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Using Sentiment to Predict GDP Growth and Stock Returns

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Abstract:

This study sheds new light on the question of whether or not sentiment surveys, and the expectations derived from them, are relevant to forecasting economic growth and stock returns, and whether they contain information that is orthogonal to macroeconomic and financial data. I examine 16 sentiment surveys of distinct respondent universes and employ the technique of principal components analysis to extract the common signals from the surveys. I show that the ability of different population groups to anticipate correctly economic growth and excess stock returns is not identical, implying that not all sentiment is the same, although there exist some common components. I demonstrate that sentiment surveys have significant predictive power for both GDP growth and excess stock returns, and that the results are robust to the inclusion of information pertaining to the macroeconomic environment and momentum. Furthermore, the findings reject the conventional wisdom that the effect of sentiment is apparent exclusively in small-capitalization stocks.

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Section 1 Introduction

The American Heritage Dictionary defines "sentiment" as "a thought, view, or attitude, especially one based mainly on emotion instead of reason." By the same token, it defines something that is "not endowed with reason" to be "irrational." Hence, "sentiment" is largely regarded as "emotional" and "irrational." Classical asset pricing theory makes no provision for such an irrational component in determining asset prices, particularly in long-run equilibrium. Yet, it remains a favorite statistic for financial media and popular press and is the source of endless commentary by market pundits and economists alike. Indeed, the financial press often credits or blames "sentiment" for a rising or falling stock market. If markets do, in fact, react to reports of changes in sentiment, then this indicates that the reality of asset pricing contradicts the theory of asset pricing. This suggests an oversight on the part of the academic literature in failing to give sentiment the importance it may warrant in the theory of asset pricing.

Academics have only recently begun to examine what role, if any, sentiment may have in the theory of asset pricing. However, consensus is lacking regarding its most basic characteristics. The literature remains divided not only about whether or not sentiment matters for asset prices, but also about what sentiment actually is, and how best to measure and incorporate it in a theoretical framework. I focus here on the empirical aspects of sentiment, its measurement, and its predictive power for the real economy as well as for financial markets.

Sentiment has no explicit role in traditional asset pricing models. The omission of sentiment from classical finance is rather curious, considering the key role played by emotion in the theories of Bentham (1781), one of the most influential early utilitarian philosophers. Bentham's concept of utility "…meant that property in any object, whereby it tends to produce benefit, advantage, pleasure, good, or happiness…or … to prevent the happening of mischief, pain, evil, or unhappiness to the party whose interest is considered…" As Lowenstein (2000) notes, neoclassical economists later rendered the utility construct devoid of its emotional content in a process that "…culminated in the development of ordinal utility and the theory of revealed preference which construed utility as an index of preference rather than of happiness." Classical finance has evolved around the mathematical concepts of mean-variance optimization, rational maximization of preferences, equilibrium analysis, and no-arbitrage arguments, but it has largely neglected a key ingredient of financial markets: human emotion.

The pioneering work of Katona (1951, 1957, 1975) seeks to address the confluence of emotions and economics. His psychological approach to consumption prescribes that both *capacity* and *willingness* to buy are primary determinants of the consumption function. From this treatment one can infer that sentiment, i.e., something generally regarded as irrational, should be considered a bona fide component of expectations formation. Katona's theories build upon the notion of "animal spirits" put forth by Keynes (1936). Notable contributions to the theory of emotions in economics are made by Elster (1998), Lowenstein (2000), Thaler (2000), and Romer (2000). Romer succinctly echoes Katona's theories by stating that "…economists can usefully segregate decision mechanisms into two broad categories: those based on thoughts and those based on feelings…," and suggests that the profession should "…treat thoughts and feelings more symmetrically."

In this chapter, I aim to establish a definitive role for sentiment in macroeconomic forecasting and asset pricing by answering the following question: do the attitudinal data obtained from sentiment surveys

contain any predictive power for economic growth and asset prices beyond the predictive information contained in macroeconomic and financial data? To answer this question, I examine 16 popular sentiment surveys of businesses and households, and test their ability to predict GDP growth as well as aggregate excess stock returns. I construct a composite sentiment factor using all of the sentiment survey indexes and then create separate factors for the sentiments of businesses and of households, for a total of three composite measures – All (APC), Business (BPC), and Household (HPC). I use the technique of principal components analysis to extract the common elements from sentiment surveys and create the composite factors. This signal-extraction technique allows a large collection of dynamic factors to be distilled into a few key measures that illustrate the joint effects of many popular surveys.

Section 2 presents a review of the related literature. Data and methodology are discussed in Section 3. The relation between sentiment indexes and macroeconomic factors is the focus of Section 4, as is the use of sentiment surveys in conjunction with the CQM model of Klein and Sojo (1989), a high-frequency model used to forecast GDP growth.[3] Section 5 investigates the predictive power of sentiment for excess returns of aggregate stock indexes, controlling for macroeconomic factors and lagged stock returns, and section 6 concludes.

