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Real Aggregate Activity and Stock Returns

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1. Introduction

Modern finance theories emphasize systematic or common factors (e.g. Ross, 1976; Merton, 1973). Chen, Roll, and Ross (1986) (CRR) further point out: “By the diversification argument that is implicit in capital market theory, only general economic state variables will influence the pricing of large stock market aggregates.” (p. 384). Therefore, in theory, real aggregate activity, as a critically important general economic state variable, should exert important influence on stock returns.

However, to date, there is only weak empirical evidence supporting this notion. CRR initially find some associations between macroeconomic variables and security returns. Shanken and Weinstein (2006) later show that CRR's main conclusions depend on the specific method used to form test portfolios. Correcting some of CRR's standard error estimates for errors in variables further reduces the statistical importance of macro variables for equity returns. Pearce and Roley (1985) find that news about unemployment and industrial production has no significant effect on daily stock prices. Hardouvelis (1987) similarly concludes that stock responses to nonmonetary/real sector news are very weak. Flannery and Protopapadakis (2002) find that stock returns and volatility depend on seventeen macroeconomic news factors. However, popular measures of real aggregate activity, such as Industrial Production or GNP are not represented. McQueen and Roley (1993) and Boyd, Jagannathan, and Hu (2001) find a stronger relationship between stock prices and fundamental macro news after allowing for different stages of the business cycle. However, Flannery and Protopapadakis (2002) find that McQueen and Roley (1993)'s results vary considerably across alternative definitions of the economy's condition. Poitras (2004) finds that there is no state dependence of stock price responses to macroeconomic news, which casts doubt on the robustness of the results in McQueen and Roley (1993) and Boyd, Jagannathan, and Hu (2001). Chan, Karceski, and Lakonishok (1998:175) therefore state:

“The macroeconomic factors generally make a poor showing. Put more bluntly, in most cases, they are as useful as a randomly generated series of numbers in picking up return covariation. We are at a loss to explain this poor performance.”

It is, however, important to note that previous studies typically focus on macro variables which are noisy measures of real aggregate activity. Therefore, it is possible that even if real aggregate activity matters for stock returns, the effect may not show up when macro variables are used as the proxy. We conjecture that this measurement problem may explain the lack of reaction anomaly in the literature. To test our conjecture, we focus on the Chicago Fed National Activity Index, which is a single summary measure of the common factor in 85 macro variables. Our main finding is that the news component of this index does affect stock returns. The effects show up at the market level as well as at the portfolio level.

The remainder of the paper is organized as follows: Section 2 briefly discusses the intuition of our argument. Section 3 presents the data. Section 4 reports empirical methodology and results. Section 5 concludes the paper with a brief summary.

2. Macro variables and real aggregate activity

Modern finance theories of Ross (1976) and Merton (1973) focus on systematic or common factors. Therefore, in theory, real aggregate activity, as a key general economic state variable, should be relevant to stock returns. Previous studies typically use macro-economic variables to proxy for real aggregate activity. However, macro-economic variables are usually a noisy proxy of real aggregate activity. To illustrate the idea, we run a simple regression which estimates the relationship between the growth in Industrial Production (a popular macro variable used in the literature to proxy for real aggregate activity) and the Chicago Fed National Activity Index (the common factor in 85 macro-economic variables which we discuss in details in the next section). That is,

$$DIP_t = a + bNAI_t + e_t \quad (1)$$

where DIP_t is the log difference in Industrial Production, and NAI_t is the Chicago Fed National Activity Index. Table 1 shows that from 1967 to 2011 the Chicago Fed National Activity Index can explain about 44% of the variation in Industrial Production. Figure 1 is a scatter graph. The horizontal axis is the de-meaned growth in Industrial Production,¹ while the vertical axis is the Chicago Fed National Activity Index. Figure 1 shows that the popular aggregate activity proxy, the growth in Industrial Production, is a noisy proxy of real aggregate activity. For instance, in about 30% of our sample months, when Industrial Production indicates the growth is below or above the trend (average) growth, the Chicago Fed National Activity Index or the common factor indicates the opposite to be true.

Therefore, macro variables typically have a common factor component as well as an idiosyncratic component. Let

$$Z_{i,t} = aF_t + e_{i,t} \quad (2)$$

where $Z_{i,t}$ represents a macro variable such as the growth in Industrial Production, F_t represents the common factor such as the Chicago Fed National Activity Index, $e_{i,t}$ represents the idiosyncratic

¹ We use the de-meaned growth in Industrial Production, because the Chicago Fed National Activity Index has a mean value of zero representing trend growth.

Table 1. Industrial Production and CFNAI-MA3 from 1967 to 2011

Constant	NAI_t	Adj- R^2
0.19	0.57	0.44
(6.49)	(15.84)	

Table 1 report the results for the following regression

$$DIP_t = a + bNAI_t + e_t$$

where DIP_t is the log difference in Industrial Production, and NAI_t is the Chicago Fed National Activity Index.

Figure 1. The relationship between Industrial Production and the Chicago Fed National Activity Index

