap with our comprehensive analysis of a broad set of countries and commodity sector indices over an extended period of time.

In theory, futures prices may convey information that is relevant to stock markets via a commodity trade dependence channel and an information channel that is dependent upon the informativeness of commodity prices. Commodity price changes can be seen as terms of trade shocks for commodity dependent countries (Chen, Rogoff, and Rossi, 2010). Indeed, given that some countries rely heavily on trading commodities, commodity price fluctuations are likely to affect export-dependent countries in terms of revenues and import-dependent

[1]Source: Authors calculations based on UNCTADstat data from 1995 to 2016.

[2]See, e.g., Kilian (2009, 2014), Driesprong, Jacobsen, and Maat (2008)), Jacobsen, Marshall, and Visaltanachoti (2018), and Hu and Xiong (2013).

countries in terms of costs (Classens and Duncan, 1994). In addition, countries are also indirectly exposed to trade dependence on commodities by way of economic linkages with commodity dependent countries. For instance, bilateral trade and financial linkages are known to affect business cycle synchronization and lead to economic spillovers (e.g. Frankel and Rose (1998), Kalemli-Ozcan, Papaioannou, and Peydró (2013), Cesa-Bianchi, Imbs, and Saleheen (2018)), which is reflected in stock return predictability across trade-linked countries (Rizova, 2010). According to this view, commodity prices may contain information that is relevant to a country's stock market either because that country is dependent on commodity trade or because it is economically linked to countries that are.

In addition to this trade dependence channel, previous research has shown that commodity futures markets are also a valuable source of information about the strength of the global economy, as they aggregate dispersed information about commodity demand and supply.[3] As such, the information content of commodity prices should extend well beyond countries' dependence on commodity trade (e.g. Hu and Xiong (2013), Sockin and Xiong (2015)). Accordingly, the ability of commodity markets to predict stock markets should also depend on the extent to which a commodity can convey information about a country's macroeconomic fundamentals. While these two channels are not mutually exclusive, it is thus far unclear as to which one is dominant with respect to most countries in the world economy and whether or not this varies across commodity sectors.

We find that in 59 of the 70 countries in our sample, country stock market returns are predicted by the past commodity futures returns of at least one commodity sector. The majority of those stock market returns are, in fact, predicted by two to four commodity sectors. This is true for both emerging markets and developed countries. Furthermore, all commod-

[3]For example, Samuelson (1965), Black (1976), Danthine (1978), Bray (1981), Barsky and Kilian (2002, 2004), Sockin and Xiong (2015), and Brogaard, Ringgenberg, and Sovich (2018) argue that futures markets facilitate aggregation of information. However, Stein (1987), Sockin and Xiong (2015), and Brogaard, Ringgenberg, and Sovich (2018) show that, under certain circumstances, the trading in futures markets may also diminish the extent to which futures prices are informative.

ity sectors predict a wide range of countries in our sample. The Energy, Industrial Metals, and Livestock & Meats sectors predict the highest percentage of countries, ranging between 33 and 44% of all the countries in our sample, while the Precious Metals and Agriculture sectors predict around 20-25%. These results remain robust even when controlling for known stock market predictors. Hence, from a statistical significance standpoint, all sectors contain information that is relevant to stock markets around the world.

However, it is not only that commodity markets predict stock markets in many countries, it is also that the economic magnitude of this predictability is large and, for most countries, several commodity sectors contain important economic information that is not subsumed by the others. In fact, when looking within each country, we find that there are few countries for which the economic magnitude of predictability is dominated by a single sector. This is surprising given that many countries are disproportionately more dependent on trade in some commodity sectors than in others. We also show that the economic magnitude of predictability is not concentrated in the largest economies; rather it is spread evenly across the globe. For example, while the US and China have accounted for more than 30% of the world GDP in the recent past, each of them accounts for less than 7% of the global stock market variation that is predicted by commodity markets.

Furthermore, we decompose the variation in stock market returns around the world that is predicted by commodity futures markets into commodity sector shares. We find the Industrial Metals, Agriculture and Energy sectors to be the most important economically, capturing 28%, 25% and 20% of the global stock market response, respectively, when we simultaneously shock all commodity sectors in all countries. However, the shares of the remaining two sectors are still large at 11% for Precious Metals and 16% for Livestock & Meats. The fact that the shares of different sectors are so comparable is very surprising, as it is not consistent with the importance of these sectors in terms of global production and trade. For example, the 2018 world-production weights of the S&P GSCI index allocate 59% to Energy, 18% to Agriculture, 11% to Industrial Metals, 8% to Livestock and 5% to Precious Metals.[4] Furthermore, we find that the predictability of stock market returns on the basis of commodity returns is not strongly related to the dependence of countries' GDP on trade in a given commodity sector, as we see similar evidence for the presence of predictability for countries with high and low export and import dependence on our commodity sectors. Therefore, commodity sector returns must convey information that extends beyond production and trade dependence and that is relevant to stock markets around the world.

To understand the channels of information transmission, we run cross-country regressions of predictability measures on several country-level, commodity-related and macroeconomic variables. We find that the magnitude of predictability of stock market returns on the basis of commodity sector returns is strongly negatively related to the country's stage of development and, to a lesser degree, positively related to the dependence of the country's GDP on the exports and imports of commodities. Indeed, only for the Energy and the Agriculture sectors is the predictability of stock market returns significantly related to this measure of trade dependence. We also allow for the possibility that economic linkages between countries that are highly dependent on commodity trade may indirectly affect predictability. We take into consideration both financial (bilateral foreign portfolio investment) and trade (total bilateral trade) linkages in our construction of novel indirect measures of trade dependence. However, there is even less evidence that indirect trade dependence channels play an important role here.

We find strong evidence that commodity sector returns contain information about future changes in market fundamentals in a wide range of countries, i.e., the commodity sector returns predict inflation or industrial production growth rates in more than 80% of the countries in our sample. Furthermore, with the exception of the Precious Metals sector, the ability of commodity sectors to predict inflation (and, to a lesser degree, industrial production) in

[4]S&P Dow Jones Indices press release from November 9, 2017 available at www.spdji.com.

a given country is strongly related to their ability to predict stock market returns in that country, even after accounting for commodity trade dependence. This supports the idea that commodity markets convey truly global and economically meaningful information that is relevant to financial markets and the real economy and that extends beyond simple trade dependence and input/output cost effects. Overall, the ability of both country characteristics and commodity sector returns to forecast market fundamentals goes a long way in explaining cross-country differences in commodity-stock market predictability (i.e., we strongly reject the null hypothesis that these variables are not important and we find that the R^2 ranges between 20% and 50% in our cross-country regressions).

Our empirical results remain robust when subjected to a wide range of changes to our specifications. Commodity sector returns convey information about stock markets beyond well-known stock market predictors, including the short rate (e.g., Ang and Bekaert (2007), Rapach, Strauss, and Zhou (2013)), Hong and Yogo's (2012) commodity market open interest and predictors of the strength of the global economy, namely the Kilian Index, the Baltic Dry Index and the S&P 500 futures returns (Kilian (2009), Hu and Xiong (2013)). We also show that our results are robust to using real returns instead of nominal returns and to controlling for exchange rates. In our baseline regression, estimated on a country-by-country basis, we use overlapping observations, but our results are robust when we use non-overlapping observations, gross returns instead of excess returns, when controlling for contemporaneous commodity sector returns and when focusing on different subsamples. We also rule out the possibility that our coefficients vary over time, thereby addressing concerns about alternative explanations related to structural breaks, crises and financialization of commodity markets. Finally, we find similar evidence of predictability when running our predictive regressions on a pooled sample of countries, as opposed to a country-by-country basis.

We contribute to several strands of literature. The literature that is substantively closest to our work documents the predictability of stock market returns on the basis of commodity futures returns. Previous research, however, has focused predominantly on the role of oil futures prices in developed economies (e.g., Kilian (2009, 2014), Driesprong, Jacobsen, and Maat (2008)), with few exceptions. Jacobsen, Marshall, and Visaltanachoti (2018) study the ability of the Industrial Metals sector to predict stock market returns in a sample of 11 developed countries and Hu and Xiong (2013) study the ability of oil, copper and soybean futures returns to predict stock market returns in five emerging and developed countries in Asia. Hong and Yogo (2012) study the predictability of U.S. stock returns on the basis of commodity market open interest, rather than returns. We contribute to this stream of literature by examining a comprehensive set of commodities and countries over a longer period of time, as well as by studying the economic relevance of predictability, and the channels of information transmission.

We also contribute to the literature that analyzes the relation between commodity prices and macro fundamentals. Commodity prices are known to feed into the production of manufactured goods (Garner, 1989), affect inflation (e.g., Breeden (1980), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Cologni and Manera (2008), and Bekaert and Wang (2010)), and precede most economic recessions in the United States (e.g., Hamilton (2009)). Black (1976), Bray (1981) and Sockin and Xiong (2015) show that commodity futures prices can reveal a great deal and can, therefore, provide useful information for commodity production and processing. Moreover, Kilian (2009), Hu and Xiong (2013) and Sockin and Xiong (2015) argue that commodity markets also contain information about the future strength of the global economy. However, most of these studies focus exclusively on the U.S. market, and we do not know whether or not these findings have global relevance in the sense of being applicable to other countries. We show that commodity sector returns also predict inflation and industrial production growth rates and that this predictability exists in many countries around the world, both emerging and developed.

A related question is why there is a delay in information from commodity markets reaching stock markets? First, commodity markets facilitate price discovery (e.g., Working (1948), Garbade and Silber (1983), and Hong and Yogo (2012)) and may, thus, contain relevant information that reaches other markets with a delay. Second, limited market participation (e.g., Hirshleifer (1988)) and slow information diffusion among investors with limited information-processing capacity (as in, for example, Merton (1987) and Hong and Stein (1999)) may cause a delay in information transmission. Most of the studies that have been carried out on the issue of slow information diffusion look at lead-lag effects in stock markets between firms or industries in a single-country context (e.g. Hou and Moskowitz (2005), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), and Menzly and Ozbas (2010)) or in a cross-country, international setting (Rapach, Strauss, and Zhou, 2013). One exception here is Pan and Poteshman (2006) who find that information diffuses slowly from option markets to stock markets. We contribute to this literature by providing evidence of information diffusing slowly across markets, as we show that the ability of commodity sector returns to predict stock market returns is related to their ability to predict macro fundamentals.

Finally, our results also speak to the classic literature on the informativeness of commodity prices. On the one hand, Black (1976), Danthine (1978), Bray (1981) and Sockin and Xiong (2015), among others, show that commodity markets provide valuable information by aggregating dispersed information and even providing information about the strength of the global economy. On the other hand, Stein (1987), Sockin and Xiong (2015), and Brogaard, Ringgenberg, and Sovich (2018) show that futures markets can be contaminated with informational noise and can actually reduce the welfare of firms that rely on futures prices for guidance in planning and making production decisions. We show that commodity sector returns systematically forecast stock market returns and macro fundamentals. This constitutes new evidence that commodity futures markets play an important information discovery role in financial markets and the real economy.

1 Data and Variable Definitions

1.1 Commodity Market Returns

We use daily commodity prices and open interest for the 28 most liquid, exchange-traded commodities from the Commodity Research Bureau (CRB). We compute (uncollateralized) futures returns using a roll-over strategy of first or second nearest-to-maturity contracts. We roll out of the first nearest contract (and into the second nearest contract) at the end of the month, before the month prior to maturity. In this way, we guard against the possible confounding effect of the erratic price and volume behavior that is commonly observed close to maturity. We use the short end of the futures curve because these contracts are typically the most liquid. Furthermore, to increase liquidity and reduce the impact of non-synchronous trading, we exclude daily returns if we do not observe positive trading volume on that day. We also compute the growth rate of commodity market interest in accordance with Hong and Yogo (2012).

Commodities are partitioned into six sectors: *Energy*, *Industrial Metals*, *Agriculture I & II*, *Livestock & Meats*, and *Precious Metals*. We sub-divide the agriculture sector into two different sectors based on the correlation structure of individual commodities, as this sector is the most heterogeneous.[5] For each sector, we compute the equally-weighted returns of all commodities in that sector. We also construct an equally-weighted index of all 28 commodities (EWI) and use the production-weighted, S&P GSCI Total Return Index (GSCI) sourced from Global Financial Data.

Detailed information on the composition of each sector, the name of the exchange in which each contract is traded, sample periods and delivery months of each contract, is provided in Table OA.1 in the Online Appendix.

[5] This subdivision roughly corresponds to the *Grains* and *Softs* sectors in Gorton and Rouwenhorst (2006).

1.2 Stock Market Returns

We use daily, country-level price indices (code MSRI) from the MSCI data. All of these indices are free-float-adjusted, market-capitalization weighted. Excess returns are expressed in national currency, in line with Solnik (1993), Ang and Bekaert (2007),Hjalmarsson (2010), and Rapach, Strauss, and Zhou (2013). We compute excess returns with respect to country-specific proxies of the risk-free rate specified in the Global Financial Data (GFD). Depending on the availability of data on the risk-free rate, we either use the *Total Return T-bill Index* or *Total Return Daily T-Bill* series constructed by the GFD, 3-month Treasury Bill Yields, Interbank interest rates, overnight interest rates or deposit rates. Table OA.2 in the Online Appendix specifies the risk-free rate proxy used for each country. We also extract daily prices for the S&P 500 futures from Global Financial data.

1.3 Trade Dependence Variables

We use annual data on total bilateral trade (export and import) flows from the International Monetary Fund (IMF) Direction of Trade Statistics (DOT) data on bilateral export and import flows across countries and the United Nations Conference on Trade and Development (UNCTADstat) granular data on export and import flows of specific goods. This data is available from 1995 onwards. We match each of our 28 individual commodities to 3-digit SICT codes in UNCTADstat and retrieve, data on total export and import flows from each country to the rest of the world, for each commodity-country-year.[6] We also use annual data on country-level, bilateral financial flows from the International Monetary Fund's (IMF) Coordinated Portfolio Investment Survey (CPIS). Data on portfolio investment security holdings, discriminating between short-term debt, long-term debt, equity and total investment (equity plus debt) holdings is available from 2001 onwards.

[6] We describe our matching procedure in detail in the Online Appendix.

