State-Switching Return Predictability

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Abstract

Return predictability may be hidden from view if the same information has different meanings at different times, especially if information is good news in one state but bad news in another. We illustrate, using price changes in industrial metals, how conclusions on stock market return predictability vary with the number of expansions and contractions in our sample. We also show how state-switching affects predictability results in other studies. Even one strong contraction, like the recent financial crisis, in a sample can fundamentally alter overall conclusions. Since traditional regression tests ignore state-switching, standard tests may favor market efficiency.

Keywords: industrial metals, state-switching, regime switching, return predictability, gradual information diffusion, business cycle

JEL classification codes: G11, G14

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1. Introduction

A new strand of the stock market return predictability literature suggests that predictability caused by time-varying risk premia depends on the state of the economy. These return predictors tend to give stronger signals in economic contractions than in expansions (see, for instance, Henkel, Martin, and Nardari, 2011; Dangl and Halling, 2011; Rapach, Strauss, and Zhou, 2011). This literature appears to be part of a larger trend as the importance of regime changes in financial markets in general is attracting increasing attention (e.g., Ang and Timmerman, 2011). If return predictability itself is time-varying, this poses an interesting new question: Can we find situations where the predictability relation not only weakens but even switches sign in different states? This could be due to the same information signaling good news in one state and bad news in another. If positive predictability in one state offsets negative predictability in the other, this would open the possibility that in standard predictability tests actual predictability remains hidden from view. In fact, this might even happen if a predictive relation is very strong in one state, which occurs infrequently (recession), but less so in the other state, which is more common (expansion). In that case, predictability may dilute upon aggregation over states.

Our study answers the above question in the affirmative. We give several examples and discuss two in detail. First, we provide evidence of state-switching return predictability when we consider whether economically important industrial metals returns predict stock returns. Second, we revisit the well-known study of Hong, Torous, and Valkanov (2007), which shows how industry returns predict the broader market. In many cases, not only the strength but also the sign of the predictability relation differs across contractions and expansions, and if one does not allow for this state switch, it goes undetected by the traditional return predictability tests and thus stays hidden from view. For instance, when we consider the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) industrial metal index in our regression test for the full sample period (1977–2010), there emerges no evidence of predictability. If, however, we focus on the last decade (2000–2010), which includes the financial crisis of 2008, we find a strong and significant positive relation, with a t-statistic greater than 2. Higher industrial metals prices predict significantly higher stock market prices. However, during the 1990's the relation is reversed. We find a strong negative relation, with a t-statistic of almost negative 3. Once we allow for predictability to vary between contractions and expansions—using a simple regression approach that separates out states—it seems that this sign switch is due to information signaling good news in one state and bad news in another. Higher industrial metals returns predict higher stock market returns in contractions, in line with popular belief that these higher returns signal increases in demand. In expansions, higher industrial metals prices seem to indicate higher inflation, thus driving future stock market prices down. Since the contraction result is particularly strong, this means that even if recessions are short-lived, they can have a substantial and surprising effect on the results for the overall sample.

Our industrial metals results pass all standard robustness checks. The results are both statistically and economically significant, robust across countries, and are robust over time. They are also robust to different business cycle measures (National Bureau of Economic Research—NBER and Chicago Fed National Activity Index—CFNAI). We also show that time-varying risk premia are an unlikely explanation for our findings.

Industrial metals seem a natural candidate for return predictors that generate state-switching return predictability, due to asymmetric information responses to their price movements.

Industrial metals are often discussed in the financial news media as being important leading indicators of the economy and equity markets. Increasing industrial metals prices are cited as being a positive sign when the economy is depressed.[1] However, in expansions, rising industrial metals prices are frequently seen as signaling an overheating economy and inflation, which is widely viewed as bad news.[2] Further, in contrast to other commodities, industrial metals seem to be relatively unaffected by confounding factors.[3] In 2008, US Federal Reserve Chairman Bernanke (2008) asked: *"What signal should we take from recent changes in commodity prices about the strength of global demand or about expectations of future growth and inflation?"* This paper seems to provide an answer to Chairman Bernanke's question. Economically important industrial metal (aluminum and copper) price increases are good news for equities during strong contractions and bad news during strong expansions and, as we demonstrate, may include signals not found in many economic series.

But state-switching return predictability is not limited to industrial metals. We revisit the results of Hong, Torous, and Valkanov (2007) on sectors predicting the stock market. We show their conclusions drastically strengthen and become state dependent once we allow for the possibility of state-switching. These authors show that about one-third of industries lead the market. We document that the vast majority of sectors have predictive power if one

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1 For instance: "*Some analysts saw encouraging signs in the rise in copper since the start of the year. Its past correlation with industrial demand supported hopes that the economy had started to make small steps towards recovery and healthy inflation—rather than sliding into a protracted, severe period of falling prices and shrinking output*." (Mandaro, 2009).

http://www.marketwatch.com/story/dr-coppers-forecasting-ability-tested-year

2 For example, Sandra Pianalto, President of the Federal Reserve Bank of Cleveland (2006): "*Understanding why the prices of commodities, like copper, increase or decrease is one of the many pieces of the puzzle that we as policymakers try to fit together to help us figure out how the economy and inflation will perform in the future… the elevated inflation numbers concerned me, and indeed they still do*."

3 Energy prices may be influenced by political uncertainty and seasonalities in demand, agricultural commodities tend to be seasonal, and precious metals also serve as safe havens.

separates out contraction and expansion predictability. Some sectors seem to lead the market during expansions; a higher return during expansions suggests generally lower returns for the markets. Other sectors seem to lead the market in contractions; however, during recessions, price increases for these sectors predict higher general market returns.

This paper contributes to the literature on several levels. First, it is a new predictability study. We document how economically important variables such as prices of industrial metals have predictive ability for the stock market. These results are new and interesting in themselves and are relevant to practitioners because, as we show, it is possible to generate highly significant outperformance using a simple trading strategy based on actual CFNAI data to make real-time forecasts. The out-of-sample R^2's tend to be high, ranging mostly between 5% and 10%. This indicates the strength of the predicative ability and is in stark contrast to Goyal and Welch (2008), who find that a range of popular predictors have higher forecasting errors than the historical mean.

Second, these results show that return predictability can be state dependent. Third, our revisiting of Hong, Torous, and Valkanov (2007) brings forth interesting new results relevant to practitioners and, perhaps more importantly, suggests that stock market predictability based on industry returns is state-switching. Again, we find that a trading strategy based on the state-switching approach beats the market and increases the out-of-sample R^2's compared with the standard approach.

Fourth, the linear regression we use can be seen as the simplest regime switching model of its kind, as we simply use dummy variables for recessions and expansions. We find this simple approach works well in many practical return predictability settings. The advantage of this approach is that it is easy to estimate. The disadvantage is that it is an ad hoc way of specifying the regimes or the definition of dummy variables; however, in applications where there is a good economic reason to differentiate between states and when objective dating procedures exist, the benefits of simplicity may exceed the costs.

The main contribution of our paper, however, is more general, as it has major implications for the interpretation of market efficiency tests. From a historical perspective, our results are important because they suggest that return predictability in past studies may have been understated and that state-switching anomalies may have been overlooked. The example that we focus on, industrial metals, does not appear to be unique—our findings could apply to previous studies that find no predictability in their sample. For instance, suppose that investors in an expansion see a series of market price increases as bad news (fear of overvaluation) and recent price increases in a recession as good news (sign of recovery). Then, depending on the mixture of expansions and contractions in that sample, state-switching return predictability may have gone unnoticed if the famous Demon of Chance dealt several researchers a wrong hand of positive and negative states in the past. [4] Controlling for possible state-dependent switches might also strengthen previous research findings that document predictability because some of the predictability may have been offset by, for instance, a relatively large number of expansions over contractions; Hong, Torous, and Valkanov (2007) is a clear example of this.

Our results also seem to warrant a strong word of caution because of the recent financial crisis. Past predictability of results may appear to disappear if the sample includes the recent

[4] When we revisit the seminal Kendall (1953), but allow for the possibility of different predictability in different states, we find a negative relation between past and current weekly returns in expansions and a positive relation in recessions.

financial crisis. For instance, Driesprong, Jacobsen, and Maat (2008) document strong predictability of stock returns based on oil price returns on data up to April 2004. If we use S&P 500 returns and West Texas crude oil price changes, we find a similar, strong effect (coefficient of -0.099 and t-statistic of -3.53) over these authors' sample period, and over an extended period to the end of 2007 (-0.093 and t-statistic of -3.59). However, these authors' results seem to be driven by a strong negative relation during expansions. During contractions, especially the recent financial crisis, we find a strong and statistically significant positive effect, sometimes so strong that even very few observations render the overall results insignificant. In these authors' scenario, however, including the recent crisis leads to a change in t-value that no longer indicates significance: -1.62 (coefficient -0.05). If one is unaware of the state switch, one might conclude that predictability has disappeared and that markets may have become more efficient. Our results point to an alternative explanation: adjusting for the state switch in the contraction periods restores the overall oil price predictability documented in Driesprong, Jacobsen, and Maat (2008). This is just one example; the same phenomenon could occur for many other previously documented predictability results. As such, our results have implications for the use of standard regression tests to analyze return predictability. In the presence of state-switching return predictability, such tests may incorrectly favor the random walk model.

This paper relates to four strands of the literature. The first is represented by the work of McQueen and Roley (1993) and Boyd, Hu, and Jagannathan (2005), who show that identical macroeconomic announcements can mean different things for the stock market in different economic states. For example, Boyd, Hu, and Jagannathan (2005) show that an increase in unemployment is seen as good news for the stock market in expansions, as it is interpreted as indicating a reduced chance of interest rate increases. However, increasing unemployment in contractions is seen as a negative signal indicating that future profits and dividends are likely to be lower. Andersen, Bollerslev, Diebold, and Vega (2007) show that this differential reaction to US macroeconomic news announcements across the business cycle also exists in British and German stock markets, and in bond and foreign exchange markets. More recently, Gilbert (2011) finds that the link between macroeconomic-news-announcement day returns and future revisions differs between recessions and expansions. Our paper adds that the notion that the same news may mean different things at different times also applies to return predictability.

This paper also relates to the gradual-information-diffusion literature. The Hong and Stein (1999) theoretical model suggests that return predictability can result from information being reflected gradually in returns. Moreover, Hong, Torous, and Valkanov (2007) suggest slow-information diffusion can lead to cross-asset return predictability. They note that important information from one market may reach investors in another market with a delay and, as a result of less than perfect informational processing capacity, investors are unable to extract all relevant information from another asset class for the asset class they are focused on. The industrial metals index, copper, and aluminum seem natural candidates for gradual-information diffusion.[5] They are important inputs in the economy yet, as noted by Chairman Bernanke in the quote provided earlier, it is not always clear what pointer should be taken from price movements in important commodities such as these. Driesprong, Jacobsen, and Maat (2008) show that information contained in oil price changes takes time to diffuse into the stock market. We are the first to document that information contained in economically important industrial metals prices also gradually diffuses into stock returns, albeit in a

[5] See Driesprong, Jacobsen, and Maat (2008) Section 3.1 for more information on cross-asset class gradual information diffusion.

different manner. We are also the first to find that the Hong, Torous, and Valkanov (2007) results may constitute evidence of state-switching predictability.