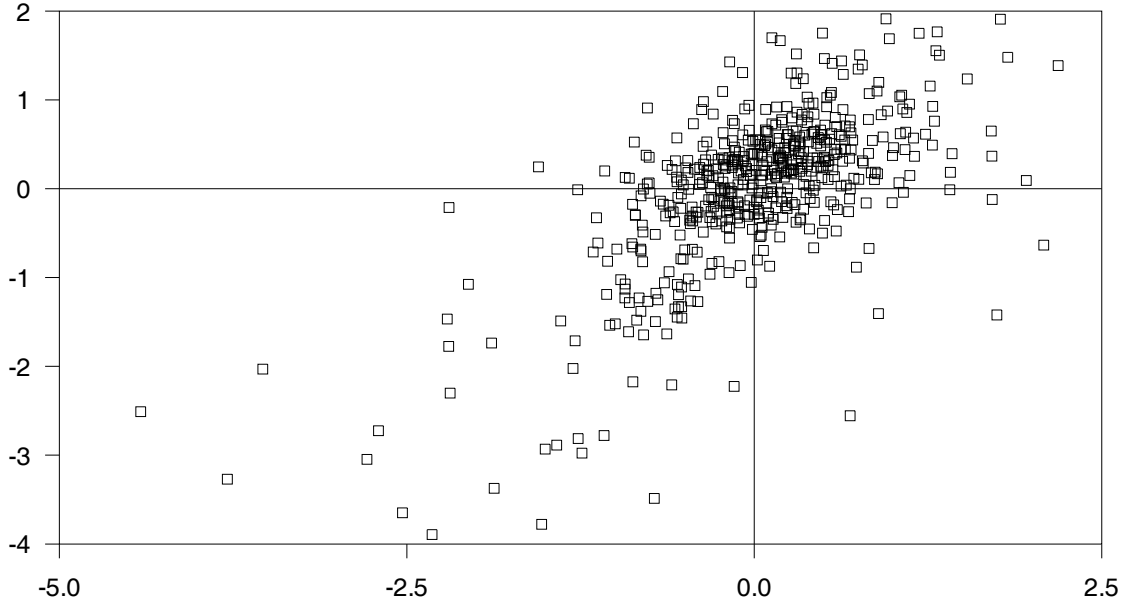


Figure 1 is a scatter graph. The horizontal axis is the de-meaned growth in Industrial Production, while the vertical axis is the Chicago Fed National Activity Index. We use the de-meaned growth in Industrial Production, because the Chicago Fed National Activity Index has a mean value of zero representing trend growth.

component, and $\text{cov}(F_t, e_{i,t}) = 0$ by definition. Then, it is clear that using macro variables can result in underestimation in empirical tests. Specifically, the unexpected (news) component of the macro variable is

$$\begin{aligned} z_{i,t} &= Z_{i,t} - E_{t-1}(Z_{i,t}) \\ &= a[F_t - E_{t-1}(F_t)] + [e_{i,t} - E_{t-1}(e_{i,t})] \\ &= a\Delta F_t + \Delta e_{i,t} \end{aligned} \tag{3}$$

where ΔF_t is the unexpected (news) component of the common factor, and $\Delta e_{i,t}$ is that of the idiosyncratic component. Eq. (3) shows that the news of a macro variable is a noisy measure of the news of real aggregate activity (the common factor), because it also includes the news of its idiosyncratic

component ($\Delta e_{i,t}$), which is irrelevant to asset pricing according to finance theories of Ross (1976) and Merton (1973).

Previous studies of return sensitivity to macroeconomic variables regress stock returns on the news of macro variables. In the simplest, single-factor case, researchers regress the market return on a potential macro variable's news or surprise:

$$MKT_t = \alpha + \beta z_{i,t} + \varepsilon_t \quad (4)$$

where MKT_t is the excess market return, and $z_{i,t}$ is the news of a macro variable. The idiosyncratic component of a macro variable is irrelevant for asset pricing, because by definition it is orthogonal to the common factor. That is, $\text{cov}(MKT_t, \Delta e_{i,t}) = 0$. Therefore, the OLS coefficient of the news becomes

$$\begin{aligned} \beta &= \frac{\text{cov}(MKT_t, z_{i,t})}{\text{var}(z_{i,t})} \\ &= \frac{\text{cov}(MKT_t, a\Delta F_t)}{\text{var}(a\Delta F_t) + \text{var}(\Delta e_{i,t})} \\ &= \frac{\text{var}(a\Delta F_t)}{\text{var}(a\Delta F_t) + \text{var}(\Delta e_{i,t})} \bar{\beta} \end{aligned} \quad (5)$$

where $\bar{\beta}$ is the “true” sensitivity of the market return to the common factor. It is easy to see if the idiosyncratic news component, $\text{var}(\Delta e_{i,t})$, is large enough, the estimated β can be substantially smaller than the true β or $\bar{\beta}$, resulting in underestimation in empirical tests. This measurement problem might explain the weak reaction of stock returns to real aggregate activity documented in the previous studies. We test this hypothesis in this paper.

3. Chicago Fed National Activity Index

To test our conjecture, we use the Chicago Fed National Activity Index (CFNAI) as the measure of the common factor.² This index is discussed in details in Background on the Chicago Fed National Activity Index (2011) (Hereafter, Background). What follows is a brief summary.

The economic indicators comprising the index are taken from four categories of macroeconomic data: 1) production and income (23 series), 2) employment, unemployment, and hours (24 series), 3)

² This index was originally proposed by Stock and Watson (1999). Boyd, Jagannathan, and Hu (2001) use the Stock and Watson activity index to identify the state of economy.

personal consumption and housing (15 series), and 4) sales, orders, and inventories (23 series). All of the data are adjusted for inflation. To construct the index,

1. Each monthly data series is first filtered by a stationary-inducing transformation,³ then de-meaned and standardized to have a mean of zero and a standard deviation of one.
2. The monthly CFNAI index is constructed as the first principal component of these 85 standardized monthly data series. Thus, the CFNAI also has a mean value of zero and a standard deviation of one over the long run, with a reading of zero corresponding to trend growing. The monthly CFNAI is very volatile due to the volatilities in the underlying data series. To focus on the persistent rather than transitory component of the index, the three-month moving average of the CFNAI, the CFNAI-MA3, is focused by the Fed Chicago and used in this paper.

The CFNAI index is usually released with a one month lag, because the underlying data series are released with at least one-month delay. In fact, the initial release of the CFNAI includes projected monthly values for roughly one-third of the 85 series. Therefore, in this regard, the index is a “real-time” statistical measure of the common factor, which is relevant to market participants because it may change investors’ expectations about the future (e.g. Fama, 1990; Schwert, 1990).⁴

The CFNAI is revised after the initial release for mainly two reasons. First, as we have mentioned, about one-third of the underlying data series are released with more than one-month delay. Thus, when these missing data become available, CFNAI needs to be revised to correct for the projection error in the initial release. Second, over time, the 85 underlying data series are systematically revised by the original reporting institutions. Hence, CFNAI also needs to be revised accordingly. The Federal Reserve Bank of Chicago refers to the CFNAI data based on the initial release as historical data, and those after revision as current data. The Federal Reserve Bank of Chicago began releasing the CFNAI and CFNAI-MA3 in March, 2001. Figure 2 shows the current CFNAI-MA3 series from 1967 to 2011 with the shaded areas corresponding to recession periods dated by the NBER. In general, the index tracks the US aggregate economic activity well.