We define the direct trade dependence of country i on commodity sector s as:

$$TD_{i,s} = T^{-1} \sum_{t=1}^{T} \frac{X_{i,t,s} + M_{i,t,s}}{Y_{i,t}} \tag{1}$$

where $X_{i,t,s}$ is the total value of the export flows of all goods matched to commodity sector s from country i to the rest of the world in year t; $M_{i,t,s}$ is the total value of the import flows of all goods matched to commodity sector s to country i from the rest of the world; and $Y_{i,t}$ is the GDP of country i in year t. $TD_{i,s}$ measures the importance of the trade in a given commodity sector relative to the country's GDP.

We are also interested in capturing each country's indirect trade dependence on each commodity sector. We define the indirect trade dependence of country i by measuring the trade dependence of a country's trading partners or countries with which country i has the strongest financial links. Our choice of these measures is informed by the bilateral trade dependence measures used the international business cycle synchronization literature (see, for instance, Imbs (2004) and Frankel and Rose (1998)).

First, we define the trade and financial linkages between countries in the following way:

$$T_{i,k,t} = \frac{X_{i,k,t} + M_{i,k,t}}{Y_{i,t}}, \tag{2}$$

$$F_{i,k,t} = \frac{A_{i,k,t} + L_{i,k,t}}{Y_{i,t}}. \tag{3}$$

$T_{i,k,t}$ measures the importance of trade flows between country i and its trading partners relative to country i's GDP. $X_{i,k,t}$ ($M_{i,k,t}$) is the total export (import) flows from country i to country k in year t. Financial linkages between countries, $F_{i,k,t}$, are measured analogously, but instead of the trade flows between countries, we use bilateral financial flows between countries. $A_{i,k,t}$ is the asset side of the investment exposure of country i with respect to country k, that is the dollar value of portfolio investment in country k held by country i;

$L_{i,k,t}$ is the liability side of the investment exposure.[7]

The indirect trade dependence of country i on commodity sector s is then defined as:

$$ITD_{i,s} = T^{-1}K^{-1}\sum_{t=1}^{T}\sum_{k=1}^{K} T_{i,k,t} \times \frac{X_{k,t,s} + M_{k,t,s}}{X_{w,t,s} + M_{w,t,s}}, \tag{4}$$

$$IFD_{i,s} = T^{-1}K^{-1}\sum_{t=1}^{T}\sum_{k=1}^{K} F_{i,k,t} \times \frac{X_{k,t,s} + M_{k,t,s}}{X_{w,t,s} + M_{w,t,s}}. \tag{5}$$

The indirect trade dependence of country i on commodity sector s, $ITD_{i,s}$, is the average of the product of the trade importance of country i's trading partner relative to its GDP and the importance of that trading partner in the world trade of commodity s. The more important country i's trading partner is in the world trade of a particular commodity sector or the more important that trading partner is relative to country i's GDP, the higher the indirect trade dependence. The indirect financial dependence of country i on commodity sector s, $IFD_{i,s}$, is defined in an analogous way. The stronger the financial linkages between the countries, or the more important that country is in the world trade of the given commodity sector, the higher the indirect financial dependence of country i on commodity sector s.

1.4 Market Fundamentals

We use two variables to capture the overall state of a country's economy: the inflation rate and real industrial production growth rates. We rely on the Global Financial Data (GFD) to extract the monthly consumer price index and industrial production series. We use the consumer price index to compute inflation rates and to deflate industrial production growth.

We exclude the bottom and top 1% of outliers from the inflation rate series and the industrial production growth rate series, as we observe inflation rates as high as 1789% and industrial production growth rates of 26700% in our sample.

[7] We use "derived liabilities" variables in CPIS to construct our measures.

1.5 Summary Statistics

Table 1 presents summary statistics for our data. Panel A reports the annualized means and standard deviations for the commodity indices; the within-sector correlations, which are average correlations across all pairs of individual commodity returns composing a given sector; and across-sector correlations, which are calculated as the average correlation across all sectors (based on either sector or individual commodity returns). Panel B reports average excess returns and standard deviations for groups of countries. We follow the MSCI database classification of countries and split our 70 countries into 47 emerging and 23 developed countries. We further categorize our 70 countries based on whether their direct export (import) dependence for each of the six commodity sectors is above or below the median direct export (import) dependence in the sample. Panel C provides means and standard deviations for our economic variables. Our sample period runs from November 1979 to February 2016. We observe the trade and economic variables for a shorter sample period, however, which we specify in Table OA.3 in the Online Appendix.

[Table 1 About Here]

Commodity returns in Panel A vary a great deal across sectors, ranging from negative average annual returns for Agriculture sectors to more than 6% p.a. return for the Industrial Metals sector. Looking at the correlations, we see that, with the exception of the Agriculture II sector, the commodities within each sector are more strongly correlated with each other than they are with the commodities outside that sector. This is the main reason why we have kept the agriculture sector split into two sub-sectors.

Of the 70 countries in our sample, 47 are classified as emerging and 23 as developed countries (Panel B). Emerging countries have lower average excess returns, but higher standard deviation than the developed countries. We also split our 70 countries into several subgroups based on whether the direct export (import) dependence of each country for each of our sectors is above or below the median. For example, we find an average annual excess return of 1.2% for the 35 countries whose export of energy commodities is above median, versus 1.9% p.a. for the 35 countries whose export of energy commodities is below the median. The difference on the import side for energy commodities is even bigger, with a 0.5% return for countries whose import of energy commodities is above the median, versus 2.6% for those below the median. In general, commodity dependent countries whose direct export (import) is above the median tend to have lower average excess returns than those below the median. This is reminiscent of the well-known natural resource curse (der Ploeg (2011)).

In Panel C we report summary statistics for our economic variables. Due to data limitations, we do not observe economic indicators for all countries in our sample. We are missing inflation information for three countries and industrial production for eight countries. Emerging countries have much higher inflation rates and smaller real industrial production growth rates than developed countries. Both economic variables are much more volatile for the emerging countries than for the developed countries.

2 Do Commodity Returns Predict Stock Market Returns?

We analyze the predictability of stock market returns around the world using country-level regressions of excess stock market returns on lagged commodity futures returns, controlling for other stock market predictors. Our baseline regression is as follows:

$$r_{i,t:t+19} = \beta_{i,0} + \sum_{s} (\beta_{i,s,1} r^{c}_{s,t-21:t-2} + \beta_{i,s,2} r^{c}_{s,t-41:t-22}) + \phi_i r_{i,t-20:t-1} + \varepsilon_{i,t:t+19}, \qquad (6)$$

where $r_{i,t:t+19}$ denotes the monthly excess return of country i compounded from 20 daily returns between time t and $t+19$; $r^{c}_{s,t-21:t-2}$ and $r^{c}_{s,t-41:t-22}$ are lagged monthly commodity futures returns for sector s compounded from daily prices. We refer to these returns as one-month and two-month lag returns, respectively. We skip one full day between stock market return and commodity return given that, at present, many of our commodities are traded almost 24 hours a day.[8] We control for lagged stock returns, as autocorrelation in the series of stock returns can generate spurious evidence of predictability in the presence of contemporaneous correlation between commodity and stock returns (Boudoukh, Rishardson, and Whitelaw (1994); Chordia, Roll, and Subrahmanyam (2005)). We consider the following sectors: Energy, Industrial Metals, Agriculture I & II, Livestock & Meats and Precious Metals.

Panel A of Table 2 summarizes the key results from running regression (6) country-by-country for all 70 countries. In columns three to ten, for each commodity sector and the overall indices, we report the total number (T) and percentage (%) of countries for which we find significant slope coefficients at the 10% level, as well as the number of positive (P) and negative (N) coefficients that are statistically significant at the 10% level, separately for each lag and jointly across horizons. We use Newey-West standard errors with 19 lags to account for overlapping observations. Column 11 contains the number of countries that are predicted by at least one of the six sectors (excluding EWI and GSCI). The last two rows report overall regression statistics: average, median, max and min values of the individual R^2s, and the number of countries for which the Wald test of joint significance of all commodity slopes rejects the null hypothesis at the 10% level.

[Table 2 About Here]

Several results emerge from our analysis. First, we find strong evidence of predictability across a large number of countries and sectors, which is our first piece of evidence in support of the global relevance of the information content of commodity sector returns. The majority

[8]For example products traded via CME ClearPort Clearing are traded from 6:00 p.m. to 5:00 p.m. EST with only a one hour break each day.

of countries in our sample (84%) are predicted by at least one commodity sector at at least one horizon, while 70% are predicted with a one-month lag and 66% with a two-month lag. The Energy, Industrial Metals, and Livestock & Meats sectors predict the highest percentage of countries at at least one horizon, ranging from 44% for Energy to around 35% for Industrial Metals and Livestock & Meats. Precious Metals and Agriculture sectors predict around 20% to 26% of all the countries in our sample.

Second, looking at the R^2s, commodity sector returns predict stock market returns with an average R^2 of 5.50%, with a high of 22.76%. These values are economically large. Using data for 18 countries from 1970 to 1989, based on international, monthly predictive regressions of country excess stock market returns on six non-commodity world market predictors, Ferson and Harvey (1993) find an average adjusted R^2 of 7.2% across countries. When extending the predictive model to include lags of the dividend yield, short-term interest rate, term yield and local excess stock market return, they find an average adjusted R^2 of 8.1%. Despite focusing only on commodity world market predictors and trying to explain a much larger number of local variables (stock market excess returns), our predictive model is comparable in terms of fit to that of Ferson and Harvey (1993).[9] Accordingly, the joint test for the significance of all slope coefficients shows that for 35 countries (50%), we cannot reject the null hypothesis that commodity returns are important predictors of stock market returns.

Third, we observe both positive and negative slopes for almost all sectors, with Energy coefficients being predominantly negative and Industrial Metals and Livestock & Meats coefficients generally being positive. The overall commodity indices predict the stock markets with a positive sign in most cases. If futures prices matter most in terms of the cost channel,

[9]For a list of R^2s found in other studies, refer to Table I of Ferson, Sarkissian, and Simin (2003). The reported R^2s therein range from less than 1% to 7.8%. For a discussion of how small R^2s over short return horizons translate into large R^2s over longer horizons, refer to Fama and French (1988) and Cochrane (2008). From a portfolio allocation perspective, Kandel and Stambaugh (1996) and Fleming, Kirby, and Ostdiek (2001) show that even models with R^2s as small as 0.24% can be associated with high sensitivities of portfolio weights with respect to the predictive variables.

we would expect the signs to be related to the export (import) dependence of each country on a given commodity sector. The cost channel predicts a negative impact of increases in commodity prices for countries that rely on the import of commodities via higher input costs, and a positive impact for the exporters due to increased sales price. The fact that we observe predominantly positive signs for most sectors and for the overall indices may suggest that commodity futures markets matter not only in terms of the cost channel but perhaps also in terms of the information channel through which commodity futures markets convey important information about the future state of the global economy (e.g., Danthine (1978), Sockin and Xiong (2015)). We analyze this point in more detail in the subsequent sections.

Finally, predictability also varies across horizons. Energy predicts, largely, with a one-month lag, while Industrial Metals and the Agriculture sectors predict up to a two-month lag. However, there are very few countries that are predicted by commodity sectors at both horizons. As such, the results across horizons reflect the fact that the information from a given sector may reach different countries with different degrees of delay due to, for example, differences in cross-country market efficiency and/or dependence of a country's economy on a given commodity sector.

In Panel B, we split our 70 countries into several groups. First, we divide up our countries based on whether the export (import) of each country relative to its GDP is above or below the median for each commodity sector. We find similar predictability across these subgroups of countries. Moreover, within each subgroup, we observe both positive and negative slope coefficients. These results suggest that direct trade dependence may not be the only channel through which information from commodity markets reaches stock markets.

Next, we differentiate between emerging and developed countries, and find similar evidence of predictability for both groups of countries. For the emerging countries, we once again observe both positive and negative slope coefficients within a given sector, while the developed countries seem to be more homogeneous, with the signs of the slope coefficients being either all positive or all negative.

Figure 1 further illustrates which countries are predicted by a given number of sectors at at least one horizon. The majority of the countries (35 out of 70) are predicted by three to four commodity sectors: 10 of these countries are developed and 25 are emerging. 11 out of 70 countries are not predicted by any commodity sector and Nigeria and the Netherlands are the only countries predicted by all six sectors.

[Figure 1 About Here]

Overall, all commodity sectors are predictive for a wide range of countries in our sample. This shows that commodity futures markets aggregate dispersed information with a truly global predictive value and that this (global) value is not confined to the Energy and Industrial Metals sectors. These results build upon findings from the previous literature that predominantly focuses on oil futures and developed countries (e.g., Kilian (2009, 2014), Driesprong, Jacobsen, and Maat (2008)), with some exceptions (e.g., Jacobsen, Marshall, and Visaltanachoti (2018), Hu and Xiong (2013)). We find that in addition to Energy, other sectors, Agriculture in particular, predict a substantial number of stock market returns and that whether predictability is present or not seems unrelated to a country's stage of development or its direct export (import) dependence in a given commodity sector. The fact that we find strong predictability stemming from Agriculture to stock market returns in the different subgroups of countries shows that, contrary to widely held assumptions about this sector, the information it conveys seems relevant not only to agriculture-based economies, which are typically less developed, but also to developed countries and countries whose direct export (import) dependence on agriculture commodities is low. The predictability of stock market returns on the basis of commodity returns is thus widely applicable across countries and sectors. In Section 5, we show that the evidence of predictability is robust even with the addition of a variety of controls to our baseline regression and that the results are not driven by time variation in the coefficient estimates.

3 Is Predictability from All Commodity Sectors and in All Countries Important?

The analysis presented above is informative about the number of countries predicted by each sector and the overall goodness-of-fit of our model. As such, it yields only an incomplete picture. For example, we would like to be able to understand whether the predictable part of country-specific and global stock market return variation responds substantially more to shocks to the Energy sector relative to other sectors or whether all sectors contribute to a comparable share of that predictable variation. In fact, despite the fact that all sectors predict a large number of countries in a statistical sense, finding that Energy has an overwhelmingly dominant share would hardly be surprising given its much higher production value relative to other sectors. It is also possible that the bulk of the information content in commodity markets pertains to the stock markets of big players in the global economy and international trade, like the US and China. This would imply that the economic importance of the information content of commodity markets with respect to stock markets is not truly global.

