Sentiment Across Asset Markets*

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First draft: October 31, 2017
Current version: June 20, 2018

*We are grateful to seminar participants at Washington University in St. Louis for helpful comments.

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Abstract

In this paper, we study investor sentiment in five major asset markets: stocks, bonds, commodities, currencies, and housing. Based on Thomson Reuter's sentiment measures extracted from several thousand news and social media sources, we find that each market is predicted by its own sentiment. Cross-markets, kitchen sink regressions reveal that the stock market is influenced only by bond sentiment, while bond market is affected just by currency market, which is largely unexplained by others; the commodities are related to currencies and housing, and housing can be predicted by stock and bond sentiment. In an efficient information aggregation by the partial least square (PLS), the predictability of each market increases substantially by using information of all markets vs using only its own sentiment.

Keywords: Sentiment

JEL Classification: G12, G14

1 Introduction

There have been a large number of investor sentiment studies since Baker and Wurgler (henceforth BW, 2006) presented their sentiment measures which are based on stock market trading statistics. With the advance in textual analysis, new measures are proposed, including those quantifying the news contents of Wall Street Journal (Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008), Dow Jones News Service (Tetlock, Saar-Tsechansky, and Macskassy, 2008), New York Times (Garcia, 2013) and Google searches (Da, Engelberg, and Gao, 2015). Typically these measures are developed based one news source or media. Recent expection is Calomiris and Mamaysky (2018) who develop a classification methodology using all the English written news articles from Reuters News and find their sentiment measures forecasting both developed and emerging markets.

In this paper, we study investor sentiment in five major asset markets: stocks, bonds, commodities, currencies, and housing. To the best of our knowledge, our paper is the first to study sentiment across asset markets. We address four important questions. First, how important is sentiment in each of the major five asset markets? Second, does sentiment in one market predict the return of another market? Third, what are the interactions of sentiment across the markets? Fourth, how to best predict the return on one market based on all available sentiment information?

Our motivation stems from three sources: First, there are several studies showing a cross-link of returns across asset classes. For example, Asness, Moskowitz, and Pedersen (2013) show value and momentum appear in all asset classes. By the same token, we ask whether sentiment is everywhere in asset markets. Second, most sentiment studies focus a single market (see Soo (2018) for housing market, Gao and Suss (2015) for commodity market, Yu (2013) for currency market, Greenwood, Hanson, and Jin (2016), López-Salido, Stein, and Zakrajšek (2017), and Guo, Lin, Wu, and Zhou (2016) for bond market). It is thus of interest to provide a comprehensive study of all the major markets to understand cross-asset relation that enhances our understanding of each market. Third, existing studies use ad hoc measures of each market. In contrast, Thomson Reuter's sentiment measures use the same methodology for each market, though each market has its own dictionary. Moreover, while the sentiment literature concentrate mostly on traditional news sources or social media, Thomson Reuter's are based on several thousand international news and social media sources. The breath of information is likely to reflect more accurately on the true sentiment across the asset markets.

More specifically, for each financial market, Thomson Reuter (TR) extracts the amount of relevant positive and negative terms related to each asset market and weights them based on preceding terms (adjectives) and visibility of the terms (headlines are weighted more heavily than text bodies). The sentiment measure is formed as positive minus negative weighted terms divided by the amount of asset related references. The measure is in the same line as the other measures applying textual analysis to study market sentiment from newspapers and managerial sentiment from company reports Loughran and McDonald (2018) but differs in the fact that it uses more sources than any of the previous studies, providing sentiment for many asset classes and using separate lexicons for traditional media and social media sources. Similar text analysis based techniques have been previously used in a smaller scale for example for internet message boards by Antweiler and Frank (2004), newspaper articles by Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), and Garcia (2013), 10-K reports by Loughran and McDonald (2011) and Jegadeesh and Wu (2013), Jiang et al. (2018), social media platform by Chen et al. (2014) and for Google searches by Da, Engelberg, and Gao (2015).

Since news content related sentiment measures capture information related to both, asset fundamentals and sentiment, we filter the variable by several financial market related variables and study both, the raw and filtered variables in our estimations. Empirically, we find that TR stock sentiment measure has substantial predictive power on the stock market and is complimentary to the well known BW measure. For stocks, bonds, currency, commodities, and housing, a one-standard-deviation increase in the sentiment index for each asset class is associated with 0.62%, 1.22% and 0.09% increase in stock, commodity, and housing monthly returns, and 0.10% and 0.24% decrease in bond and currency monthly returns.

We show that sentiment in some market matter to others and some may have no impact on others at all.

We construct cross-market sentiment indices that use efficiently information of all the market sentiment measure by using the partial least square (PLS). The predictability of each market increases substantially by using information of all markets vs using only its own sentiment. Considering long-term predictability, the TR measures predict stock returns up to six month and a reversal appears in the second year. The predictability lasts for 2 years for currency and housing, and 6 months for bond and commodity. In addition, we examine whether there is a lead-lag pattern among sentiment across markets.

We apply VAR and Granger Causality to further examine the relation among the cross-market sentiment measures. There are three observations. First, currency sentiment lags stock and housing sentiment. This evidence is related to the high correlation among sentiment in these three markets. The kitchen sink regression shows the predictive power of currency sentiment disappears once we control either stock or housing sentiment, thereby suggesting these three sentiment seems to provide similar information. Second, housing and stock sentiment Granger cause each other explaining why housing return is predicted by stock sentiment and the sentiment and returns correlations between housing and stock markets are highest among different pairs of assets. Third, bond and commodity sentiment do not lead or lag other sentiment. Finally, previous studies argues that firms that are hard to value and arbitrage should have the largest sensitivity to sentiment (e.g., Baker and Wurgler, 2006, 2007; Lemmon and Portniaguina, 2006; Kumar and Lee, 2006; Baker, Wurgler, and Yuan, 2012; Ben-Rephael, Kandel, and Wohl, 2012; Da, Engelberg, and Gao, 2015). We find that the TRMI measures behave similarly across-asset markets, and predict better the returns of hard-to-value assets.

The rest of this paper is organized as follows. Section 2 reviews the literature. Section 3 introduces data and key variables. Section 4 presents the results of predicting returns with raw and filtered sentiment indexes. Section 6 concludes.

2 The Extant Measure of Sentiment in Each Asset Class

2.1 Stock market

Several studies have applied textual analysis to capture sentiment from media, company reports, and social media. For market sentiment, Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008) are the first to study media influence to asset prices by applying textual analysis to New York Times to capture sentiment. They show sentiment predict market prices, trading volume and earnings. Garcia (2013) apply the same measure on an article from Wall Street Journal to study sentiment and stock returns over a century. He finds the predictability of sentiment on stock returns appears only during the crisis. Applying the same technique to capture sentiment, Loughran and McDonald (2011) and Jegadeesh and Wu (2013) study 10-K reports. Chen, De, Hu, and Hwang (2014) study the role of peer-based advices and show social media affects the stock market. Using household Google searchers, Da, Engelberg, and Gao (2015) and Gao et al. (2017) recognize the state of the economy and sentiment related words such as “recession”, “default”, and “gold prices”, and their foreign equivalences from millions of Internet searchers and aggregate them to form their sentiment measures. Of the non-textual analysis based measures, Baker and Wurgler (2006) and its variants and extensions are most often used sentiment measure (see, e.g., Baker and Wurgler, 2007; Yu and Yuan, 2011; Baker, Wurgler, and Yuan, 2012; Huang, Jiang, Tu, and Zhou, 2015). Other commonly used measure for investor sentiment are the survey results (see, e.g., Brown and Cliff, 2005; Lemmon and Portniaguina, 2006; Schmeling, 2009), weather related variables such as amount of sunshine, precipitation, temperature and length of the day (see, e.g., Kamstra, Kramer, and Levi, 2003; Hirshleifer and Shumway, 2003; Cao and Wei, 2005; Bassi, Colacito, and Fulghieri, 2013; Kaustia and Rantapuska, 2016), significant events such as aviation disasters (Kaplanski and Levy, 2010) and results from soccer games (Edmans, Garcia, and Norli, 2007) and asset market outcome based measures (overnight returns measure by Aboody, Even-Tov, Lehavy, and Trueman (2018)). Typical findings are that the sentiment predicts future returns with return reversal and the effects are larger for negative sentiment than positive one.

2.2 Bond market

Greenwood, Hanson, and Jin (2016) present a model in which sentiment is driven by investors' extrapolation of past credit market outcome. Following the calm period with low or no defaults, investors maintain their belief about the service of their debt. Following the turbulent periods, investors believe the default will remain high. Guo, Lin, Wu, and Zhou (2016) propose a residual from the regression of bond yield spread on risk factors and find their measure predict corporate bond returns cross-sectionally. López-Salido, Stein, and Zakrajšek (2017) propose a sentiment measure in credit market based on two steps approach. First, they regress credit spread (the spread between yield on seasoned long-term Baa-rated industrial bonds and yields on comparable maturity Treasury securities) on the level of credit spreads and junk bond shares as of year $t-2$, and the level of term spread (the difference between the yields on long- and short-term Treasury securities). In the second step, they apply the fitted value from the first step to predict returns. Hulburt's website provides the Hulbert Bond Newsletter Sentiment Index (HBNSI) reflects the average recommended bond exposure among a subset of short-term bond timers, back to 1985.[1] Greenwood and Hanson (2013) show debt issuance of low-quality firms forecasts bond returns.

2.3 Commodity market

Gao and Suss (2015) study sentiment in the commodity market. As sentiment proxies, they use CBOE's VIX and SKEW indexes, which measure the return volatility and skewness implied in S&P 500 index options. In addition, they compute a daily version of the closed-end fund discount and the dividend premium. So far,

[1] http://hulbertratings.com/bond-sentiment/

these proxies have only appeared at a monthly or even lower frequency in the literature, such as in Baker and Wurgler (2006). To reduce the dimension of these exogenous variables, they construct a composite sentiment using PLS and find commodity futures with low open interest growth, high volatilities, low momentum, or low futures basis are more sensitive to change in sentiment.