Section 2 Literature Review

Section 2.1 Sentiment Measures

There are various purported measures of investor sentiment in the literature, but most of the measures are indirect, and no consensus has been reached regarding the appropriate measure. Perhaps the most controversial of these hypothesized sentiment proxies has been the closed-end fund discount (CEFD), i.e.,

[3] Please refer to the chapter "The Making of National Economic Forecasts – Introduction" by Lawrence R. Klein for more details regarding the CQM high frequency forecasting model for the United States.

the difference between the price of the fund and its net asset value.[4] The closed-end fund discount is first noted by Wiesenberger (1946). The concept is later refined by Zweig (1973), Malkiel (1977), and Lee, Shleifer, and Thaler (1991), and further investigated by Swaminathan (1996), with all of these authors claiming that the discount on closed-end funds is a measure of investor sentiment that has predictive power for stock returns. Lee, et. al. (1991) contend that closed-end funds are held mainly by individual investors and the discount shows a relation to the performance of small stocks, which are also disproportionately held by individual investors; hence, the discount reflects the sentiments of individual investors. However, other researchers, including Chen, Kan, and Miller (1993) and Elton, Gruber, and Busse (1998), dispute the validity of the CEFD as a measure of investor sentiment and its ability to predict returns.

Other researchers construct sentiment measures from a variety of indicators, extracting purported sentiment factors from a collection of noisy proxies. Brown and Cliff (2004) use the Kalman filter technique and principal components analysis to create a sentiment factor from a collection of indicators, including the number of advancing issues to declining issues on the NYSE, the Arms index, the percent change in margin borrowing, the percent change in short interest, the odd-lot ratio, the ratio of CBOE equity puts to calls, the number of IPOs, and net purchases of mutual funds. They report that the sentiment proxies have little ability to predict short-run stock returns, but display a strong contemporaneous relationship with returns. Baker and Wurgler (2006) use principal components analysis to construct a sentiment factor from the CEFD, NYSE share turnover, the number of IPOs, the average first-day returns on IPOs, the share of equity issues in total equity and debt issues, and the dividend premium. The authors note an inverse relationship between their purported sentiment measure and subsequent returns.

[4] Alternatively measured as the fund premium divided by net asset value.

Evidence on the ability of the commonly cited indirect sentiment measures to forecast stock returns is mixed. The conventional wisdom seems to be that if these measures have any power to predict returns, they can do so only for small-capitalization stocks. The problem with using market-based statistics as proxies for investor sentiment is that these indirect measures might be reflections of sentiment, but they might also be the result of other market forces. For example, Chen, et. al. (1993) point out that the closed-end fund discount may not be a proxy for market-wide investor sentiment, but only an indication of investor confidence in the closed-end funds themselves. Manski (2004) emphasizes that "…observed choice behavior may be consistent with many alternative specifications of preferences and expectations." Because market measures are indirect, their accuracy as measures of investor sentiment cannot be known with any degree of certainty, as they are merely by-products of market activity, and that activity need not necessarily be a result of sentiment. Therefore, it is possible that the indirect measures, i.e., sentiment proxies, and the direct measures, i.e., sentiment surveys, may not measure the same thing.

Section 2.2 Survey Data

The most obvious way to measure investor sentiment is by directly polling market participants and soliciting their opinions. Surveys ask respondents to report probabilistic expectations of significant personal financial or general economic events. Financial market participants can be broadly categorized as either Households or Businesses. Households participate in markets as both investors and consumers. Consumers influence stock prices not only by purchasing goods and services from publicly traded companies thereby affecting sales and reported earnings, but also because consumer spending represents approximately two-thirds of GDP in the U.S. With the increased popularity of discount brokerages and online investing over the past couple of decades, many consumers are now also individual investors involved in direct trading, in addition to participating in the stock market via mutual funds and 401Ks.

Households, consisting of consumers and investors, have gained increased exposure to, and influence in, the stock market in recent years.

Businesses are also important market participants. They are the listed companies themselves, or the suppliers, customers, or strategic partners of the listed companies, and their economic health determines general economic growth as well as the discount rates used in asset valuation. Thus, today's stock market brings together Households and Businesses like never before, highlighting the need to identify a direct and sensible way to measure the perceptions, sentiments, and expectations of these market participants and determine whether or not they contain any predictive power for economic quantities of interest.

Over the years, survey data has had its share of detractors who sought to discredit its use in economic forecasting. Opponents argue that people do not always do as they say, and many economists dismiss the use of subjective data out of hand. Nevertheless, there are some legitimate concerns about the quality of the data elicited from surveys. Campbell (2004) points out that the most serious concern is whether respondents answer survey questions accurately. Most surveys cannot be used to track expectations of particular individuals through time, since they are series of cross-sections and not complete panels. Additionally, surveys are always subject to sampling error and other measurement issues. Additional concerns pertain to the manner in which questions are posed and responses elicited. Dominitz and Manski (2003) point out that certain phrases in survey questions such as "better off" may be subject to interpretation. Survey data are imprecise because they represent an attempt to construct a *quantitative* measure of human attitudes, which are inherently *qualitative*.