³ “For example, the employment and industrial production data are log-differenced so that they are in growth rates.” (Background, p. 2)

⁴ “The Chicago Fed's goal in releasing this index monthly is to provide an objective, “real-time” statistical measure of coincident economic activity derived from a wide range of monthly indicators. Research studies by economists at Harvard University, Princeton University, and the Federal Reserve Bank of Chicago have shown that the CFNAI often provides early indications of business cycle turning points and changes in inflationary pressure.” (Background, p. 1)

Figure 2. Current CFNAI-MA3 from 1967 to 2011

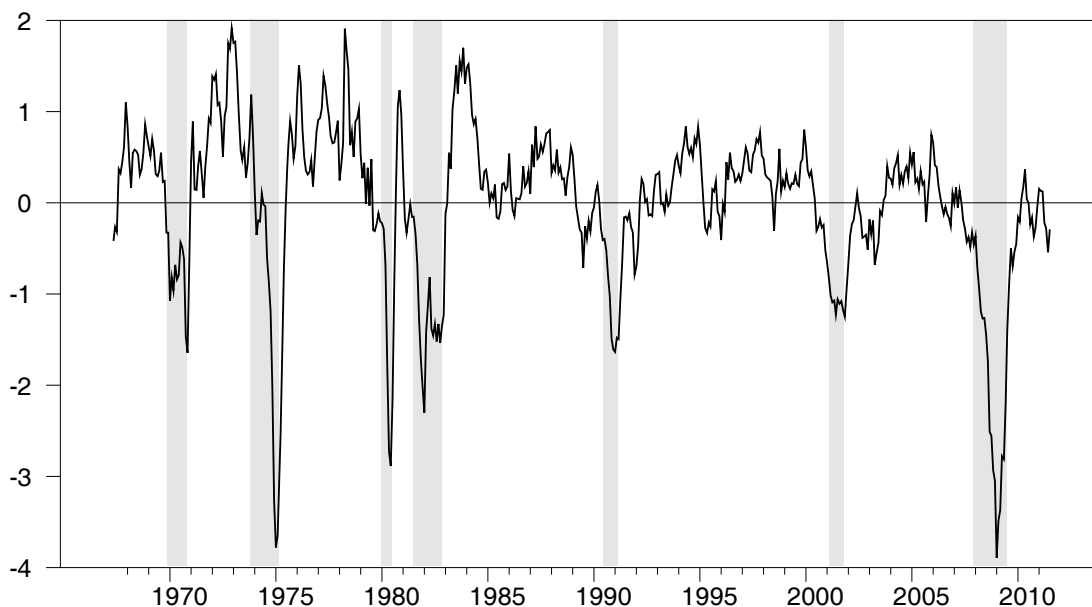


Figure 2 shows the current CFNAI-MA3 with the shaded areas corresponding to recession periods dated by the NBER.

4. Empirical methodology and results

We carry out two complementary tests in this paper. Following previous studies, our first test is an event study in which we examine the real-time reaction of the market to the initial release of the CFNAI-MA3 (i.e. historical data). Our sample period thus is limited to 2001:3 to 2011:6. The start of the sample period coincides with the initial availability of index data from the Federal Reserve Bank of Chicago, while the end coincides with the availability of the daily Fama and French stock return data.⁵ There are a total 125 CFNAI-MA3 announcements between March 2001 and June 2011.

One drawback of the event study is its short sample period (only 11 years). To utilize the complete current CFNAI-MA3 data from 1967 to 2011, we conduct a second test in which we employ the tracking portfolio approach of Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001) to examine whether stock returns are driven by the news about future aggregate activity (measured by future CFNAI-MA3). The idea is that if the market is efficient, we expect investors might be able to come up with a similar measure of the common factor (after all, the CFNAI is simply the first principal component of 85 macro data series). Therefore, the current CFNAI data may be considered as a proxy of such information investors might have had since 1967. Next, we discuss the details of our two tests.

⁵ We thank Fama and French for making the data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

4.1 An Event Study Approach

4.1.1 Market reaction

Following the relevant research (e.g. Bernanke and Kuttner, 2005), we first use an event-study approach. The first step is the construction of the unexpected (surprise) component of the CFNAI-MA3. Previous studies (e.g. McQueen and Roley, 1993) use the survey data to construct the surprise component of macro variables. However, survey data is not available for the CFNAI-MA3. Alternatively, we could use a structural model to estimate the surprise component. However, doing so results in a joint test of the validity of the model of what constitutes surprise and the validity of our hypothesis that real aggregate activity matters for financial markets. To circumvent this issue, we take a simple time series approach.

Specifically, starting from the second announcement in April 2001, we first estimate the best ARMA model for the CFNAI-MA3 based on AIC with all observations available before the announcement day. That is, we use the historical data released in March 2001 to estimate the best ARMA model for the CFNAI-MA3, because only those data were available before April 2001 for market participants in real time. Then we forecast the expected index value based on this model, and calculate the surprise component as the difference between the announced index value in April 2001 and the expected value in March 2001. Next we repeat the same process announcement by announcement in a similar fashion.

To estimate the market reaction to the aggregate activity, we follow Bernanke and Kuttner (2005) and run the following cross-sectional regressions:

$$MKT_k = a + bNAI_k + \varepsilon_k \quad (6)$$

$$MKT_k = a + b^e NAI_k^e + b^u NAI_k^u + \varepsilon_k \quad (7)$$

where MKT_k is the daily CRSP value-weighted excess market return associated with announcement (or event) k , NAI_k is the corresponding CFNAI-MA3, and NAI_k^e and NAI_k^u are the associated expected and the unexpected components of the index. A decrease in the CFNAI-MA3 indicates a worse economic condition which should depress the market. Therefore, we expect the coefficient of the (surprise) component to be positive, and focus on one-sided tests. White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account.

The results are reported in Panel A of Table 2. The response to the CFNAI-MA3 is insignificant. However, when the CFNAI-MA3 is broken down into its expected and unexpected components, the estimated stock market response to the latter is positive and significant at the 5% level for a one-sided test (the coefficient of the unexpected component is 1.46 with a t-ratio of 1.92). The positive relationship

Table 2. Market reaction to CFNAI-MA3 from 2001 to 2011

Historical (initially released) CFNAI-MA3				
	Panel A: OLS		Panel B: LAD	
Intercept	0.01 (0.07)	-0.03 (-0.22)	0.01 (0.08)	-0.04 (-0.24)
NAI_k	-0.06 (-0.17)	-	0.06 (0.37)	
NAI_k^e	-	-0.25 (-0.63)		-0.09 (-0.51)
NAI_t^u	-	1.46 (1.92)		1.11 (1.69)
Adj-R ²	-0.01	0.03		
	Panel C: OLS		Panel D: LAD	
Intercept	0.01 (0.09)		0.01 (0.05)	
NAI_k^e	-0.42 (-1.00)		-0.26 (-1.43)	
NAI_t^u	-0.29 (-0.47)		0.48 (0.54)	
$D_k \times NAI_t^u$	3.84 (2.48)		3.81 (2.79)	
Adj-R ²	0.08			
Current (revised) CFNAI-MA3				
	Panel E: OLS		Panel F: OLS	
Intercept	0.04 (0.40)		0.07 (0.79)	
NAI_k^e	-0.22 (-0.68)		-0.45 (-1.56)	
NAI_t^u	2.69 (2.74)		-0.21 (-0.33)	
$D_k \times NAI_t^u$			5.93 (3.22)	
Adj-R ²	0.11		0.24	