Specifically studying agriculture futures market, Wang (2001) argues the usefulness of trader-position-based sentiment index for forecasting futures prices in six major agricultural futures markets. He finds that large speculator sentiment forecasts price continuations. In contrast, large hedger sentiment predicts price reversals. Small trader sentiment hardly forecasts future market movements. He proposes the sentiment index similar to the Commitments of traders (COT) index. [2] Studying whether jumps in energy spot and futures markets are related to sentiment, Maslyuk-Escobedo, Rotaru, and Dokumentov (2017) use a commercial sentiment proxy (Thomson Reuters News Analytics (TRNA) database) and find the greatest frequency of jumps occurred in spot markets as well as in crude oil and natural gas sentiment indices. They detect several types of co-jumps including those between spot and futures pairs of energy commodities; those across energy commodities; and those between energy markets and relevant sentiment indices. Deeney, Cummins, Dowling, and Bermingham (2015) propose a measure of sentiment for West Texas Intermediate (WTI) and Brent crude oil futures based on stock indices, exchange rates, financial costs, crude inventory levels, supply proxies, and economic activity of the Organization of Petroleum Exporting Countries. They find that sentiment does affect futures prices of crude oil.

2.4 Currency market

In the currency area, researchers have used BW index, survey data and sentiment from Twitter. Yu (2013) builds a model to analyze the sentiment's impact on the foreign exchange. He applies monthly BW sentiment for the US and annual sentiments from Baker, Wurgler, and Yuan (2012) for Canada, France, Germany, Japan and the UK; and survey data on expected business conditions for Australia, Belgium, Denmark, Italy, the Netherlands, New Zealand and Switzerland). He concludes that sentiment is related to exchange rate changes and partly explain the forward premium puzzle.

Menkhoff and Rebitzky (2008) study financial market professionals' expectations on the future US-dollar/Euro movements. Their data comes from a monthly survey of the Center of European Economic

[2] Commitmentsoftraders(COT)reportsthathavebeenpublishedperiodicallybytheCommodityFuturesTradingCommission(CFTC) sincetheearly1980sdetailpositionstakenbythethreetypesoftraderslargespeculators,largehedgers, andsmalltradersinU.S.futuresmarkets./

Research at Mannheim (ZEW) which asks the participants (about 300 respondents, 75% of these work in the financial sector and the rest should also be familiar with financial markets) to reveal their qualitative expectations, i.e. "up", "down", or "no change" on various economic and financial variables. The time horizon of the expectations is six months. The sentiment measure is a scaled difference in "up" and "down" answers. They find that their investor sentiment measure is not related to exchange rate movements at shorter periods (less than 12 months) but become significant once the time horizon increases to longer than two years . Thus, exchange rate sentiment can have a long-term effect on the exchange rates. Heiden, Klein, and Zwergel (2013) examine the relationship between sentiment and EUR/USD market. They apply study data provided by 'sentix behavioral indices' (`www.sentix.de`), a weekly online survey of private and institutional (mostly German) investors' expectations regards to stocks, bonds and foreign exchange rates for a horizon of six months. Sentiment measure is formed similarly as in Menkhoff and Rebitzky (2008). The results show that institutional sentiment has a significant and positive predictive relationship with returns over different medium-term (8-76 week) horizons of EUR/USD market but not for the USD/JPY market.

Gholampour and van Wincoop (2017) build a Twitter foreign exchange (FX) sentiment for Euro/USD exchange rate by examining tweets by FX traders. In general, the Twitter FX sentiment does not predict the magnitude of the future exchange rate changes and Sharpe ratios estimated it from are very imprecise. There is evidence of predictability of the direction of the exchange rate change from accounts with a lot of followers. Uhl (2017) studies the relationship between currency sentiment and USD/EUR exchange rate with a text analysis-based sentiment measure from Thomson Reuters News Analytics. The results indicate that filtered sentiment measure can both, explain and predict subsequent USD/EUR changes. Au, Chan, Wang, and Vertinsky (2003) study how mood affects FX trader's behavior and find that traders in a good mood made less accurate decisions than those in neutral or bad moods.

2.5 Housing market

Kaplanski and Levy (2012) find real estate prices exhibit persistent seasonality. In detail, they find highest rate of returns in Spring and early summer while lowest rate of returns in fall. They argue daylight hours, the latitude of the area zone, and the Seasonal Affective Disorder (SAD) explain their findings. Using Google data, Chauvet, Gabriel, and Lutz (2016) collect sensitive information directly from individuals seeking assistance via internet search on issues of mortgage default and home foreclosure. They call such Google housing index as mortgage default risk index (MRDI) and find it predicts housing prices. Soo (2018) proposes housing market sentiment based on news and finds her sentiment predicts housing prices.

3 Data and Sentiment Index

3.1 Our sentiment index

Thomson Reuters MarketPsych Indices (TRMI) are available at company, asset-class, and market levels for daily frequency, measured at half an hour before the close of the New York Stock Exchange at 19:30 or 20:30 GMT (adjusted for daylight savings time) using data from the past 24 hours as their observation period.[3] TRMI evaluates the data from news and social media contents and identifies both, the entities from the article (companies, countries, currencies, commodities etc.) and macroeconomic, financial and emotions related words that are relevant for the entity. Subsequently, the volume and tone of phrases and words are converted into measurable variables. TRMI data are provided for three source sets: traditional news, social media, and the combined content. Our main results are based on the combined dataset but we also provide results separately for news and social media.

In total, TRMI Companies data covers more than 12,000 active companies from over 75 countries, 122 country-financial market and industry related indices, 45 currencies, 36 agricultural, energy and material related commodities and country level data for 187 countries and regions. In our analysis, we concentrate only on the US markets and apply TRMI sentiment indices constructed specifically for stocks, real estate, bonds, currency, and commodities. For stocks, we use the average of S&P500 constituents sentiment; for real estate, the US residential real estate sector related sentiment; for bonds, the US bonds related sentiment; for currencies, the US dollar sentiment. For commodities, we take an equal weight average of the TRMI Sentiment index of the constituents of Thomson Reuters Commodity Index to be consistent with the way the price index is constructed.[4] Our sample period ranges from January 1, 1998, when the TRMI is first available, till the end of December 2016.

[3]The timestamp of the data is chosen so that the US and Canadian investors would still be able to make their investments using the same day TRMI data.

[4]Index Components: Cocoa, Coffee, Copper, Corn, Soybeans, Cotton, Crude Oil, Gold, Heating Oil, Lean Hogs, Live Cattle, Natural Gas, Platinum, Silver, Soy Oil, Sugar and Wheat.

3.2 Returns

We collect the price index of S&P500, 3-year government bond, US dollar price, Thomson Reuters commodity price, and Housing Price Index (HPI) Seasoned Adjusted. To validate our measure, we collect the price of assets with varying difficult-to-value degree. For stocks, we test stocks formed by market beta collected from Ken French's library. For bonds, we collect the data of government bonds with different maturities from 1, 2, 3, 5, 10, and 30 years. For commodities, we collect prices of portfolios sorted by basis and for currencies, we collect prices of commodities sorted by interest rate differentials. The data of commodities and currency portfolios are from Lettau, Maggiori, and Weber (2014). For housing, we gather prices of ten Case-Shiller futures with different time to maturities.

Table 1 presents summary statistics of sentiment and returns. Panel A presents raw sentiment of our measure. Most asset classes have negative sentiment except for housing market. Bond and commodities sentiment have negative skewness. Correlation matrix shows the first evidence sentiments across asset classes are comoved. The correlation between stocks and housing market is highest among all pairs with (78%) followed by correlation between stocks and currency sentiment (60%), currency and housing (56%), commodity and housing (31%) and commodity and stocks (29%).

Panel B presents the summary statistics of filtered sentiment. To exclude macroeconomic news, we regress raw sentiment on five macroeconomic variables including dividend-price ratio (EP), dividend-earnings ratio (DE), T-bill rate (TBL), CBOE volatility index (VIX), and the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016) and use residual as filtered sentiment. We comply with the sentiment literature and orthogonalize filtered sentiment. In addition to bond and commodity, the filtered sentiments of currency and housing market also have negative skewness. Stocks is the only asset that has positive skewness but its skewness is marginally above zero (0.01). In term of correlation, the order is similar to raw sentiment. That is, housing and stock markets have highest correlation followed by currency and stock, housing and currency, housing and bond, and stocks and bonds. Panel C presents summary statistics of risk-free rate adjusted returns. Monthly excess return is highest for stock (0.37%), followed by housing (0.30%), bond (0.10%) and commodity (0.09%). Currency has negative return of 0.29%. Stocks has the highest risk followed by commodity, currency, bond and housing. Taken together, risk-adjusted returns is highest for housing followed by bonds, stocks, commodities and currencies. Panel C shows the first sign of comovement between sentiment and returns. Housing and stocks have the highest correlation, followed by correlation of stocks and currency, housing and currency, bond and stocks and currency and commodity. Interestingly, the first top three correlations belong to the same 3 pairs of assets regardless whether we compute correlation from returns or sentiments. That is, there seems to be a connection between sentiment and returns comingled across markets.

Figure 1 presents the times series of raw and filtered sentiment across markets. An evident pattern emerges for stocks and housing markets. During the dot-com bubble and subprime mortgage crises (two grey stripes areas), raw sentiment of stocks and housing markets decreases whereas filtered sentiment of both markets exhibits increasing trends. This pattern suggests macroeconomic variables are a major component of raw sentiment in both markets and the market seems to responds correctly with filtered sentiment. For bond, the contrast between raw and filtered sentiment is not eminent in the same way as stocks and housing markets; however, we can see bond returns seem to responds more rationally to filtered sentiment than to raw sentiment. For commodities and currencies, raw and filtered sentiment exhibit similar pattern.