But, it is clear that observed choice data alone are insufficient for empirical analysis of decisions made when the information set is imperfect, as in the sense of Grossman and Stiglitz (1980), or incomplete.

Manski (2004) contends that the assumption of rational expectations is implausible in decision-making with partial information. He advocates measuring expectations with survey data using subjective probabilities rather than the standard practice of revealed preference analysis, i.e., inferring decision processes from data on observed choices. The goal is to use self-reported data on expectations to relax or validate the assumptions regarding expectations that underlie economic models.

It appears that survey data may indeed be on the verge of a renaissance, with many researchers now taking an interest in sentiment surveys, and exploring their ability to explain how investors form expectations and their usefulness in forecasting the economy and asset returns.

Section 2.3 The Predictive Power of Survey Data – The Evidence So Far

Section 2.3.1 Consumer Sentiment – Macroeconomic Literature

Most of the early work on expectations derived from surveys examines the University of Michigan's Surveys of Consumers and its ability to predict consumer spending. Klein and Lansing (1955) find that survey questions on buying intentions, feelings of financial well-being and price expectations are predictive of consumer expenditures on durable goods.[5] Mueller (1963) reports that lagged values of the University of Michigan surveys have predictive power for household expenditures on durable and non-durable goods.

Some researchers contend that surveys lose their predictive power once other financial and macroeconomic variables enter the specification. Hymans, et. al. (1970) find that the University of Michigan Index of Consumer Sentiment (ICS) can forecast automotive spending, but that lagged values of income, consumer prices, and changes in stock prices can forecast the ICS. Mishkin (1978) finds that the

[5] Klein and Lansing (1955) studied a "re-interview" sample of the 1953 Survey of Consumer Finances conducted by the Survey Research Center of the University of Michigan, a precursor to the University of Michigan's Index of Consumer Sentiment.

University of Michigan ICS significantly predicts consumer expenditures on durable goods, but this relationship does not hold once financial variables are taken into account. Leeper (1992) uses a vector autoregression (VAR) framework to examine the relationship between consumer sentiment, industrial production, and unemployment, and also finds that the relationship significantly weakens once stock prices and T-bill rates are included in the analysis.

Garner (1991) asserts that consumer confidence indexes aid in forecasting aggregate consumption only during major economic or political events. Similarly, Throop (1992), using a five-variable vector-error-correction model (VECM), finds that in times of turbulence such as the Gulf War and the 1987 stock market crash, consumer sentiment can move independent of economic fundamentals, thus providing unique insights about future consumer expenditures. However, Throop noted that during normal periods, forecast results are slightly worse when sentiment is included in the specification than when it is omitted. The notion that sentiment is a particularly valuable forecasting tool during times of turmoil concurs with Katona's (1975) suggestion that the University of Michigan Surveys of Consumers reflect psychological factors that become pronounced during extraordinary periods of social, political, or economic upheaval.

Matsusaka and Sbordone (1995) find that fluctuations in consumer sentiment account for between 13 percent and 26 percent of the variance of GNP innovations, even after controlling for a collection of economic indicators, demonstrating that expectations play a non-trivial role in forecasting output. Bram and Ludvigson (1998) run a horserace of the University of Michigan ICS versus the Conference Board's Consumer Confidence Index (CCI) and compare their relative abilities to forecast five categories of household expenditures: total, motor vehicles, all goods excluding motor vehicles, services, and durable goods excluding motor vehicles. The authors report that sentiment can help predict consumption, even after including control variables, and also suggest that consumer attitudes may provoke economic

fluctuations.[6] Howrey (2001) finds that the University of Michigan ICS is a statistically significant predictor of real GDP growth and provides an informative signal about the probability of recession. Klein and Ozmucur (2002) and (2004) demonstrate that models incorporating sentiment surveys of consumers, producers, or managers to forecast economic quantities such as personal consumption expenditures, personal income, and industrial production perform significantly better than models that do not include the surveys.