The third relevant strand of the literature is the recent work on state-dependent return predictability. Pesaran and Timmermann (1995) show that different variables are better at predicting US stock returns at different times. These authors note (p. 1224) that the usefulness of economic variables such as inflation is related to "economic regime switches." More recently, there is acknowledgement that changing predictability relations may be the norm rather than the exception. Dangl and Halling (2011) use a model that allows for coefficient time-variation and document evidence of much stronger predictability in a range of variables in contraction periods. Henkel, Martin, and Nardari (2011) also find that predictability is stronger in contractions, which they attribute to "counter-cyclical risk premiums" (p. 560). However, these authors find that there is typically no predictability in expansions. In related work, Rapach, Strauss, and Zhou (2011) show that US equity returns lead international equity returns and that this effect is stronger in contractions. Our results suggest that there can be not only a difference in strength but also a difference in sign across different states, which may not only weaken but may even mask the actual predictability present. Moreover, we show how our predictability results cannot be attributed to time-varying risk premia, mainly because industrial metals returns frequently predict negative excess stock returns in both expansions and contractions. Negative excess returns cannot, by definition, be compensation for risk, so this result allows us to rule out a risk-based explanation for predictability (e.g., Schwert, 2003; Driesprong, Jacobsen, and Maat, 2008).

Finally, as pointed out above, our paper relates to the regime switching literature. A recent study by Ang and Timmerman (2011) provides an excellent overview of the use of regime switching models in finance. Our model can be seen as a very simple version of a regime switching model where not the data but the user imposes the states. We discuss the relation with regime switching models in more detail in Section 5.

2. Data

We use the S&P GSCI Industrial Metals Index and the two industrial metals (aluminum, copper) that are the most important economically. S&P GSCI determines the most important commodities in the global economy and weights them accordingly. As of June 28, 2010, copper had the highest weighting of the industrial metals, followed by aluminum. These two metals dominant the other industrial metals (nickel, zinc, and lead) in terms of economic performance. For instance, in June 2010, the weight of copper in the S&P GSCI index is over 4 times, 5 times, and 8 times that of nickel, zinc, and lead respectively.

We obtain the Standard and Poor's Goldman Sachs aluminum, copper, and industrial metals series from Thomson Reuters Datastream. These series commence in 1991, 1977 respectively. We also test the S&P GSCI Industrial Metals Index, which begins in 1977. We focus on futures data because these are more liquid and receive more attention in the media. However, results are similar for spot market data. For the US, we use the S&P 500 price index, while the international equity market series are typically MSCI country indices. These series are from Thomson Reuters Datastream and are in local currency.[6] The risk-free rates from each country are also sourced from Thomson Reuters Datastream. We use two proxies for US business cycle contraction and expansion phases. The first is National Bureau of Economic

[6] MSCI indices are not available for Finland, Ireland, Luxembourg, and Portugal for the entire time period, so we use the extended Global Financial Data series.

Research (NBER) business cycle data,[7] and the second is the Chicago Fed National Activity Index (CFNAI).[8] We follow the Chicago Fed and define a period as a contraction period when the CFNAI-MA3 is less than -0.7, and as an expansion period when the CFNAI-MA3 is greater than -0.7. The Chicago Fed has found that this definition best aligns with the NBER business cycle, which is identified only in retrospect.[9] The international business cycle data are from the Euro Area Business Cycle Dating Committee.[10] The endpoint for our analysis is December 31, 2010. Summary statistics for the entire period and for NBER expansions and contractions are presented in Appendix 1.

3. Main Results

3.1. Mixed Predictability Results

[Please insert Table 1 here]

The results in Table 1 illustrate the main point of our paper. They show how a researcher testing the predictive ability of movements in the industrial metals index for equity market returns using all available data (1977–2010) and the standard predictive regression $R_t = \alpha + \beta IM_{t-1} + \varepsilon_t$ would conclude that industrial metals have no predictive ability. A researcher focusing on the 1977–1990 period would reach a similar conclusion. However, a researcher analyzing the most recent decade (2001–2010) would conclude that industrial metals have

[7] http://www.nber.org/cycles.html

[8] http://www.chicagofed.org/webpages/publications/cfnai

[9] http://www.chicagofed.org/digital_assets/publications/cfnai/background/cfnai_background.pdf

[10] http://www.cepr.org/data/dating

strong positive predictive power. To the contrary, a researcher testing the relation at the beginning of the last decade using the most recent 10 years' data at that point (1991–2000) would conclude that increases in the price of industrial metals predict negative equity returns the following month.[11] We now test whether state-switching return predictability across the business cycle may cause these sample-specific results.

3.2. State-switching Predictability Across the Business Cycle

3.2.1. US Results

Could the inconsistent predictive ability of industrial metals price changes be related to different states of the economy? We address this question in Tables 2 and 3. Our methodology combines the standard return predictability approach with the business cycle framework of Boyd, Hu, and Jagannathan (2005). The state-switching return predictability regression specification is given as follows:

$$R_t = \alpha + \beta_1 Expansion_{t-1} IM_{t-1} + \beta_2 Contraction_{t-1} IM_{t-1} + \varepsilon_t , \quad (1)$$

where R_t is the return on the equity market in month *t*; IM_{t-1} is the return on the industrial metal in month *t-1*; $Expansion_{t-1}$ is a dummy variable that equals 1 if the economy is expanding and zero if it is contracting; and $Contraction_{t-1}$ is a dummy that equals 1 if the economy is contracting and zero if it is expanding. We designate each month as either contractionary or expansionary. We use the designation of the NBER business cycle dating

[11] All t-statistics are based on Newey-West (1987) standard errors.

committee. Then, we use the standard CFNAI business cycle definition. In each instance, we use the business cycle series that is available at the end of 2010.[12]

Note that econometrically, the proposed model nests the standard regression model used widely in the predictability literature. In Appendix 2 we discuss their relations in terms of model misspecification and hypothesis testing. The two models are nested when the slope coefficients of the predicted variables are equal, which includes the null hypothesis of no predictability. If the state-switching return predictability model is correct, then the standard return predictability model is misspecified in a way similar to an omitted variables problem. However, if the standard return predictability model is correct, the state-switching model still provides consistent but less efficient estimates.

A priori, there is no reason why the constant could not vary across states as well. In that case, a better specification might be to separate out expansion effects and contraction effects for the constant as well. However, when we test this possibility, we find no significant difference for the constant in our example. If anything, allowing the constant to vary across states only seems to strengthen our findings with respect to industrial metals. As discussed in the introduction, our model shows similarities with the regime switching literature. We discuss the link with the regime switching literature in more detail in Section 5.

We estimate regression 1 separately for the five industrial metals and for the industrial metals index. β_1 and β_2 represent the stock return reaction to a change in industrial metals prices in expansions and contractions, respectively.

[12] These series include revisions so could not be used by investors in real time. We consider this issue more closely in Section 4.3.

[Please insert Table 2 here]

Table 2 shows that an increase in industrial metals prices is bad news for equity prices in expansions. β_1 is negative and the relation is statistically significant for the industrial metals index and for the economically most important metals: aluminum and copper. This relation holds regardless of whether business cycles are defined based on the NBER or CFNAI. β_2, on the other hand, is positive for all commodities. Increasing industrial metals prices are good news for equities in contractions. The effect is very strong $-$ even though the number of contractions is very limited. This is important, as it means that only a few observations are needed of the opposite sign in a sample to find no significant results overall. Not surprisingly, the difference between the two coefficients ($\beta_1 - \beta_2$) is highly significant in all cases. Again, this relation holds regardless of whether we measure business cycles using NBER or CFNAI data. The last two columns contain results for the standard predictive regression $R_t = \alpha + \beta IM_{t-1} + \varepsilon_t$. None of the t-values are significant using all available data (1977–2010). Thus, using the traditional return predictability regression and not allowing for state switches may completely mask predictability results.

3.2.2. International Results

We next analyze whether the difference in the predictive relationship of industrial metals for stock returns between expansions and contractions holds outside the US as well.

[Please insert Table 3 here]

In Table 3, we present results for the 11 original European Union countries. These business cycle data are from the Euro Area Business Cycle Dating Committee and are estimated for the Europe region as a whole. These results are unlikely to be as strong as their US equivalents, as these countries do not all move from expansion to contraction and vice versa at precisely the same time, as implied by the use of Euro area business cycle series. Moreover, given its size and the role of the United States in the world, investors in Europe are likely to respond to news about the US business cycle as well. The correlations between the European business cycle and the US business cycle (as measured by NBER and CFNAI) are 0.61 and 0.54, respectively. We therefore also present European results based on the US business cycle. The European business cycle results show that there is a statistically significant difference in prediction relation between expansions and contractions in individual countries and in the European Union overall, on average. The predictability relation between industrial metal index price changes and equity returns is positive in contractions in 10 countries and in the equally weighted average European equity market. In expansions, the relation is negative in 6 of the 11 countries and in the average European equity market. The Panel B and C results for aluminum and copper respectively are similar. Increases in both metals predict increasing (decreasing) equity returns in contractions (expansions) in the majority of countries. The US CFNAI business cycle results are even stronger. There is a statistically significant difference in the prediction relation in nine countries when we use the US business cycle and the industrial metal index and in ten countries when either aluminum or copper are used. In summary, these results show that the state-switching predictive power of industrial metals is not exclusively a US phenomenon.

While results are consistently strong across business cycle measures and for different industrial metals, we still must verify whether these results are robust and economically relevant, and whether time-varying return predictability may be the cause of this predictability. We address these issues in the sections below.

4. Economic Explanations for Differing Predictability in Expansions and Contractions

The likely best test to assure that our results are robust is to test directly whether price changes in industrial metals predict economic variables. The idea that industrial metals price changes may provide important information about the economy is widely documented in the financial press. For instance:

> *… copper has a PhD in economics. Because copper is used in everything from electrical wiring to water pipes, it is seen as a good measure of the economy. If demand for copper falls, then it's believed the economy is slowing.*[13]

Empirical studies, such as Garner (1989) also show that movements in commodity prices lead inflation. Garner (1989) provides two reasons for this. Firstly, commodities are inputs in the production process. Secondly, the fact commodity prices are set in auction markets means they "respond more rapidly than the prices of manufactured goods and services to demand pressures or supply shocks" (p. 508). More recently, Awokuse and Yang (2003) show that commodity prices can be used to predict industrial production. We add to this literature by investigating whether movements in the industrial metals index and each of the individual industrial metals predict a range of economic series using the regression: $ES_t = \alpha + \beta IM_{t-1} + \varepsilon_t$, where ES_t is the change in the economic series in month *t*. The economic series include: Consumer Price Index: All Items; Consumer Price Index: All Items Less Food & Energy; University of Michigan: Consumer Sentiment; ISM Manufacturing: PMI Composite Index, Industrial Production Index; Capacity Utilization: Total Industry; Total Nonfarm

[13] http://www.whocrashedtheeconomy.com/?p=34

Payrolls: All Employees, Civilian Unemployment Rate; Housing Starts: Total, New Privately Owned Housing Units Started; Personal Consumption Expenditures (PCE); and Retail Sales. All series are sourced from the Federal Reserve Bank of St. Louis, with the exception of Producer Price Index (PPI), which we obtain from the Bureau of Labor Statistics.