In order to answer the question of whether predictability is concentrated in key sectors or key countries, we develop four measures of economic significance:

$$WS_{i,s} = \frac{\sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}}{\sum_s \sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}}, \tag{7}$$

$$BS_{i,s} = \frac{\theta_i \sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}}{\sum_i \left[\theta_i \sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}\right]}, \tag{8}$$

$$GC_i = \frac{\theta_i \sum_s \sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}}{\sum_i \left[\theta_i \sum_s \sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}\right]}, \tag{9}$$

$$GS_s = \frac{\sum_i \theta_i \left[\sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}\right]}{\sum_s \sum_i \theta_i \left[\sum_h |\beta^*_{i,s,h}| \mathbf{1}_{i,s,h}\right]}, \tag{10}$$

where $|\beta^*_{i,s,h}|$ is the absolute value of the standardized regression coefficient obtained from regression (6) with respect to sector s, country i, and horizon h; h corresponds to one-month and two-month lag returns as defined in Equation (6); $\mathbf{1}_{i,s,h}$ is an indicator variable equal to unity if the coefficient $\beta^*_{i,s,h}$ is significant at the 10% level; and θ_i is an adjustment to yield infinite-horizon interpretation. This is important, as less efficient stock markets will react more slowly to the same information, so an accurate economic significance analysis should take that into account. This variable is defined as $\theta_i = \frac{1}{1-|\phi_i|}$, where ϕ_i is estimated in regression (6). $|\phi_i|$ can be interpreted as a market inefficiency metric. The more autocorrelated the series of stock returns are, i.e., the farther away $|\phi_i|$ is from 0, the larger θ_i will be. In the case of full market efficiency, in the sense that past stock returns are completely irrelevant to predicting next period returns, it must be the case that $\phi_i = 0$ and, as a consequence, $\theta_i = 1$ has no bite.[10]

The interpretation of all measures is intuitive. For each sector, the distribution of the within-country measure ($WS_{i,s}$) is plotted in Figure 2a. $WS_{i,s}$ quantifies which sectors are the most prominent within each country. It captures the share of country i's stock market response to a one standard deviation shock to all commodity sectors and at all lags that is attributable to commodity sector s. We further define sector s to strongly dominate other sectors in country i if and only if $WS_{i,s} > 75\%$.

[Figure 2 About Here]

We see that only for a small fraction of countries does the response of a particular sector dominate the responses of the other sectors. For example, the Energy sector is predictive for many countries, however, this sector strongly dominates all other sectors in only six out of 31 countries (19% of the countries it is predictive for). The picture is very similar for Industrial Metals, Livestock & Meats and Precious Metals, which also strongly dominate

[10]Derivation of the infinite-horizon adjustment is provided in the Online Appendix.

in around 20% of the countries they predict. For the Agriculture sectors, we find strong dominance in at most one country per sector. Hence, for those countries, there is a single commodity sector that contains the majority of the relevant information that flows from commodity markets to that country. However, for the majority of the countries, i.e., around 80% of the countries whose stock markets are predicted by non-Agriculture sectors and almost 100% of the countries predicted by the Agriculture sectors, the information contained in that particular sector does not strongly dominate the other sectors. As such, when looking within countries, the economic magnitude of predictability based on different sectors is rather evenly spread.

Figure 2b illustrates the distribution of the between-country sector measure ($BS_{i,s}$) for each sector; this value quantifies whether or not predictability from a given commodity sector is evenly distributed across countries. For all sectors, if we shock the commodity sector at all lags by one standard deviation, for the majority of the countries (between 65% and 100% depending on the sector), the share of the global stock market response attributable to each individual country is lower than 7.5%. Even though there are a few countries for which predictability is dominated by the Energy sector within that country, when looking across countries, the country shares of the global response to a Energy shock is, at most, 7.5% (in three countries), while for 9 countries, the shares are less than 2.5%. For one country, the share of the global response to a commodity shock to either Agriculture I, Agriculture II, Livestock & Meats or Industrial Metals is, at most, 13%. In the case of Precious Metals, there are two such countries with shares of at most 13%. This suggests that all sectors are also, in large part, equally important across our countries.

[Figure 3 About Here]

This conclusion is further supported by Figure 3a, which shows the cross-country distribution of the between-country global commodity measure (GC_i). This measure captures the share of the response of country i if we shock all commodity sectors in all countries at all horizons by one standard deviation. In other words, it quantifies whether predictability from all commodity sectors is evenly distributed across countries. The impact of all sectors taken together is evenly distributed across stock markets around the world, as no single country has a share of more than 7%. Out of the 59 countries that are predicted by at least one sector, 54 countries have shares of no more than 3% and, of those, 42 have shares of less than 2%.

Finally, Figure 3b shows the global sector measure (GS_s), which quantifies whether or not predictability across all countries is evenly distributed across sectors. This measure captures the share of the global stock market response that is attributable to sector s if we shock all commodity sectors in all countries at all horizons by one standard deviation. We find that all sectors are important globally. If we shock all sectors in all countries, the Agriculture I and II sectors capture 25% of the global response, while all the other sectors capture around 20% each (Industrial Metals (27.5%), Energy (20.3%), Livestock & Meats (15.6%) and Precious Metals (11.2%)). This is surprising if we contrast these values with the production values of each commodity sector in the global economy. For example, in 2018, the S&P GSCI index allocated a share of 58.6% to Energy, 18.3% to Agriculture and 10.9% to Industrial Metals (copper, alone, has a share of only 4.4%), 7.5% to Livestock & Meats and 4.7% to Precious Metals. Hence, our results suggest that the importance of the information flows from many of our commodity sectors is different from their importance in terms of their global production value.

4 Economic Channels of Information Transmission

In this section, we explore possible channels through which the information may flow from commodity to stock markets.

On the one hand, the information content of commodity markets in a given country is likely to depend on country characteristics, such as the degree of stock market efficiency and development and, crucially, the exposure of that country to commodity markets through commodity trade. Some countries heavily export and import a given commodity, thus making their economy directly dependent on that particular commodity. This includes direct terms of trade effects related to import costs and export revenues (Chen, Rogoff, and Rossi, 2010), as well as more nuanced effects such as political stability and the ability to attract foreign direct investment (Classens and Duncan, 1994). Other countries do not depend directly on trading a given commodity, but may be indirectly exposed to other commodity-dependent countries via bilateral trade or financial linkages. These linkages are known to be important determinants of business cycle synchronization and economic spillovers (e.g. Frankel and Rose (1998), Kalemli-Ozcan, Papaioannou, and Peydró (2013), Cesa-Bianchi, Imbs, and Saleheen (2018)) and lead to stock return predictability across trade-linked countries (Rizova, 2010). Therefore, if a country's balance of payments, either through its current account (exports and imports) or capital account (foreign portfolio investment and foreign direct investment), is very sensitive to the state of the economy of another commodity-dependent country, the former country is indirectly exposed to commodities. According to this line of reasoning, the information content of commodity markets is largely a function of the dependence of a country on commodity trade.

On the other hand, if commodities aggregate dispersed information about the state of the global economy, their information content should extend well beyond countries' dependence on commodity trade (e.g. Hu and Xiong (2013), Sockin and Xiong (2015)). In this case, the ability of commodity markets to predict stock markets should strongly depend on the extent to which a commodity conveys other information about a country's market fundamentals, even after controlling for trade dependence and other country characteristics like stock market efficiency and stage of development. While there is no reason to regard these hypotheses as mutually exclusive, we aim to understand which effect dominates.

4.1 Commodity Trade Dependence Channel

We start with cross-country regressions of the estimated predictability coefficients on several country characteristics. These characteristics relate to the stage of development of a country's stock market as well as direct and indirect trade-related exposures to commodity markets.

$$\beta_{i,s} = \gamma_{0,s} + \gamma_e E_i + \gamma_\theta \theta_i + \gamma_{TD,s} TD_{i,s} + \gamma_{ITD,s} ITD_{i,s} + \gamma_{IFD,s} IFD_{i,s} + \varepsilon_{i,s}, \tag{11}$$

where $\beta_{i,s}$ is an average of the absolute values of the slope coefficients across the two horizons from our per-country, predictive regressions provided in Equation (6).[11] E_i is a dummy variable that equals one if a country is emerging rather than developed. θ_i is the infinite horizon adjustment variable that we use in computing our economic significance measures in Section 3. This variable is defined such that the higher θ_i is, the more autocorrelated the stock returns of country i are. Therefore, we can interpret this measure as a market efficiency measure. $TD_{i,s}$, $ITD_{i,s}$, and $IFD_{i,s}$ are direct and indirect trade dependence measures defined in Section 1.3. The motivation for including these variables stems from the international business cycle synchronization literature, including Frankel and Rose (1998) and Imbs (2004), which suggests that trade and finance integration can lead to cross-country spillovers and output synchronization. Due to the availability of trade data, the sample period is restricted to the period between January 1995 and February 2016 and we re-estimate the slope coefficients from our per-country, predictive regressions on this restricted sample.

[Table 3 About Here]

[11] We use absolute values because, while we observe both positive and negative slope coefficients, our hypotheses are about the strength of the predictability (not about the sign). We take the average across the two horizons to reduce dimensionality and noise - given that a smaller fraction of countries is predicted separately at each horizon than jointly across both horizons.

In Panel A of Table 3, we report the results of regression (11) for each sector, which means that we use a maximum of 70 cross-country observations. In the last column, we pool all six sectors together and use sector fixed effects to focus on within-sector variation. We report the estimated coefficients, their t-statistics, the R^2 of the regressions and the p-values of the test of whether or not all the explanatory variables are jointly significant at the 10% level. We also report the number of observations included in each regression.

Overall, we find that our country characteristics are important in explaining cross-country differences in predictability. The average R^2 varies across sectors between 15% and 35%, except for Precious Metals where it is only 5.5%. In the pooled regression, we find an R^2 of 19%. For all sectors, except Precious Metals, as well as in the pooled regression, we reject the null hypothesis that our country characteristics are insignificant in explaining the cross-country variation in return predictability.

When looking at the results of the pooled regression, we find predictability to be stronger in emerging countries, as compared to developed countries. This is true for all but two sectors: Agriculture I and Precious Metals. Therefore, despite the fact that in previous sections we find that we can predict a similar percentage of countries in both groups, commodity sector returns move stock market prices more in emerging markets than they do in developed countries. Second, predictability is stronger in countries whose trade dependence on a given commodity sector is higher. This is not surprising given that high trade dependence on a given commodity sector exposes that countries' income, tax revenues and political stability to commodity markets. The surprising outcome is that we find significant effects only for the Energy and Agriculture sectors, which suggests that at least a substantial part of the information in global commodity markets is not explained by trade dependence effects. This is further supported by the fact that the indirect trade dependence measures do not seem to play a role either. In contrast, if we look at country i's financial partners, the more they depend on Energy, the less predictable country i's stock market returns are on the basis of

Energy returns. However, neither of these indirect measures are significant in the pooled regression.[12]

In Panel B we split the direct trade dependence measure into export and import respectively.[13] We find that most of the effect of direct trade dependence comes from the export side, as we find predictability on the basis of the Energy and Agriculture I sectors to be stronger in countries in which a larger share of their GDP is tied to the export of Energy and Agriculture I commodities. This is also the case for the pooled regression. Import dependence does not seem to matter much, as it is insignificant for all sectors as well as in the pooled regression. This is in line with the fact that, for some countries, export dependence on primary commodities is significantly higher than import dependence. This is especially the case for oil-dependent countries, such as Russia or Kuwait.

Our results, thus far, indicate that predictability of stock market returns on the basis of commodity sector returns exists across a wide array of different countries and that it is stronger in emerging economies. Trade dependence on commodities, though important for three sectors, does not seem to offer a full explanation of the observed commodity-stock market predictability. This suggests that commodities might convey information that is relevant to stock markets around the world and that goes beyond trade dependence on commodities.

4.2 Do Commodities Carry Information Beyond Trade Dependence?

Next, we analyze what kind of information this might be. Previous research has shown that commodity prices facilitate price discovery (e.g., Working (1948); Garbade and Silber

[12] In the case of Energy, the results are consistent with theoretical models and empirical evidence of trade (financial) integration leading to more (less) output synchronization. For trade, refer to, for instance, Frankel and Rose (1998) and Imbs (2004). For financial integration, refer to Kalemli-Ozcan, Papaioannou, and Peydró (2013), Cesa-Bianchi, Imbs, and Saleheen (2018) and references therein.

[13] Due to the limitations in the data, we are not able to reliably split indirect trade dependence measures.

(1983); and Hong and Yogo (2012)) and, therefore, may convey relevant information that reaches other markets with a delay. Limited market participation (e.g., Hirshleifer (1988)) can also cause a delay in information diffusion to the markets. Hong, Torous, and Valkanov (2007) show that cross-market predictability can be generated between segmented markets such that investors are not able to process all information from both markets (as in models of slow information diffusion among investors with limited information-processing capacity, e.g., Merton (1987) and Hong and Stein (1999)). Commodity markets have historically been rather segmented from stock markets, being populated by commodity producers and consumers willing to hedge their price risks, and specialized commodity speculators willing to assume that risk for a premium (e.g., Goldstein, Li, and Yang (2013), Boons, Roon, and Szymanowska (2014)). As such, commodity sector returns may predict stock market returns if they convey information about future changes in market fundamentals or economic activity that takes time for stock market investors to process.

To test this hypothesis, we consider two economic indicators, namely, the inflation rate and the real industrial production growth rate. We use the inflation rate because changes in commodity prices are known to precede changes in general price level, affecting them indirectly as they feed into the production of manufactured goods (Garner (1989)) and directly as they feed into inflation itself (e.g., Breeden (1980), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Cologni and Manera (2008), and Bekaert and Wang (2010)). The real industrial production growth rate captures the information that is relevant to the users and producers of commodities. For example, Black (1976), Bray (1981), Sockin and Xiong (2015) and Brogaard, Ringgenberg, and Sovich (2018) show that futures prices may provide information that is useful to commodity production and processing. Moreover, Sockin and Xiong (2015), Hu and Xiong (2013) and Kilian (2009) argue that commodity markets may also provide information about the future strength of the global economy which, in turn, can also affect commodity production planning as well as stock market fundamentals.