Section 2.3.2 Surveys and the Stock Market – Asset Pricing Literature

Despite their potential methodological shortcomings, surveys uniquely provide a direct measure of investor expectations. Yet, most of the literature concerning the predictive power of surveys has focused on macroeconomic forecasting and limited use has been made of examining the predictive power of sentiment surveys in forecasting stock market returns. De Bondt (1993) considers the American Association of Individual Investors (AAII) survey and finds that the sentiment of small investors displays a bias towards extrapolation of past market trends. Otoo (1999) examines the relation between stock returns and the University of Michigan ICS and Conference Board CCI surveys, and reports that returns share a strong contemporaneous relation with the surveys, but lagged changes in sentiment have no explanatory power for stock returns. Fisher and Statman (2000) investigate the Merrill Lynch survey of sell-side strategists, the AAII survey of individual investors, and the Investors Intelligence (II) survey of investment newsletter writers, and conclude that the sentiments of these three groups of market participants are not identical.[7] Lee, Jiang, and Indro (2002) employ a GARCH (Generalized

[6] Bram and Ludvigson (1998) estimate the relation between the difference of logs in consumption and the ICS and CCI sentiment indexes, and include a vector of control variables that contains the lagged dependent variable, lagged growth in real labor income, lagged log first difference in the real S&P500 index, and lagged first difference of the three-month T-bill rate.

[7] These three surveys were omitted from this study because they are of questionable value. The Merrill Lynch survey of sell-side strategists is likely to have a pronounced optimistic bias towards over-weighting stocks in its recommended asset allocation. The AAII survey suffers from self-selection bias (members can take the survey as often as they wish on the AAII website), while the II survey depends on a subjective classification of newsletter writers, which can be influenced by the personal opinions or cognitive biases of the newsletter readers who determine the classification.

Autoregressive Conditional Heteroskedasticity) model to examine the relation between the II survey and stock returns and report that sentiment is a significant factor in explaining both excess returns and the conditional volatility of returns.

Guzmán (2003) finds that the Union Bank of Switzerland/Gallup Index of Investor Optimism surveys have significantly more predictive power than either the University of Michigan ICS or the Conference Board CCI surveys. Brown and Cliff (2005) study the relationship between the II survey and market-implied pricing errors from an independent valuation model, and find that the relationship is positive. Additionally, they report that sentiment is negatively related to future returns over multi-year horizons. Charoenrook (2005) examines the University of Michigan ICS and finds a negative relation with future excess returns at horizons of one month and one year. In addition, the author reports that the predictive power of consumer sentiment appears to be unrelated to economic cycles or time-varying expected returns. Lemmon and Portniaguina (2006) investigate the relationship between returns and the University of Michigan ICS and Conference Board CCI, and determine that the surveys forecast returns of small stocks and stocks with low institutional ownership. Finally, Verma and Verma (2007) use the II survey as a proxy for the sentiments of institutional investors and the AAII survey as a proxy for the sentiments of individual investors, and conclude that the former are more rational than the latter.

To my knowledge, this chapter is the first to examine a large collection of sentiment surveys of distinct respondent universes, extract their common signal, and test its ability to predict GDP growth and excess stock returns.

Section 3 Data and Methodology

I study a total of 16 sentiment surveys. They are:

1) Institute for Supply Management Purchasing Managers' Index (ISM)

2) National Association of Purchasing Management - Chicago Business Barometer Index (NPM)

3) The Philadelphia Federal Reserve Business Outlook Survey (FED)

4) National Association of Home Builders-Wells Fargo Builders Index - Headline (HMI)

5) National Association of Home Builders-Wells Fargo Builders Index - Next 6 Months (HM6)

6) National Association of Home Builders-Wells Fargo Builders Index - Present Conditions (HMP)

7) National Association of Home Builders-Wells Fargo Builders Index - Traffic (HMT)

8) University of Michigan Index of Consumer Sentiment - Headline Preliminary (MIP)

9) University of Michigan Index of Consumer Sentiment - Current Conditions Preliminary (MCP)

10) University of Michigan Index of Consumer Sentiment - Expectations Preliminary (MXP)

11) Conference Board Consumer Confidence Index - Headline (CBH)

12) Conference Board Consumer Confidence Index - Present Situation (CBP)

13) Conference Board Consumer Confidence Index - Expectations (CBX)

14) Union Bank of Switzerland/Gallup Index of Investor Optimism - Headline (UBS)

15) Union Bank of Switzerland/Gallup Index of Investor Optimism - Personal Financial (UBP)

16) Union Bank of Switzerland/Gallup Index of Investor Optimism - Economic (UBE)

Broadly speaking, the first seven of these can be classified as surveys of Businesses and the remainder can be classified as surveys of Households. A brief description of each survey follows.

The Institute for Supply Management™ (ISM) publishes the Manufacturing ISM Report On Business® (ROB) each month. The ROB is based on data compiled from purchasing and supply executives nationwide. The Purchasing Managers Index (PMI) is a composite index featured in the ROB based on the seasonally adjusted diffusion indexes for the following five indicators, with varying judgmental weights applied: New Orders 30%, Production 25%, Employment 20%, Supplier Deliveries 15%,

Inventories 10%. A PMI reading above 50 percent indicates that the manufacturing economy is generally expanding; below 50 percent indicates that it is generally contracting.[8]

The National Association of Purchasing Management - Chicago compiles a monthly survey and a composite diffusion index of business conditions in the Chicago region. The Chicago Business Barometer™ Survey registers manufacturing and non-manufacturing activity. Investors care about this indicator because the Chicago region mirrors the nation in its distribution of manufacturing activity. The NAPM-Chicago survey often moves together with the ISM index, but is reported one day in advance.[9]