The results presented in Table 4 confirm that commodity price movements lead movements in inflation and industrial production. Increases in the industrial metals index, aluminum, and copper indicate an increase in industrial production and inflation, as measured by the Producers Price Index. Increases in the industrial metals index and copper also lead to a decrease in Civilian Unemployment and an increase ISM Manufacturing and Capacity Utilization in the following month. It is clear that industrial metals price movements predict changes in economic variables.

[Please insert Table 4 here]

An interesting question that follows from Chairman Bernanke's question quoted in the Introduction is whether commodity price movements may contain information beyond that contained in the economic series. Our results suggest they do. We investigate this by regressing each of the industrial metals return series on all economic series. We then take the residuals from these regressions and check whether these residuals can predict equity market movements. Predictability from these residuals would indicate that information from industrial metals returns beyond that contained in the economic series predicts equity returns. While the results (documented in Appendix 3) become less strong, the results remain statistically significant.

5. Out-of-Sample Trading Rule Returns

5.1. Extended Period Out-of-Sample Results

To be practically relevant, a trading rule should be capable of beating the market out-of-sample. We measure the out-of-sample performance of the trading rule using a number of approaches. We calculate the Sharpe ratio for each trading rule and compare these to the buy-and-hold Sharpe ratio.[14] We then compute the out-of-sample R^2 used by Campbell and Thompson (2008) and Goyal and Welch (2008) among others. This is specified as:

$$R_{OS}^2 = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$$

or (2)

$$R_{OS}^2 = 1 - \frac{MSE_{SSRP}}{MSE_{Mean}} \ ,$$

where $\hat{r}_t$ and $\bar{r}_t$ are the fitted value from the state-switching predictive regression and the average historical return (both estimated for period t-1), respectively. R_{OS}^2 denotes the reduction (in percentage terms) in the forecasting error of the state-switching return prediction model relative to the historical mean model. MSE_{SSRP} and MSE_{Mean} are the mean square predicted errors of the state-switching and historical mean models. Following Goyal and Welch (2008), we also calculate change in root mean squared predicted error (RMSE).

$$\Delta RMSE = \sqrt{MSE_{Mean}} - \sqrt{MSE_{SSRP}} \ . \qquad (3)$$

[14] We use the 1994 version of this ratio, which involves calculating the variance of excess returns.

We determine statistical significance based on bootstrapped critical values of the R_{OS}^2 and the change in root mean squared predicted error. The method we apply is as explained by Goyal and Welch (2008). As they note, this is based on the work of Mark (1995) and Kilian (1999). We split the sample into two 17-year periods for the industrial metal index and copper results. The first (1977 – 1993) is the in-sample period and the second (1994 – 2010) is the out-of-sample period. Since the aluminum data starts in 1991 and our model requires one contraction and one expansion in the in-sample period, we are unable to calculate aluminum results for the 1994 – 2010 out-of-sample period, but, in Section 5.3, we show the results for shorter in-sample and out-of-sample periods are qualitatively similar.

5.1.2. US Results

The results presented in Table 5 indicate that trading rules based on economically important industrial metals returns are highly economically significant. The returns to the industrial metal index and copper trading rules generate positive returns that are considerably (around 50%) greater than buy-and-hold returns. The Sharpe ratios from the trading rules are over 200% greater than the buy-and-hold Sharpe ratio. The out-of-sample R^2 of the industrial metals index and copper are all in excess of 6.5%. This indicates just how strong the predictive ability is here. The change in root mean squared predicted error results are consistent with these results. The change in root mean squared predicted error is positive for the industrial metals index, and copper, and it is statistically significant.

[Please insert Table 5 here]

5.1.3. International Results

The Euro Area Business Cycle Dating Committee is similar to the NBER Business Cycle Dating Committee in that it determines business cycle peaks and troughs some months after the event. For instance, the Euro Area Business Cycle Dating Committee did not conclude that economic activity had peaked in the first quarter of 2008 until March 31, 2009.[15] These business cycle data are therefore difficult to apply to prediction. Given this, and the correlation between the more timely US CFNAI business cycle data and the Euro area business cycle data documented in Section 4.2, we use CFNAI data to make out-of-sample European equity market predictions. We apply the same model as for the United States to each European market.[16]

[Please insert Table 6 here]

The Table 6 results are similar to the results for the United States. There is strong evidence that industrial metals returns and a state-switching model can be used to predict European equity returns out-of-sample. The Sharpe ratios from the trading rule are larger than their buy-and-hold equivalents. With the exception of Finland (based on industrial metals) and Finland and Portugal (based on copper), each country has a positive out-of-sample R^2. These are statistically significant in each case, except for Germany, and average 4.3% (3.5%) across the 11 countries based on the industrial metal index (copper). Some countries (e.g., Austria and Ireland) have larger out-of-sample R^2 than those in the U.S. The change in root mean squared

[15] http://www.cepr.org/data/dating/

[16] We use local short-term interest rates as a proxy for the local risk free rate in each instance.

predicted error is statistically significant in each country other than Finland and Portugal, as well as for the European Union index we create.

5.2. CFNAI Real-time Data

If out-of-sample results are based on information that an investor did not have available to them at the time then they can be subject to hindsight bias. We address this issue in more detail in this section. As noted in Section 2, a CFNAI-MA3 reading above (below) -0.7 indicates an expansionary (recessionary) period. This threshold was determined by back-testing, and the CFNAI data series was back filled in historical periods, so, to ensure hindsight bias is not driving the results, the out-of-sample tests in this section use only CFNAI data that have been available to investors in real-time and that investors knew of the -0.7 threshold at this time.

The first release of the CFNAI was in March 2001; this release makes mention of the -0.7 recession threshold. The March 2001 announcement related to the state of the economy in January 2001. Our out-of-sample tests therefore start with a prediction of the April 2001 equity market return. For each month, we regress the S&P 500 return for month t-1 on the industrial metals return for month t-2 to generate a beta coefficient. This coefficient, together with the state of the economy at t-1 and the industrial metals return at t-1 are then used to make a forecast for the S&P 500 return in month t. If this forecast is greater than the risk-free rate in month t-1, a long S&P 500 position is established. If the forecast is lower, we assume the investment is in the risk-free asset. In the example above where the April 2001 S&P return is predicted, we need to use the known state of the economy at the end of March 2001. The real-time information available at this point is the January CFNAI (released on March 5).

Some other 2001 and 2002 monthly results were released with a two-month lag, but from June 2002 onward, all monthly results were released at the end of the following month.[17] This means that to predict, for instance, the July 2002 S&P return as at the end of June, the May CFNAI result and the June industrial metals return are used.

The US results presented in Table 7 indicate that trading rules applied solely to the period when CFNAI data was available in real time are stronger than those in Section 5.1. The Sharpe ratios from the trading rules are all positive while the buy-and-hold Sharpe ratio is negative. The out-of-sample R^2 of the industrial metals index, aluminum, and copper are all in excess of 7.5% and are as large as 8.98%. The change in root mean squared predicted error is also positive and statistically significant for the industrial metals index and aluminum and copper. The international results in Table 8, which are also based on real-time CFNAI data, show a similar trend. Results are stronger when the out-sample analysis is limited to data that was available in real time. For instance, the average out-of-sample adjusted R^2 across all countries is 6.43%, 4.75%, and 5.06% when the industrial metal index, aluminum, and copper are used respectively. This proves that hindsight bias is not driving the results.

[Please insert Table 7 here]

[Please insert Table 8 here]

[17] All announcements and release dates are available at:

http://www.chicagofed.org/webpages/publications/publications_listing.cfm

6. Robustness Checks

6.1. Volatility, Contemporaneous Effects, and Other Predictors

To further assure that these results are robust, we perform a number of checks. Our results are not driven by volatility effects. Estimating a GARCH model with exogenous regressors, we find that industrial metals price increases predict lower stock market volatility during recessions, but that this does not affect mean estimates (Appendix 4). Results are not affected if we allow for contemporaneous effects of industrial metals on stock returns (Appendix 5). Industrial metals returns are also not correlated with other variables known to predict stock returns, such as dividend yields and interest rates (see Appendix 6).

6.2. Time-Varying Risk Premia

Our results seem unlikely to be related to time-varying risk premia, for several reasons. First, contrary to time-varying risk premia, the effect we document tends to be short-lived. It disappears after one month, which seems more in line with the gradual information diffusion explanation of Driesprong, Jacobsen and Maat (2008) and Hong, Torous and Valkanov (2007). Time-varying risk premia predictors tend to predict over horizons longer than just one month. Second, industrial metals returns have very low correlations with changes in economic variables, such as default spread, term structure, dividend yield, and short-term interest rates, which have been shown to predict time-varying risk premia. The correlations, which we report in Appendix 6, are typically less than 0.1 (in absolute terms).

Third, if one considers the coefficients for industrial metals returns in the contraction–expansion regressions, it is evident that these frequently predict negative excess stock returns in both expansions and contractions. As shown in Schwert (2003), negative excess returns are unlikely to serve as compensation for risk. Fourth, industrial metals also satisfy the more formal test in Driesprong, Jacobsen and Maat (2008), which provides evidence against a time-varying risk premia argument. We discuss this in Appendix 7.

7. Link with Regime Switching Models

Our linear regression can be seen as the simplest regime switching model of its kind, as we simply use dummy variables for recessions and expansions. The advantage of this approach is its simplicity. This simple approach seems to work well in our setting when there is a good economic reason to separate between states and when objective dating procedures exist. The disadvantage is the ad hoc method of specifying the regimes and the definition of the dummy variables.

We compare our results to those from regime switching models. The most obvious specification for the regime switching model in relation to our approach is $R_t = \alpha + \beta IM_{t-1} + \varepsilon_t$, where the beta is allowed to vary between two states based on the data. The regime switching model (based on Perlin, 2010) detects that beta switches sign between states and significantly so. We find that beta in state 1 is 0.4684 with a t-statistic of almost 5, and that the beta in state 2 is -0.0645 with a negative 1.89 t-statistic. However, as shown in Table 9, panel A, the correlations between states from this model and NBER and CFNAI states are small and negative (-0.05 and -0.04, respectively). The states from the simple regime switch coincide with those from the business cycle variables around the global financial crises, but not at other times. It seems that in this particular specification, the regime switching model quickly shifts states due to extreme shocks rather than being in expansion or contraction as in states for prolonged periods of time. We see very short moments—often one month—where the system is in a recession-like state, but most of time the system is in another state. Note that this approach forces the regime switching model to infer the state from stock returns, lagged industrial metals returns, or from a switch in the relation between the two. Therefore, the results for this specification are not surprising, as this specification does not explicitly contain a proxy for the business cycle variable.[18]

[Please insert Table 9 here]

An alternative approach would be to introduce another variable (like real GNP) and to use a regime switching model to define recessions and expansions based on this variable. The Hamilton (1989) results imply that this approach may work well. We use the Real GNP series from the Federal Reserve Bank of St. Louis and the Hamilton (1989) model to determine states. We find a correlation of 0.799 between the states from this model and NBER states, and a correlation of 0.653 with CFNAI states. However, if we use the Hamilton (1989) approach we implicitly pay the same price as in our approach: an ad hoc way of specifying the regimes now determined by the choice of the economic business cycle variable. In Table 9 Panel B, we report results using our state-switching equation (1) with states determined by the Hamilton (1989) regime switching model rather than the NBER or CFNAI business cycle data. These results are generally weaker than those in Table 2, but still show evidence of differing predictability across expansions and contractions. Increases in both the industrial

[18] We reach similar conclusions if we allow the constant to vary and also if we allow the variance to vary over time. In both cases these correlations of the states with NBER and CFNAI variable remains low.

metals index and aluminum predict a decrease in the stock market the following month in economic expansions, while increases in aluminum, lead, nickel, and zinc predict increases in the stock market the next month in economic contractions. Each commodity has a statistically significantly different coefficient in expansions and contractions.