To set the stage, we run predictive regressions similar to Equation (6), but with the aim of predicting the two economic indicators we consider. In particular, for each of our economic indicators, we run the following long-horizon regression per country:

$$Z_{i,t:t+h} = \alpha_i + \sum_s \lambda_{i,s,h} r^c_{s,t:t-1} + \phi_i X_{i,h} + \mu_{i,t:t+h}, \tag{12}$$

where $Z_{i,t:t+h}$ is the growth rate of the economic indicator Z between months t and $t+h$ in country i. For each economic indicator, we run this regression for the three horizons, h, at 1, 6 and 12 months. The controls, $X_{i,h}$, include the lagged excess stock market return of country i, and up to three lags of the economic indicator, as in Hong, Torous, and Valkanov (2007). We use Newey-West standard errors with $h+1$ lags.

[Table 4 About Here]

Table 4 summarizes the results. In Panel A, we report the total number of countries for which commodity sectors returns predict future inflation rates and production growth rates at at least one horizon at the 10% significance level for each commodity sector and jointly across sectors. We also repeat the number of significant slope coefficients from predicting stock markets returns as in Equation (6), but re-estimate them on a sample period restricted to January 1995 to February 2016. This is dictated by the availability of data on trade variables and economic indicators.[14] Finally, at the bottom of that panel, we present the number of countries for which a given commodity sector predicts both the stock market and that country's economic indicator at at least one horizon. Panel B splits the countries for which commodity sectors predict their economic indicators into emerging and developed countries. Panel C divides countries according to whether their ratios of sector-specific exports and imports to GDP is above or below the median.

[14] We report full results of the estimation on this shorter sample period in Panel C of Table OA.4 in the Online Appendix.

First, in Panel A, commodity sector returns predict market fundamentals in a wide range of countries. More than 80% of countries see their inflation and industrial production growth rates predicted by at least one commodity sector at at least one horizon. Different commodity sectors seem to convey different information about the future state of the economy, however. Energy seems to be the most important predictor of country specific inflation rates, while Agriculture sectors are the most important in terms of predicting industrial production growth rates. While Energy is the most important predictor of inflation rates, Industrial Metals, Agriculture, and Precious Metals also convey information about inflation rates in a large number of countries.

Second, almost all countries in which stock market returns are predicted by at least one of the commodity sectors also see their economic variables predicted by these sectors. For 60 countries, commodity sector returns jointly predict stock market returns and future inflation rates and, for 57 countries, they predict stock market returns and industrial production growth rates. This joint predictability, however, varies per sector and per economic variable. Energy and Industrial Metals also predict stock market returns in at least half of the countries in which they predict both economic variables. The Agriculture I sector predicts stock market returns in around a third of the countries in which it predicts both economic variables, while Precious Metals predicts a half of the stock market returns of countries in which it predicts inflation rates, and a third of the countries in which it predicts industrial production growth rates. All the other sectors jointly predict stock market returns and economic variables in relatively few countries.

Third, the information that commodity sector returns convey about country-specific inflation and industrial production growth rates is spread out across emerging and developed countries (Panel B) and across countries with direct export (import) dependence above and below the median (Panel C). This result reinforces our earlier evidence that neither the development stage of the stock markets nor trade dependence can fully explain the predictability we document here.

Now that we established the extent to which commodity market sectors have information about future economic activities, we test whether the predictability of countries' stock market returns is related to the predictability of countries' economic indicators in the following cross-country regression:

$$\beta_{i,s} = \gamma_{0,s} + \Phi_s \lambda_{i,s} + \gamma_e E_i + \gamma_\theta \theta_i + \gamma_{TD,s} TD_{i,s} + \varepsilon_{i,s} \tag{13}$$

where $\lambda_{i,s}$ is the average, across the three horizons, of the absolute values of the slope coefficients from predicting our economic variables in the per-country regressions given in Equation (12), analogous to the way we define $\beta_{i,s}$ in regression (11). We control for the country characteristics that we find significant in estimating regressions given in Equation (11). E_i is a dummy variable that equals one if a country is emerging rather than developed; θ_i is our measure of market efficiency; and $TD_{i,s}$ is the direct trade dependence measure defined in Section 1.3. Due to the availability of the trade data, the sample period is restricted to the period between January 1995 and February 2016 and all slope coefficients from our per-country predictive regressions are estimated on this abbreviated sample.

[Table 5 About Here]

In Table 5, we report the results of regression (13) for each sector, meaning we use 70 cross-country observations, at most. In the last column, we pool all six sectors and use sector fixed effects to focus on within sector variation. We report the estimated coefficients, their t-statistics, the R^2 of the regressions and the p-values of the test of whether or not all the explanatory variables are jointly different from zero. We also report the number of observations included in each regression. Given that we observe economic indicators for a different number of countries, we first estimate this regression separately for the inflation rates in Panel A and the industrial production growth rates in Panel B. Panel C presents the results when we use both economic variables in one regression.

The results in Panel A show that the country's stock market predictability is significantly related to the predictability of its inflation rates for all sectors separately (with the exception of Industrial Metals and Precious Metals) and in the pooled regression, controlling for other country characteristics. The slope coefficients are all positive, which means that the better a given sector predicts the inflation rate of a country, the better it also predicts its stock market returns. In the pooled regression the effect is extremely statistically significant, with a t-statistic of 4.58. In contrast, the t-statistic for trade dependence in the pooled regression, albeit high, is much smaller at 2.69.

The predictability of real industrial production growth rates (Panel B) is less strongly related to the predictability of stock market returns, as it is only significant for the Energy sector and in the pooled regression. In fact, the evidence in Table 4 also shows that commodity sector returns predict the industrial production growth rate in fewer countries , as compared to the inflation rate. It is also interesting to recall that the Agriculture sector predicted industrial production growth in the largest number of countries. It seems, however, that predictability on the basis of the Agriculture sector is more related to its ability to forecast future inflation rates (Panel A) and whether or not a country's trade depends on Agriculture commodities (Table 3), rather than to its ability to predict future industrial production growth.

Panel C shows that the relation between a sector's ability to predict economic indicators and stock market returns is very similar when we include both indicators in the regressions. The main difference is in the Industrial Metals sector. Unlike in Panel A, a country's stock market predictability is now also related to the predictability of its inflation rate by this sector. For all sectors, except Precious Metals, we reject the null hypothesis that country characteristics and commodity sectors' ability to forecast economic variables are not important in terms of explaining cross-country variation in stock market predictability. For five out of six sectors, the R^2 varies between 20% and more than 50%, while in the pooled regression we find an R^2 of 26%. Overall, we find that our country characteristics and the ability of commodity sectors to forecast economic variables explain quite a large fraction of cross-country variation in stock market predictability from commodity sector returns.

5 Robustness Checks

In this section, we show that our results are robust to the inclusion of stock market predictors from the literature as well as Hong and Yogo's (2012) commodity market open interest predictor. We also provide evidence that our results are not driven by time-varying coefficients, which allows us to rule out explanations that are purely related to the financialization of commodity markets, such as Basak and Pavlova (2016), business cycle variation in predictability (Jacobsen, Marshall, and Visaltanachoti, 2018) and other structural breaks and exogenous shocks like crises. Furthermore, we show that our results are robust to controlling for the dollar exchange rate of each country and to using real commodity and stock market returns instead of nominal returns. This helps alleviate concerns that our results are mechanically driven by the inflation component of nominal returns or that the results are confounded by exchange rate predictability.

5.1 Controlling for Other Stock Market Predictors, Exchange Rates and Inflation

Hong and Yogo (2012) argue that open interest may be more informative in terms of predicting asset returns than futures prices and may, thus, constitute a new channel for information transmission from commodity markets to stock markets. They find that movements in open interest predict commodity returns and to a lesser degree stock, bond and currency returns. In light of this, we control for aggregate commodity open interest in our predictive regressions.[15]

We analyze the role of commodity market interest in Panel A of Table 6. Consistent with their weaker results related to stock market predictability, we find that the role of commodity market open interest is rather limited in terms of being able to predict stock market returns in the countries in our sample. The results of our analysis of predictability on the basis of commodity sector returns remains virtually unchanged when we control for commodity open interest. Moreover, open interest's ability to predict almost always coincides with the ability of sector returns to predict; as such, it does not represent a separate channel of information transmission.

[Table 6 About Here]

Next, in Panel B, we analyze our evidence of predictability by subjecting our analysis to two types of controls: the well-known country-specific stock market return predictors and predictors of the strength of the global economy.

Given the data limitations inherent to working with so many developing countries, we are only able to consistently use one known predictor of stock market returns across all countries, namely the short rate (e.g., Ang and Bekaert (2007); Rapach, Strauss, and Zhou (2013)).[16] To approximate the strength of the global economy, we use two proxies: the Kilian Index (Kilian, 2009) and the S&P 500 futures returns (Hu and Xiong, 2013).[17]

Our results, reported in Panel B, are robust with respect to these additional controls. The average R^2 increases by one and a half percentage points relative to the baseline regressions, which is consistent with the fact that these controls are accepted predictors of stock mar-

[15] We follow Hong and Yogo (2012) in constructing the growth rate of commodity market interest.

[16] In unreported results, conditional upon data availability, we experimented with the inclusion of the dividend yield, as well, and found that the results are robust.

[17] We thank Lutz Kilian for making this data available on his website. To overcome the mismatch between the daily frequency of the analysis and the monthly frequency of the Kilian index, we assign the month-t index value to all days of month t. The results are robust to using the Baltic Dry Index (sourced from Global Financial Data), which is available at a daily frequency. We report results using the Kilian index because data for the Baltic Dry Index is only available from 1999 onwards.

kets behavior; however, the predictability on the basis of commodity sector returns remains significant in a comparable number of countries.

An additional concern is that our results are maybe driven by the common component of inflation across countries and that inflation is serially autocorrelated (e.g. Ciccarelli and Mojon (2005)). Moreover, recent evidence suggests that commodity returns may be informative for the exchange rates of commodity-exporting countries (e.g. Kohlscheen, Avalos, and Schrimpf (2016)). It is thus possible that our tests fail to disentangle stock market predictability from predictability from inflation and/or exchange rate predictability. As shown in Panel C, our qualitative results are robust to using real commodity returns and real stock returns and to controlling for the dollar exchange rate of each country, thus alleviating these concerns.

Our results withstand a range of additional tests. Thus far, our analysis has been based on running 70 per-country predictive regressions, specified in Equation (6). In Panel D, we show that our results are robust when running pooled predictive regressions instead. We report the estimated coefficients and t-statistics using asymptotic standard errors, calculated following Driscoll and Kraay (1998), which are robust to heteroscedasticity and general forms of cross-sectional and temporal dependence when the time dimension becomes large.

Given the heterogeneity observed in the signs of our slope coefficients, we cannot pool all 70 countries together. Instead, we split our countries based on the signs of the slope coefficients from the country-specific regressions, and estimate pooled regressions on a group of countries with the same sign for each commodity sector based on the first two lags. We report the number of countries that are pooled together for each commodity sector. Depending on the sector, we were able to run the pooled regression on as many as 30-40 countries. The results are consistent with those reported in Panel A of Table 2, with Energy, Industrial Metals, Agriculture II and Livestock & Meats predicting stock market returns at one- and two-month lags, Agriculture I predicting at the two-month lag and Precious Metals not predicting.

Table OA.4 in the Online Appendix shows the robustness of running our baseline regression, specified in Equation (6), country-by-country, for all 70 countries when using non-overlapping observations (Panel A), gross returns (Panel B), and in a sample using only post-1995 observations beyond which point trade dependence data is available (Panel C).

In Table OA.5 in the Online Appendix, we allow for both contemporaneous and lagged commodity sector returns up to three-month lag, in line with evidence on slow information diffusion presented in the literature. For example, Rapach, Strauss, and Zhou (2013), and Jacobsen, Marshall, and Visaltanachoti (2018) find that about 70-80% of the predictive information across markets and/or industries is incorporated contemporaneously and the rest is incorporated after a delay. In line with these findings, we find a stronger contemporaneous relation between commodity sector returns and stock market returns around the world, with 99% of the countries exhibiting a significant contemporaneous relation between at least one of the commodity sectors and stock market returns. More importantly, our predictive results are robust to including this contemporaneous effect, as more than 60% of our countries see stock market returns that are still predicted by commodity sector returns, with a delay up to three months.

5.2 Time Varying Stock Market Predictability from Commodity Sector Returns

Previous literature has identified two reasons for which the commodity-stock market predictability might potentially vary over time: ongoing globalization and integration of markets and business cycle variation.

Historically, commodity markets were thought to be segmented from stock markets, as evidenced by the relative inability of stock market risk factors to explain the cross-section of commodity futures returns (e.g. Dusak (1973), Bessembinder (1992), Bessembinder and

Chan (1992), Erb and Harvey (2006)). Investors willing to be exposed to commodities typically did so either via physical investments in commodities or via commodity-related equity investments (Lewis (2007)). Around 2003-2004, however, we observe a sharp increase in the presence of traditionally equity-based institutional investors in commodity futures markets, either directly or via commodity index funds. Tang and Xiong (2012) refer to this as the "financialization" of commodity markets. As a consequence, the relation between commodity and stock markets may have changed.

Tang and Xiong (2012) find that correlations between commodity markets and stock markets in emerging countries that were virtually zero before 2004, started to increase gradually in the 2004-2009 period, peaking at around 60% in 2009. Basak and Pavlova (2016) study a model that features financial institutional investors alongside traditional futures market participants and find that prices and volatilities of all commodity futures increase, as do equity-commodity correlations, due to the presence of financial index traders. Boons, Roon, and Szymanowska (2014) show that, after 2004, commodity and stock markets became linked due to investors' need to hedge commodity price risk. Hu and Xiong (2013) find little predictability of East Asian stock markets on the basis of commodity futures returns before 2005 and very strong predictability with positive signs in the period 2005-2012. This increased activity of financial investors in the commodity markets may have also affected the informational content of commodity prices (e.g., Sockin and Xiong (2015), Brogaard, Ringgenberg, and Sovich (2018)), though some papers argue that price fluctuations and volatility are still driven by fundamental changes in demand and supply, and are only exacerbated by the inflow of financial traders (e.g. Sanders and Irwin (2010), Stoll and Whaler (2010), Kilian and Murphy (2014), Hamilton and Wu (2015) and Brunetti, Büyükşahin, and Harris (2016)).