The Philadelphia Federal Reserve Business Outlook Survey has been produced monthly since 1968. This survey is a check-box variety sent to about 250 large manufacturing firms located in the Third Federal Reserve District.[10] Participants indicate the direction of change in overall business activity and in the various measures of activity at their plants: employment, working hours, new and unfilled orders, shipments, inventories, delivery times, prices paid, and prices received.[11]

The National Association of Home Builders (NAHB) and Wells Fargo & Company produce the National Association of Home Builders-Wells Fargo Builders Index, a monthly survey of home builder sentiment, to gauge the demand side of the single-family housing market in the U.S. The headline Housing Market Index (HMI) is a weighted average of responses to survey questions asking respondents to rate three aspects of their local market conditions: current sales of single-family detached new homes, expected

[8] Source: Institute for Supply Management website: http://www.ism.ws/ISMReport/content.cfm?ItemNumber=10706&navItemNumber=12957.
[9] Source: National Association of Purchasing Management – Chicago website: http://napm-chicago.net/home/content/view/22/43/.
[10] The Third Federal Reserve District comprises Delaware, New Jersey, and Pennsylvania.
[11] Source: The Philadelphia Federal Reserve website: http://www.philadelphiafed.org/econ/bos/.

sales of single-family detached new homes over the next 6 months, and traffic of prospective buyers in new homes.[12]

The University of Michigan Surveys of Consumers are conducted by the Survey Research Center at the University of Michigan and were developed in 1946 under the direction of George Katona. Each monthly survey comprises approximately 50 core questions covering three broad areas of consumer sentiment: personal finances, business conditions, and buying conditions. Five of these core questions form the Index of Consumer Sentiment (ICS). The survey is based on approximately 500 telephone interviews of adult men and women living in households in the coterminous United States. The sample is designed to maximize the study of change by incorporating a rotating panel sample design in an ongoing monthly survey program. This design provides for the regular assessment of change in attitudes and behavior, both at the aggregate and at the individual level. Three indexes from the University of Michigan Surveys of Consumers are considered in this study: University of Michigan Index of Consumer Sentiment - Headline Preliminary (MIP), University of Michigan Index of Consumer Sentiment - Current Conditions Preliminary (MCP), University of Michigan Index of Consumer Sentiment - Expectations Preliminary (MXP).[13, 14]

The Conference Board Consumer Confidence Survey is conducted monthly by TNS.[15] The Consumer Confidence Index is based on responses to five questions included in the survey. The questionnaires are mailed to a nationwide representative sample of 5,000 households, of which roughly 3,500 typically respond. Each month, a different panel of 5,000 households is surveyed. The survey asks respondents to

[12] Source: National Association of Home Builders.
[13] Source: Surveys of Consumers, Survey Research Center at the University of Michigan.
[14] The Final values for the Michigan ICS, Current, and Expectations Indexes are omitted in order to avoid information overlap, as the Final indexes are sometimes released in the first few days of the subsequent month.
[15] A caveat is in order regarding The Conference Board data. The data published by The Conference Board are revised data and the organization states it does not maintain the preliminary data. The preliminary number is released at the end of the month for any given survey month. However, this number is overwritten with the final number at the end of the subsequent month. Thus, the data may suffer from look-ahead bias. The Conference Board claims that the difference between the preliminary and final number is not statistically significant, so they were included in the analysis.

give their: (1) appraisals of current business conditions, (2) expectations regarding business conditions six months hence, (3) appraisals of the current employment conditions, (4) expectations regarding employment conditions six months hence, and (5) expectations regarding their total family income six months hence. The Indexes are then averaged together as follows: the Consumer Confidence Index is the average of all five Indexes; the Present Situation Index is the average of Indexes for questions 1 and 3; and the Expectations Index is the average of Indexes for questions 2, 4, and 5.[16]

Union Bank of Switzerland and The Gallup Organization formed a partnership in October of 1996 to create a new index that would systematically track investor perceptions of the economy on a monthly basis. For the Union Bank of Switzerland/Gallup Index of Investor Optimism, an investor is defined as a male or female head of household, with investments totaling $10,000 or more.[17] "Average investors" are those having between $10,000 and $100,000 of investable assets and represent about two-thirds of all investor households, while households having investments of $100,000 or more are classified as "substantial investors" and account for one-third of all investor households. Gallup interviews a random sample of approximately 1,000 U.S. investor households during the first two weeks of every month, and the results are reported at the end of the month. The survey methodology is the same as that used for the Gallup poll.[18] Seven questions are used to construct the Index of Investor Optimism. The questions are designed to measure two dimensions of optimism: three questions measure the personal financial dimension and four questions measure the general economic dimension.