The real GNP series is subject to large revisions through time. The results we discuss above are based on the series as at the end of 2010 and include revisions. An investor who wishes to implement a trading rule does not have time to await revisions, so we check the correlation between the states derived from the "as reported" Real GNP series and the states from the other business cycle proxies. Table 9 Panel C shows that in the 2001–2010 period, during which the CFNAI data were available to investors (typically with a one month lag), there is a correlation of 0.914 between the states from the "as reported" CFNAI and the states from the series as at the end of 2010, which included revisions. Revisions do not seem to change this series appreciably. The correlation between the states derived from the revised real GNP series and the as-reported CFNAI series is 0.642. However, the correlation between the states derived from the as-reported real GNP series and the as-reported CFNAI series is just 0.346. This indicates that real GNP numbers are heavily revised. The as-reported numbers are clearly estimated with a non-negligible error, which reduces their worth for real-time forecasting.

8. Published Results: An Example

We illustrate how state-switching return predictability may affect results from past studies by considering the impact on the results in Hong, Torous, and Valkanov (2007). In a standard regression in which these authors include both the lagged market and lagged industry returns,[19] 14 sectors out of 34 are found to significantly predict future returns at the 10% level or better. Ten industries (Real Estate, Apparel, Print, Leather, Transport, TV, Utilities, Retail, Money, and Services) do so positively. An increase in these sectors indicates higher returns in the next month for the general market on average. Price increases in four industries, Mines, Stone, Petroleum, and Metal predict negative future market returns.

We generate results based on the standard regression approach: $R_t = \alpha + \beta I_{t-1} + \gamma R_{t-1} + \varepsilon_t$. R_t is the excess S&P 500 monthly return and $I_{t-1}$is the excess industry return.[20] A lagged market return variable R_{t-1} is included as a control variable, as per Hong, Torous, and Valkanov (2007). We also apply a state-switching model: $R_t = \alpha + \beta_1 Expansion_{t-1} I_{t-1} + \beta_2 Contraction_{t-1} I_{t-1} + \beta_3 Expansion_{t-1} R_{t-1} + \beta_4 Contraction_{t-1} R_{t-1} + \varepsilon_t$.

We first check results for the same period (1946–2002) and find similar results for the standard regression approach (not reported). We then produce standard regression and state-switching results for the 1946–2010 period; these are reported in Table 10.

[Please insert Table 10 here]

Using the Hong, Torous, and Valkanov (2007) approach, we find 10 industries that significantly predict future market returns between 1946 and 2010. However, if we allow for state-switching, we see that the return predictability that these authors observe typically takes place in either contractions or expansions, but not in both. Mines, Stone, Smoke, Petroleum,

[19] They also include several well-known predictors as control variables, but these do not appear to have much impact on their results, as we obtain similar results without these variables using the same time period.

[20] These data are sourced from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html . We thank Ken French for making these data available.

and Metal are predictive in expansions, but not in contractions. Other sectors, such as Real Estate, Food, Textiles, and Apparel are predictive in contractions but not in expansions. We also seem to uncover more widespread predictability. Results that are significant in the original study but lose significance when the recent sample is included (e.g., Metals) become significant again once predictability is divided between expansions and contractions. Allowing for state-switching reveals that almost all (28 out of 34) industries predict well in either expansions or contractions.

We next consider whether allowing predictability to vary across states adds value to out-of-sample predictions. Table 11 contains the estimation results for two different prediction strategies. The first is the traditional Hong, Torous and Valkanov (2007) approach. The second is our approach of allowing the predictability relation to vary over the business cycle. The CFNAI data starts in 1967 so the first out-of-sample period is based on the second half of this data (1989 – 2010). The period is shorter (it begins in April 2001, as this is the first point at which up-to-date CFNAI business cycle data are available) but contains no hindsight bias. Our approach is broadly consistent with that outlined in Section 5.2. The main differences are that we use combined prediction models (across all industries) in each instance and that we predict S&P500 price index returns. For the traditional approach, we derive a set of market predictions from all individual industry regressions that show significant predictability relation in the January 1946–end of our in-sample period using a standard regression specification.[21] We then average these predictions and use that prediction as our market forecast for that month. Our process is similar for the second, state-switching approach. The difference here is that we use our state-switching regression specification (with CFNAI business cycle data) to identify industries that have statistically significant predictive ability

[21] The in-sample period ends in December 1988 for the first set of tests and March 2001in the second set.

in-sample. We then use each of these industries to generate forecasts (as explained in Section 5.1) and then take the average of these forecasts as our market forecast.

The results set forth in Table 11 indicate that the Sharpe ratios from the state-switching approach are over 4 times larger those from a buy-and-hold strategy and over 20% higher than those generated from the standard regression approach in the 1989 – 2010 out-of-sample period. Moreover, the out-of-sample R^2 is 1.96% for the state-switching approach compared to 0.10% for the Hong, Torous and Valkanov (2007) specification. The results are even stronger in the shorter out-of-sample period that contains no hindsight bias with the out-of-sample R^2 increasing to 5.56% for the state-switching approach compared to 2.72% for the traditional specification. These results clearly indicate that a state-switching model leads to superior out-of-sample predictability. Again, changes in root mean squared predicted error are also consistent with this result.

[Please insert Table 11 here]

9. Conclusions

We show that state-switching return predictability can have major implications for conclusions regarding return predictability. If state-switching return predictability is present, it may go undetected even in long-term samples. Traditional predictability regressions would not be able to reject the random walk model, even when returns are actually predictable. We illustrate how a researcher who selects a sample period that includes both expansions and contractions may incorrectly conclude that there is no relation between industrial metals price movements and stock returns. Alternatively, if a period that is dominated by recessions (expansions) is chosen, a researcher may conclude that there is always a strong positive (negative) relation between industrial metals price changes and stock returns. Our results are economically significant, with large out-of-sample R^2's, and are robust to a range of tests. They hold whether we define the business cycle based on NBER or CFNAI measures, are valid for different countries, and are not due to time-varying risk premia.

Our state-switching return predictability results have broader implications for the return predictability literature—not only for past results but for future work as well. For example, we show that the results of Hong, Torous, and Valkanov (2007) strengthen dramatically when we allow for state-switching return predictability. The number of industries that lead the stock market increases from 10 to 28 (out of 34). Increases in some industries are good news for the market in contractions—the market increases on average in the following month, while increases in other industries are bad news for the market and signal a decline in the next month in expansions. We also show that for a trading strategy based on these results, state-switching return predictability gives superior performance to a strategy based on the traditional model. In addition, we verify that the Driesprong, Jacobsen, and Maat (2008) results on strong stock return predictability based on oil price returns holds up until the end of 2007. However, once we include the recent financial crisis, the results no longer remain significant. This seems to be due to a very strong reverse relation during the financial crisis. Even a few observations render these authors' results insignificant. This suggests a word of caution for future return predictability studies that incorporate the financial crisis of 2008 in their sample.

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Table 1. Overall and Sub-Period Equity Market Predictability

	α	t-Statistic	β	t-Statistic	Adj. R^2	N
All Data (1977-2010)	0.006	**2.589**	0.001	0.025	-0.2%	406
1977-1989	0.007	**2.204**	-0.049	-1.523	0.1%	166
1991-1999	0.011	**3.996**	-0.184	**-2.206**	3.6%	120
2001-2010	-0.002	-0.423	0.185	**2.168**	6.1%	120

The S&P GSCI Industrial Metals Index and S&P 500 data are sourced from Thomson Reuters Datastream. The predictive regression $R_t = \alpha + \beta IM_{t-1} + \varepsilon_t$ is run, where R_t is the S&P 500 monthly return and IM_{t-1} is the industrial metals return. t-statistics statistically significant at the 10% level or better are in bold. The t-statistics are computed based on the Newey-West (1987) method and are heteroskedasticity and autocorrelation consistent.

Table 2. US Equity Market Predictability across the Business Cycle

	Expansion			Contraction				
	β_1	t-Statistic	N	β_2	t-Statistic	N	$\beta_1 - \beta_2$	F-Test
Panel A: NBER – State-Switching Model								
IM Index	-0.065	**-2.078**	350	0.207	**1.675**	56	-0.272	**4.525**
Aluminum	-0.115	**-2.403**	210	0.386	**2.331**	28	-0.500	**8.081**
Copper	-0.051	**-1.795**	350	0.187	**2.142**	56	-0.238	**6.750**
Panel B: CFNAI – State-Switching Model								
IM Index	-0.073	**-2.510**	343	0.299	**3.118**	63	-0.372	**13.946**
Aluminum	-0.152	**-3.257**	202	0.384	**3.054**	36	-0.536	**16.231**
Copper	-0.060	**-2.231**	343	0.249	**4.232**	63	-0.309	**23.238**

Panel C: Standard Model		
	β	t-Statistic
IM Index	0.001	0.025
Aluminum	0.035	0.390
Copper	0.010	0.220

The S&P GSCI Industrial Metals Index, aluminum, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. The regression $R_t = \alpha + \beta_1 Expansion_{t-1} IM_{t-1} + \beta_2 Contraction_{t-1} IM_{t-1} + \varepsilon_t$ is run for each industrial metal series. R_t is the return on the equity market in month *t*, IM_{t-1} is the return on the industrial metal in month t-1, $Expansion_{t-1}$ is a dummy variable that equals 1 if the economy is expanding and zero if it is contracting. $Contraction_{t-1} = 1 - Expansion_{t-1}$. Expansion and contraction in the economy are separately measured using NBER and CFNAI data. We use the F-test to determine whether β_1 and β_2 are statistically significantly different. Newey-West t-statistics and F-statistics statistically significant at the 10% level or more are in bold. Panel C contain results for the standard predictive regression $R_t = \alpha + \beta IM_{t-1} + \varepsilon_t$, where R_t is the S&P 500 monthly return and IM_{t-1} are the industrial metal returns.