Table 2 reports the results of the following cross-sectional regressions:

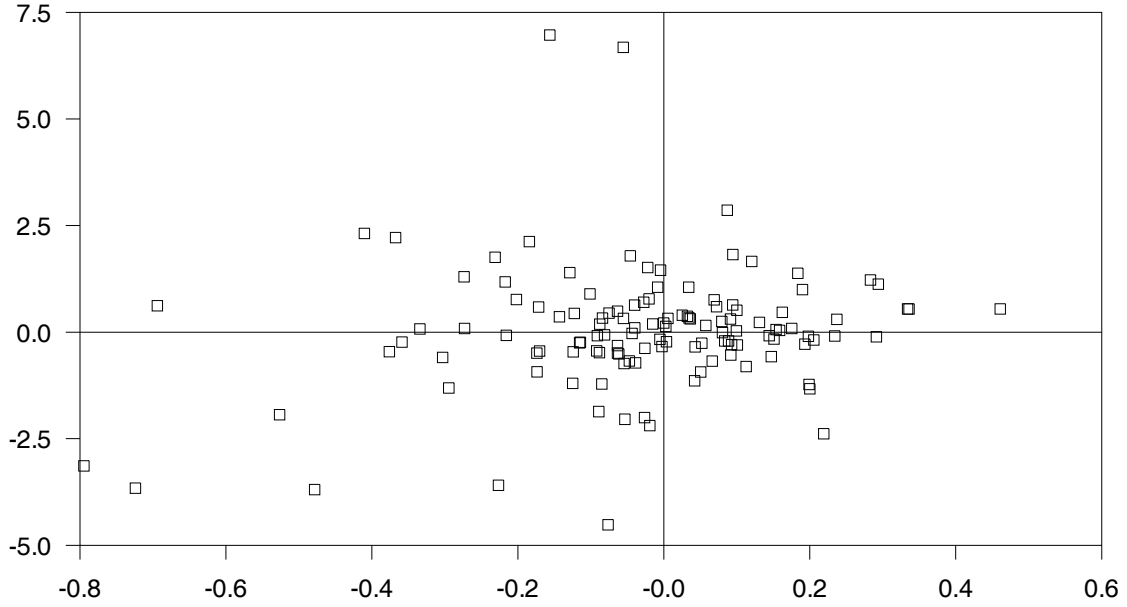
$$MKT_k = \alpha + \beta NAI_k + \varepsilon_k$$

$$MKT_k = \alpha + \beta^e NAI_k^e + \beta^u NAI_k^u + \varepsilon_k$$

$$MKT_k = a + b^e NAI_k^e + b^u NAI_k^u + c(D_k \times NAI_k^u) + \varepsilon_k$$

where MKT_k is the daily CRSP value-weighted excess market return associated with announcement k , D is a recession dummy consistent with the NBER reference dates, NAI_k is the CFNAI-MA3, and NAI_k^e and NAI_k^u are the expected and the unexpected components of the index. White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account.

Figure 3. Market reaction to the surprise component of CFNAI-MA3



The positive relationship between index surprises and stock returns is visible in Figure 3, where the horizontal axis measures the surprise component of the index and the vertical axis measures the corresponding daily market return.

between the unexpected component of the CFNAI-MA3 and market returns is visible in Figure 3, where the horizontal axis measures the unexpected component of the CFNAI-MA3 and the vertical axis measures the corresponding market return.

However, Figure 3 also suggests that the relationship between the unexpected component of CFNAI-MA3 and the market return may be driven by a few outliers. To test whether their relationship is robust, we re-estimate Eqs. (6) and (7) with the least absolute deviations (LAD) regression which is robust to outliers. The results based on LAD are presented in Panel B of Table 2. As we can see, the stock market response to the unexpected CFNAI-MA3 is still positive and significant at the 5% level for a one-sided test (the coefficient is 1.10 with a t-ratio of 1.68), indicating that the relationship between the unexpected component of CFNAI-MA3 and the market return is robust to outliers. Because the market in theory and in practice mainly responds to the unexpected component of the CFNAI-MA3, we focus on Eq. (7) in the subsequent tests and discussion.

Previous studies (e.g. McQueen and Roley, 1993; and Boyd, Jagannathan, and Hu, 2001) suggest that the impact of macro news on the stock market may vary with the state of the economy. We therefore extend our Eq. (7) to allow for asymmetric reaction. That is,

$$MKT_k = a + b^e NAI_k^e + b^u NAI_k^u + c(D_k \times NAI_k^u) + \varepsilon_k \quad (8)$$

where D_k is a recession dummy consistent with the NBER reference dates. The results based on OLS are presented in Panel C of Table 2. Again, White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account. As we can see, the impact of the unexpected CFNAI-MA3 on the stock market is particularly strong in recession periods with a coefficient of 3.84 (t-ratio = 2.48). The model's adj. R^2 also increases significantly from 3% in Panel A to 8% in Panel C, confirming the strong asymmetric effects of the CFNAI-MA3 on the stock market. Again, for robustness, we also re-estimate Eq. (8) with LAD which is robust to outliers. The results are in Panel D of Table 2. As we can see, again, the asymmetric impact of the unexpected CFNAI-MA3 on the stock market is robust to outliers. Because our results are in general robust to outliers, we focus on OLS in our subsequent discussion.⁶

As we have discussed, the CFNAI-MA3 is systematically revised to take into account the projection error in the initial release and the revision of the underlying data by the original reporting institutions. Therefore, the historical (initially released) CFNAI-MA3 data we have been using in Panels A through D may have some measurement error. We therefore re-estimate Eqs.(7) and (8) with the current (revised) CFNAI-MA3 data. The results are shown in Panels E and F in Table 2. As we can see, correcting for the measurement error increases the statistical significance of the test substantially, confirming that the stock market does react to the unexpected (news) component of real aggregate activity.