This study examines the *changes* in survey-derived expectations and their relation to GDP growth and excess stock returns. Therefore, most of the survey data are transformed using the difference of logs. The exceptions are The Philadelphia Federal Reserve Business Outlook Survey, which is transformed using

[16] Source: The Conference Board.
[17] According to UBS/Gallup, in 1996, about one in three households qualified as investors based upon this definition. By 2003, the proportion had increased to about 40%.
[18] Source: UBS/Gallup.

the first difference, and Union Bank of Switzerland/Gallup Index of Investor Optimism - Personal Financial and Economic indexes, which are transformed using the first relative difference.[19] Note that the Union Bank of Switzerland/Gallup survey was conducted sporadically from October 1996 through January 1999, and has been conducted monthly since February 1999.[20] For the purposes of this study, data from October 1996 through January 1999 are interpolated to create a monthly series of comparable length to the other series.[21, 22]

Table 1 provides summary statistics for the transformed series of sentiment survey changes, quarterly observations from February 1997 to May 2007.[23] The time series properties are also presented. Autocorrelations for each series are provided at 1, 3, and 12 lags, and none display significant autocorrelation. Augmented Dickey-Fuller tests reject at better than the 1% level the hypothesis that any of the series has a unit root. Some of the data are highly correlated, hence it is intuitively appealing to extract the common elements from this group of surveys and test the predictive power of the shared components.

Two main data techniques are employed in this chapter – the Almon or polynomial distributed lag (PDL) technique and principal components analysis (PCA). They are described briefly in this section.

A polynomial distributed lag is employed for the sentiment factor on the right-hand side of several regression equations. This is because the data are significant at more than one lag, but using more than one individual lag may induce multicollinearity and produce biased t-statistics on the individual regression coefficients. The PDL allows the use of more than one lag (with some constraints on

[19] This is because these series contained negative values, hence it was not possible to use difference of logs.
[20] As of January 2008, UBS and Gallup dissolved their partnership to conduct the surveys.
[21] Regression results were virtually identical using the interpolated series beginning in October 1996 and the non-interpolated monthly series beginning in February 1999.
[22] The sample period under study begins in February 1997 due to the availability of TIPS data, which are used to calculate the implied inflation expectation that is included among the indicators employed in constructing the macroeconomic factor.
[23] Quarterly observations are calculated as quarterly averages.

coefficients) and alleviates the multicollinearity concern. Additionally, the use of a PDL is consistent with Katona's (1975) notion that expectations follow a slow social learning process. Hence, the sentiment variable is assumed to follow a simple distributed lag of finite length n:

$$y_t = \sum_{i=0}^{n} w_i X_{t-i} + \varepsilon_t \qquad \text{for } t = 1, 2, \ldots, T. \quad (1)$$

This is based on the assumption that the lag weights lie on a polynomial of degree $p < n$:

$$w_i = \sum_{j=0}^{P} \lambda_j i^j \qquad \text{for } i = 0, 1, \ldots, n. \quad (2)$$

The specification used throughout the chapter is $p = 2$ (quadratic polynomial) and $n = 3$ lags.[24] End-point restrictions are imposed, with both the near-end and the far-end constrained to zero. Experiments with alternate PDL specifications did not improve the model. The sum of the PDL coefficients is reported.

Principal components analysis is a technique used to reduce multidimensional data sets to lower dimensions for analysis.[25] The use of PCA allows for a large set of correlated variables to be employed together, without the problem of multicollinearity, as the extracted factors are pairwise orthogonal. Sensitivity to units of measurement is avoided by standardizing the variables to have mean zero and unit variance, before calculating the principal components. Principal components of the indicators are formed by extracting the characteristic root of the correlation matrix of the variables. The result is a linear combination of the indicators that allows for a common signal to be distilled from the data, measuring the collective impact of several indicators at once while conserving degrees of freedom. I use PCA to extract a composite sentiment factor $S_{i,t}$ from a large set of survey indexes $X_{i,t-n}$. The survey data are set at the

[24] The specification includes contemporaneous and three lags, with near and far endpoint restrictions imposed.
[25] Please refer to the chapter "Current Quarter Model for Turkey" by Lawrence R. Klein and Suleyman Ozmucur for an excellent exposition on the method of principal components.

appropriate *n*-period data reporting lag, to reflect how they enter the information set, i.e., at time *t*, the *t-n* value of the sentiment surveys are known. Let the *i-th* principal component of the sentiment surveys be denoted:

$$S_{j,t} = \sum_{i=1}^{m} \gamma_{ij} X_{i,t-n} \qquad \text{for } i = 1, 2, \ldots, m. \tag{3}$$

Principal components are calculated using the 16 surveys: ISM, NPM, FED, HMI, HM6, HMP, HMT, MIP, MCP, MXP, CBH, CBP, CBX, UBS, UBP, and UBE. The goal is to capture the common variation among the different sentiment indexes, and test whether their joint effect has any predictive power for GDP growth and stock returns.