4 Forecasting Power of News Sentiment Indexes in Different Markets

4.1 Sentiment in different markets

In this section, we perform predictive regression of the raw sentiment and filtered sentiment and report the results in Table 2. Our main regression is defined as follows:

$$R_{j,t+1} = \alpha + \beta S_{j,t} + \varepsilon_{t+1} \tag{1}$$

where $j = 1, \cdots, N$. Excess return is the return of each asset within asset class adjusted by 1-year risk-free rate. $S_{j,t}$ is sentiment of asset j at time t.

We compare our results with the predictive regression of BW and in the last specification, to examine whether our measure provides additional information to BW, we include both BW and filtered sentiment. Panel A shows results for stocks. First, BW negatively predicts return. In the second regression, raw sentiment is just below conventional significant levels but in third and fourth regressions, filtered sentiment is significant before and after controlling for BW. The coefficient is reduced in size from 0.70 to 0.62, but the significance level remains the same at 5%. For bonds, BW positively predict returns. Raw sentiment is not significant whereas filtered sentiment is at 5% level. Similar to stocks, controlling for BW, filtered sentiment is significant at the same level. Notably, BW is positive while our measure is negative. For commodity, BW is not significant. Raw and filtered sentiment positively predict returns and the magnitude of beta and significance level are similar. After controlling for BW, filtered sentiment is still significant at 1% whereas BW becomes weakly significant at 10%. For currency, BW negatively predict returns, so do raw and filtered sentiment. Both raw and filtered sentiment have similar predictive power. For housing, only our measure is significant and the sign of our sentiment is consistent with that of Soo (2018). Housing is the only asset where raw sentiment is more impactful than filtered sentiment. Stocks and bonds are the only two assets whose R^2 from BW predictive regression is higher than that of our sentiment regression. BW has no predictive power on commodity and housing. It has similar power as ours for currency market. Among all assets, our sentiment has strongest predictability power for commodities (R^2 of 8.6%), followed by housing (2.2%), stocks (2%), bonds (1.8%), and currency (1.4%). Except for currency, the significance and sign of BW remain similar in all regressions when we include our sentiment measure to the model. For currency, there seems to be overlapped information between BW and our measure as the significances for both measures decrease from 5% to 10% after both are included. Taken together, our sentiment advances and provide different information than BW.

Table 2 shows filtered sentiment is more powerful than the raw sentiment for almost all assets. Thus we apply filtered sentiment to the rest of the analyses.[5]

4.2 Sentiment across assets

Does sentiment have predictive power across assets? Table 3 presents kitchen sink regressions where in each panel, we regress individual asset's returns on month $t+1$ with its own sentiment in month t and then in another regression, we add sentiment of another asset on top of its own sentiment. There are six specifications for each assets. The last one pools sentiment of all assets into one regression. For stock, a standard deviation increase of positive stock sentiment increases stock returns by 0.70%. When we add bond sentiment, the impact of stock sentiment decreases. That is, a standard deviation increase in positive stock and bond sentiment increases stock returns by 0.57% and 0.56%, respectively, suggesting there is an overlap of information between stock and bond sentiment. When stock sentiment is included with currency sentiment or housing sentiment, the impact of stock sentiment increases by 23 and 38 basis points, respectively whereas currency and housing sentiments are insignificant and their coefficients are negative.

[5]The results from raw sentiment are available upon request.

This might be due to the high correlation between stock and housing sentiment (0.72%), stock and currency sentiment (0.53%), and housing and currency sentiment (0.46%). Specifically, in the last specification where we pool all sentiments, one percent increases in sentiment of stocks, bonds, and commodity increases excess returns of stocks by 1.09%, 0.65%, and 0.60% next month, respectively. Coefficient of determination also increases substantially from 2.04% to 5.37% betweeen rows 1 and 6. In Panel B, higher bond sentiment predicts lower bond excess returns and the size and significance of the coefficient remains stable across the estimations. This is probably due to its low correlation with other sentiment measures. Other sentiments do not predict bond returns individually but once all are included to the model, sentiment from currency market increases bond excess returns with the same magnitude as sentiment of bond. This also leads to an increase in R^2. For commodity in Panel C, sentiment of commodity predicts positively commodity excess returns. Individually, stock sentiment has a negative relation with future commodity returns, but once all the other sentiments are included, the effects coming from highly correlated currency and housing sentiments dominate the effects of stock sentiment. The negative relation between the sentiment of currency and future commodity returns can be explained with the close ties of currency and commodities. Once the sentiment of US dollar increases, commodity prices might increase and thus lower the return. In Panel D, for currency, sentiment of currency has a predictive power when we do not include any other sentiment, and when we include either bond, or commodity sentiment. It loses predictive power when we include either stock sentiment, housing sentiment, or sentiment of all assets, suggesting stock and housing sentiment provide the same information as currency sentiment. This is evident from high correlation among currency, stock and housing sentiment. In Panel E, housing excess returns are positively predicted by its own sentiment and positively and negatively predicted by bonds and stocks sentiment, respectively. Housing market is tied to stock markets, thus it is not surprising to see stock sentiment predicts the housing market. The effect of bond sentiment might come via the effects on interest rates which should affect both, bond and housing returns. It should also be noted that the R^2 increases substantially when bond sentiment is included to estimation model. Taken together, the kitchen sink regression show that sentiment appears to spillover across markets.

4.3 Sentiment composite indexes

To further study the effects of sentiment on different markets, we build two aggregate sentiment indices. First, we apply principle component analysis (PCA) and extract the first principle component of the five asset market sentiments. This component should capture the largest common component among the five sentiments and it is same for all the markets. However, it has been shown that sentiment has stronger predictability power once it is extracted and aligned properly (BW 2006, Huang et al (2015)). As a second method, we apply partial least square approach (PLS) which finds a market specific sentiment index for each market. While PCA provides an index capturing most of the common variation in the separate sentiment indices, PLS aims to find optimal weighting for each of the sentiment indices for each market. Both PCA and PLS reduce the dimension of the sentiment across markets.

Table 4 presents the results. Panel A shows the PCA results for all the individual markets. Compared to asset specific sentiments of Table 2, coefficients are rather similar for stocks, currency and housing. PCA does not have significant predictive power for bond market but the most interesting case is commodity market where the sign of the coefficient flips. This indicates that the commodity sentiment is segmented from the common market sentiment. This is also shown by the R^2_{OS}s which compared to Table 2, decrease for commodity, are about the same for currency and increase substantially for the rest of the markets.

Panel B presents the results for PLS indexes. As expected, the predictive power of all assets is highly significant for all markets. Comparing with the market specific sentiment indices in the third specification of Table 2, PLS increases the predictive power of stock, bond commodity, currency and housing sentiment by 32, 3, 15, 16, and 7 basis points, respectively, and the R^2_{OS}s are notably larger for all the markets except for currency. In sum, building a market specific sentiment index from individual sentiments improves the predictive power. This is another indication of sentiment spillover.

4.4 Long-horizon predictability of sentiments

The results so far show stock, commodity and housing sentiment positively predicts returns while bond and currency sentiment negatively predict returns. In theory, mispricing caused by sentiment should reverse in the future but there is no certainty when the reversion should happen. Alternatively, as Calomiris and Mamaysky (2018) argue, news based sentiment might capture such aspects of news that are not understood when the articles are published but of which relevance increases in time thus leading to no reversal of returns.

Table 5 documents how long the predictability of sentiment lasts. In Table 5 Panel A, we regress returns of individual assets for months from $t+1$ to $t+3$, $t+4$ to $t+6$, $t+7$ to $t+12$, and $t+13$ to $t+24$ on its own sentiment measured at month t. Interestingly, we find stock sentiment positively predict returns up to 6 months and the reversal is not apparent until one year after. Our result might be difficult to fathom from the rational expectation perspective, but it is consistent with the evidence shown by Calomiris and Mamaysky (2018). Housing and commodity sentiments also positively predict their own returns up until the next six months with no reversal during the next 2 years for either of them. The result of our housing sentiment is consistent with that in Soo (2018) who shows positive prediction and no reversal pattern up to one year. She explains this evidence might be due to the transaction process and frictions in the housing market. Our result for positive predictability of commodity sentiment is consistent with Gao and Suss (2015). For bonds and currency, the predictability decays over time but is still weakly significant in the second year. Interestingly, the predictability of sentiment for all assets disappears after the first six month, but then reemerge after one year for stock, bond, and currency.

As a comparison, Panel C shows the long-term predictability of sentiment from PLS approach. Consistent with the PLS result in Table 4 Panel B, PLS does strengthen not only the predictability of sentiment for all assets but also the persistence of sentiment for currency and housing whose predictability lasts until two years. Stock sentiment still loses significant during the period from month $t+7$ to $t+12$ but similarly to Panel A, there is a reversal during period from $t+13$ to $t+24$.

Panel B illustrates the predictability of sentiment across markets extracted by PCA. Comparing the results with Table 4, Panel A, it can be noticed that the sentiment from PCA loses predictability for stock market after one month. However, for currency and commodity, PCA negatively predicts returns until 2 years.

In aggregate, Table 5 shows interesting observations. First, currency returns are most affected by the aggregate sentiment indexes. For currency, the length of the predictability period increases considerably for aggregate sentiment indices, the R^2s are substantially larger compared to Panel A, and the magnitude of the coefficients in Panels B and C are very similar. Thus, of the studied markets, the currency market is most sensitive to the information in other sentiment indices at longer time periods.

Second, other market sentiments together with PLS method magnify the effect of sentiment on housing market returns in terms of length of the horizon, size of the coefficients and the predictive power (measured with R^2s). Third, the predictability of bond sentiment on its own asset returns is attenuated by sentiment of other assets. Fourth, the effect of common PCA sentiment index on commodity returns is negative and predicts returns until two years while PLS index is positive and loses its predictive power already after six months. Fifth, stock market seems to be the only on which experiences return reversal.