Table 3. International Equity Market Predictability across the Business Cycle

	Expansion			Contraction				
	β_1	t-Statistic	N	β_2	t-Statistic	N	$\beta_1 - \beta_2$	F-Test
Panel A: Euro Business Cycle – Industrial Metal Index								
Austria	0.024	0.410	322	0.339	**1.792**	84	-0.315	2.572
Belgium	-0.035	-0.656	322	0.217	1.177	84	-0.252	1.727
Finland	0.039	0.808	322	-0.061	-0.698	84	0.100	0.910
France	-0.124	**-2.118**	322	0.215	**2.058**	84	-0.339	**7.927**
Germany	-0.104	**-1.952**	322	0.197	**1.710**	84	-0.301	**5.619**
Ireland	0.002	0.040	322	0.339	**2.383**	84	-0.337	**4.932**
Italy	-0.046	-0.869	322	0.185	1.434	84	-0.231	**2.747**
Luxembourg	0.043	0.852	322	0.238	**1.708**	84	-0.194	1.699
Netherlands	-0.024	-0.706	322	0.171	1.558	84	-0.196	**2.910**
Portugal	0.113	1.539	321	0.188	**2.378**	84	-0.075	0.448
Spain	-0.011	-0.252	322	0.203	**2.468**	84	-0.214	**5.169**
European Union	-0.049	-1.537	322	0.164	**1.763**	84	-0.213	**4.683**
Panel B: Euro Business Cycle - Aluminum								
Austria	0.078	0.832	187	0.578	**2.168**	51	-0.500	**3.106**
Belgium	-0.050	-0.690	187	0.417	**2.223**	51	-0.466	**5.493**
Finland	0.024	0.283	187	-0.232	-1.452	51	0.256	**1.938**
France	-0.056	-0.820	187	0.314	**2.364**	51	-0.371	**5.930**
Germany	-0.012	-0.131	187	0.344	**2.208**	51	-0.356	**3.708**
Ireland	0.051	0.651	187	0.377	**1.757**	51	-0.326	**1.997**
Italy	0.086	1.087	187	0.254	1.365	51	-0.168	0.674
Luxembourg	0.150	**1.984**	187	0.376	**1.883**	51	-0.226	1.112
Netherlands	-0.056	-0.812	187	0.332	**2.473**	51	-0.388	**6.527**
Portugal	0.125	1.490	187	0.205	**1.833**	51	-0.080	0.307
Spain	-0.019	-0.255	187	0.266	**1.987**	51	-0.285	**3.322**
European Union	-0.038	-0.672	187	0.255	**1.884**	51	-0.294	**3.919**
Panel C: Euro Business Cycle - Copper								
Austria	0.020	0.396	322	0.271	**1.880**	84	-0.250	**2.732**
Belgium	-0.036	-0.800	322	0.172	1.261	84	-0.208	**2.124**
Finland	0.007	0.152	322	-0.053	-0.754	84	0.061	0.456
France	-0.097	**-1.845**	322	0.174	**2.417**	84	-0.270	**9.195**
Germany	-0.102	**-2.270**	322	0.170	**1.961**	84	-0.272	**7.825**
Ireland	-0.011	-0.243	322	0.282	**2.772**	84	-0.293	**6.853**
Italy	-0.042	-0.863	322	0.162	**1.770**	84	-0.204	**3.894**
Luxembourg	0.024	0.573	322	0.199	**1.983**	84	-0.175	**2.615**
Netherlands	-0.018	-0.569	322	0.121	1.542	84	-0.139	**2.761**
Portugal	0.086	1.396	321	0.137	**2.396**	84	-0.050	0.346
Spain	-0.013	-0.330	322	0.163	**2.626**	84	-0.176	**5.557**

European Union	-0.044	-1.522	322	0.131	**1.948**	84	-0.175	**5.744**
Panel D: US Business Cycle – Industrial Metal Index								
Austria	0.011	0.232	343	0.521	**2.628**	63	-0.510	**6.318**
Belgium	-0.059	-1.295	343	0.420	**2.896**	63	-0.478	**10.105**
Finland	0.020	0.473	343	-0.027	-0.217	63	0.046	0.124
France	-0.120	**-2.248**	343	0.340	**4.710**	63	-0.460	**25.906**
Germany	-0.101	**-2.081**	343	0.311	**3.006**	63	-0.413	**13.040**
Ireland	-0.001	-0.024	343	0.492	**3.645**	63	-0.493	**12.255**
Italy	-0.053	-1.065	343	0.309	**2.621**	63	-0.362	**8.013**
Luxembourg	0.039	0.861	343	0.335	**2.176**	63	-0.295	**3.426**
Netherlands	-0.032	-1.041	343	0.282	**2.905**	63	-0.314	**9.523**
Portugal	0.102	1.587	342	0.264	**2.871**	63	-0.163	2.184
Spain	-0.015	-0.358	343	0.309	**3.540**	63	-0.324	**11.371**
European Union	-0.054	**-1.870**	343	0.271	**3.420**	63	-0.325	**14.676**
Panel E: US Business Cycle – Aluminum								
Austria	0.039	0.440	202	0.661	**2.676**	36	-0.623	**5.589**
Belgium	-0.093	-1.409	202	0.506	**2.964**	36	-0.599	**10.766**
Finland	0.017	0.187	202	-0.224	-1.450	36	0.242	**1.736**
France	-0.103	**-1.624**	202	0.408	**4.046**	36	-0.510	**17.346**
Germany	-0.030	-0.344	202	0.385	**2.783**	36	-0.416	**6.222**
Ireland	-0.034	-0.483	202	0.542	**3.305**	36	-0.576	**10.643**
Italy	0.019	0.238	202	0.383	**2.631**	36	-0.365	**4.780**
Luxembourg	0.135	**1.803**	202	0.407	**2.111**	36	-0.272	**1.736**
Netherlands	-0.086	-1.287	202	0.395	**3.512**	36	-0.480	**12.847**
Portugal	0.104	1.288	202	0.246	**2.416**	36	-0.142	1.160
Spain	-0.087	-1.166	202	0.397	**4.150**	36	-0.484	**14.904**
European Union	-0.088	**-1.652**	202	0.353	**3.324**	36	-0.441	**12.976**
Panel F: US Business Cycle – Copper								
Austria	0.002	0.039	343	0.420	**3.210**	63	-0.419	**9.379**
Belgium	-0.057	-1.484	343	0.316	**3.041**	63	-0.373	**11.679**
Finland	-0.005	-0.130	343	-0.031	-0.325	63	0.026	0.059
France	-0.096	**-2.039**	343	0.264	**5.755**	63	-0.360	**29.858**
Germany	-0.101	**-2.462**	343	0.259	**3.981**	63	-0.360	**22.158**
Ireland	-0.014	-0.348	343	0.390	**4.348**	63	-0.403	**17.407**
Italy	-0.044	-0.966	343	0.240	**3.113**	63	-0.284	**10.092**
Luxembourg	0.018	0.466	343	0.281	**2.798**	63	-0.264	**6.176**
Netherlands	-0.029	-1.027	343	0.205	**3.189**	63	-0.235	**11.304**
Portugal	0.074	1.334	342	0.198	**2.844**	63	-0.124	**2.032**
Spain	-0.017	-0.453	343	0.237	**3.794**	63	-0.254	**12.382**
European Union	-0.051	**-1.931**	343	0.211	**4.189**	63	-0.262	**21.213**

S&P GSCI Industrial Metals Index, aluminum, and copper data are sourced from Thomson Reuters Datastream. Equity market data are from Thomson Reuters Datastream and Global Financial Data. The method is the same as that described in Table 2. In Panels A-C, expansions and contractions are measured using Euro Area Business Cycle Dating Committee data, which define one business cycle for the entire Euro area. In Panel D-F, expansions and contractions are measured based on the CFNAI US business cycle. The F-test is used to determine whether β_1 and β_2 are statistically significantly different. Newey-West t-statistics and F-statistics statistically significant at the 10% level or better are in bold.

Table 4. Industrial Metals Predicting Economic Series

	IM Index		Aluminum		Copper	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Capacity Utilization	0.018	**3.117**	0.028	**2.266**	0.015	**3.143**
Civilian Unemployment	-0.065	**-2.758**	-0.058	-1.265	-0.052	**-2.608**
Consumer Confidence	0.058	1.611	0.043	0.700	0.045	1.439
CPI All	0.007	1.252	0.011	1.339	0.008	1.409
CPI Less Food Energy	-0.001	-0.300	-0.001	-0.295	-0.001	-0.257
Housing Starts	0.050	0.628	0.122	1.310	0.045	0.641
Industrial Production	0.016	**2.696**	0.026	**1.943**	0.013	**2.486**
ISM Manufacturing	0.123	**2.990**	0.096	1.530	0.108	**3.167**
Nonfarm Payrolls	0.000	0.013	-0.005	-0.376	0.004	0.621
PCE	0.012	**2.231**	0.015	**1.728**	0.010	**2.120**
PPI	0.037	**2.466**	0.059	**2.260**	0.035	**2.589**

S&P GSCI Industrial Metals Index, aluminum, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. All economic series are sourced from the Federal Reserve Bank of St. Louis, with the exception of Producer Price Index (PPI), which we obtain from the Bureau of Labor Statistics. The regression: $ES_t = \alpha + \beta IM_{t-1} + \varepsilon_t$ is estimated in each instance. ES_t is the monthly change in the economic series. t-statistics statistically significant at the 10% level or better are in bold.

Table 5. US Out-of-sample Economic Significance

	IM Index	Copper	Buy-and-Hold
Mean	0.701%	0.709%	0.473%
Std. Dev.	4.097%	4.191%	4.601%
Sharpe Ratio	10.393%	10.348%	4.312%
OoS R^2	6.516%***	6.505%***	
95% Bootstrap Critical Value	1.256%	1.248%	
99% Bootstrap Critical Value	2.137%	2.196%	
ΔRMSE	0.152%***	0.152%***	
95% Bootstrap Critical Value	0.029%	0.029%	
99% Bootstrap Critical Value	0.049%	0.051%	

S&P GSCI Industrial Metals Index, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. A trading rule that signals a long equity market position or a T-bill position the following month based on the industrial metals return is tested. Monthly Sharpe ratios are presented in Panel A. Panel B contains out-of-sample (OoS) R^2's and ΔRMSE's for forecasts based on the state-switching model versus forecasts based on the historical average return. Statistical significance is determined with a bootstrap procedure. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All results relate to a 17-year (1994–2010) out-of-sample period and are in percent.