Finally, predictability may also vary over the business cycle. Jacobsen, Marshall, and Visaltanachoti (2018) show that Industrial Metals predict US stock returns with a positive sign in recessions and a negative sign in expansions.

In Table 7, we analyze whether or not predictability in our 70 countries and six commodity sectors' returns varies over time. For ease of comparison, we include our main results for the full sample once again in Panel A. Panel B shows that the number of countries whose stock market returns are predicted by our commodity sector returns is either similar or smaller when we restrict our sample to the time period after 2005. This suggests that our evidence of predictability is not an artifact of the financialization of commodity markets.

Panel C presents the Hansen (1992) tests for parameter instability in our baseline predictive regressions. These tests do not require ex ante specified break points, which allows for more flexible testing than does our subsample analysis above. The table presents number of countries for which we find parameter instability, separately for each commodity slope coefficient at each lag and jointly for all commodity sectors at all lags (or all lags for the overall commodity indices). On an individual basis, we see indications of possible instability in very few countries. For the Industrial Metals sector, there is evidence of instability in 10 countries. For all other sectors and lags, we see possible instability for, at most, six countries, and often none. Jointly across sectors and horizons, we find possible instability for two countries, and none when looking at the overall indices.

6 Conclusions

This paper shows that commodity sector returns convey relevant information pertaining to a wide range of countries and their market fundamentals. We analyze predictability in 47 emerging and 23 developed countries and find that 84% of their stock market returns are predicted by returns from at least one of the commodity sectors. In the majority of countries, stock market returns are predicted by two to four sectors. In more than 80% of the countries, commodity sector returns predict economic fundamentals, such as inflation and industrial production growth rates.

In addition, we extend our analysis beyond statistical significance and develop new intuitive measures of the economic importance of commodity-stock market predictability, which allow us to characterize the information content of commodity futures markets in novel and rich ways. We find that the economic importance of predictability is evenly distributed across the countries and sectors we include in our analysis and that this extends beyond the role of commodities in global production and trade. Despite the greater weight of Energy in terms of global production value relative to other sectors and the extreme dependence of some countries on the export and import of Energy, our measures of economic significance show that all sectors are important to a comparable extent. Similarly, even though the US and China, alone, account for over 30% of world GDP, we find that no country accounts for more than 7% of the global stock market variation predicted by commodity markets.

We also explore the economic channels of information transmission. We find strong evidence that the ability of commodities to predict stock market returns is strongly related to the degree to which they aggregate information about inflation rates, even after accounting for stock market efficiency, countries' dependence on commodity trade and stage of development. This is in contrast with the more limited extent to which countries' dependence on commodity trade explains cross-country differences in predictability, which is only relevant in terms of the Energy and Agriculture sectors. Even when accounting for the possibility that indirect dependence on commodity trade may affect predictability through non-commodity trade and financial linkages across countries, we are unable to find evidence that the commodity trade dependence channel plays a major role.

Overall, this paper deepens our understanding of commodity-stock market predictability by leveraging an extensive dataset spanning 70 countries, six commodity sectors and forty years to show that the information flow from commodity markets to stock markets is a pervasive global phenomenon. In addition, our evidence is consistent with the idea that all commodity sectors provide complementary and economically important information for stock markets around the world. This information role extends well beyond simple trade dependence and direct input/output cost channels. Commodity futures markets are able to aggregate macroeconomic information that is dispersed around the globe in a complex manner. Therefore, these markets play a unique and truly global information discovery role in financial markets and the real economy.

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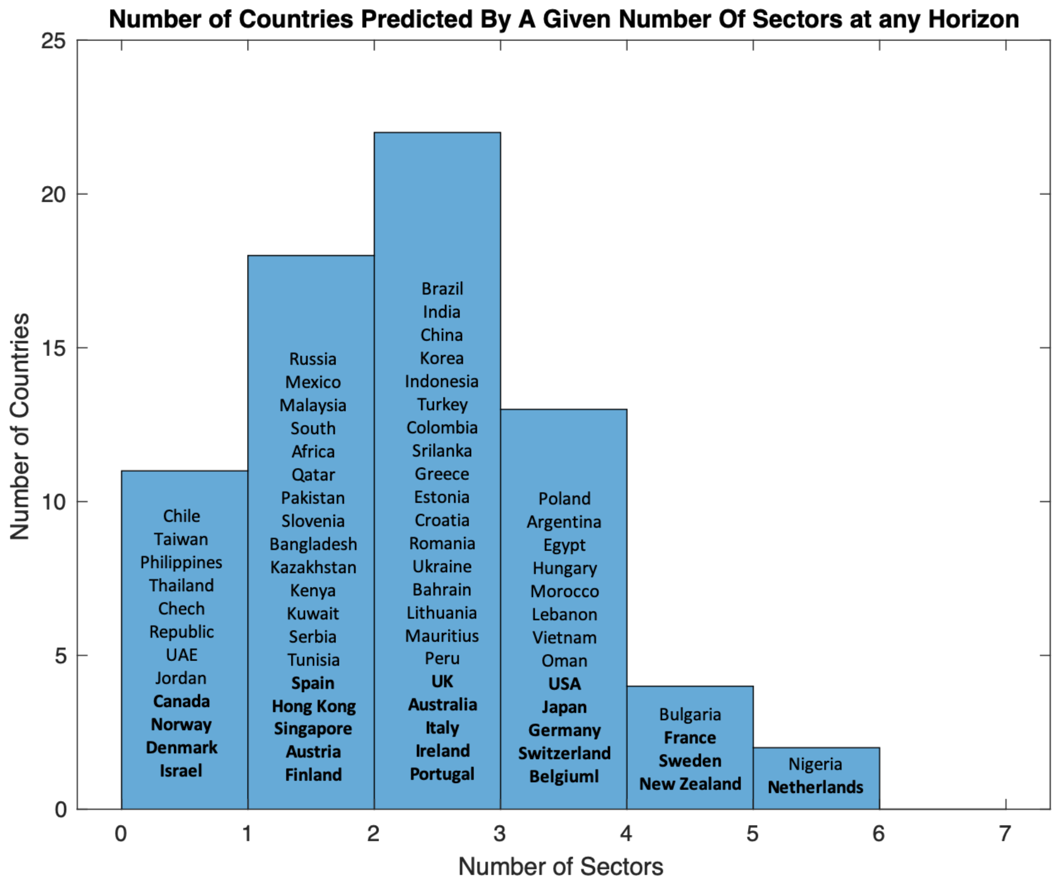
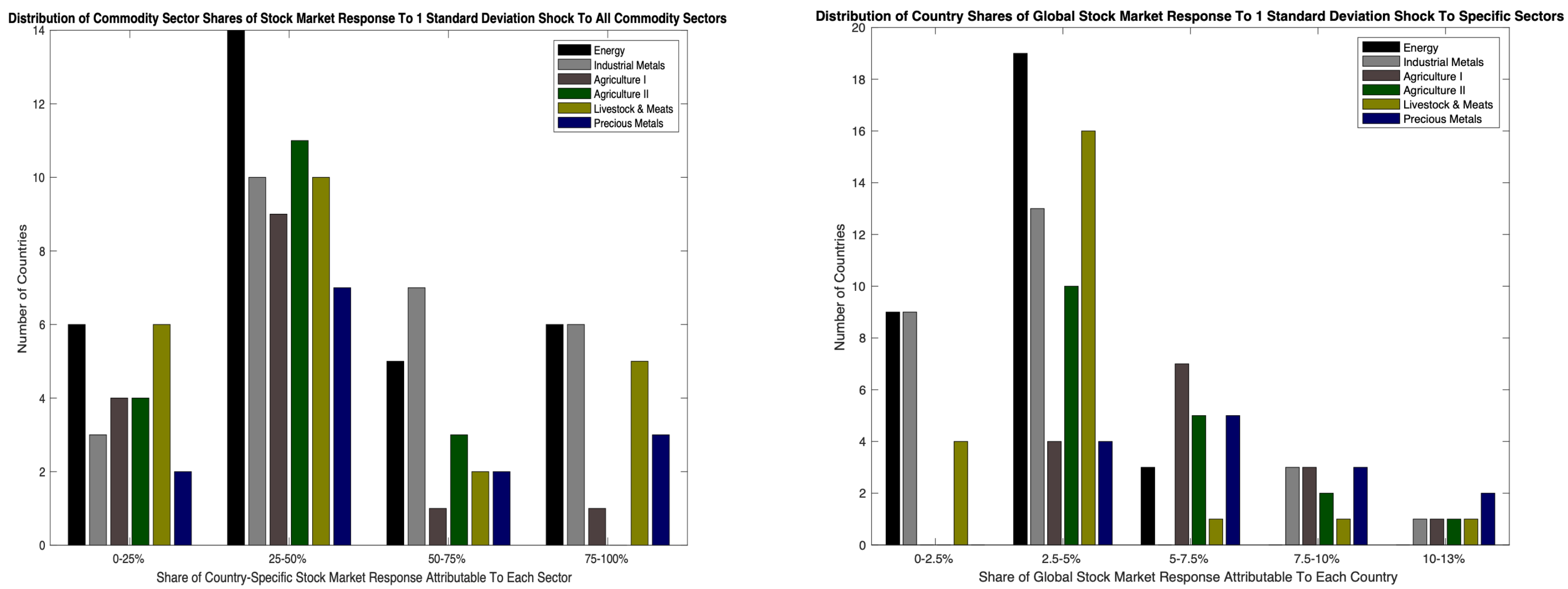


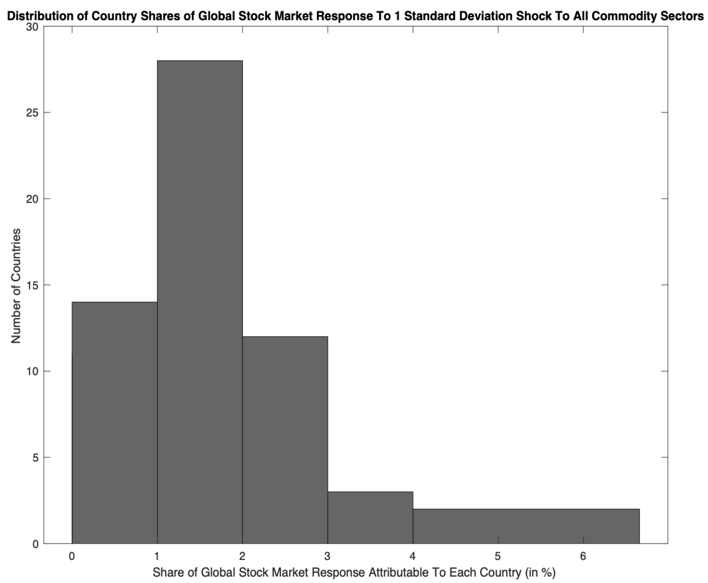
Figure 1: Predictability across countries.
The histogram shows the number of countries for which monthly stock market excess returns are predicted by a given number of commodity sector futures returns with either a 1-month, 2-month or 3-month lag. The figure also shows which countries fall into each category and distinguishes between emerging and developed countries (in bold).



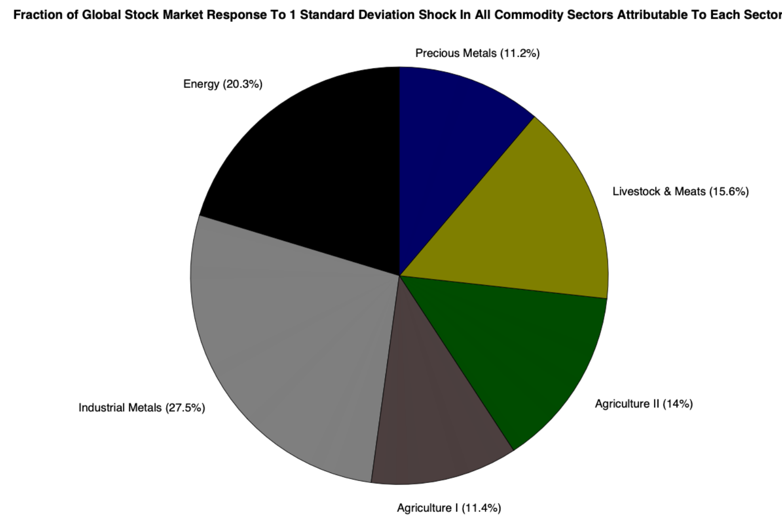
(a) Within-country Sector Measure

(b) Between-country Sector Measure

Figure 2: Within-Country and Between-Country Measures of Economic Significance of Predictability.
In (a), we plot the within-country sector measures, $WS_{i,s}$, which capture the sector-s share of the response of the stock market of country i to a one standard deviation shock to all commodity sectors. The distribution of $WS_{i,s}$ depicts the relative importance of different sectors within countries. In (b), we plot the between-country sector measures, $BS_{i,s}$, which correspond to country-i's share of the global stock market response to a one standard deviation shock to a specific commodity sector s. The distribution of $BS_{i,s}$ provides information about whether or not predictability on the basis of a given commodity sector is evenly distributed across countries.



(a) Global Commodity Measure



(b) Global Sector Measures

Figure 3: Global Measures of Economic Significance of Predictability.
This figure shows the global stock market responses to a one standard deviation shock to all commodity sectors. In (a), we plot the between-country global commodity measure, GC_i, to assess whether or not the global economic magnitude of predictability on the basis of all commodity sectors is evenly distributed across countries. In (b), we plot the global sector measure, GS_s, to assess whether the global economic magnitude of predictability is evenly distributed across all sectors.