4.5 Cross-sectional predictability of sentiments

So far, we have examined the predictability of sentiment within and across markets but the results are based on time-series analysis. Next, we examine the predictive power of our sentiment cross-sectionally. The results will also help us validate our measure. BW (2006) argue a valid sentiment measure should have stronger predictability for hard-to-value assets. In this section, we regress excess returns of assets sorted by some characteristics capturing hard-to-value property on the PLS sentiments which should best capture the sentiment for all the markets. For stocks, we sort portfolios based on CAPM betas available in Ken French's library. For bonds, we regress excess returns of government bonds sorted by time to maturity from one to thirty years. For commodities, the five portfolios are sorted by basis. Basis at time t is defined as:

$$\left(\frac{P_t^{T_2} - P_t^{T_1}}{P_t^{T_1}}\right)\left(\frac{360}{T_2 - T_1}\right),$$

where P_t^T implies time to futures prices with maturity T. T_1 is the time to maturity of the nearest-to-maturity contract whereas T_2 implies time t maturity of subsequent contract. Gao and Suss (2015) show commodities with low basis are more sensitive to sentiment. For currency, Cur1 to Cur6 present excess returns of six currency portfolios sorted on the interest rate differential (from low to high). For housing, CMETRc1 to CMETRc10 present excess returns of ten Case-Shiller futures contracts ranked by maturities. CMETRc1 is closest to maturity while CMETRc10 has the longest time left before a maturity. The closer to time to maturity the futures contract is, the lower the basis risk, and thus the more the sensitivity to sentiment.

Table 6 validates our measure. For stocks, our measure has strongest power for the highest beta portfolio. Even though, the relation is not monotonic, the predictive power appears to decrease across beta portfolios. The lowest beta portfolio is least impacted by sentiment. For bonds, the predictive power of our measure monotonically increases with time to maturity. The economic difference in predictive power for bonds with hard-to-value property is striking. For one standard deviation increase in bond sentiment, 30 year-government bond returns decrease by 0.73%, which is about 9 times larger than a decrease of returns by 2-year government bonds. For commodities, the predictability of our measure decrease with portfolios ranked by basis, but the results are imperfect as our measure still does a moderate job predicting a portfolio with lowest basis (CF5) . For currency, our measure perform the best for the top two portfolios with highest interest rate differential (Cur5 and Cur6). Similar to commodity, our measure is not perfect as it still moderately predicts the third portfolio of currency ranked by (Cur3). For housing, our measure is stronger for Case-Shiller futures that are closed to time to maturity; however, the results are not monotonic.

4.6 Traditional media vs social media sentiments

One of the good attributes offered by the TRMI measure is that it allows us to test the impact of news and social media individually. In 7, we exploit that attribute and show news appear to explain excess returns better only for stock, bond, and commodity, but less for currency and housing. Further tests are needed for us to draw any conclusion on the difference of their influence on asset returns.

4.7 Sentiment dynamics

The results in Tables 4 and 5 support our conjecture that the impact of sentiment spills over across assets. The results in Tables 1 and 3 provide further evidence of this. More specifically, Table 1 shows high correlations between the of stock, currency and housing sentiments and Table 3 shows that besides its own sentiment, stock returns are predicted by sentiments from bond and commodity, bond returns by currency sentiment, commodity returns by currency and housing sentiments, currency returns by stock and housing sentiment, and housing returns by stock and bond sentiment. Moreover, stock and housing sentiment affect currency returns by providing similar information as the currency sentiment.

To better understand the interrelationship, we examine whether there is a lead and lag pattern of sentiment across markets. Table 8 Panel A shows VAR(1) and Panel B shows Granger Causality of sentiment across markets. As Table 1 already showed, sentiment measures are quite persistent, and not surprisingly, in Panel A, we find that last months sentiment predicts next month sentiment. Across markets, there are three observations. First, stock and housing sentiment have a lead-lag relationship in which stock sentiment is both positively predicted by housing market sentiment and also positively predicts housing market sentiment. Second, currency sentiment seems to respond to both, stocks and housing sentiment but it does not predict either one of them. Third, bond and commodity sentiments do not lead or lag any other sentimnts.

Granger Causality results in Panel B confirm the evidence of VAR. That is, stock and housing sentiment Granger cause each other. Also, currency sentiment is Granger caused by housing and stock sentiments but does not Granger cause other sentiments. This result supports the conclusion from the kitchen sink regression in Table 3 that stock and housing sentiment seems to provide similar information to currency sentiment and housing sentiment is negatively predicted by stock sentiment. Bond and commodity sentiment are not impacted by any other sentiments and do not Granger cause other sentiments.

This segmentation of bond and commodity sentiments is also evident in Table 3 where the size and sign of coefficients of bond and commodity sentiments remain the same across the six specifications and further supported by the PCA results in Tables 4 and 5 where the aggregate sentiment cannot predict bond returns and changes a sign for commodity returns.

5 Persistence of Sentiment

Persistence of a time series is defined as the tendency of that time series to revert slowly to its equilibrium or long run levels (fundamental) after a shock. Under the univariate approach, we investigate persistence from the univariate time series of any variable. To perform the test, the literature assumes an investigated series follows a stationary autoregressive process of order p (e.g., $AR(p)$).

Suppose that the sentiment series S_t is a covariance-stationary $AR(P)$ process:

$$S_t = a + \sum_{j=1}^{p} \beta_j S_{t-j} + \varepsilon_t, \qquad \text{where } |\beta_j| < 1. \tag{2}$$

Sentiment is said to be persistent if a shock to the disturbance terms drives sentiment converges slowly to its mean. The extant literature shows there are three existing scalar measures to estimate the degree of persistence or the speed with which a time series converges to its long run level after a shock (Dias and Marques, 2010).

In this paper, we consider three measures of persistence. The first is the sum of the autoregressive coefficient (ρ)

$$\rho = \sum_{j=1}^{p} \beta_j. \tag{3}$$

The larger the ρ, the larger the cumulative impact of the shock will be. The second persistent measure is cumulative impulse response (CIR). Andrews and Chen (1994) show this measure summarizes the information contained in the impulse response function (IRF) and is a good measure of persistence. Under an $AR(p)$ process,

$$\text{CIR} = \frac{1}{1-\rho}. \tag{4}$$

The third measure is the half-life measures the speed of mean reversion defined as the number of periods so that the magnitude of forecast becomes half of that of the forecast origin or the number of periods for which the effect of a unit shock to the variable of interest remains above 0.5. At time t, we want to make a forecast h time units in a future, $\hat{r}_t(h)$, then $\hat{r}_t(h) = E[r_{t+h}|I_t]$, where I_t is the information available at time t, provided that we use the mean squared error method.

Assuming our returns are mean reverting, the speed of mean reversion or the half-life is a time horizon that the process needs to halve its distance from the mean. Setting $\hat{x}_t(h) = \hat{r}_t(h) - \mu$ where μ is the mean of r_t, we get $\hat{x}_t(h) = \beta\hat{x}_{t-1}(h)$ and thus $\hat{x}_t(h) = \beta^h x_t$.

If h is half-life, then $\hat{x}_t(h) = \frac{1}{2}x_t$ and suggests the half-life is

$$h = \frac{\log(0.5)}{\log(|\beta|)}.$$

Table 9 shows, among all assets, stock sentiment, is the most persistent. Its half-life of 8.8 suggests on average it takes 8.8 months for which the effect of a unit shock to sentiment remains above 0.5. For housing sentiment, it takes 6 months, followed by currency (2.4 months), bond (2.2 months), and commodity (1.3 months). Notably, the half-life of stocks and bond sentiment is about 5 months apart from the average half-life of bond, currency, and commodity. This result seems to be related to two evidence we have documented. First, the long-term predictability of stocks, housing and currency that lasts until 2 years (5). Second, stock and housing sentiment seems to co-move (stocks and housing are Granger causing each other as shown in 8) and be highly correlated (highest correlation of 72% among all pairs in 1). In unreported results, we decompose sentiment into news and social media and find the gap of persistence between stocks and housing is wider making stocks the asset that has longest half-life and isolating it from the other assets. The persistence of stock sentiment is much higher than that of other assets for social media. Another interesting observation is only stocks and housing sentiment is more persistent under social media than news. It seems the sentiment from social media is more persistent for assets that are traded by retail investors such as stocks and housing. For assets that are mostly traded by institutions, their sentiment from news is more persistent than that from social media.

Further, we estimate auto correlation in Table 1. Autocorrelation is high and significant for sentiment of all assets. For most assets except commodities, sentiment from news and social media is over 50%. Autocorrelation presents the same pattern as the three measures of persistence above. That is, stock has the highest AC (88%) followed by housing (81%), bonds (53%), currency (57%) commodities (16.5%). Sentiment from news and social media presents the same ranking. Consistent with the above three measures of sentiment, autocorrelation of sentiment from social media is higher than that from news for stocks, currency, and housing.

6 Conclusion

Given the importance sentiment has on the predictability and the cross-sectional variation of equities, it is paramount to understand whether the same properties of sentiment are applied to other markets or whether sentiment is contagious among assets.

In this study, we exploit the uniqueness of sentiment data provided by Thomson Reuters MarketPsych Indices (TRMI), generated using proprietary dictionary and textual analysis for each asset using several thousand traditional news and social media sources. In terms of coverage, we are the most comprehensive study of sentiment studying not only stock, but also bond, commodity, currency, and housing markets. For all the markets, we first find sentiment to predict their returns with varying coefficient sizes and persistence.

We continue by studying the propagation of sentiment across asset markets and report several predictive linkages between market returns and foreign sentiments. Besides its own sentiment, stock returns are predicted by bond sentiment; bond returns by currency sentiment; commodity returns by currency and housing sentiment; currency returns by housing sentiment; and housing returns by stock and bond sentiment.

As the sentiment of one market propagates to another, we form two additional sentiment indices extracted from the individual sentiment measures. Principal component analysis (PCA) based sentiment captures the common component of all the sentiments while market specific partial least squares (PLS) based sentiment index uses only the information from the measures that is useful for the predictive purposes. Not surprisingly, PLS increases the predictive power and persistency substantially.