4.1.2 Industry portfolio reaction

The market reaction we documented in Table 2 is informative for understanding how the stock market as a whole responds to real activity news. However, some stocks might be more sensitive to such news than other stocks. Therefore, following Bernanke and Kuttner (2005), we examine the reaction of 10 industry portfolios to the CFNAI-MA3, which also serves as a robustness check. Essentially, we run the following cross-sectional regression model for each industry.

$$r_{i,k} = a_i + b_i^e NAI_k^e + b_i^u NAI_k^u + c_i (D_k \times NAI_k^u) + \varepsilon_{i,k} \quad (9)$$

where $r_{i,k}$ is the daily excess return of an industry portfolio associated with announcement (event) k .

Again, we expect the coefficient of the unexpected component to be positive (in recessions), and White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account. The results are reported in Tables 3. Eight out of ten industry portfolios have statistically significant

⁶ Technically, OLS is preferred because we can apply White's (1980) procedure to take possible heteroskedasticity into account, and LAD is also well-known to be unstable.

coefficients on the interaction term of the unexpected component of the CFNAI-MA3 and the recession dummy, which provides further evidence that stock returns are affected by real aggregate activity.

An important question is whether the pattern of responses of industry portfolios is consistent with the implications of the standard asset pricing model (e.g. the CAPM). To answer this question, we follow Bernanke and Kuttner (2005) and examine whether the observed responses from Table 3 are proportional to the response implied by the CAPM. The industry response implied by the CAPM is calculated in two steps. First, we estimate the standard CAPM for each industry to obtain its CAPM beta, $\hat{\beta}_i$. Then, the industry response implied by the CAPM is calculated as

$$\hat{c}_i^{CAPM} = \hat{\beta}_i \hat{c} \quad (10)$$

where \hat{c} is the estimated response of the CRSP value-weighted market return to the interaction term of the unexpected component of the CFNAI-MA3 and the recession dummy from Table 2. Panel A of Figure 4 depicts these implied responses against the estimated responses from Table 3, along with the 45-degree line that the points would lie on if the estimated responses are perfectly consistent with the CAPM. The values on the horizontal axis are the industry stock return responses implied by the CAPM. The vertical axis values are the estimated industry return responses from Table 3. As we can see, the points line up along the 45-degree line reasonably well, suggesting that the estimated responses are generally in line with the CAPM.

Again, the historical (initially released) CFNAI-MA3 may have some measurement error. We therefore repeat our tests with the current (revised) CFNAI-MA3 data. The estimated industry responses are reported in Table 4. Again, consistent with the market reaction results in Table 2, correcting for the measurement error increases the statistical significance of the test substantially, confirming that the industry portfolios also do react to the unexpected (news) component of real aggregate activity. We also examine whether the pattern of responses of industry portfolios is consistent with the implications of the CAPM in the same way. Panel B of Figure 4 depicts these implied responses against the estimated responses in the same fashion as Panel A. Again, the points line up along the 45-degree line reasonably well, suggesting that the estimated responses are in line with the CAPM.

4.2 A tracking-portfolio approach

One drawback of the event study is its short sample period (only 11 years). Thus, we supplement the event-study approach with a tracking portfolio approach proposed by Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001), and applied by Vassalou (2003). This approach allows us to utilize the complete current CFNAI-MA3 series from 1967 to 2011.

Figure 4. Estimated industry responses and CAPM implications based on the event study approach

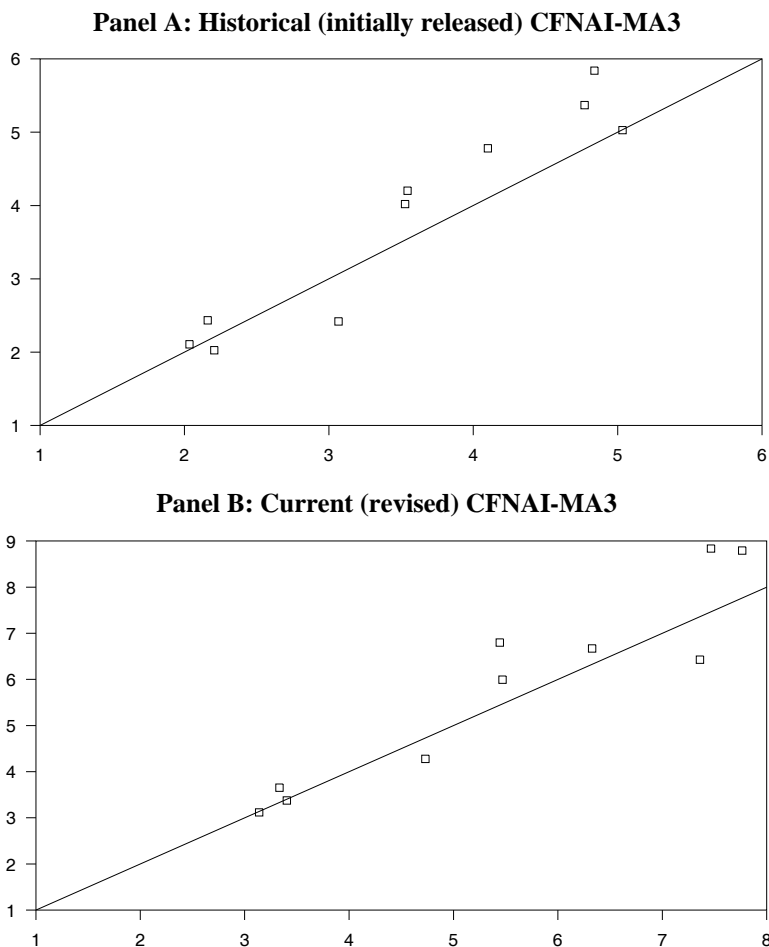


Figure 4 depicts the implied responses against the estimated responses, along with the 45-degree line that the points would lie on if the estimated responses are perfectly consistent with the CAPM. The values on the horizontal axis are the industry stock return responses implied by the CAPM. The vertical axis values are the estimated industry return responses. Panel A is based on the historical CFNAI-MA3, where Panel B is based on the current CFNAI-MA3.

Let $CNAI_{t+12}$ be the average CFNAI-MA3 over the next one year, and define $\Delta E_t(CNAI_{t+12}) = E_t(CNAI_{t+12}) - E_{t-1}(CNAI_{t+12})$ as the news component in month t . Then we have the tautology

$$CNAI_{t+12} \equiv E_{t-1}(CNAI_{t+12}) + \Delta E_t(CNAI_{t+12}) + \omega_{t+12}, \quad (11)$$

which decomposes the future average CFNAI-MA3 in a previously expected component, a news component, and a noise component.