Table 1: Descriptive Statistics

Panel A presents descriptive statistics for the six commodity sector returns, the S&P GSCI Total Return Index (GSCI) and the equally-weighted index (EWI). Correlations under the heading "Within" are the average of pairwise correlations between individual commodities making up a given sector. Correlations under the heading "Across (sec)" are the average of pairwise correlations between a commodity sector and the remaining sectors. Correlations under the heading "Across (ind)" are defined analogously, except that the correlations are computed at the individual commodity level rather than at the sector level. In Panel B, we show the descriptive statistics for the country excess returns. We split the countries into emerging countries, developed countries and countries with a value of sector-specific exports or imports relative to GDP above or below the sample median. Panel C presents descriptive statistics for economic indicators at a monthly frequency. The sample period is from November 1979 to March 2016.

Panel A: Commodity Sectors Returns (Annualized)

				Correlations	
	Mean	Std	Within	Across (sec)	Across (ind)
Energy	3.7%	28.8%	54%	20%	12%
Industrial Metals	6.2%	25.5%	100%	30%	17%
Agriculture I	-1.7%	18.5%	46%	29%	12%
Agriculture II	-0.5%	15.9%	8%	27%	10%
Livestock & Meats	0.2%	16.0%	46%	12%	12%
Precious Metals	3.0%	23.6%	60%	29%	14%
EWI	-0.1%	12.6%	16%	54%	
GSCI	2.5%	18.9%			

Panel B: Country Excess Stock Returns (Annualized)

	Total	Emerging	Developed
No countries	70	47	23
Avg. Excess Return	1.5%	0.9%	2.8%
Avg. Std	26.5%	29.5%	20.5%

Avg. Excess Return	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals
Export > Median	1.2%	1.6%	1.1%	0.9%	1.3%	2.8%
Export < Median	1.9%	1.5%	2.0%	2.2%	1.9%	0.3%
Import > Median	0.5%	0.9%	1.3%	-0.4%	0.5%	0.9%
Import < Median	2.6%	2.2%	1.8%	3.5%	2.6%	2.2%

Avg. Std	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals
Export > Median	28.8%	26.6%	28.7%	26.2%	25.7%	27.9%
Export < Median	24.3%	26.5%	24.4%	26.9%	27.4%	25.2%
Import > Median	26.2%	26.4%	25.3%	25.6%	25.4%	25.1%
Import < Median	26.9%	26.7%	27.8%	27.5%	27.7%	28.0%

Panel C: Economic Indicators

	Total	Emerging	Developed
		Inflation Rate	
No countries	67	46	21
Avg.	1.01%	1.32%	0.34%
Avg. Std	1.97%	2.61%	0.56%
		Real Industrial Production Growth	
No countries	62	41	21
Avg.	0.23%	0.19%	0.31%
Avg. Std	4.38%	4.94%	3.29%

Table 2: Baseline Predictive Regressions Summary
This table summarizes the results of the following regression for each country i:

$$r_{i,t:t+19} = \beta_{i,0} + \sum_s (\beta_{i,s,1} r^c_{s,t-21:t-2} + \beta_{i,s,2} r^c_{s,t-41:t-22}) + \phi_i r_{i,t-20:t-1} + \varepsilon_{i,t:t+19}$$

Panel A shows the number of countries for which monthly stock market excess returns ($r_{i,t:t+19}$) are predicted by sector-s one-month ($r^c_{s,t-21:t-2}$) and two-month ($r^c_{s,t-41:t-22}$) lagged commodity futures returns at the 10% significance level (based on Newey-West standard errors with 19 lags). *T*, *%*, *P* and *N* stand for total number, percentage, number of positive and number of negative countries (out of 70), respectively. We also present the counts of significant coefficients across all lags, for at least one sector and for at least one lag. The last two rows show the descriptive statistics for the regression R^2s and *p(Wald) < 10%* which denotes the number of countries for which we reject the null hypothesis that all commodity sector returns fail to predict stock market excess returns. Panel B shows the counts of significant coefficients for at least one lag for a sub-sample of countries with sector-specific exports or imports relative to GDP above or below the sample median, in developed and emerging countries. The sample period is from November 1979 to March 2016.

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI	At least one sector
					Panel A: Full Sample Country Counts					
	T	22	13	4	11	16	6	6	13	49
	%	31%	19%	6%	16%	23%	9%	9%	19%	70%
$r^c_{s,t-21:t-2}$	P	4	8	3	11	14	5	6	7	
	N	18	5	1	0	2	1	0	6	
	T	10	18	11	11	9	10	14	17	46
	%	14%	26%	16%	16%	13%	14%	20%	24%	66%
$r^c_{s,t-41:t-22}$	P	2	17	3	8	6	10	14	17	
	N	8	1	8	3	3	0	0	0	
	T	1	5	0	4	2	2	3	6	
All Horizons	%	1%	7%	0%	6%	3%	3%	4%	9%	
	T	31	26	15	18	23	14	17	24	59
At least	%	44%	37%	21%	26%	33%	20%	24%	34%	84%
one horizon	P	6	21	6	15	19	13	17	18	
	N	25	5	9	3	5	1	0	6	
R^2	mean	5.50%	median	3.83%	max	22.76%	min	1.26%		
p(Wald) < 10%	T	35	50%							

Table 2 continued

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI
		Panel B: Subsamples (Country Counts)							
Export > Median	T	13	10	8	10	11	10	7	10
	%	37%	29%	23%	29%	31%	29%	20%	29%
	P	1	6	2	10	9	10	7	6
Export < Median	T	18	16	7	8	12	4	10	14
	%	51%	46%	20%	23%	34%	11%	29%	40%
	P	5	15	4	5	10	3	10	12
Import > Median	T	14	10	9	11	10	6	9	14
	%	40%	29%	26%	31%	29%	17%	26%	40%
	P	2	8	2	9	9	6	9	11
Import < Median	T	17	16	6	7	13	8	8	10
	%	49%	46%	17%	20%	37%	23%	23%	29%
	P	4	13	4	6	10	7	8	7
Emerging	T	16	20	10	10	17	7	14	15
	%	34%	43%	21%	21%	36%	15%	30%	32%
	P	6	18	6	7	13	6	14	15
Developed	T	15	6	5	8	6	7	3	9
	%	65%	26%	22%	35%	26%	30%	13%	39%
	P	0	3	0	8	6	7	3	3

Table 3: Cross-Country Regressions: Predictability and Country-Level Characteristics
This table shows the results from cross-country regressions relating predictability and country-level characteristics. Panel A shows the results from the following regression:

$$\beta_{i,s} = \gamma_{0,s} + \gamma_e E_i + \gamma_\theta \theta_i + \gamma_{TD,s} TD_{i,s} + \gamma_{ITD,s} ITD_{i,s} + \gamma_{IFD,s} IFD_{i,s} + \varepsilon_{i,s}$$

where $\beta_{i,s} = \frac{1}{2}\sum_{h=1}^{2} |\beta_{i,s,h}|$, i.e., the average of the absolute values of the slope coefficients across the two lags k from the per-country predictive regressions specified in Equation (6). E_i is a dummy variable that equals one if country i is emerging. θ_i is the infinite horizon adjustment variable that we use to compute the economic significance measures in Section 3. $TD_{i,s}$, $ITD_{i,s}$, and $IFD_{i,s}$ are direct and indirect trade dependence measures defined in Section 3. The last column shows the results of a pooled regression with sector fixed effects and with the imposition of equal coefficient estimates across sectors. Panel B is based on a similar regression excluding the indirect dependence measures and distinguishing between the export and import sides of direct trade dependence. T-statistics are based on heteroskedasticity-consistent standard errors.

	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	Pooled SFE
Panel A: Direct and Indirect Trade Dependence							
coefficients							
$\gamma_{0,s}$	0.10	0.07	-0.07	-0.20	-0.14	-0.11	-0.09
E_i	0.02	0.05	0.01	0.03	0.05	0.01	0.03
θ_i	-0.08	-0.03	0.11	0.22	0.20	0.15	0.10
$TD_{i,s}$	0.08	-0.25	2.13	0.71	-1.30	-0.04	0.09
$ITD_{i,s}$	50.54	-31.56	26.97	9.37	-56.57	-4.10	-4.50
$IFD_{i,s}$	-18.38	10.85	-8.30	-24.09	-15.01	-0.13	-6.20
t-stats							
$\gamma_{0,s}$	1.80	0.70	-0.81	-1.87	-0.99	-1.07	-1.49
E_i	2.00	3.73	0.40	2.21	2.21	0.69	8.14
θ_i	-1.42	-0.30	1.25	2.19	1.49	1.60	1.66
$TD_{i,s}$	2.20	-0.53	2.02	2.22	-0.95	-0.14	2.32
$ITD_{i,s}$	1.56	-0.79	0.57	0.18	-0.74	-0.09	-0.23
$IFD_{i,s}$	-2.10	0.64	-0.71	-1.48	-0.71	-0.02	-1.60
R^2	35.41%	20.30%	16.55%	33.45%	23.37%	5.51%	19.40%
p(Wald)	0.00	0.01	0.04	0.00	0.00	0.60	0.00
No obs	69	69	69	69	69	69	414
Panel B: Direct Export and Import Trade Dependence							
coefficients							
$\gamma_{0,s}$	0.07	0.06	-0.05	-0.16	-0.12	-0.10	-0.08
E_i	0.03	0.05	0.01	0.05	0.06	0.01	0.04
θ_i	-0.05	-0.01	0.08	0.17	0.17	0.14	0.08
Export $TD_{i,s}$	0.09	-0.19	4.22	0.73	-1.02	-0.04	0.09
Import $TD_{i,s}$	0.06	-0.65	-0.24	0.52	-3.33	-0.08	0.00
t-stats							
$\gamma_{0,s}$	1.28	0.52	-0.61	-1.59	-0.92	-1.04	-1.42
E_i	3.52	3.95	1.15	3.55	3.23	0.75	9.24
θ_i	-0.96	-0.12	1.13	1.81	1.33	1.62	1.60
Export $TD_{i,s}$	2.98	-0.40	3.75	1.51	-0.62	-0.04	2.40
Import $TD_{i,s}$	0.67	-0.29	-0.19	0.66	-1.31	-0.08	0.00
R^2	28.99%	19.42%	25.96%	29.57%	21.71%	5.64%	19.02%
p(Wald)	0.00	0.01	0.00	0.00	0.00	0.43	0.00
No obs	70	70	70	70	70	70	420

Table 4: Predictive Regressions of Economic Indicators

This table summarizes the results of the following long-horizon regression for each country i:

$$Z_{i,t:t+h} = \alpha_i + \sum_s \lambda_{i,s,h} r^c_{s,t:t-1} + \phi_i X_{i,h} + \mu_{i,t:t+h}$$

where $Z_{i,t:t+h}$ is the growth rate of the economic indicator Z between months t and $t+h$ in country i. $r^c_{s,t:t-1}$ is the lagged one-month futures market return of commodity sector s. The economic indicator is either the inflation rate, the real industrial production growth rate or excess stock market return. For each economic indicator, we run this regression at the 1, 6, and 12 month horizons. The controls, $X_{i,h}$, include the lagged excess stock market return and three lags of the economic indicator. Panel A displays the number (T) and percentage ($\%$) of countries for which commodity returns have predictive power over a given set of economic indicators for at least one horizon h. Panel B shows country counts by development stage. Panel C shows country counts for subsamples of countries with ratios of imports or exports of a given commodity sector to GDP above or below the sample median. The counts are based on the 10% significance level and Newey-West standard errors with $h+1$ lags. The sample period is from January 1995 to March 2016.

	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	At least one sector
Panel A: Full Sample Country Counts							
Inflation T	45	25	26	19	11	29	62
Inflation %	64%	36%	37%	27%	16%	41%	89%
Production T	16	17	32	24	17	15	59
Production %	23%	24%	46%	34%	24%	21%	84%
Returns T	37	45	24	15	33	32	68
Returns %	53%	64%	34%	21%	47%	46%	97%
Ret & Infl T	23	15	10	3	5	16	60
Ret & Prod T	7	12	9	6	5	5	57
Panel B: Development Stage Subsample Country Counts							
Inflation							
Developing T	28	18	17	14	6	15	41
Developed T	20	6	10	3	2	18	21
Production							
Developing T	8	10	15	15	10	10	21
Developed T	5	10	17	11	7	2	15
Panel C: Trade Dependence Subsample Country Counts							
Inflation							
Export > Median	22	11	14	8	6	13	
Export < Median	23	14	12	11	5	16	
Import > Median	20	12	14	10	7	18	
Import < Median	25	13	12	9	4	11	
Production							
Export > Median	8	10	15	8	7	10	
Export < Median	8	7	17	16	10	5	
Import > Median	6	7	13	12	8	9	
Import < Median	10	10	19	12	9	6	

Table 5: Cross-Country Regressions: Slow Information Diffusion and The Informational Content of Commodity Markets

This table summarizes the results of the following cross-country regression:

$$\beta_{i,s} = \gamma_{0,s} + \Phi_s \lambda_{i,s} + \gamma_e E_i + \gamma_\theta \theta_i + \gamma_{TD,s} TD_{i,s} + \varepsilon_{i,s}$$

where $\lambda_{i,s} = \frac{1}{3}\sum_{h\in\{1,6,12\}} |\lambda_{s,i,h}|$, i.e., the average of the absolute values of the slope coefficients across the three horizons h, obtained by predicting a given economic indicator in the per-country regressions specified in Equation (12). E_i is a dummy variable that equals zero if a country is developed. θ_i is our measure of market efficiency. $TD_{i,s}$ is the direct trade dependence measure defined in Section 1.3. In Panels A and B, $\lambda_{i,s}$ is based on the inflation rate and the real industrial production growth rate, respectively. In Panel C, we include $\lambda_{i,s}$ for both the inflation rate and the real industrial production growth rate as explanatory variables. The last column shows the results of a pooled regression with sector fixed effects and with the imposition of equal coefficient estimates across sectors. The t-statistics are based on heteroskedasticity-robust standard errors.