Individual, market specific sentiments predict returns for six months for all markets, although with decaying significance levels. For stocks, we also report a reversal for the second year returns. The more general, PCA sentiment, predicts currency and commodity returns for two years and the asset specific PLS sentiment provides stronger and longer predictions for stock, currency and housing markets. Based on the PCA results, it seems that bond and commodity sentiment are segmented from the other three as the PCA does not predict their returns (bonds) or predicts with varying sign (commodities).

We further examine the lead-lag relationships between sentiments with VAR(1) method and Granger causality test and find indeed that while both, stock and housing sentiment lead currency sentiment and each other, the currency sentiment does not lead either one. Moreover, there are no lead-lag relationships with bond and commodity sentiments.

Future research should try to explain the underlying reason behind our findings. Possible explanations might be fund flows, volatility, trading volume spillover, or the nature of institutional vs. retail holdings.

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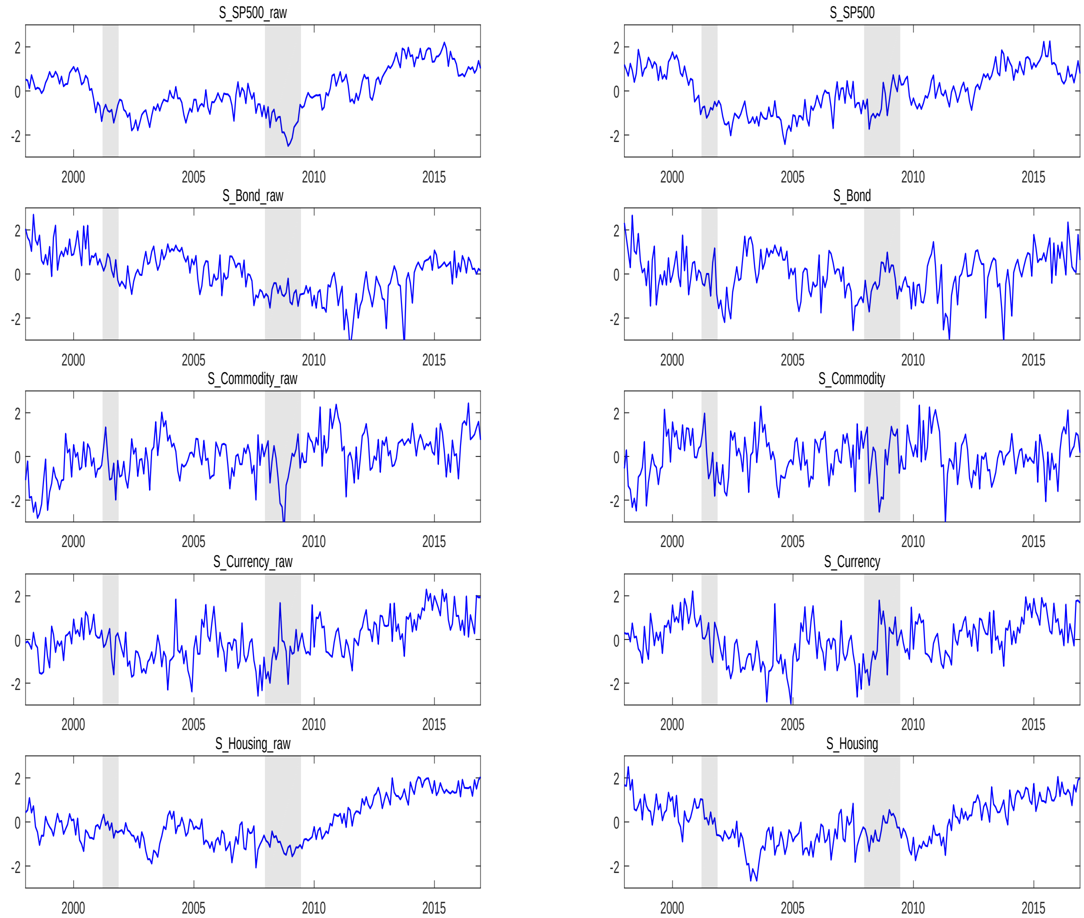

Figure 1 Time-series of raw and filtered sentiment indexes in different markets

This figure plots the dynamics of sentiment in different asset markets. The left panel is about raw sentiment indexes and the right panel is about filtered sentiment indexes, in which sentiment is the residual from the regression of raw sentiment index on macroeconomic variables to filtered out fundamental information, where the macro variables include the dividend-price ratio, dividend-earnings ratio, T-bill rate, VIX, and the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016). The sample period is 1998:01–2016:12.

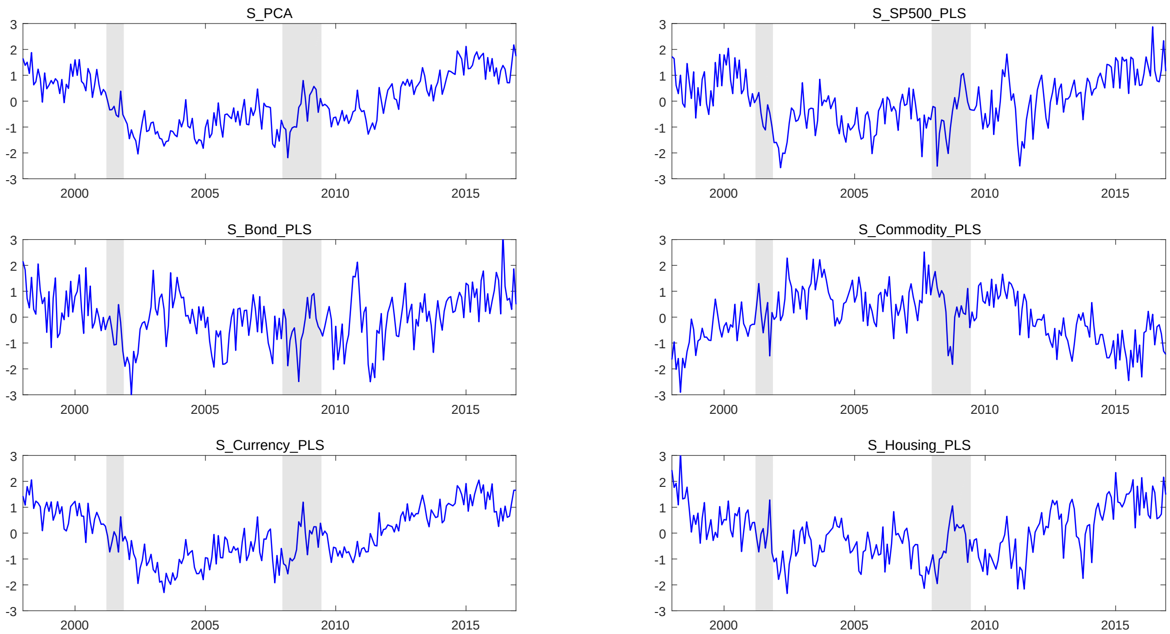

Figure 2 Time-series of sentiment indexes with the PCA and PLS approaches

This figure plots the dynamics of the PCA and PLS sentiment indexes, where the PCA index is the first principal component of sentiments across the five markets, and the PLS index is extracted for each market. The sample period is 1998:01–2016:12.

Table 1 Summary statistics of sentiment and return in different asset markets

This table reports summary statistics of sentiment and excess return across market. Filtered sentiments refers to the residuals from the regression of raw sentiment indexes on macroeconomic variables, where the macro variables include the dividend-price ratio, dividend-earnings ratio, T-bill rate, VIX, and the economic policy uncertainty (EPU) index from Baker, Bloom, and Davis (2016). AC(1) is the first-order autocorrelation. The sample is 1998:01–2016:12.

Panel A: Descriptive statistics and pirewise correlations of raw sentiments

	Mean	Std	Skew	Kurt	Min	Max	AC(1)
S_Stock	−0.03	0.03	0.07	2.39	−0.11	0.05	0.93
S_Bond	−0.12	0.05	−0.41	3.54	−0.29	0.01	0.76
S_Commodity	−0.07	0.02	−0.44	3.53	−0.14	−0.02	0.59
S_Currency	−0.05	0.04	0.06	2.70	−0.16	0.04	0.63
S_Housing	0.01	0.07	0.40	2.17	−0.12	0.15	0.90

	S_Stock	S_Bond	S_Commodity	S_Currency	S_Housing
S_Stock	1.00	0.18	0.29	0.60	0.78
S_Bond		1.00	−0.14	0.10	0.03
S_Commodity			1.00	0.19	0.31
S_Currency				1.00	0.56
S_Housing					1.00

Panel B: Descriptive statistics and pirewise correlations of filtered sentiments

	Mean	Std	Skew	Kurt	Min	Max	AC(1)
S_Stock	0.00	1.00	0.01	2.05	−2.42	2.26	0.89
S_Bond	0.00	1.00	−0.33	3.17	−3.09	2.66	0.54
S_Commodity	0.00	1.00	−0.19	2.97	−3.01	2.34	0.44
S_Currency	0.00	1.00	−0.21	2.73	−2.94	2.21	0.57
S_Housing	0.00	1.00	−0.08	2.49	−2.67	2.50	0.82

	S_Stock	S_Bond	S_Commodity	S_Currency	S_Housing
S_Stock	1.00	0.23	0.04	0.53	0.72
S_Bond		1.00	−0.01	0.21	0.25
S_Commodity			1.00	−0.02	−0.05
S_Currency				1.00	0.46
S_Housing					1.00

Panel C: Descriptive statistics and pirewise correlations of excess returns

	Mean	Std	Skew	Kurt	Min	Max	AC(1)
R_Stock	0.37	4.43	−0.80	4.54	−18.36	10.35	0.10
R_Bond	0.10	0.72	0.04	3.87	−2.33	2.20	0.13
R_Commodity	0.09	4.00	−0.49	4.64	−17.68	9.75	0.06
R_Currency	−0.29	2.03	−0.66	5.17	−9.78	5.14	0.12
R_Housing	0.30	0.52	−1.39	4.52	−1.78	1.16	0.72