From these 16 surveys, three composite sentiment factors are constructed: 1) an aggregate sentiment factor constructed from All surveys of the various respondent groups, APC, using all 16 surveys (*m*=16); 2) a Business sentiment factor, BPC, formed from the 7 surveys of businesses (*m*=7); and 3) a Household sentiment factor, HPC, constructed from the 9 surveys of households, comprising consumers and investors (*m*=9). The principal components are formed using the quarterly average values of changes in the surveys.

Table 2 shows the eigenvectors and the variance proportions captured by the first three principal components of each group: All, Business, and Household. The first principal component of All surveys, APC1, explains 42.3% of the variance, while the first three principal components, APC1, APC2, and APC3, together capture 72.6% of the total variance of the system. The first principal component of Business surveys, BPC1, explains 52.9% of the variance, while the first three principal components, BPC1, BPC2, and BPC3 reflect 90.2% of the total variance of the Business group. The first principal component of Household surveys, HPC1, explains 64% of the variance, while the first three principal

components, HPC1, HPC2, HPC3 collectively represent 89.8% of the total variance of the Household group.

A macroeconomic factor $M_{i,t}$ is also constructed using principal components analysis. The goal is to determine if sentiment surveys merely reflect macroeconomic information, as some researchers have postulated, or if the surveys contain unique information. A broad collection is formed of 30 macroeconomic variables that are generally regarded as indicative of the economic cycle, such as new orders, housing starts, inflation, unemployment, industrial production, etc. The set of 30 macroeconomic indicators, hypothesized to have *a priori* importance for economic growth and asset prices, is loosely based on Matsusaka and Sbordone (1995), Klein and Ozmucur (2002), and Stock and Watson (2002). I construct the composite macroeconomic factor $M_{i,t}$ using principal components at time t with each indicator $I_{i,,t-n}$ lagged appropriately to reflect its own n-period data reporting lag. For example, CONSUMER_CREDIT enters the information set with a two-period reporting lag, while INDUSTRIAL_PRODUCTION is reported with a one-period lag. Thus, the principal components are calculated with each variable lagged to reflect how it enters the agent's information set at time t. Let the *i-th* principal component of the macroeconomic indicators be denoted:

$$M_{j,t} = \sum_{i=1}^{16} \gamma_{ij} I_{i,t-n} \qquad \text{for } i = 1, 2, \ldots 30 \quad (4)$$

Table 1 presents descriptive statistics for the macroeconomic indicators, as well as their associated data reporting lags. Most of the indicators were transformed using the difference of logs, with the exception of ratios and yield data, which were transformed using first differences. Whenever possible, the pre-update series is used rather than the revised historical series, as the goal is to replicate as closely as possible the real-time information set that is available to market participants. The Augmented Dickey-Fuller tests reject at the 1% level the hypothesis that any series has a unit root, with the exception of the three-month U.S. Treasury Bill (TBILL_3M) and total non-farm employment (NON-FARM_EMPLOYMENT) for

which the unit root hypothesis is rejected at the 5% level, and federal government net receipts as a percent of GDP (NET_GOV_RECEIPTS), for which the hypothesis cannot be rejected. The data are transformed and standardized prior to computing the principal components. Once again, quarterly average values are utilized.

Only the first principal component is employed in the analysis, and it captures 17.3% of the total variance of the system of macroeconomic indicators. The eigenvector of the first principal component of macroeconomic indicators is given by:

M1 = 0.057 NEW_ORDERS(t-2) + 0.046 UNFILLED_ORDERS(t-2) - 0.099 HOUSING_STARTS(t-1)
+ 0.093 CONSTRUCTION(t-2) - 0.079 BUILDING_PERMITS(t-1) - 0.132 HOURLY_EARNINGS(t-1)
+ 0.050 AVG_WEEKLY_HOURS(t-1) + 0.155 CPI(t-1) + 0.147 PPI(t-1) - 0.047 RETAIL_SALES(t-1)
- 0.025 TRADE-WEIGHTED_EXCHANGE_RATE(t-1) - 0.230 MONEY_SUPPLY(t-1)
- 0.143 CONSUMER_CREDIT(t-2) + 0.008 INVENTORY_SALES_RATIO(t-2) - 0.052 NET_GOV_RECEIPTS(t-1)
- 0.156 UNEMPLOYMENT_RATE(t-1) + 0.175 TIPS-IMPLIED_INFLATION(t-1) + 0.284 FED_FUNDS_RATE(t-1)
+ 0.280 PRIME_RATE(t-1) + 0.269 CORPORATE_BOND_RATE(t-1) + 0.328 TBILL_3M(t-1)
+ 0.060 EXPORT_IMPORT_RATIO(t-2) + 0.371 TBOND_YIELD_1YEAR(t-1) + 0.282 TBOND_YIELD_10YEAR(t-1)
+ 0.253 TBOND_YIELD_20YEAR(t-1) + 0.281 30-YR_FIXED_MORTGAGE(t-1)
+ 0.025 DISPOSABLE_PERSONAL_INCOME(t-1) + 0.161 INDUSTRIAL_PRODUCTION(t-1)
+ 0.200 NON-FARM_EMPLOYMENT(t-1) - 0.009 MANUFACTURING_AND_TRADE_SALES(t-1)

The eigenvector of the first principal component reveals that the factor is essentially a proxy for the slope of the yield curve. The coefficient loadings of the eigenvector elements are also the correlation coefficients between the principal component and the underlying variables.