	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	Pooled SFE
			Panel A: Inflation				
coefficients							
$\gamma_{0,s}$	0.03	0.05	-0.04	-0.10	0.10	0.05	-0.02
E_i	0.02	0.04	0.00	0.03	0.04	0.00	0.03
θ_i	-0.02	-0.01	0.07	0.11	-0.04	0.00	0.02
Inflation $\lambda_{i,s}$	0.37	0.86	0.82	0.89	1.05	0.44	0.81
$TD_{i,s}$	0.10	-0.11	1.80	0.81	-2.62	-0.11	0.11
t-stats							
$\gamma_{0,s}$	0.47	0.49	-0.45	-1.02	0.73	0.53	-0.55
E_i	3.11	2.62	0.10	2.42	2.08	0.24	6.43
θ_i	-0.28	-0.14	0.81	1.15	-0.30	-0.01	0.63
Inflation $\lambda_{i,s}$	1.65	1.55	1.86	3.39	2.22	1.02	4.58
$TD_{i,s}$	3.17	-0.22	1.71	2.95	-2.09	-0.42	2.69
R^2	32.43%	20.79%	18.87%	38.62%	27.45%	2.46%	22.95%
p(Wald)	0.00	0.01	0.01	0.00	0.00	0.81	0.00
No obs	67	67	67	67	67	67	402
			Panel B: Industrial Production				
coefficients							
$\gamma_{0,s}$	0.01	0.11	-0.03	-0.11	0.22	-0.01	-0.01
E_i	0.02	0.05	0.01	0.05	0.05	0.00	0.03
θ_i	0.00	-0.08	0.06	0.11	-0.16	0.06	0.01
Production $\lambda_{i,s}$	0.24	0.35	0.10	0.09	0.08	0.04	0.09
$TD_{i,s}$	0.08	-0.40	2.58	1.11	-2.26	-0.08	0.10
t-stats							
$\gamma_{0,s}$	0.15	0.89	-0.26	-0.87	1.42	-0.12	-0.16
E_i	2.67	3.37	0.71	3.51	3.19	0.37	8.13
θ_i	-0.05	-0.66	0.53	0.95	-1.07	0.58	0.24
Production $\lambda_{i,s}$	2.35	1.60	0.73	1.07	0.54	0.43	1.85
$TD_{i,s}$	2.68	-0.71	2.34	3.52	-1.70	-0.29	2.52
R^2	35.70%	20.85%	15.36%	38.79%	25.88%	2.04%	19.71%
p(Wald)	0.00	0.01	0.05	0.00	0.00	0.88	0.00
No obs	62	62	62	62	62	62	372

Table 5 continued

	Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	Pooled SFE
			Panel C: Inflation and Industrial Production				
coefficients							
$\gamma_{0,s}$	0.00	0.10	0.02	-0.14	0.16	-0.01	-0.02
E_i	0.02	0.03	0.00	0.03	0.03	0.00	0.02
θ_i	0.00	-0.07	0.01	0.13	-0.11	0.05	0.01
Inflation $\lambda_{i,s}$	0.34	1.34	1.05	1.02	1.43	0.32	0.96
Production $\lambda_{i,s}$	0.23	0.33	0.06	0.04	0.04	0.04	0.07
$TD_{i,s}$	0.09	-0.16	1.97	1.11	-2.40	-0.08	0.12
t-stats							
$\gamma_{0,s}$	-0.01	0.83	0.15	-1.23	1.09	-0.05	-0.35
E_i	2.26	2.11	-0.12	2.67	1.97	0.19	5.62
θ_i	0.08	-0.65	0.08	1.27	-0.76	0.47	0.30
Inflation $\lambda_{i,s}$	1.53	2.17	2.12	3.64	2.79	0.70	5.68
Production $\lambda_{i,s}$	2.31	1.53	0.47	0.45	0.30	0.42	1.38
$TD_{i,s}$	2.87	-0.30	1.77	3.90	-1.91	-0.30	2.76
R^2	38.28%	26.99%	21.63%	50.52%	34.95%	2.88%	26.48%
p(Wald)	0.00	0.00	0.02	0.00	0.00	0.89	0.00
No obs	62	62	62	62	62	62	372

Table 6: Predictive Regressions with Additional Controls and Pooled Regressions
This table summarizes the results of the following regression for each country i:

$$r_{i,t:t+19} = \beta_{i,0} + \sum_s (\beta_{i,s,1} r^c_{s,t-21:t-2} + \beta_{i,s,2} r^c_{s,t-41:t-22}) + \phi_i r_{i,t-20:t-1} + \kappa_i X + \varepsilon_{i,t:t+19}$$

where X is a set of controls. It shows the number of countries for which monthly stock market excess returns ($r_{i,t:t+19}$) are predicted by sector-s one-month ($r^c_{s,t-21:t-2}$) and two-month ($r^c_{s,t-41:t-22}$) lagged commodity futures returns at the 10% significance level (based on Newey-West standard errors). T and $\%$ stand for total number and percentage of countries (out of 70). In Panel A, we control for lagged stock returns and open interest growth. In Panel B, we also control for the short rate, the Kilian Index and the S&P 500 futures returns. Both panels A and B show descriptive statistics for the regression R^2 and counts of significant coefficients for at least one sector and for at least one lag. *p(Wald) < 10%* denotes the number of countries for which we reject the null hypothesis that all commodity sector returns fail to predict stock market excess returns. Panel C shows the coefficient estimates and the Driscoll and Kraay (1998) t-statistics for pooled regressions estimated on groups of countries with the same coefficient sign (P for positive and N for negative) for each commodity sector based on the first two lags. The sample period is from November 1979 to March 2016.

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI	At least one sector
Panel A: Controlling for lagged stock returns and open interest (Country Counts)										
$r^c_{s,t-21:t-2}$	T	21	13	4	12	16	7	7	13	49
	%	30%	19%	6%	17%	23%	10%	10%	19%	70%
$r^c_{s,t-41:t-22}$	T	9	19	11	11	8	10	13	18	47
	%	13%	27%	16%	16%	11%	14%	19%	26%	67%
At least one horizon	T	29	27	15	20	22	15	16	25	62
	%	41%	39%	21%	29%	31%	21%	23%	36%	89%
R^2	mean	5.84%	median	3.88%	max	28.78%	min	1.27%		
p(Wald) < 10%	T	37	53%							
Panel B: Controlling for lagged stock returns, open interest, short rate, Kilian Index and S&P 500										
$r^c_{s,t-21:t-2}$	T	22	13	3	12	15	7	7	10	46
	%	31%	19%	4%	17%	21%	10%	10%	14%	66%
$r^c_{s,t-41:t-22}$	T	12	18	15	12	8	10	10	13	51
	%	17%	26%	21%	17%	11%	14%	14%	19%	73%
At least one horizon	T	30	26	18	21	21	15	14	19	66
	%	43%	37%	26%	30%	30%	21%	20%	27%	94%
R^2	mean	7.03%	median	4.68%	max	32.03%	min	1.63%		
p(Wald) < 10%	T	44	100%							

Table 6 continued

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI	At least one sector
Panel C: Using real returns and controlling for exchange rate (N=54) (Country Counts)										
$r^c_{s,t-21:t-2}$	T	19	10	5	9	10	7	2	11	37
	%	35%	19%	9%	17%	19%	13%	4%	20%	69%
$r^c_{s,t-41:t-22}$	T	9	17	6	8	5	7	7	9	38
	%	17%	31%	11%	15%	9%	13%	13%	17%	70%
At least one horizon	T	26	24	11	15	15	11	9	17	54
	%	48%	44%	20%	28%	28%	20%	17%	31%	100%
R^2	mean	9.13%	median	7.53%	max	30.89%	min	2.08%		
p(Wald) < 10%	T	49	70%							
Panel D: Pooled Regression Estimates (Sign-based Subsamples)										
$r^c_{s,t-21:t-2}$	P: coef	0.03	0.09	0.02	0.08	0.05	0.03	0.06	0.05	
	P: t-stat	1.24	2.68	0.55	2.39	1.86	1.47	1.19	1.58	
	N: coef	-0.06	-0.04	-0.05	-0.04	-0.06	-0.03	-0.03	-0.06	
	N: t-stat	-3.07	-1.65	-1.38	-0.80	-1.17	-0.61	-0.44	-1.89	
$r^c_{s,t-41:t-22}$	P: coef	0.04	0.06	0.07	0.08	0.06	0.03	0.08	0.08	
	P: t-stat	1.46	2.01	2.19	2.59	2.04	1.07	1.81	2.55	
	N: coef	-0.04	-0.03	-0.07	-0.04	-0.09	-0.03	-0.04	-0.03	
	N: t-stat	-1.73	-1.25	-2.09	-0.95	-1.70	-0.36	-0.67	-0.93	
	P: No obs	14	29	15	35	33	39	42	28	
	N: No obs	31	5	24	9	7	6	5	18	

Table 7: Time-Variation in the Predictive Regressions
This table summarizes the results of the following regression for each country i:

$$r_{i,t:t+19} = \beta_{i,0} + \sum_{s}(\beta_{i,s,1} r^c_{s,t-21:t-2} + \beta_{i,s,2} r^c_{s,t-41:t-22}) + \phi_i r_{i,t-20:t-1} + \varepsilon_{i,t:t+19}$$

Panels A through D show the number of countries for which monthly stock market excess returns ($r_{i,t:t+19}$) are predicted by sector-s commodity futures returns at either the one-month ($r^c_{s,t-21:t-2}$) or two-month ($r^c_{s,t-41:t-22}$) lag (based on Newey-West standard errors and 10% significance level). *T*, *%*, *P* and *N* stand for total number, percentage, number of positive and number of negative countries (out of 70), respectively. We also show descriptive statistics for the regression R^2 and counts of significant coefficients for at least one sector and for at least one lag. *p(Wald) < 10%* denotes the number of countries for which we reject the null hypothesis that all commodity sector returns fail to predict stock market excess returns. Panel A shows the full sample counts without sample splits. In Panel B, we report the counts for the period after 2005 using the full sample of 70 countries. In Panel C, we show the number of countries for which we reject the null hypothesis of no time variation in the individual coefficients, as well as the null hypothesis that all coefficients are stable over time using the Hansen (1992) parameter instability test. The sample period is from November 1979 to March 2016.

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI
Panel A: Full sample Country Counts (N=70)									
	T	31	26	15	18	23	14	17	24
At least	%	44%	37%	21%	26%	33%	20%	24%	34%
one horizon	P	6	21	6	15	19	13	17	18
	N	25	5	9	3	5	1	0	6
R^2	mean	5.50%	median	3.83%	max	22.76%	min	1.26%	
p(Wald) < 10%	T	35	50%						
Panel B: After 2005 Subsample Country Counts (N=70)									
	T	23	15	9	9	14	18	14	20
At least	%	33%	21%	13%	13%	20%	26%	20%	29%
one horizon	P	6	14	5	8	11	14	14	20
	N	17	1	4	1	4	4	0	0
R^2	mean	8.02%	median	6.64%	max	22.76%	min	3.59%	
p(Wald) < 10%	T	34	49%						
Panel C: Hansen (1992) Parameter Instability Tests (Country Counts)									
1-Month Lag	T	2	1	0	1	0	1	1	3
	%	2.86%	1.43%	0.00%	1.43%	0.00%	1.43%	1.43%	4.29%
2-Month Lag	T	4	9	0	0	0	1	1	3
	%	5.71%	12.86%	0.00%	0.00%	0.00%	1.43%	1.43%	4.29%
Jointly	T	2						0	0
all coeffs	%	2.86%						0.00%	0.00%

Online Appendix to "The Information Content of Commodity Futures Markets"

In this Online Appendix, we present a detailed description of the procedure we used to match our commodities with the UNCTADstat data on export and import dependence, as well as the results of a variety of robustness checks.

1 Matching commodities to UNCTADstat data

We identify all the SICT codes in UNCTADstat that match the individual commodities included in each of our six sectors. We match each of the 28 individual commodities to SICT codes up to the fifth digit based on commodity names. For each matched five-digit code, we retrieve the associated three-digit code to conduct a further matching round; this is the highest level of granularity in the data that is available for download. There are cases in which a perfect match at the five-digit level coexists with a poor match at the three-digit level. For instance, we were able to perfectly match the commodity *wheat* to three-digit codes *041 - wheat, including spelt, and meslin , unmilled* - and *046 - meal and flour of wheat and flour of meslin* - as all the subcategories of *041* and *046* explicitly refer to the word *wheat*. However, while we were also able to textually match *wheat* to category *081.26 - bran, sharp and other residues, whether or not in the form of pellets, derived from sifting, milling or other working of cereals or of leguminous plants of wheat* -, we were not able to match it to any other of the many five-digit categories within three-digit category *081*. Therefore, *wheat* was not matched to *081* SICT code but it was matched to *041 and 046*. It may be the case that while most of the five-digit subcategories within *081* cannot be matched to one specific commodity, it might still be possible to match most of them to one of our sectors as a whole (Agriculture I or Agriculture II, in this case). In this case, we still assign the corresponding three-digit category to a sector. For instance, we could not match *289.19 - ores and concentrates of other precious metals* - to any specific commodity, but we could match it broadly to the Precious Metals sectors. Since it turns out that we were able to match every subcategory within *289 - ores and concentrates of precious metals; waste, scrap and sweepings of precious metals (other than gold)* - to Precious Metals, we matched *289* to the sector Precious Metals. As a general rule aimed at minimizing noise, we require that a matching at the three-digit level is only appropriate if the ratio of the number of matches to all possible matches is at least 1:2 at the five-digit level. In practice, the ratio is either much higher or much lower than 1:2 and the decision to match or not match is unambiguous.

2 Derivation of the Infinite-Horizon adjustment

Without loss of generality assume T is an arbitrarily large integer and $|\gamma_i| < 1$. Then, we can re-write (6) as:

$$\begin{aligned} r_{i,T:T+19} &= \beta_{i,0} + \sum_s (\beta_{i,s,1} r^c_{s,T-21:T-2} + \beta_{i,s,2} r^c_{s,T-41:T-22}) + \phi_i r_{i,T-20:T-1} + \epsilon_{i,T:T+19} \\ &= \sum_{k=0}^{T-41} \phi_i^{T-41-k} (\beta_{i,0} + \sum_s (\beta_{i,s,1} r^c_{s,k+20:k+39} + \beta_{i,s,2} r^c_{s,k:k+19}) \\ &+ \epsilon_{i,k+41:k+60}) + \phi_i^{T-40} r_{i,21:40} \end{aligned}$$

The commodity sector-specific infinite-horizon marginal effect is defined as the sum of the absolute values of marginal effects over time, discounted by an appropriate power of ϕ_i. Mathematically, the infinite-horizon marginal effect for the commodity sector s is computed as:

$$\lim_{T\to\infty} \left(\sum_{k=0}^{T-41} \left| \frac{\partial r_{i,T+19:T}}{\partial r^c_{s,k+20:k+39}} \right| + \left| \frac{\partial r_{i,T+19:T}}{\partial r^c_{s,k:k+19}} \right| \right) = \lim_{T\to\infty} \sum_{k=0}^{T-41} |\phi_i^{T-41-k} (\beta_{i,s,1} + \beta_{i,s,2})| = \sum_{h=1}^{2} \theta_i |\beta_{i,s,h}|$$

where $\theta_i = \frac{1}{1-|\phi_i|}$

Table OA.1: Individual Commodities Summary Information

This table summarizes the list of commodities, the sector to which each commodity belongs, the exchange on which the commodities are traded, the delivery months, and starting dates for each commodity's time series of commodity futures returns.