	R_Stock	R_Bond	R_Commodity	R_Currency	R_Housing
R_Stock	1.00	−0.36	0.05	0.59	0.60
R_Bond		1.00	−0.09	−0.03	−0.11
R_Commodity			1.00	0.26	0.07
R_Currency				1.00	0.53
R_Housing					1.00

Table 2 Predicting market returns with BW sentiment and news sentiment indexes

This table reports the results of predicting asset returns with BW sentiment index, raw, and filtered sentiment indexes, repsectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	BW sentiment		Raw sentiment		Filtered sentiment		adjR^2
	β	t-value	β	t-value	β	t-value	
Panel A: R_Stock							
	-0.94^{***}	-2.86					4.06
			0.57	1.63			1.20
					0.70^{**}	2.43	2.04
	-0.88^{***}	-2.70			0.62^{**}	2.24	5.58
Panel B: R_Bond							
	0.15^{***}	3.08					3.92
			-0.09^{*}	-1.94			1.06
					-0.11^{**}	-2.13	1.81
	0.14^{***}	2.96			-0.10^{*}	-1.90	5.29
Panel C: R_Commodity							
	-0.35	-1.63					0.34
			1.19^{***}	4.23			8.51
					1.19^{***}	4.27	8.61
	-0.43^{*}	-1.91			1.22^{***}	4.38	9.36
Panel D: R_Currency							
	-0.26^{**}	-2.28					1.26
			-0.27^{**}	-2.13			1.37
					-0.27^{**}	-2.17	1.39
	-0.22^{*}	-1.89			-0.24^{*}	-1.86	2.13
Panel E: R_Housing							
	-0.01	-0.41					-0.40
			0.14^{***}	4.68			6.69
					0.09^{***}	2.78	2.20
	-0.01	-0.50			0.09^{***}	2.81	1.82

Table 3 Incremental forecasting power of other market sentiments

This table reports the results of predicting return $R_{i,t+1}$ of asset i with sentiment from its self and other markets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

S_Stock$_t$	t-value	S_Bond$_t$	t-value	S_Commodity$_t$	t-value	S_Currency$_t$	t-value	S_Housing$_t$	t-value	adjR^2
Panel A: Forecasting R_Stock$_{t+1}$										
0.70**	2.43									2.04
0.57**	1.99	0.56**	2.17							3.11
0.67**	2.33			0.64*	1.79					3.69
0.93**	2.54					−0.44	−1.29			2.32
1.08**	2.52							−0.53	−1.42	2.28
1.09**	2.30	0.65**	2.51	0.60*	1.71	−0.43	−1.28	−0.48	−1.26	5.37
Panel B: Forecasting R_Bond$_{t+1}$										
		−0.11**	−2.13							1.81
−0.03	−0.60	−0.10**	−2.02							1.55
		−0.11**	−2.14	−0.05	−1.07					1.91
		−0.12**	−2.41			0.07	1.46			2.40
		−0.11**	−2.11					0.01	0.25	1.40
−0.12	−1.57	−0.12**	−2.23	−0.04	−0.91	0.11**	2.00	0.04	0.67	2.85
Panel C: Forecasting R_Commodity$_{t+1}$										
				1.19***	4.27					8.61
−0.43*	−1.92			1.21***	4.33					9.40
		−0.39*	−1.67	1.19***	4.34					9.14
				1.18***	4.38	−0.74***	−3.37			11.60
				1.16***	4.14			−0.65***	−2.97	10.88
0.36	0.98	−0.20	−0.83	1.14***	4.30	−0.62**	−2.20	−0.58*	−1.82	11.78
Panel D: Forecasting R_Currency$_{t+1}$										
						−0.27**	−2.17			1.39
−0.25	−1.56					−0.14	−0.84			2.05
		0.05	0.42			−0.28**	−2.19			1.00
				0.22	1.46	−0.27**	−2.16			2.18
						−0.13	−0.87	−0.32**	−2.28	2.91
−0.11	−0.58	0.11	0.95	0.22	1.42	−0.11	−0.69	−0.26	−1.56	3.09
Panel E: Forecasting R_Housing$_{t+1}$										
								0.09***	2.78	2.20
−0.08**	−2.04							0.15***	3.60	2.98
		0.15***	4.89					0.05*	1.75	9.34
				−0.04	−0.95			0.08***	2.70	2.29
						0.00	0.11	0.08**	2.36	1.77
−0.10**	−2.44	0.15***	5.25	−0.03	−0.78	0.01	0.32	0.11***	2.94	10.30

Table 4 Forecasting asset return with sentiment extracted across markets

Panel A considers predictability of the PCA index, which is the first principal component of the five asset market sentiments, and Panel B considers the predictability of the PLS sentiment index, where we extract one sentiment index for each market with the PLS approach. In calculating the R^2_{OS}, we use the first 2/3 sample as the parameter training and the rest 1/3 as the out-of-sample evaluation (i.e., the out-of-sample period is 2010:09–2016:12). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	β	t-stat	R^2	R^2_{OS}
Panel A: Forecasting with PCA aggregate index				
R_Stock	0.51^{**}	1.97	0.89	9.01^{***}
R_Bond	−0.03	−0.60	−0.25	9.24^{***}
R_Commodity	-0.76^{***}	−3.46	2.21	1.97^{**}
R_Currency	-0.36^{***}	−3.21	2.76	1.25^{*}
R_Housing	0.09^{***}	2.62	2.30	15.38^{***}
Panel B: Forecasting with PLS sentiment index				
R_Stock	1.02^{***}	3.73	4.83	4.90^{***}
R_Bond	-0.14^{***}	−2.89	3.56	7.31^{***}
R_Commodity	1.34^{***}	6.03	10.88	11.24^{***}
R_Currency	-0.43^{***}	−3.83	4.15	−1.27
R_Housing	0.16^{***}	4.92	8.59	28.69^{***}

Table 5 Long-horizon predictability

This table reports the results of predicting cumulative return $R_{t,t+h}$ with sentiment, where $R_{t,t+h} = \frac{1}{h}\sum_{j+1}^{h} R_{t+j}$. Panel A considers predictability from each market, Panel B considers predictability with the PCA index, which is extracted from the five asset markets, and Panel C considers the predictability of the PLS sentiment indexes. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$R_{t+1,t+3}$			$R_{t+4,t+6}$			$R_{t+7,t+12}$			$R_{t+13,t+24}$		
	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2
Panel A: Forecasting with individual sentiment index												
R_Stock	0.60^{**}	2.36	4.55	0.40^{*}	1.66	1.86	0.07	0.31	−0.33	-0.35^{**}	−2.02	4.92
R_Bond	-0.09^{**}	−2.17	3.49	-0.09^{*}	−1.91	3.12	−0.03	−1.07	0.57	-0.05^{*}	−1.67	3.89
R_Commodity	0.81^{***}	3.19	9.80	0.36^{**}	2.22	1.55	−0.19	−0.98	0.39	−0.11	−0.95	0.15
R_Currency	-0.32^{**}	−3.32	5.74	-0.20^{*}	−1.87	1.93	−0.08	−0.55	0.21	-0.12^{*}	−1.85	2.06
R_Housing	0.09^{**}	2.03	3.33	0.10^{**}	2.05	3.58	0.10	1.50	3.85	0.08	0.99	2.29
Panel B: Forecasting with PCA aggregate index												
R_Stock	0.35	1.57	1.31	0.33	1.36	1.07	0.21	0.73	0.59	−0.31	−1.55	3.67
R_Bond	−0.05	−0.99	0.61	−0.03	−0.73	0.11	0.01	0.16	−0.43	0.04	1.11	3.19
R_Commodity	-0.67^{***}	−3.49	6.53	-0.55^{**}	−2.24	4.24	−0.35	−1.30	2.60	-0.37^{**}	−2.33	6.66
R_Currency	-0.38^{***}	−3.64	8.42	-0.32^{***}	−2.70	5.71	-0.28^{**}	−2.03	7.65	-0.36^{***}	−4.55	22.58
R_Housing	0.10^{*}	1.94	3.64	0.10^{*}	1.94	3.93	0.09	1.42	3.60	0.07	1.01	2.03
Panel C: Forecasting with PLS index												
R_Stock	0.79^{***}	2.95	8.38	0.53^{**}	2.07	3.50	0.04	0.14	−0.43	-0.40^{**}	−2.33	6.63
R_Bond	-0.12^{***}	−3.08	7.09	-0.08^{*}	−1.71	2.31	0.00	0.08	−0.46	−0.02	−0.91	0.61
R_Commodity	1.03^{***}	6.01	16.18	0.65^{***}	3.11	6.17	0.14	0.48	0.00	0.17	1.18	1.08
R_Currency	-0.44^{***}	−4.81	11.57	-0.38^{***}	−3.50	8.32	-0.28^{**}	−2.11	7.51	-0.36^{***}	−4.66	22.41
R_Housing	0.16^{***}	3.57	10.76	0.16^{***}	3.57	11.11	0.17^{***}	2.84	13.08	0.11^{**}	2.00	4.99