If real aggregate activity, as a key general economic state variable, matters for asset pricing, innovations in the excess returns of base assets should reflect innovations in expectations about future CFNAI-MA3. That is,

Table 3 Industry portfolios reaction to historical (initially released) CFNAI-MA3 from 2001 to 2011

Industry	Intercept	Expected	Unexpected	D _k ×Unexpected	Adj-R ²
NoDur	0.07 (0.84)	-0.21 (-0.93)	0.33 (0.90)	2.11 (2.14)	0.10
Durbl	0.07 (0.38)	-0.59 (-0.98)	-0.66 (-0.76)	5.84 (2.91)	0.10
Manuf	0.10 (0.83)	-0.39 (-0.94)	-0.32 (-0.52)	4.20 (2.74)	0.11
Enrgy	-0.00 (-0.00)	-0.55 (-1.26)	-0.24 (-0.29)	4.02 (2.21)	0.07
HiTec	0.05 (0.30)	-0.37 (-0.95)	-1.67 (-1.53)	5.37 (2.17)	0.04
Telcm	-0.02 (-0.13)	-0.53 (-1.27)	-1.07 (-1.40)	4.78 (2.77)	0.08
Shops	-0.02 (-0.15)	-0.36 (-1.12)	0.02 (0.03)	2.42 (1.53)	0.04
Hlth	0.02 (0.17)	-0.23 (-1.06)	0.17 (0.34)	2.43 (3.09)	0.08
Utils	0.06 (0.57)	-0.40 (-1.65)	0.39 (0.68)	2.03 (1.30)	0.07
Other	-0.08 (-0.53)	-0.57 (-0.84)	-0.65 (-0.86)	5.03 (2.47)	0.07

Table 3 reports the results based on the following regression model:

$$r_{i,k} = a_i + b_i^e NAI_k^e + b_i^u NAI_k^u + c_i (D_k \times NAI_k^u) + \varepsilon_{i,k}$$

where $r_{i,t}$ is the excess return of an industry portfolio, D is a recession dummy consistent with the NBER reference dates, NAI_k^e and NAI_k^u are the expected and the unexpected components of the CFNAI-MA3 index. White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account.

$$\Delta E_t(CNAI_{t+12}) = b\tilde{R}_t + \eta_t \quad (12)$$

where \tilde{R}_t represents a column vector of unexpected returns $\tilde{R}_t = R_t - E_{t-1}(R_t)$, with R_t a column vector of excess returns of base assets in month t , and η_t the component of news that is orthogonal to the unexpected returns of the base assets.

Assume that the base asset return in month t is a linear function of Z_{t-1} , a vector of conditioning economic variables known at period $t-1$, and that $E_{t-1}(CNAI_{t+12})$ is a linear function of Z_{t-1} and Z'_{t-1} , where Z'_{t-1} is a vector of conditioning variables known at period $t-1$ that may help predict CFNAI-MA3. That is, $E_{t-1}(R_t) = dZ_{t-1}$ and $E_{t-1}(CNAI_{t+12}) = fZ_{t-1} + gZ'_{t-1}$. Then, we have from Eqs. (11) and (12) that

$$\begin{aligned} CNAI_{t+12} &= E_{t-1}(CNAI_{t+12}) + \Delta E_t(CNAI_{t+12}) + \omega_{t+12} \\ &= fZ_{t-1} + gZ'_{t-1} + b(R_t - dZ_{t-1}) + \eta_t + \omega_{t+12}, \end{aligned}$$

or

$$CNAI_{t+12} = gZ'_{t-1} + bR_t + eZ_{t-1} + \varepsilon_{t+12}, \quad (13)$$

Table 4. Industry portfolios reaction to current (revised) CFNAI-MA3 from 2001 to 2011

Industry	Intercept	Expected	Unexpected	$D_k \times \text{Unexpected}$	Adj-R ²
NoDur	0.11 (1.57)	-0.20 (-1.28)	0.36 (0.73)	3.12 (2.54)	0.23
Durbl	0.16 (1.15)	-0.59 (-1.48)	-1.02 (-0.97)	8.84 (3.69)	0.25
Manuf	0.17 (1.68)	-0.39 (-1.46)	-0.19 (-0.28)	5.99 (3.45)	0.27
Enrgy	0.07 (0.52)	-0.61 (-2.23)	-0.47 (-0.57)	6.80 (3.57)	0.22
HiTec	0.09 (0.55)	-0.41 (-1.51)	-0.88 (-0.91)	6.43 (3.04)	0.10
Telcm	0.05 (0.42)	-0.54 (-1.89)	-0.83 (-1.08)	6.67 (3.30)	0.20
Shops	0.05 (0.52)	-0.34 (-1.50)	-0.16 (-0.24)	4.28 (2.65)	0.14
Hlth	0.06 (0.59)	-0.22 (-1.78)	-0.04 (-0.06)	3.65 (3.60)	0.18
Utils	0.12 (1.17)	-0.38 (-2.61)	0.23 (0.37)	3.38 (2.40)	0.15
Other	0.01 (0.09)	-0.69 (-1.41)	-0.55 (-0.62)	8.79 (2.89)	0.27

Table 4 reports the results based on the following regression model:

$$r_{i,k} = a_i + b_i^e NAI_k^e + b_i^u NAI_k^u + c_i (D_k \times NAI_k^u) + \varepsilon_{i,k}$$

where $r_{i,t}$ is the excess return of an industry portfolio, D is a recession dummy consistent with the NBER reference dates, NAI_k^e and NAI_k^u are the expected and the unexpected components of the CFNAI-MA3 index. White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account.

with $e = -bd + f$, and $\varepsilon_{t+12} = \eta_t + \omega_{t+12}$. Tracking portfolio returns are defined here as $r_t = bR_t$. The OLS regression given by equation (13) can be used to estimate the portfolio weights, b so as to obtain bR_t , the tracking portfolio returns of expectations about future CFNAI-MA3.

Following Vassalou (2003), we focus on news concerning next year's aggregate activity ($CNAI_{t+12}$). We also follow Vassalou (2003) and use the six Fama-French size/book-to-market portfolios as the base assets. As conditioning variables – the Z_{t-1} in equation (13) – we again largely follow Vassalou (2003) and use some macro variables which are known to predict equity returns. They are the risk-free rate (RF), the term premium (TERM), the default premium (DEF), and a detrended wealth variable, cay , computed by Lettau and Ludvigson (2001). We use the lagged CFNAI-MA3 over past one year as the control variable in Z' .⁷

⁷ Our macro-economic variables are from the Fed St. Louise, where our stock return data again are from Kenneth French's website.