Commodity	Symbol	Exchange	Delivery Months	First Observation
Energy				
Heating oil	HO	NYMEX	All	19791101
Crude oil	CL	NYMEX	All	19830404
Gasoline	HU/RB	NYMEX	All	20051101
Natural gas	NG	NYMEX	All	19900501
Gas-Oil-Petroleum	LF	ICE	All	20001229
Propane	PN	NYMEX	All	20001229
Industrials				
Copper	HG	NYMEX	1,3,5,7,9,12	19791101
Agriculture I				
Corn	C-	CBOT	3,5,7,9,12	19791101
Oats	O-	CBOT	3,5,7,9,12	19791101
Wheat	W-	CBOT	3,5,7,9,12	19791101
Soybean Oil	BO	CBOT	1,3,5,7,8,9,10,12	19791101
Soybean Meal	SM	CBOT	1,3,5,7,8,9,10,12	19791101
Soybeans	S-	CBOT	1,3,5,7,8,9,11	19791101
Rough Rice	RR	CBOT	1,3,5,7,9,11	19860821
Agriculture II				
Cotton	CT	ICE	3,5,7,10,12	19791101
Lumber	LB	CME	1,3,5,7,9,11	19791101
Coffee	KC	ICE	3,5,7,9,12	19791101
Sugar	SB	ICE	3,5,7,10	19791101
Cocoa	CC	ICE	3,5,7,9,12	20001229
Milk	DE	CME	2,4,6,8,9,12	20001229
Livestock				
Feeder Cattle	FC	CME	1,3,4,5,8,9,10,11	19791101
Live Cattle	LC	CME	2,4,6,8,10,12	19791101
Lean Hogs	LH	CME	2,4,6,7,8,10,12	19791101
Pork Bellies	PB	CME	2,3,5,7,8	19791101
Precious Metals				
Gold	GC	NYMEX	2,4,6,8,10,12	19791101
Silver	SI	NYMEX	3,5,7,9,12	19791101
Palladium	PA	NYMEX	3,6,9,12	19791101
Platinum	PL	NYMEX	1,4,7,10	19791101

Table OA.2: Proxies for the Risk Free Rate
This table presents a summary of the different proxies used to approximate the risk-free rate in each country in our sample. Developed countries are listed in bold. *GFD* stands for Global Financial Data, which is where all the data on risk-free rates was sourced.

	Total Return Indices - Bills	
Austria	Korea	**Singapore**
Bulgaria	Lithuania	Slovenia
Chile	Malaysia	**Spain**
China	Mexico	Turkey
Finland	**Norway**	UAE
Hong Kong	**Portugal**	**USA**
Ireland	Romania	Vietnam
Jordan*	Russia	
	Treasury Bill Yields	
Australia	Greece	Nigeria
Bahrain	Hungary	Pakistan
Bangladesh	India	Philippines
Belgium	**Israel**	Poland
Brazil	**Italy**	Serbia
Canada	**Japan**	South Africa
Croatia	Kazakhstan	Sri Lanka
Czech Republic	Kenya	**Sweden**
Denmark	Lebanon	**Switzerland**
Egypt	Mauritius	Taiwan
France	**Netherlands**	Tunisia
Germany	**New Zealand**	**UK**
	GFD Indices - Bonds	
Argentina	Colombia	Indonesia
	Deposit Rates	
Estonia	Peru	
	Interbank Interest Rates	
Kuwait	Ukraine	Qatar
	Overnight Interest Rates	
Jordan*	Oman	
	Central Bank Interest Rates	
Morocco		

* For Jordan we use the overnight interest rate from November 1996

Table OA.3: Starting Dates for Country-Specific Variables
This table shows the starting dates for all country-specific variables: gross returns, risk-free rates, inflation rates and real industrial production growth. Developed countries are listed in bold. A blank entry indicates that we did not observe data for that country and variable in our sample. Inflation is not available for three countries and industrial production for eight countries.

Country Name	Gross Returns	Risk Free Rates	Inflation Rates	Industrial Production	Country Name	Gross Returns	Risk Free Rates	Inflation Rates	Industrial Production
	Emerging economies					*Developed economies*			
Brazil	199501	199501	199501	200002	**USA**	197911	197911	197911	199102
India	199302	199302	197911	199102	**Japan**	197911	197911	197911	199102
China	199301	199301	198601	199702	**UK**	197911	197911	197911	199102
Russia	199501	199501	199202	199202	**Germany**	197911	197911	197911	199102
Korea	198801	198801	197911	199102	**France**	197911	197911	197911	199102
Mexico	198801	198801	197911	199102	**Australia**	197911	197911		
Chile	198801	198801	197911	199102	**Italy**	197911	197911	197911	199102
Indonesia	198801	198801	197911	199102	**Canada**	197911	197911	197911	199102
Malaysia	198801	198801	197911	199102	**Spain**	197911	197911	197911	199102
Poland	199301	199301	198301	199102	**Switzerland**	198002	198002	197911	199102
Taiwan	198801	198801	197911	199102	**Hong Kong**	197911	197911	197911	199102
South Africa	199301	199301	197911	199102	**Norway**	197911	197911	197911	199102
Philippines	198801	198801	197911	199102	**Singapore**	197911	197911	197911	199102
Thailand	198801	198801	197911	199102	**Sweden**	197911	197911	197911	199702
Turkey	198801	198801	197911	199102	**Austria**	197911	197911	197911	199102
Argentina	198801	198801	197911	199310	**Denmark**	197911	197911	197911	199702
Colombia	199301	199301	197911	199102	**Finland**	198612	198612	198701	199102
Chech Republic	199501	199501	197911	199302	**Netherlands**	197911	197911	197911	199102
Egypt	199501	199501	197911	200403	**Belgium**	197911	197911	197911	199102
Qatar	200506	200506	200301	200301	**Ireland**	198801	198801	199701	199702
Hungary	199501	199501	197911	199102	**New Zealand**	198201	198201		
UAE	200506	200506	200702	200702	**Portugal**	198801	198801	197911	199102
Morocco	199501	199501	197911	199102	**Israel**	199301	199301	197911	199102
Pakistan	199301	199301	197911	199102					
Srilanka	199301	199301	197911	201002					
Greece	198801	198801	197911	199302					
Bulgaria	200506	200506							
Estonia	200206	200206	199008	199802					
Croatia	200206	200206	197911						
Lebanon	200206	200206	200801						
Romania	200512	200512	199011	199102					
Slovenia	200206	200206	197911	199202					
Vietnam	200612	200612	199502	199502					
Ukraine	200606	200606	199202	200202					
Bahrain	200506	200506	197911						
Bangladesh	200912	200912	197911	199102					
Jordan	198801	198801	197911	199102					
Kazakhstan	200512	200512	199202	199902					
Kenya	200206	200206	197911						
Kuwait	200506	200506	197911	199108					
Lithuania	200806	200806	199206	199601					
Mauritius	200206	200206	197911						
Nigeria	200206	200206	197911	199102					
Oman	200506	200506	199605	199606					
Peru	199301	199301	197911	199102					
Serbia	200806	200806	197911	199102					
Tunisia	200406	200406	197911	199102					

Table OA.4: Robustness Tests for the Predictive Regressions

This table summarizes the results of the following regression with overlapping observations for each country i:

$$r_{i,t:t+19} = \beta_{i,0} + \sum_{s} (\beta_{i,s,1} r^c_{s,t-21:t-2} + \beta_{i,s,2} r^c_{s,t-41:t-22}) + \phi_i r_{i,t-20:t-1} + \varepsilon_{i,t:t+19}$$

It shows the number of countries for which monthly stock market excess returns ($r_{i,t:t+19}$) are predicted by sector-s one-month ($r^c_{s,t-21:t-2}$) and two-month ($r^c_{s,t-41:t-22}$) lagged commodity futures returns at the 10% significance level (based on Newey-West standard errors). T and *%* stand for total number and percentage of countries (out of 70). In Panel A, we run the predictive regressions using monthly non-overlapping stock market excess returns. In Panel B, we use gross returns instead of excess returns. In Panel C, we estimate the baseline regression using post-1995 data only. The table also shows descriptive statistics for the regression R^2 and counts of significant coefficients for at least one sector and for at least one lag. *p(Wald) < 10%* denotes the number of countries for which we reject the null hypothesis that all commodity sectors fail to predict stock market excess returns. The full sample refers to the period from November 1979 to March 2016.

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI	At least one sector
Panel A: Full sample, non-overlapping returns										
$r^c_{s,t-21:t-2}$	T	18	10	13	3	6	9	7	10	41
	%	26%	14%	19%	4%	9%	13%	10%	14%	59%
$r^c_{s,t-41:t-22}$	T	4	17	5	23	7	19	15	5	49
	%	6%	24%	7%	33%	10%	27%	21%	7%	70%
	T	21	24	18	26	12	25	18	13	59
At least one horizon	%	30%	34%	26%	37%	17%	36%	26%	19%	84%
R^2	mean	6.07%	median	3.87%	max	37.52%	min	0.0076		
p(Wald) < 10%	T	41	59%							
Panel B: Full sample, gross returns										
$r^c_{s,t-21:t-2}$	T	24	13	5	12	17	8	6	14	50
	%	34%	19%	7%	17%	24%	11%	9%	20%	71%
$r^c_{s,t-41:t-22}$	T	9	16	12	11	9	9	13	17	44
	%	13%	23%	17%	16%	13%	13%	19%	24%	63%
	T	31	24	17	20	24	15	16	25	61
At least one horizon	%	44%	34%	24%	29%	34%	21%	23%	36%	87%
R^2	mean	5.64%	median	3.76%	max	22.59%	min	1.26%		
p(Wald) < 10%	T	35	50%							
Panel C: Starting sample in January 1995										
$r^c_{s,t-21:t-2}$	T	11	8	5	5	14	2	7	8	37
	%	16%	11%	7%	7%	20%	3%	10%	11%	53%
$r^c_{s,t-41:t-22}$	T	12	36	9	7	6	3	12	21	53
	%	17%	51%	13%	10%	9%	4%	17%	30%	76%
	T	22	41	14	11	18	5	16	23	60
At least one horizon	%	31%	59%	20%	16%	26%	7%	23%	33%	86%
R^2	mean	5.90%	median	4.39%	max	22.76%	min	1.90%		
p(Wald) < 10%	T	33	47%							

Table OA.5: Contemporaneous and Predictive Regressions
This table summarizes the results of the following regression with overlapping observations for each country i:

$$r_{i,t:t+19} = \alpha_i + \sum_s (\beta_{i,s,0} r^c_{s,t:t+19} + \beta_{i,s,1} r^c_{s,t-21:t-2} + \beta_{i,s,2} r^c_{s,t-41:t-22} + \beta_{i,s,3} r^c_{s,t-62:t-42}) + \phi_i r_{i,t-20:t-1} + \varepsilon_{i,t:t+19}$$

It shows the number of countries for which monthly stock market excess returns ($r_{i,t:t+19}$) are predicted by sector-s contemporaneous ($r^c_{s,t:t+19}$) and one-month ($r^c_{s,t-21:t-2}$), two-month ($r^c_{s,t-41:t-22}$) and three-month ($r^c_{s,t-61:t-42}$) lagged commodity futures returns at the 10% significance level (based on Newey-West standard errors). *T*, *%*, *P* and *N* stand for total number, percentage, number of positive and number of negative countries (out of 70), respectively. The table also shows descriptive statistics for the regression R^2 and counts of significant coefficients at all lags, for at least one sector and for at least one lag. *p(Wald) < 10%* denotes the number of countries for which we reject the null hypothesis that all commodity sector returns fail to predict stock market excess returns. The sample period is from November 1979 to March 2016.

		Energy	Industrial Metals	Agriculture I	Agriculture II	Livestock & Meats	Precious Metals	EWI	GSI	At least one sector
		Separate Regression per country, controlling for lagged stock return								
$r^c_{s,t:t+19}$	T	24	50	15	48	6	29	68	58	69
	%	34%	71%	21%	69%	9%	41%	97%	83%	99%
	P	21	48	15	46	4	29	68	58	
	N	3	2	0	2	2	0	0	0	
$r^c_{s,t-21:t-2}$	T	25	23	6	14	16	9	8	16	53
	%	36%	33%	9%	20%	23%	13%	11%	23%	76%
	P	3	9	3	13	13	4	5	6	
	N	22	14	3	1	3	5	3	10	
$r^c_{s,t-41:t-22}$	T	8	8	19	12	10	14	9	11	45
	%	11%	11%	27%	17%	14%	20%	13%	16%	64%
	P	2	7	3	6	7	13	3	11	
	N	6	1	16	6	3	1	6	0	
$r^c_{s,t-61:t-42}$	T	13	9	8	6	20	12	7	9	45
	%	19%	13%	11%	9%	29%	17%	10%	13%	64%
	P	3	6	5	2	20	10	6	9	
	N	10	3	3	4	0	2	1	0	
All Lags	T	0	2	0	4	0	1	3	3	
	%	18.57%	12.86%	11.43%	8.57%	28.57%	17.14%	10.00%	12.86%	
At least one lag	T	46	58	36	52	26	42	68	61	70
	%	66%	83%	51%	74%	37%	60%	97%	87%	100%
	P	23	53	20	48	20	37	68	59	
	N	28	16	19	7	8	6	8	10	
R^2	mean	15.77%	median	13.84%	max	42.89%	min	4.98%		
p(Wald) <10%	T	70	100%							