Table 6 Cross-sectional predictability

This table reports the results of predicting excess returns of component portfolios in different markets with the PLS sentiment indexes. Beta portfolios are from Ken French data library, commodity futures portfolios are sorted based on basis from low to high (Lettau, Maggiori, and Weber, 2014), currency portfolios are sorted on the interest rate differential from low to high, and housing portfolios are sorted by time to maturity of Case-Shiller futures from short o long time-to-maturity; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	β	t-value	adjR^2		β	t-value	adjR^2
Panel A: Beta portfolios				Panel B: Bond portfolios			
Low beta	0.77***	3.49	4.35	GovBond1y	−0.03**	−2.15	1.67
2	1.10***	4.37	6.99	GovBond2y	−0.08**	−2.63	2.90
3	0.92***	3.17	3.74	GovBond3y	−0.14***	−2.86	3.46
4	1.09***	3.66	4.60	GovBond5y	−0.26***	−3.12	3.96
5	1.21***	3.55	5.05	GovBond10y	−0.43***	−3.02	3.48
6	1.27***	3.65	4.69	GovBond30y	−0.73***	−3.04	2.94
7	1.11***	2.71	2.72				
8	1.50***	3.42	4.13				
9	1.72***	3.15	3.70				
High beta	1.95***	2.78	3.08				
Panel C: Commodity futures portfolios				Panel D: Currency portfolios			
CF1	1.22**	2.55	4.59	Cur1	−0.13	−0.88	−0.16
CF2	1.28***	3.08	6.52	Cur2	−0.19	−1.36	0.48
CF3	0.89*	1.85	2.45	Cur3	−0.24*	−1.95	1.57
CF4	0.86**	2.20	3.32	Cur4	−0.16	−1.36	0.23
CF5	1.08***	2.85	4.80	Cur5	−0.36*	−1.91	1.71
				Cur6	−0.51**	−2.20	2.57
Panel E: Housing market portfolios							
CMETRc1	0.42***	2.58	3.62				
CMETRc2	0.30**	2.15	1.68				
CMETRc3	0.44**	2.45	3.02				
CMETRc4	0.38*	1.76	1.04				
CMETRc5	0.43*	1.94	1.86				
CMETRc6	0.46**	2.28	2.99				
CMETRc7	0.28	1.08	0.22				
CMETRc8	0.37*	1.76	1.35				
CMETRc9	0.28	1.39	0.47				
CMETRc10	0.20	0.73	−0.30				

Table 7 Social media and news sentiment indexes

This table reports the results of predict asset returns with social media and news sentiment indexes, where each index is constructed the same as the previous index. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Social media index			News index		
	β	t-value	adjR^2	β	t-value	adjR^2
R_Stock	0.61**	2.12	1.42	0.78**	2.46	2.65
R_Bond	−0.06	−1.18	0.17	−0.10**	−2.04	1.62
R_Commodity	0.67**	2.25	2.41	1.12***	4.05	7.53
R_Currency	−0.28**	−2.33	1.51	−0.23*	−1.83	0.86
R_Housing	0.09***	3.37	2.74	0.07**	2.46	1.51

Table 8 Sentiment dynamics and Granger causality test

This table reports the VAR(1) results and Granger causality tests of sentiment across five markets, where the lag is chosen based on the Bayesian Information Criterion (BIC). $p(i, j)$ corresponds to the p-value of the test that sentiment i is not caused by sentiment j, and the joint test corresponds to the p-value that sentiment i is not caused by any sentiment j, where $j \neq i$. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: VAR(1)

	S_Stock$_t$	S_Bond$_t$	S_Commodity$_t$	S_Currency$_t$	S_Housing$_t$	adjR^2
S_Stock$_{t+1}$	0.78***	−0.01	−0.02	0.03	0.13***	79.55
	(17.85)	(−0.44)	(−0.59)	(0.77)	(3.20)	
S_Bond$_{t+1}$	−0.07	0.50***	−0.03	0.10	0.11	32.48
	(−0.74)	(8.67)	(−0.53)	(1.50)	(1.46)	
S_Commodity$_{t+1}$	0.01	0.03	0.43***	0.07	−0.09	20.03
	(0.12)	(0.45)	(7.60)	(0.95)	(−1.01)	
S_Currency$_{t+1}$	0.15*	0.02	0.04	0.42***	0.16**	39.08
	(1.93)	(0.46)	(0.91)	(6.72)	(2.01)	
S_Housing$_{t+1}$	0.13**	0.04	−0.03	0.04	0.69***	69.03
	(2.35)	(0.82)	(−0.81)	(1.01)	(12.49)	

Panel B: p-value of Granger-causality test

	S_Stock	S_Bond	S_Commodity	S_Currency	S_Housing	Joint test
S_Stock	0.00	0.59	0.52	0.36	0.00	0.00
S_Bond	0.44	0.00	0.56	0.11	0.13	0.13
S_Commodity	0.91	0.64	0.00	0.33	0.31	0.76
S_Currency	0.05	0.62	0.34	0.00	0.04	0.00
S_Housing	0.01	0.31	0.38	0.28	0.00	0.01

Table 9 Persistence of sentiment

This table reports the sum of the autoregressive coefficient (ρ), cumulative impulse response (CIR), half-life measure (h), and autocorrelation (AC(S)) of sentiment, as well as the autocorrelations of the first- and second-order change of sentiment (AC(ΔS) and AC($\Delta^2 S$)), respectively.

	ρ	CIR	h	AC(S)	AC(ΔS)	AC($\Delta^2 S$)
S_Stock	0.89	8.77	5.73	0.88	−0.26	−0.48
S_Bond	0.54	2.19	1.14	0.53	−0.38	−0.59
S_Commodity	0.17	1.20	0.39	0.17	−0.50	−0.72
S_Currency	0.58	2.35	1.25	0.57	−0.44	−0.65
S_Housing	0.83	5.82	3.68	0.81	−0.42	−0.64

Online Appendix

Sentiment Across Asset Markets

(not for publication)

A TRMI Data Formation

TRMI data are based on word recognition techniques which aim to extract economics, finance, business and psychological relevant information from financial news, social media, conference calls transcripts and executive interviews TRMI data covers more than 12,000 active companies from over 75 countries, 122 country-financial market and industry related indices, 45 currencies, 36 agricultural, energy and material related commodities and country level data for 187 countries and regions. Data are available from 1998 onwards. Only text written in English is used in the analysis.

A.1 Data analysis

Previous studies mostly use a lexical analysis method where an article text is compared to pre-specified context relevant lexicon and their frequencies are subsequently counted. The most significant limitation of this method is that it concentrates only on one dimension of sentiment (positive vs. negative) and ignores other, partly interrelated, dimensions. Also, some open-source sentiment dictionaries might misclassify business-and finance-related terms. TRMI word recognition technique uses extensive customization and curation of lexicons and aims to identify and score hundreds of sentiment dimensions using different grammatical frameworks to different text sources based on their special traits and also considers the structure of the sentences and articles. When applied to text, the confluence of the various text processing described below generates over 400 psychological variables (PsychVars), each with the potential to be applied to a different entity. It should be emphasized that the method aims to identify word interrelationships and calculates the score based these, instead of using frequency analysis on individual words. The following goes through the methods used for word recognition and content quantifying method used in the data formation.

A.2 Source type differences

TRMI data are extracted from both traditional news media and from social media sources which creates challenging environment for word recognition techniques. Thus, the data analysis is customized for each source due to differences in communication styles between social and news media. Unlike news media, which uses standardized terms and appropriate tone in its contents, social media contains substantial amounts of sarcasm and irony, colloquial meanings, incomplete thoughts, misplaced punctuation, misspellings, non-standard grammar, case insensitivity and crude language. The expressions of emotions between news and social media also vary. In social media, authors tend to use nationally and regionally developed emotions (e.g., “:)”) and acronyms (e.g., “LOL”) to express themselves. In addition, unlike journalists of traditional news media, who are trained to offer multiple perspectives on the underlying story and go through editorial process, authors in social media have a tendency to express their own opinions and emotional states more directly. In the news, the role of journalists is to describe the emotional states of those they are reporting on. As a result, information obtained from social media is typically less inclusive of contrary viewpoints and more emotionally expressive from the first-person perspective than news information. As a result of all these differences, text analytical models are used to calibrate the text analytics by source type and different models are used for news, social media forums, tweets, SEC filings and earnings conference call transcripts.

A.3 Entity identification

Entities are identified with a list containing more than 60,000 entity names and their aliases which include e.g. different language specific writing forms of locations and firms. TRMI uses anti-correlate filters to exclude irrelevant entities. For example, gold and silver are typically mentioned every two years during the Olympic Games but they are not related to gold and silver commodities. Similarly, references to South Korean Won could be either used to refer to victories achieved by South Korean athletes or to South Korea's currency. Also, the entities should have a correct co-references. For example, "breakfast oats" are not counted as a correct reference to commodity Oats unless it is accompanied with key identification correlates such as "prices" or "futures".

A.4 Timing

TRMI has several variables referring to expectations. The text-analytics software is calibrated to identify verb tenses in every phrase and is able to recognize when the references are future-oriented and hence related to expectations. For example, "Optimism" is a difference between references to future-oriented positive and negative comments and for example to "Uncertainty", any references to past uncertainties are excluded from the analysis.

A.5 Modifiers and negations

Modifier words change the meaning or tone of a phrase or sentence by modifying its impact. For example, words or phrases that increase the significance of an adjective, such as "large", (e.g., "large loss") are multiplicative on the weighting of the modified word whereas minimizers like "a little" and "a handful" multiply the meaning score by 0.5. Modifiers can either increase (maximizers) or decrease (minimizers) the score of a key term and thus affect the scoring of textual meaning. In cases of frequent meanings based on simple word relationships, like the word "new", a multiplier is used to minimize the weight of the meaning. For example, in the case of "new" the multiplier is 0.1 when that meaning is used in the Innovation index. Data also takes into account the differences between news headlines and article bodies. Headlines have a multiplicative weight of 3, subtitles a weight of 2 and bodies a weight of 1 in the data formation. In addition to the maximizing and minimizing operations, the data formation takes into account negations. For example, the phrase "I'm not worried about the earnings release" connotes that the author is not afraid, and as a result, the extracted fear score is negated (-1).

A.6 Source texts

The TRMI measures are from two groups of sources, news and social media, and the data consists of three feeds: news feed, social media feed and an aggregate feed of combined news and social media content. TRMI processes more than two million articles daily and the data are updated minutely. Each minutely value is an average of the past 24 hours of observations about the target entity. As sources, TRMI uses data from the largest and most important news organizations, global internet news coverage, and a broad and credible range of social media sources. The TRMI news indices are derived from content delivered in Thomson Reuters News Feed Direct and two Thomson Reuters news archives: a Reuters-only one from 1998 to 2002 and one with Reuters and select third-party wires from 2003 onwards. In 2005, Moreover Technologies aggregate news feed was incorporated to the data adding 50 000 internet news sites to the sources. In addition, hundreds of financial news sites and finance specific sources widely read by professional investors are also included in the data. MarketPsych social media content has been downloaded from public social media sites from 1998 onwards and the data from Moreover Technologies aggregate social media feed, which is derived from more than four million social media sites, was incorporated to TRMI in 2009.