Table 5. Tracking Portfolios and Diagnostic Tests from 1967 to 2011

Panel A. Tracking Portfolio Regressions		
	Coeff	<i>t</i> -ratio
BA ₁	0.000	0.00
BA ₂	0.001	0.03
BA ₃	0.002	0.06
BA ₄	0.006	0.36
BA ₅	0.034	1.07
BA ₆	-0.007	-0.34
Constant	-0.567	-1.76
NAI _{t-12}	0.433	3.60
RF _t	0.449	0.69
DEF _{t-1}	-0.002	-0.01
TERM _{t-1}	0.338	3.66
CAY _{t-1}	-4.230	-1.09
<i>Adj-R</i> ²	0.30	
χ^2 p-value	0.01	
Panel B. Lower Bounds of Tracking Portfolio Explanatory Power		
<i>Lower Bound</i>	0.05	

The results for the regression of Eq. (13), $CNAI_{t+12} = gZ'_{t-1} + bR_t + eZ_{t-1} + \varepsilon_{t+12}$, are in Panel A, where $R_t = (SL_t, SM_t, SH_t, BL_t, BM_t, BH_t)'$ represents the excess returns of the Fama-French size-BM portfolios. $Z_{t-1} = (RF_t, DEF_{t-1}, TERM_{t-1}, CAY_{t-1})'$, which are, respectively, the risk free rate, the lagged default risk premium, the lagged term premium, and the lagged Cay factor from Lettau and Ludvigson. Z'_{t-1} is our lagged NAI change. Panel B provides the R-square of the regression in Eq. (14).

Table 5 presents the construction and diagnostic tests of the CFNAI tracking portfolios based on equation (13) with the six Fama-French size-BM portfolios as the base assets and the macro variables used also by Vassalou (2003) as conditioning variables. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12. Since we require one year of data to compute $CNAI_{t+12}$ (the average CFNAI-MA3 over next one year), our sample ends in 2010. The chi-square test rejects the hypothesis that the coefficients on the base assets are jointly zero at the 1% level, indicating that the base assets have some tracking ability. We next evaluate the ability of the tracking portfolio to forecast the average CFNAI-MA3 for the upcoming year, with the following regression suggested by Lamont (2001):

$$CNAI_{t+12} - E_{t-1}(CNAI_{t+12}) = h \cdot [bR_t - E(bR_t | Z_{t-1})] + u_{t+12} \quad (14)$$

The R-square from this regression provides an indication of the tracking ability of the factor mimicking portfolio. It gives a *lower bound* for the tracking ability because from equation (11) the left-hand side of equation (14) is only a noisy measure of the news component. The R-square in Panel B is 5%. So it appears that our tracking portfolio has some ability to track CFNAI-MA3 movements. In comparison, the ability of the tracking portfolios to track news related to future GDP growth in Vassalou (2003) varies

Figure 5. Estimated industry responses and CAPM implications based on the tracking portfolio approach

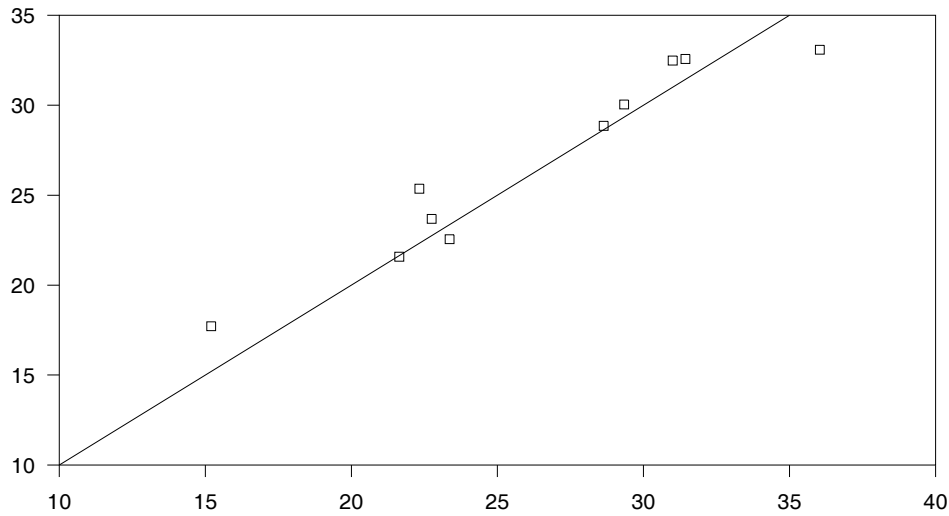


Figure 5 depicts the implied responses to the tracking portfolio returns against the estimated responses from Table 6, along with the 45-degree line that the points would lie on if the estimated responses are perfectly consistent with the CAPM. The values on the horizontal axis are the industry stock return responses implied by the CAPM. The vertical axis values are the estimated industry return responses from Table 6.

between 3% and 8%. Therefore, the tracking ability of the CFNAI mimicking portfolio appears to be reasonable.

To examine whether stocks react to the news about the future aggregate activity, we run the following regression.

$$r_{i,t} = \alpha_i + \beta_i(bR_t) + \varepsilon_{i,t} \quad (15)$$

where bR_t represents tracking portfolio returns. The results for the market return as well as for the 10 industry portfolios are presented in Table 6. Again, the results are generally consistent with the results in Tables 2 through 4, providing further evidence that stock returns are affected by real aggregate activity.

Again, to examine whether the pattern of responses of industry portfolios is consistent with the implications of the CAPM in the same fashion as in Section 4.1. More specifically, the industry response implied by the CAPM is calculated as the product of the industry CAPM beta and the estimated response of the CRSP value-weighted market return to the tracking portfolio returns from Table 6. Figure 5 depicts these implied responses to the tracking portfolio returns against the estimated responses from Table 6, along with the 45-degree line that the points would lie on if the estimated responses are perfectly consistent with the CAPM. The values on the horizontal axis are the industry stock return responses implied by the CAPM. The vertical axis values are the estimated industry return responses from Table 6.