Table 6. International Out-of-sample Economic Significance

	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Lux	Neth	Portugal	Spain	EU
Panel A: Sharpe Ratios – Industrial Metal Index												
Mean	0.511	0.656	0.733	1.326	0.535	0.650	0.188	0.615	0.657	0.486	0.812	0.536
Std. Dev.	5.992	4.490	7.761	7.164	5.596	5.195	6.100	6.141	6.135	5.590	5.925	4.347
Sharpe Ratio	8.468	8.915	6.161	10.200	4.810	7.658	0.662	4.370	6.398	4.217	19.768	5.024
Buy-Hold Sharpe Ratio	1.379	-2.714	4.619	-3.386	1.685	-1.443	-0.700	1.239	-2.783	-0.356	6.324	0.079
Panel B: Sharpe Ratios – Copper												
Mean	0.39	0.44	0.68	1.23	0.63	0.45	0.17	0.61	0.66	0.49	0.85	0.51
Std. Dev.	6.13	4.78	7.72	7.11	5.55	5.66	6.10	6.17	6.13	5.61	5.97	4.36
Sharpe Ratio	6.28	3.88	5.54	8.69	6.49	3.59	0.09	4.26	6.42	4.33	20.77	4.36
Panel C: Out-of-Sample R^2 and Root Mean Squared Errors – Industrial Metal Index												
OoS R^2	8.518***	7.183***	-1.801	5.601***	3.438***	10.121***	3.182**	2.778**	4.199***	2.129	1.997**	4.932***
95% Crit Val.	0.825	1.017	2.361	2.133	1.339	2.057	2.295	1.717	1.488	2.995	1.518	1.447
99% Crit Val.	2.326	2.052	3.238	3.229	2.284	3.325	3.413	3.271	2.329	4.353	2.501	2.301
ΔRMSE	0.295***	0.219***	-0.074	0.159***	0.112***	0.316***	0.101	0.093***	0.122***	0.065*	0.063***	0.120***
95% Crit Val.	0.019	0.023	0.055	0.050	0.031	0.048	0.053	0.040	0.034	0.070	0.035	0.033
99% Crit Val.	0.054	0.047	0.076	0.075	0.053	0.078	0.080	0.076	0.054	0.102	0.058	0.053
Panel D: Out-of-Sample R^2 and Root Mean Squared Errors – Copper												
OoS R^2	7.660***	4.843***	-2.192	4.478***	4.188***	9.343***	3.016**	2.297**	2.986***	-0.012	1.532**	4.572***

95% Crit Val.	0.871	1.008	2.382	2.104	1.365	2.044	2.307	1.688	1.487	3.004	1.511	1.475
99% Crit Val.	2.319	2.070	3.299	3.190	2.477	3.383	3.255	2.996	2.387	4.173	2.606	2.390
ΔRMSE	0.265***	0.147***	-0.090	0.127***	0.137***	0.291***	0.095***	0.077***	0.087***	0.000	0.049**	0.111***
95% Crit Val.	0.020	0.023	0.056	0.049	0.032	0.048	0.054	0.039	0.034	0.070	0.035	0.034
99% Crit Val.	0.054	0.048	0.077	0.074	0.057	0.079	0.076	0.070	0.055	0.098	0.060	0.055

S&P GSCI Industrial Metals Index. aluminum, and copper data are sourced from Thomson Reuters Datastream. Equity market returns are from Thomson Reuters Datastream and Global Financial Data. A trading rule similar to that in Table 5 is tested. Monthly Sharpe ratios are presented in Panel A, and out-of-sample (OoS) R^2 and ΔRMSE's for forecasts based on the state-switching model versus forecasts based on the historical average return are presented in Panel B. Statistical significance is determined with a bootstrap procedure. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The results are for a 17-year (1994–2010) out-of-sample period and are in percent. "Lux" refers to Luxembourg, "Neth" refers to The Netherlands, and "EU" is the average result for the European Union.

Table 7. US Out-of-sample Economic Significance Based on Real-Time CFNAI

	IM index	Aluminum	Copper	Buy-and-Hold
Panel A: Sharpe Ratios				
Mean	0.352	0.406	0.343	0.069
Standard Deviation	3.940	3.720	4.117	4.738
Sharpe Ratio	4.542	6.241	4.126	-2.185
Panel B: Out-of-Sample R^2 and Root Mean Squared Errors				
OoS R^2	8.647***	7.519***	8.976***	
95% Bootstrap Critical Value	2.583	3.226	2.555	
99% Bootstrap Critical Value	3.800	4.686	3.654	
ΔRMSE	0.211***	0.183***	0.219***	
95% Bootstrap Critical Value	0.062	0.078	0.061	
99% Bootstrap Critical Value	0.092	0.113	0.088	

S&P GSCI Industrial Metals Index, aluminum, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. The trading rule and all results are equivalent to that described in Table 5 except they relate to a ten-year (2001–2010) out-of-sample period during which CFNAI data was available in real time.

Table 8. International Out-of-sample Economic Significance Based on Real-Time CFNAI

	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Lux	Neth	Portugal	Spain	EU
Panel A: Sharpe Ratios – Industrial Metal Index												
Mean	0.973	0.497	0.247	0.280	0.217	0.286	-0.557	0.586	0.139	0.238	0.184	0.275
Std. Dev.	6.291	4.491	5.973	6.516	5.709	5.505	6.389	6.878	6.742	4.868	5.891	4.419
Sharpe Ratio	15.399	6.542	0.791	3.050	0.294	1.549	0.017	5.607	-2.954	0.767	14.245	1.695
Buy-Hold Sharpe Ratio	3.307	-8.603	-1.650	-3.255	-3.932	-11.152	0.787	0.526	-11.955	-7.413	4.989	-5.799
Panel B: Sharpe Ratios – Aluminum												
Mean	0.435	0.170	-0.135	0.234	0.009	0.002	-0.447	0.380	0.339	0.184	0.226	0.132
Std. Dev.	5.287	4.772	6.226	6.414	5.969	5.621	6.396	6.428	6.509	4.551	5.972	4.504
Sharpe Ratio	8.154	-0.638	-5.366	2.477	-3.196	-3.506	3.286	2.800	2.676	-0.358	15.252	-1.504
Panel C: Sharpe Ratios – Copper												
Mean	0.760	0.080	0.254	0.339	0.303	-0.054	-0.539	0.555	0.148	0.212	0.244	0.182
Std. Dev.	6.531	4.962	5.958	6.473	5.661	6.230	6.402	6.913	6.733	4.924	5.972	4.463
Sharpe Ratio	11.574	-2.407	0.904	4.012	1.804	-4.058	0.538	5.120	-2.688	0.242	16.084	-0.412
Panel D: Out-of-Sample R^2 and Root Mean Squared Errors – Industrial Metal Index												
OoS R^2	11.873***	8.933***	-3.261	8.218***	5.402	13.635***	6.262***	3.682*	6.120***	5.310**	3.628**	6.850***
95% Crit Val.	1.918	2.705	4.405	3.737	2.659	4.393	4.170	3.695	3.091	5.187	2.679	2.841
99% Crit Val.	4.289	4.462	5.711	5.268	4.152	6.704	5.806	5.856	4.435	7.240	4.297	4.159
ΔRMSE	0.463***	0.312***	-0.114	0.237***	0.188***	0.489***	0.188***	0.141**	0.194***	0.156**	0.115***	0.177***

95% Crit Val.	0.046	0.065	0.107	0.091	0.064	0.107	0.101	0.090	0.074	0.127	0.064	0.068
99% Crit Val.	0.103	0.107	0.140	0.128	0.100	0.164	0.142	0.143	0.107	0.179	0.103	0.100
Panel E: Out-of-Sample R^2 and Root Mean Squared Errors – Aluminum												
OoS R^2	11.927***	6.672***	-4.140	8.817***	4.610**	10.959***	5.802***	3.137*	7.392***	1.548	3.908*	7.729***
95% Crit Val.	1.479	2.739	5.356	3.411	3.343	4.075	3.191	3.757	4.064	2.438	4.247	3.257
99% Crit Val.	4.328	5.967	7.250	5.092	5.140	6.863	4.900	6.792	5.860	4.640	5.920	5.018
ΔRMSE	0.466***	0.231***	-0.145	0.253***	0.161***	0.388***	0.172***	0.120**	0.236***	0.044*	0.125**	0.200***
95% Crit Val.	0.035	0.066	0.131	0.082	0.080	0.099	0.077	0.091	0.098	0.058	0.103	0.078
99% Crit Val.	0.104	0.144	0.179	0.123	0.124	0.167	0.118	0.166	0.142	0.111	0.144	0.121
Panel F: Out-of-Sample R^2 and Root Mean Squared Errors – Copper												
OoS R^2	10.730***	5.963***	-4.131	7.425***	6.098***	12.543***	6.069***	3.158*	4.574***	1.052	2.923**	6.335***
95% Crit Val.	1.978	2.752	4.358	3.787	2.747	4.310	4.269	3.708	2.988	5.308	2.709	2.790
99% Crit Val.	4.163	4.678	5.696	5.243	4.214	6.398	5.916	5.724	4.334	7.138	4.190	4.060
ΔRMSE	0.417***	0.206***	-0.145	0.214***	0.213***	0.448***	0.182***	0.121**	0.145***	0.031	0.093**	0.164***
95% Crit Val.	0.047	0.066	0.106	0.092	0.066	0.105	0.104	0.090	0.072	0.130	0.065	0.067
99% Crit Val.	0.100	0.113	0.139	0.128	0.101	0.156	0.144	0.139	0.105	0.176	0.101	0.098

S&P GSCI Industrial Metals Index. aluminum, and copper data are sourced from Thomson Reuters Datastream. Equity market returns are from Thomson Reuters Datastream and Global Financial Data. S&P GSCI Industrial Metals Index, aluminum, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. The trading rule and all results are equivalent to that described in Table 6 except they relate to a ten-year (2001–2010) out-of-sample period during which CFNAI data was available in real time.

Table 9. State Correlations and Predictability Based on Regime Switching States

Panel A: Full Period State Correlations

	NBER	CFNAI	Hamilton RS
CFNAI	0.767		
Hamilton RS	0.799	0.653	
Basic RS	-0.050	-0.038	-0.088

Panel B: State-switching Return Predictability Based on Hamilton States

		Expansion			Contraction			
	β_1	t-Statistic	N	β_2	t-Statistic	N	$\beta_1 - \beta_2$	F-Test
IM Index	-0.053	**-1.788**	358	0.162	1.220	48	-0.2148	**2.533**
Aluminum	-0.105	**-2.306**	218	0.440	**2.550**	20	-0.5447	**8.953**
Copper	-0.042	-1.526	358	0.155	1.563	48	-0.1968	**3.731**

Panel C: 2001–2010 State Correlations

	CFNAI Revised	Hamilton Revised	CFNAI (As Reported)	Hamilton (As Reported)
Hamilton RS (Revised)	0.705			
CFNAI (As Reported)	0.914	0.642		
Hamilton (As Reported)	0.337	0.093	0.346	
Basic RS	0.086	0.072	0.059	0.106

Panel A contains state correlations for the business cycle data, and the Basic and Hamilton (1989) regime switching approaches described in Section 5. The business cycle data and the real GNP input numbers in the Hamilton (1989) approach include subsequent revisions. The Panel B results are based on Hamilton (1989) states. Newey-West t-statistics and F-statistics statistically significant at the 10% level or better are in bold. The correlations in Panel C distinguish between the states determined when the "as reported" series and series that include subsequent revisions are used.