A.7 Quantifying the articles

Each TRMI variable constitutes of a combination of minor components called PsychVars. To form a TRMI variable, the absolute values of PsychVars are first determined using 24 hours of observations. These absolute values are then summed for all constituents to get the Buzz-variable. More specifically, Buzz is calculated as follows:

$$Buzz_t(a) = \sum_{c \in C(a), p \in P} |PsychVar_{c,p,t}|,$$

where t denotes time, a is the entity, $C(a)$ is the set of all constituents of a (for example, for indices, $C(a)$ consists of all individual assets comprising the index) and $P(s)$ is the set of all PsychVars relevant to a particular TRMI variable s.

For the other TRMI variables, the values are calculated as follows:

$$TRMI_{s,t}(a) = \frac{\sum_{c \in C(A), p \in P(s)} I_t(s,p) \times PsychVar_{p,t}(c)}{Buzz_t(a)},$$

where $I_t(s,p)$ defines whether a PsychVar $p \in P(s)$ is additive or subtractive to a TRMI variable s at time t:

$$I_t(s,p) = \begin{cases} +1, & \text{if additive at time } t; \\ -1, & \text{if subtractive at time } t. \end{cases}$$

A single PsychVar can contribute to multiple TRMI variables. For example, EarningsUp_f PsychVar (see below for an example) is a constitute of all, EarningsForecast, Sentiment, Optimism and FundamentalStrength TRMI variables.

A.8 Sentence-level Example

The following shows an example of the TRMI data generating process using the above mentioned principles. Consider the following sentence:

"Analysts expect Mattel to report much higher earnings next quarter"

The language analyzer performs the following sequence:

1. Associates ticker symbol MAT with entity reference "Mattel".
2. Identifies "earnings" as an Earnings word in the lexicon.
3. Identifies "expect" as a future-oriented word and assigns future tense to the phrase.
4. Identifies "higher" as an Up-Word (positive reference).
5. Multiplies "higher" by 2 due to presence of the modifier word "much".
6. Associates "higher" (Up-Word) with "earnings" (Earnings) due to proximity.

The analysis algorithm will report:

Date	Time	Ticker	PsychVar	Score
20110804	15:00.123	MAT	EarningsUP_f	2

In the example above, 2 is the raw score produced for EarningsUp_f.

Table A1 Source of Media and Social Media of the TRMI index

Item	Type	Name
1	earnings call transcripts	earning_calls
2	earnings call transcripts	streetevents
3	events	evt_call_presentation
4	events	evt_call_qa
5	events	evt_corporate_call
6	events	evt_earning_call
7	events	evt_merger
8	events	evt_other
9	events	evt_sales_call
10	events	evt_shareholder_meeting
11	news	TR_NFD
12	news	tr_factiva
13	news	associated_press_all
14	news	associated_press
15	news	associated_press_health
16	news	associated_press_politics
17	news	associated_press_science
18	news	associated_press_technology
19	news	associated_press_top
20	news	associated_press_us
21	news	associated_press_world
22	news	bloomberg
23	news	bloomberg_economy
24	news	bloomberg_regions
25	news	bloomberg_stocks
26	news	blooomberg_bonds
27	news	forbes_all
28	news	forbes_asia
29	news	forbes_business
30	news	forbes_entrepreneurs
31	news	forbes_europe
32	news	forbes_markets
33	news	forbes_personal
34	news	forbes_technology
35	news	google_business
36	news	marinet
37	news	marinet_barrons
38	news	marinet_ft
39	news	marinet_nytimes
40	news	marinet_nytimes_A

Table A1 (continued)

Item	Type	Name
41	news	marinet_nytimes_B
42	news	marinet_nytimes_C
43	news	marinet_nytimes_Other
44	news	marinet_wsj
45	news	marinet_wsj_A
46	news	marinet_wsj_B
47	news	marinet_wsj_C
48	news	marinet_wsj_Other
49	news	marketwatch
50	news	marketwatch_stocks
51	news	marketwatch_top
52	news	motley_fool
53	news	msn_money
54	news	ny_times
55	news	reuters
56	news	financial_times
57	news	wall_street_journal
58	news	time_magazine
59	news	new_york_times
60	news	usa_today
61	news	wallstreet_247
62	news	yahoo_all
63	news	yahoo_earnings
64	news	yahoo_stock_markets
65	news	yahoo_top
66	news	yahoo_us_economy
67	news	nfd_unknown
68	news	moreover_rank_1
69	news	moreover_rank_2
70	news	moreover_rank_3
71	news	moreover_rank_4
72	news	moreover_rank_5
73	news	moreover_rank_6
74	news	moreover_rank_7
75	news	moreover_rank_8
76	news	moreover_rank_9
77	news	moreover_rank_10
78	news	moreover_unknown
79	news	cnbc.com
80	news	cnn
81	news	cnn_fortune
82	news	cnn_moneymagazine
83	news	cnn_others
84	news	the_economist
85	news	benzinga
86	news	themotelyfool
87	press releases	business_wire
88	press releases	businessweek_all
89	press releases	businessweek_asia
90	press releases	businessweek_brandequity

Table A1 (continued)

Item	Type	Name
91	press releases	businessweek_byteoftheapple
92	press releases	businessweek_careers
93	press releases	businessweek_europe
94	press releases	businessweek_europeinsight
95	press releases	businessweek_eyeonasia
96	press releases	businessweek_innovate
97	press releases	businessweek_inv
98	press releases	businessweek_investinginsights
99	press releases	businessweek_smallbiz
100	press releases	businessweek_technology
101	press releases	businessweek_top
102	press releases	bwire_analysis
103	press releases	bwire_auto
104	press releases	bwire_comm
105	press releases	bwire_construction
106	press releases	bwire_consumer
107	press releases	bwire_defence
108	press releases	bwire_dividends
109	press releases	bwire_earnings
110	press releases	bwire_education
111	press releases	bwire_energy
112	press releases	bwire_entertainment
113	press releases	bwire_environment
114	press releases	bwire_health
115	press releases	bwire_investment_opinions
116	press releases	bwire_manufacturing
117	press releases	bwire_mergers_acquisitions
118	press releases	bwire_nat_resources
119	press releases	bwire_philantrophy
120	press releases	bwire_prof_services
121	press releases	bwire_public
122	press releases	bwire_ratings
123	press releases	bwire_retail
124	press releases	bwire_sales
125	press releases	bwire_science
126	press releases	bwire_split_issue_buyback
127	press releases	bwire_sports
128	press releases	bwire_technology
129	press releases	bwire_transport
130	press releases	bwire_travel
131	press releases	multivu
132	press releases	prnewswire
133	press releases	prwire_agriculture
134	press releases	prwire_auto
135	press releases	prwire_construction
136	press releases	prwire_defense
137	press releases	prwire_earning_forecasts
138	press releases	prwire_earnings
139	press releases	prwire_energy
140	press releases	prwire_entertainment

Table A1 (continued)

Item	**Type**	**Name**
141	press releases	prwire_financial
142	press releases	prwire_health
143	press releases	prwire_insurance
144	press releases	prwire_investor_opinions
145	press releases	prwire_joint_ventures
146	press releases	prwire_manufacturing
147	press releases	prwire_mergers
148	press releases	prwire_public
149	press releases	prwire_public_offerings
150	press releases	prwire_rating
151	press releases	prwire_real
152	press releases	prwire_restructuring
153	press releases	prwire_retail
154	press releases	prwire_sales
155	press releases	prwire_split
156	press releases	prwire_sports
157	press releases	prwire_tech
158	press releases	prwire_transport
159	press releases	prwire_travel
160	regulatory filings	sec_1-a
161	regulatory filings	sec_10-k
162	regulatory filings	sec_10-k-notes
163	regulatory filings	sec_10-q
164	regulatory filings	sec_10-q-mda
165	regulatory filings	sec_10-q-notes
166	regulatory filings	sec_144
167	regulatory filings	sec_2-a
168	regulatory filings	sec_4
169	regulatory filings	sec_8-a
170	regulatory filings	sec_8-k
171	regulatory filings	sec_d
172	social	seeking_alpha
173	social	SMB
174	social	global_smb
175	social	smb_old
176	social	STOCKTWITS
177	social	twitter
178	social	seeking_alpha_soc
179	social	stocktalks
180	social	instablogs
181	social	seeking_alpha_soc_articles
182	social	the_street
183	social	moreover_sm_rank_1
184	social	moreover_sm_rank_2
185	social	moreover_sm_rank_3
186	social	moreover_sm_rank_4
187	social	moreover_sm_rank_5
188	social	moreover_sm_rank_6
189	social	moreover_sm_rank_7
190	social	moreover_sm_rank_8

Table A1 (continued)

Item	**Type**	**Name**
191	social	moreover_sm_rank_9
192	social	moreover_sm_rank_10
193	social	moreover_sm_unknown
194	social	advfn
195	social	aimsoiree
196	social	austockforums
197	social	babypips
198	social	bigmiketrading
199	social	canbusiness
200	social	commodityville
201	social	dailyfx
202	social	elitetrader
203	social	forexadobe
204	social	forexfactory
205	social	forextips
206	social	hotcopper
207	social	hotstockmarket
208	social	intercativeinvestor
209	social	invested
210	social	investorshub
211	social	londonsoutheast
212	social	mt5
213	social	mystockbuddy
214	social	puntersgallery
215	social	sgtalk
216	social	shareinvestor
217	social	sharejunction
218	social	sharescene
219	social	sharesguru
220	social	silinvestor
221	social	stockbank
222	social	stockhouse
223	social	stockmarketreview
224	social	stockopedia
225	social	stockrants
226	social	superstockpiker
227	social	tfccommodities
228	social	thebull
229	social	thisismoney
230	social	topstocks
231	social	trade2win
232	social	traderslog
233	social	traderstalk
234	social	valuebuddies
235	social	valueforum