Table 6. Industry portfolios reaction to the news about future CFNAI-MA3 from 1967 to 2011

Industry	Intercept	bR_t	Adj-R ²
Market	-0.03 (-0.44)	28.38 (60.47)	0.91
NoDur	0.25 (1.93)	23.68 (17.21)	0.68
Durbl	-0.15 (-0.91)	32.58 (16.58)	0.64
Manuf	0.00 (0.03)	30.04 (34.44)	0.84
Enrgy	0.23 (1.40)	25.36 (17.82)	0.51
HiTec	-0.09 (-0.38)	33.09 (21.34)	0.57
Telcm	0.05 (0.27)	21.58 (13.21)	0.49
Shops	0.10 (0.67)	28.85 (20.31)	0.68
Hlth	0.19 (1.15)	22.55 (15.09)	0.48
Utils	0.11 (0.88)	17.71 (12.70)	0.43
Other	-0.08 (-0.82)	32.48 (32.81)	0.86

To examine whether stocks react to the news about the future aggregate activity changes, we run the following regression.

$$r_{i,t} = \alpha + \beta(bR_t) + \varepsilon_t$$

where bR_t represents tracking portfolio returns.

As we can see, the points line up along the 45-degree line reasonably well, suggesting that the estimated responses are pretty consistent with those implied by the CAPM.

In a recent paper, Hou, Karolyi and Kho (2011) find that cash flow and momentum are the most important drivers of stock price movements. We therefore examine whether our CFNAI tracking portfolio has incremental power to explain time-series variation in stock returns when cash flow and momentum are present. First, we construct the cash flow and the momentum factor-mimicking portfolios. In the same spirit of Hou, Karolyi and Kho (2011), our cash-flow mimicking portfolio returns are calculated as the highest-CF/P-quintile returns minus the lowest-CF/P-quintile returns, where the cash flow/price (CF/P) portfolio returns are from Kenneth French's website. We use the momentum factor from Kenneth French's website. Given the popularity of the Fama-French size and value factors due to Fama and French (1992, 1993), we also take into account the size and the value factors.

Table 7 Cash flow, momentum and CFNAI-MA3 from 1967 to 2011

Panel A					
	Intercept	CFNAI	Size	Value	Adj-R ²
NoDur	0.23 (1.83)	23.60 (18.38)	0.03 (0.56)	0.02 (0.21)	0.68
Durbl	-0.34 (-2.23)	32.75 (19.50)	0.25 (2.98)	0.33 (3.24)	0.67
Manuf	-0.00 (-0.01)	29.52 (32.39)	0.10 (2.32)	-0.03 (-0.58)	0.84
Enrgy	0.22 (1.31)	26.34 (17.25)	-0.16 (-2.19)	0.08 (0.84)	0.52
HiTec	0.25 (1.40)	28.52 (16.60)	0.34 (5.37)	-0.83 (-5.84)	0.74
Telcm	0.10 (0.59)	21.72 (12.12)	-0.10 (-1.25)	-0.07 (-0.56)	0.49
Shops	0.12 (0.79)	27.41 (19.25)	0.24 (2.52)	-0.11 (-1.50)	0.71
Hlth	0.46 (3.50)	21.50 (15.48)	-0.18 (-2.59)	-0.49 (-4.35)	0.56
Utils	-0.03 (-0.23)	19.45 (13.77)	-0.11 (-2.10)	0.34 (4.61)	0.51
Other	-0.17 (-1.99)	32.45 (32.25)	0.14 (1.76)	0.15 (2.43)	0.87

Panel B					
	Intercept	CFNAI	Cash flow	Momentum	Adj-R ²
NoDur	0.31 (2.59)	23.37 (17.30)	-0.11 (-2.41)	-0.01 (-0.25)	0.68
Durbl	0.05 (0.29)	31.46 (22.01)	0.07 (1.51)	-0.30 (-4.22)	0.68
Manuf	0.09 (1.18)	29.59 (33.21)	-0.12 (-3.88)	-0.04 (-1.24)	0.85
Enrgy	-0.05 (-0.34)	26.82 (18.41)	0.36 (3.47)	0.15 (2.41)	0.57
HiTec	0.28 (1.92)	31.29 (22.78)	-0.67 (-5.22)	-0.07 (-0.62)	0.69
Telcm	0.15 (0.87)	21.05 (13.50)	-0.05 (-0.70)	-0.09 (-1.41)	0.49
Shops	0.29 (1.98)	27.89 (20.26)	-0.26 (-4.21)	-0.09 (-1.60)	0.71
Hlth	0.40 (3.40)	21.62 (17.15)	-0.55 (-6.74)	0.07 (1.17)	0.64
Utils	-0.06 (-0.48)	18.57 (14.01)	0.32 (5.95)	0.03 (0.61)	0.51
Other	0.03 (0.32)	31.91 (34.99)	-0.07 (-2.46)	-0.09 (-2.42)	0.87

We examine the marginal power of our CFNAI tracking portfolio by running the following regressions:

$$r_{i,t} = \alpha_i + \beta_{1,i}(bR_t) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \varepsilon_{i,t}$$

$$r_{i,t} = \alpha_i + \beta_{1,i}(bR_t) + \beta_{2,i}CF_t + \beta_{3,i}MOM_t + \varepsilon_{i,t}$$

where CF_t and MOM_t are the cash-flow and the momentum factors. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12.

More specifically, we examine the marginal power of our CFNAI tracking portfolio by running the following regressions:

$$r_{i,t} = \alpha_i + \beta_{1,i}(bR_t) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \varepsilon_{i,t} \quad (16a)$$

$$r_{i,t} = \alpha_i + \beta_{1,i}(bR_t) + \beta_{2,i}CF_t + \beta_{3,i}MOM_t + \varepsilon_{i,t} \quad (16b)$$

where SMB_t and HML_t are the Fama-French size and value factors from Kenneth French's website, and CF_t and MOM_t are the cash-flow and the momentum factors. The results are reported in Table 7. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12. As we can see, the CFNAI mimicking factor is still a significant factor even when the popular factors are present. Thus, the evidence suggests that real aggregate activity is an important factor of stock returns.

5. Conclusions

The notion that real aggregate activity exerts important influence on stock returns has strong theoretical appeal but weak empirical support. We argue in this paper that the lack of empirical reaction to macro news might be at least partly due to that researchers focus on macro variables, not the common factor in macro variables. Intuitively, every macro variable has some information about real aggregate activity as well as some idiosyncratic noise. That is, every macro variable has a common factor component and an idiosyncratic component. Therefore, macro variables are noisy measures of real aggregate activity or the common factor. Consequently, it is possible that even if real aggregate activity matters for stock returns, the effect may not show up when macro variables are used as the proxy. We test this conjecture in this paper. To this end, we focus on the Chicago Fed National Activity Index (CFNAI-MA3), a single summary measure of the common factor in 85 macro variables. Our main finding is that the news component of this index does affect stock returns. The effects show up at the market level as well as at the portfolio level.

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