Table 10. Industry State-switching

	Standard Model		State-switching Model			
	β	t-Statistic	β_1	t-Statistic	β_2	t-Statistic
Rlest	0.117	**1.922**	0.045	0.630	0.180	**2.128**
Agric	0.025	1.009	0.021	0.866	0.043	0.607
Mines	-0.022	-0.685	-0.052	**-2.165**	0.075	1.018
Oil	-0.017	-0.590	-0.045	-1.492	0.060	1.005
Stone	-0.038	-1.524	-0.042	**-1.823**	-0.020	-0.309
Cnstr	-0.026	-0.842	-0.054	-1.632	0.064	1.098
Food	0.041	0.724	-0.016	-0.293	0.237	**2.239**
Smoke	-0.038	-1.299	-0.054	**-1.820**	0.101	0.890
Txtls	0.031	1.098	0.001	0.033	0.076	**2.395**
Apprl	0.058	**1.713**	0.033	0.818	0.126	**3.182**
Wood	0.004	0.134	-0.021	-0.681	0.074	1.599
Chair	0.027	0.689	-0.034	-0.881	0.135	**3.284**
Paper	-0.004	-0.088	-0.017	-0.337	0.051	0.582
Print	0.138	**3.133**	0.073	1.620	0.274	**5.393**
Chems	0.073	0.996	0.052	0.711	0.215	1.436
Ptrlm	-0.083	**-2.119**	-0.101	**-2.366**	-0.019	-0.244
Rubbr	0.031	0.782	0.005	0.113	0.171	**3.085**
Lethr	0.053	**1.748**	0.007	0.191	0.185	**4.973**
Glass	0.050	1.199	-0.010	-0.244	0.163	**3.206**
Metal	-0.037	-0.757	-0.083	**-2.220**	0.089	1.240
MtlPr	0.092	**1.816**	0.036	0.691	0.256	**4.068**
Machn	0.066	1.570	0.024	0.626	0.203	**2.630**
Elctr	0.061	1.620	0.029	0.727	0.215	**3.010**
Cars	-0.010	-0.200	-0.062	-1.050	0.129	**2.164**
Instr	0.062	1.352	0.034	0.731	0.172	**1.918**
Manuf	0.029	0.895	-0.008	-0.203	0.158	**3.989**
Trans	0.036	0.941	0.007	0.179	0.141	**2.021**
Phone	0.019	0.438	-0.036	-0.821	0.308	**2.675**
TV	0.087	**2.908**	0.054	**1.744**	0.200	**4.434**
Utils	0.074	1.309	0.007	0.127	0.302	**3.071**
Whlsl	0.043	0.960	0.020	0.427	0.132	**2.009**
Rtail	0.136	**2.331**	0.083	1.332	0.329	**4.819**
Money	0.191	**3.299**	0.117	**1.888**	0.301	**5.009**
Srvc	0.092	**2.307**	0.057	1.466	0.264	**4.683**

The 34 industries are those used by Hong, Torous, and Valkanov (2007). The data are from Ken French's website. The standard model, the predictive regression $R_t = \alpha + \beta I_{t-1} + R_{t-1} + \varepsilon_t$, is run, where R_t is the S&P 500 monthly excess return and $I_{t-1}$is the excess industry return. Lagged excess market return variable R_{t-1} is included as a control variable as per Hong, Torous, and Valkanov (2007). The state-switching model is: $R_t = \alpha + \beta_1 Expansion_{t-1} I_{t-1} + \beta_2 Contraction_{t-1} I_{t-1} + \beta_3 Expansion_{t-1} R_{t-1} + \beta_4 Contraction_{t-1} R_{t-1} + \varepsilon_t$. Newey-West t-statistics statistically significant at the 10% level or more are in bold.

Table 11. Industry Out-of-sample Economic Significance

	State-switching	Standard	Buy-and-Hold
Panel A: Sharpe Ratios (1989 – 2010)			
Mean	0.526	0.348	0.556
Standard Deviation	3.250	2.702	4.401
Sharpe Ratio	6.597	1.332	5.540
Panel B: Out-of-Sample R^2 and Root Mean Squared Errors (1989 – 2010)			
OoS R^2	1.958***	0.100	
95% Bootstrap Critical Value	0.747	0.757	
99% Bootstrap Critical Value	1.511	1.515	
ΔRMSE	0.043***	0.002	
95% Bootstrap Critical Value	0.016	0.017	
99% Bootstrap Critical Value	0.033	0.033	
Panel C: Sharpe Ratios (2001 – 2010)			
Mean	0.193	0.105	0.069
Standard Deviation	3.508	3.077	4.738
Sharpe Ratio	0.598	-2.184	-2.185
Panel D: Out-of-Sample R^2 and Root Mean Squared Errors (2001 – 2010)			
OoS R^2	5.560***	2.724**	
95% Bootstrap Critical Value	2.006	2.056	
99% Bootstrap Critical Value	3.214	3.340	
ΔRMSE	0.134***	0.065**	
95% Bootstrap Critical Value	0.048	0.049	
99% Bootstrap Critical Value	0.077	0.080	

The 34 industries are those used by Hong, Torous, and Valkanov (2007). The data are from Ken French's website. The industry trading rule that signals a long equity market position or a T-bill position is tested. Signals are generated from all industries that show statistically significant predictive power in-sample. The "state-switching" results are based on our state-switching model and the CFNAI business cycle. The "standard" results are based on the traditional regression approach of Hong, Torous, and Valkanov (2007). Statistical significance is determined with a bootstrap procedure. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All results are in percent.

Appendix 1: Data Summary Statistics

	Mean	Median	Max	Min	SD	Skewness	Kurtosis	N
Panel A: All Data								
IM Index	0.004	0.004	0.253	-0.345	0.068	-0.349	6.655	407
Aluminum	0.002	-0.003	0.153	-0.177	0.055	-0.038	3.589	239
Copper	0.005	0.003	0.265	-0.440	0.077	-0.531	7.161	407
S&P 500	0.006	0.010	0.124	-0.245	0.045	-0.901	6.025	407
Panel B: NBER Expansions								
IM Index	0.008	0.007	0.253	-0.286	0.063	0.192	5.346	351
Aluminum	0.004	0.000	0.153	-0.177	0.049	0.120	3.403	211
Copper	0.008	0.006	0.265	-0.286	0.071	0.165	4.631	351
S&P 500	0.008	0.011	0.124	-0.245	0.041	-0.950	7.218	351
Panel C: NBER Contractions								
IM Index	-0.020	-0.019	0.136	-0.345	0.088	-1.256	6.430	56
Aluminum	-0.016	-0.033	0.141	-0.177	0.088	0.173	2.295	28
Copper	-0.019	-0.007	0.158	-0.440	0.103	-1.622	7.879	56
S&P 500	-0.006	-0.002	0.110	-0.186	0.062	-0.416	2.872	56

This Table contains summary statistics for the entire data period and NBER expansions and contractions.

Appendix 2: Model Specification and Hypothesis Testing

This appendix shows the relation between the state-switching return predictability model and the standard return predictability model in terms of model misspecification and hypothesis testing. To simplify the notation, let y be a column vector of $R_t - E[R_t]$ or the de-meaned S&P500 return. By using the de-meaned return, we do not need the intercept in the regression. Similarly, we let x_1 be a column vector of $Expansion_{t-1}IM_{t-1}$ and x_2 be a column vector of $Contraction_{t-1}IM_{t-1}$. $Expansion_t$ and $Contraction_t$ are dummy variables and $Expansion_t = 1 - Contraction_t$. Let x be a column vector of IM_{t-1}. Given this definition, $x = x_1 + x_2$. The standard return predictability model and state-switching model can then be written as:

Standard model: $$y = \beta x + \varepsilon \quad \text{(A1)}$$

State-switching model: $$y = \beta_1 x_1 + \beta_2 x_2 + u \quad \text{(A2)}$$

The regression A1 and A2 are nested. If $\beta_1 = \beta_2 = \beta_0$ then from A2 we obtain:

$$y = \beta_0 x_1 + \beta_0 x_2 + u = \beta_0(x_1 + x_2) + u = \beta_0 x + u = \beta x + \varepsilon$$

Therefore, in this special case, both regressions are equivalent in population. Also, under the null hypothesis of no predictability, this restriction is valid.

A.1. Model Misspecification and Hypothesis Testing when the State-switching Model is Correct

If we assume that the state-switching model in A2 is correct, then the standard model in A1 is misspecified in a way similar but not equivalent to an omitted variables problem. We can estimate the coefficient for regression A1 as follows.

$$\hat{\beta} = (x^T x)^{-1} x^{T\,\prime\prime} y$$

Substitute y from the state-switching model

$$\hat{\beta} = (x^{T\prime} x)^{-1} x^{T\prime}(\beta_1 x_1 + \beta_2 x_2 + u)$$

Because $x_1 = x - x_2$, we have

$$\hat{\beta} = (x^{T\prime} x)^{-1} x^{T\prime}(\beta_1 (x - x_2) + \beta_2 x_2 + u)$$

$$\hat{\beta} = (x^T x)^{-1}(x^T x)\beta_1 + (x^T x)^{-1}(x^{T\prime} x_2)(\beta_2 - \beta_1) + (x^{T\prime} x)^{-1} x^{T\prime} u$$

There are three terms. Taking the expectation of the first term, we get β_1. Taking the expectation of the third term, we get 0 because u is uncorrelated with x. The second term needs further manipulation. Let T be the total sample size; T_1 and T_2 are the size of the sample that is in expansion and recession, respectively. Note that $x^{T\prime} x = T\sigma_x^2$; $x^T x = (x_1 + x_2)^{T\prime}(x_1 + x_2) = {x_1}^{T\prime} x_1 + {x_2}^{T\prime} x_2$; $T\sigma_x^2 = T_1 \sigma_{x_1}^2 + T_2 \sigma_{x_2}^2$; $x^{T\prime} x_2 = T_2 \sigma_{x_2}^2$. The expectation of the second term is $E[(x^{T\prime} x)^{-1}(x^{T\prime} x_2)(\beta_2 - \beta_1)] = \frac{T_2}{T}\frac{\sigma_{x_2}^2}{\sigma_x^2}(\beta_2 - \beta_1)$. Then,

$$E[\hat{\beta}] = \beta_1 + \frac{T_2}{T}\frac{\sigma_{x_2}^2}{\sigma_x^2}(\beta_2 - \beta_1) = \frac{T_1}{T}\frac{\sigma_{x_1}^2}{\sigma_x^2}\beta_1 + \frac{T_2}{T}\frac{\sigma_{x_2}^2}{\sigma_x^2}\beta_2$$

If the variance of x is the same in expansions as in recessions, $\sigma_{x_1}^2 = \sigma_{x_2}^2$ then

$$E[\hat{\beta}] = \frac{T_1}{T}\beta_1 + \frac{T_2}{T}\beta_2$$

This suggests that β is simply the weighted average of β_1 and β_2, with weights depending on the amount of time the economy is in expansion or recession, respectively. In summary, if the state-switching model is assumed to be correct, then the standard model is misspecified.

A.2. Model Misspecification and Hypothesis Testing when the Standard Model is Correct

Now we assume that the standard return predictability model is correct. Let $z = [x_1 \quad x_2]$. Then

$$\begin{pmatrix}\hat{\beta}_1\\ \hat{\beta}_2\end{pmatrix} = (z^T{}'z)^{-1}z^{T'}y = \left(z^{T'}z\right)^{-1} z^{T'}(\beta x + \varepsilon) = (z^T{}'z)^{-1}z^{T'}x\beta + (z^T{}'z)^{-1}z^T{}'\varepsilon$$

$$E\begin{bmatrix}\hat{\beta}_1\\ \hat{\beta}_2\end{bmatrix} = \left(\begin{pmatrix}x_1\\ x_2\end{pmatrix}(x_1 \quad x_2)\right)^{-1}\begin{pmatrix}x_1\\ x_2\end{pmatrix}(x_1 + x_2)\beta = \begin{pmatrix}x_1'^T x_1 & x_1'^T x_2\\ x_2{}^T{}'x_1 & x_2{}^T{}'x_2\end{pmatrix}^{-1}\begin{pmatrix}x_1{}^T{}'x_1 + x_1{}^T{}'x_2\\ x_2{}^T{}'x_1 + x_2{}^T{}'x_2\end{pmatrix}\beta$$

Note that $x_1{}^T{}'x_2 = x_2{}'^T x_1 = 0$ and $x_1{}^T{}'x_1 = T_1\sigma_{x_1}^2$and $x_2{}'^T x_2 = T_2\sigma_{x_2}^2$

$$E\begin{bmatrix}\hat{\beta}_1\\ \hat{\beta}_2\end{bmatrix} = \begin{pmatrix}T_1\sigma_{x_1}^2 & 0\\ 0 & T_2\sigma_{x_2}^2\end{pmatrix}^{-1}\begin{pmatrix}T_1\sigma_{x_1}^2\\ T_2\sigma_{x_2}^2\end{pmatrix}\beta = \begin{pmatrix}\beta\\ \beta\end{pmatrix}$$

This shows that even if the standard model is assumed to be correct, the state-switching regression still gives a consistent estimator for β. In terms of estimation efficiency, we have

$$Var(\hat{\beta}) = E\left[(\hat{\beta}-\beta)(\hat{\beta}-\beta)^T\right] = E[(z^Tz)^{-1}z^T\varepsilon\varepsilon^T z(z^Tz)^{-1}] = (z^Tz)^{-1}z^T E[\varepsilon\varepsilon^T]z(z^Tz)^{-1}$$
$$= (z^Tz)^{-1}\sigma_\varepsilon^2$$

where σ_ε^2 is the standard error of the regression. Given $x_1{}^T x_2 = 0$ and $x_2{}^T x_1 = 0$,

$$Var[\hat{\beta}] = Var\left[\begin{pmatrix}\hat{\beta}_1\\ \hat{\beta}_2\end{pmatrix}\right] = \begin{bmatrix}{x_1}^T x_1 & 0\\ 0 & {x_2}^T x_2\end{bmatrix}^{-1} \sigma_\varepsilon^2 = \begin{bmatrix}\frac{1}{T_1}\frac{\sigma_\varepsilon^2}{\sigma_{x_1}^2} & 0\\ 0 & \frac{1}{T_2}\frac{\sigma_\varepsilon^2}{\sigma_{x_2}^2}\end{bmatrix}$$

If the variance of x is the same in expansions as in recessions, $\sigma_{x_1}^2 = \sigma_{x_2}^2 = \sigma_x^2$ then

$$Var[\hat{\beta}] = Var\left[\begin{pmatrix}\hat{\beta}_1\\ \hat{\beta}_2\end{pmatrix}\right] = \begin{bmatrix}\frac{1}{T_1} & 0\\ 0 & \frac{1}{T_2}\end{bmatrix}\frac{\sigma_\varepsilon^2}{\sigma_x^2} = \begin{bmatrix}\frac{1}{T_1} & 0\\ 0 & \frac{1}{T_2}\end{bmatrix}(1 - R^2)$$

where R^2 is the R^2 from the regression of y on x. The $Var[\hat{\beta}]$ from the standard model is $(x^T x)^{-1}\sigma_\varepsilon^2$ or $\frac{1}{T}\frac{\sigma_\varepsilon^2}{\sigma_x^2}$. Given that T_1 and T_2 are less than T, both $Var(\hat{\beta}_1)$ and $Var(\hat{\beta}_2)$ are greater than $Var(\hat{\beta})$. These results are in line with the usual case for nested models: having too many redundant variables still gives consistent but less efficient estimates.

Appendix 3: Equity Market Predictability after Controlling for Economic Series Predictability

		Expansion			Contraction			
	β_1	t-Statistic	N	β_2	t-Statistic	N	$\beta_1 - \beta_2$	F-Test
				Panel A: NBER				
IM Index	-0.069	**-2.118**	338	0.241	**1.734**	56	-0.310	**4.674**
Aluminum	-0.095	**-2.049**	211	0.422	**1.708**	27	-0.518	**4.199**
Copper	-0.054	**-1.815**	338	0.221	**2.105**	56	-0.275	**6.291**
				Panel B: CFNAI				
IM Index	-0.071	**-2.255**	331	0.285	**2.191**	63	-0.356	**7.093**
Aluminum	-0.117	**-2.472**	203	0.368	**2.073**	35	-0.485	**7.062**
Copper	-0.056	**-1.940**	331	0.251	**2.642**	63	-0.306	**9.610**

S&P GSCI Industrial Metals Index, aluminum, copper, and S&P 500 data are sourced from Thomson Reuters Datastream. All economic series are sourced from the Federal Reserve Bank of St. Louis, with the exception of Producer Price Index (PPI), which we obtain from the Bureau of Labor Statistics. Each industrial metals series is regressed on all economic series (contemporaneously) and the residuals are used to predict equity market returns in contractions and expansions. Newey-West t-statistics and F-statistics statistically significant at the 10% level or better are in bold.

Appendix 4: Including GARCH Effects

	β_1	Expansion t-Statistic	N	β_2	Contraction t-Statistic	N	$\beta_1 - \beta_2$	F-Test
				Panel A: NBER				
IM Index	-0.090	**-2.473**	350	0.163	**2.880**	56	-0.253	**13.977**
Aluminum	-0.094	**-1.913**	210	0.399	**4.434**	28	-0.493	**21.774**
Copper	-0.058	**-1.916**	350	0.154	**2.860**	56	-0.212	**11.958**
				Panel B: CFNAI				
IM Index	-0.090	**-2.514**	343	0.277	**3.322**	63	-0.367	**16.415**
Aluminum	-0.111	**-2.104**	202	0.361	**3.564**	36	-0.473	**16.572**
Copper	-0.060	**-2.025**	343	0.240	**3.224**	63	-0.300	**14.480**

These results are calculated in a similar way to those in Table 2. We allow for GARCH(1,1) effects in the regression specification. t-statistics and F-statistics statistically significant at the 10% level or better are in bold.

Appendix 5: Including Contemporaneous Effects

		Expansion			Contraction			
	β_1	t-Statistic	N	β_2	t-Statistic	N	$\beta_1 - \beta_2$	F-Test
				Panel A: NBER				
IM Index	-0.057	**-1.811**	350	0.103	**1.633**	56	-0.1603	**4.904**
Aluminum	-0.108	**-2.172**	210	0.276	**2.496**	28	-0.3838	**9.482**
Copper	-0.051	**-1.770**	350	0.096	**1.735**	56	-0.1467	**5.383**
				Panel B: CFNAI				
IM Index	-0.068	**-2.290**	343	0.170	**3.658**	63	-0.2385	**18.284**
Aluminum	-0.155	**-3.115**	202	0.268	**3.537**	36	-0.4231	**23.828**
Copper	-0.062	**-2.258**	343	0.153	**3.925**	63	-0.2143	**19.925**

These results are calculated in a way similar to those in Table 2; however, we include contemporaneous industrial metals returns in both expansions and contractions as control variables. We report only the lag industrial metals variables (as per Table 2) above. Newey-West t-statistics and F-statistics statistically significant at the 10% level or better are in bold.

Appendix 6: Correlations between Industrial Metals Returns and Economic Variables

	All	NBER Expansion	NBER Contraction	CFNAI Expansion	CFNAI Contraction
Default Spread	-0.07	0.02	-0.03	-0.02	-0.04
Term Structure	0.06	0.01	0.26	0.07	0.08
Dividend Yield	0.01	0.02	-0.05	0.01	0.01
Interest Rate	-0.08	-0.06	-0.11	-0.10	-0.01

Default spread is measured as the difference between 10-year yields on BBB corporate bonds and government stock. Term structure is the 10-year government stock rate, minus the 90-day T-bill rate. Dividend yield is for the S&P 500. Interest rate is the 90-day T-bill rate. Spearman correlations are calculated based on monthly changes in these variables and industrial metals returns.

Appendix 7: Time-varying Risk Premia Tests

Panel A: Volatility

		Mean Equation			Variance Equation				
		Constant	Exp(t-1)* IM(t-1)	Con(t-1)* IM(t-1)	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$log(\sigma_{t-1}^2)$	Exp(t-1)* IM(t-1)	Con(t-1)* IM(t-1)
NBER	Coefficient	0.007	-0.076	0.223	0.091	-0.294	0.416	0.775	-4.969
		3.424	**-1.836**	**3.020**	0.749	**-4.023**	**3.155**	0.591	**-2.076**
CFNAI	t-statistic	0.007	-0.084	0.213	0.116	-0.226	0.560	1.318	-5.892
		3.379	**-2.024**	**2.647**	1.002	**-2.899**	**4.837**	1.376	**-2.342**

Panel B: Negative Excess Returns

	δ_1	ρ_1	δ_2	ρ_2	$\delta_1+\rho_1$	$\delta_2+\rho_2$	Exp null: $\delta_1+\rho_1=0$	Con null: $\delta_2+\rho_2=0$	Exp and Con null:
NBER	-0.047	-0.035	0.099	0.142	-0.083	0.241	**3.571**	**2.739**	**3.127**
CFNAI	-0.067	-0.010	**0.232**	0.099	-0.077	0.331	**4.176**	**8.984**	**6.786**

Panel A reports the EGARCH coefficient estimates. The mean equation results show that, as per Table 2, increases in industrial metals returns are good news for the equity market in contractions; they predict increases in equity returns. However, increases in industrial metals returns predict lower equity market volatility in contractions. This is inconsistent with a positive relation between risk and return. Moreover, increases in industrial metals returns predict lower equity market returns in expansions, yet the sign of the equity market volatility is positive.

In Panel B, we extend regression specification 1: $R_t = \alpha + \beta_1 Expansion_{t-1} IM_{t-1} + \beta_2 Contraction_{t-1} IM_{t-1} + \varepsilon_t$ by allowing β_1 and β_2 to vary with the sign of the predictability relation for negative excess returns. We estimate the conditional predictability model using specification 1 when $\beta_1 = \delta_1 + \rho_1 NegRPF_{t-1}$ and $\beta_2 = \delta_2 + \rho_2 NegRPF_{t-1}$, where $NegRPF_{t-1}$ is a dummy variable that takes the value 1 if the predicted excess equity market return in expansions is negative, and zero otherwise. In other words, this variable will have a value of 1 when there are relatively large increases in industrial metals returns in expansions or when there are relatively large declines in industrial metals returns in contractions.

The coefficient ρ_1 measures whether the predictability relation is different during expansions for industrial metals price increases that imply negative excess returns than predictions that imply positive excess returns. Similarly, coefficient ρ_2 shows whether there is different predictability during contractions for industrial metals declines that imply negative excess return than predictions that imply positive excess returns. If the time-varying risk premia contributes to the time-varying predictability of industrial metals, then ρ_1 and ρ_2 should be statistically significant. The results in Panel B indicate that neither ρ_1 nor ρ_2 are statistically different from zero. There is no evidence of any change in the predictability relation when negative excess returns are predicted.

The sign of the predictability relation for negative excess returns in expansions is calculated by adding the coefficient from positive excess return predictions in expansions (δ_1) to the difference in coefficients when negative excess returns are predicted (ρ_1). An equivalent approach is used in contractions. The results show that the sign of δ_1+ρ_1 is negative and that the sign of δ_2+ρ_2 is positive. Increases (decreases) in industrial metals returns do predict negative excess returns in expansions (contractions). Wald test statistics show that the null hypothesis that the sum of these coefficients is zero can be strongly rejected. t-statistics and F-statistics statistically significant at the 10% level or better are in bold.