Due to serial correlation in the residuals, Newey-West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors are employed throughout the analysis.

Section 4 Sentiment and GDP Growth

I begin by testing the ability of the sentiment factors to explain future GDP growth. The baseline regression measures the relation between GDP growth at time t, lagged GDP growth, and the lagged

composite macroeconomic factor. A fixed lag of one period and the PDL are each tested. The baseline model is:

$$GDP_t = c + \beta_1 GDP_{lag} + \beta_2 M1_{lag} + \varepsilon_t \quad (5)$$

The baseline results for the fixed lag are presented in Panel A of Table 3 and the results for the PDL are presented in Panel B. The one-period lag specification results in an adjusted R-squared of 0.079, while the PDL specification gives an adjusted R-squared of 0.277. The quarterly average macroeconomic factor, i.e., the first principal component of the macroeconomic indicators, is denoted MPC1 in Table 3, and it is significant at the 10% level for the one-period lag specification.

Next, the model is augmented to test whether any of the three composite sentiment factors (All, Business, or Household) has predictive power for future GDP growth over the baseline equation. The inclusion of a composite macroeconomic factor in a model that tests the ability of sentiment to forecast an economic variable such as GDP growth efficiently addresses the concerns of researchers such as Mishkin (1978), Leeper (1992), Carroll, et.al. (1994), and Bram and Ludvigson (1998), who hypothesized that sentiment may be made redundant by macroeconomic and financial information. If sentiment is merely a reflection of macroeconomic and financial information, then the sentiment-augmented regression should not have any incremental predictive power over the baseline equation. The sentiment-augmented model is estimated as:

$$GDP_t = c + \beta_1 GDP_{lag} + \beta_2 M1_{lag} + \beta_3 S1_{j,lag} + \varepsilon_t \quad \text{for } j = 1, 2, 3 \quad (6)$$

In the interest of parsimony, only the first principal component is utilized. Panel C of Table 3 reveals that APC1, the composite factor for All sentiment, is significant at the 5% level for one lag. The sign of the coefficient is negative. However, Table 2 indicates that the eigenvector for APC1 is negative since all of the elements have negative coefficients. Thus, APC1 is positively predictive of future GDP growth at one

lag, even after controlling for the persistence of GDP and a lagged composite macroeconomic factor. When sentiment is high, future GDP growth is high. The addition of APC1 to the model increases the adjusted R-squared by 5.8%. This result is driven mainly by the sentiment of Households rather than Businesses, since the specification with HPC1 is incrementally predictive, but the specification with BPC1 is not. The Household sentiment factor, HPC1, is statistically significant at the one percent level, and increases the adjusted R-squared by 6.2% for the one-period fixed lag. Note again that the eigenvector of HPC1 is negative, hence the factor is positively predictive of future GDP growth. The reverse is true for the PDL specification, displayed in Panel D: BPC1 is statistically significant at the one percent level and adds 2% to the adjusted R-squared, while HPC1 and APC1 are not statistically significant.

Next, I examine the predictive power of the composite sentiment factors when used in conjunction with the Current Quarter Model (CQM) of Klein and Sojo (1989), for forecasting GDP growth in the United States. The baseline relationship is estimated as:

$$GDP_t = c + \beta_1 CQM_t + \varepsilon_t \tag{7}$$

Panel A of Table 4 presents the results of the baseline model of GDP growth regressed on the average of the CQM high frequency forecasts made throughout the quarter. The relevant null hypothesis for the baseline regression is $\beta_1 = 1$. If the CQM is a good forecasting model, it should almost perfectly explain GDP growth. Indeed, the coefficient on the CQM model forecasts is statistically significant at better than the 1% level, with $\beta_1 = 1.045$. The adjusted R-squared is 0.107.

The equation is then augmented with the composite sentiment factors to determine whether sentiment can improve the performance of the CQM model. In this specification, only the first principal component of

the sentiment surveys is utilized. The macroeconomic factor is not included since this information would already be reflected in the CQM forecast. The sentiment-augmented model is estimated as:

$$GDP_t = c + \beta_1 CQM_t + \beta_2 S1_{j,lag} + \varepsilon_t \qquad \text{for } j = 1, 2, 3; \qquad (8)$$

A fixed lag of zero (contemporaneous relation), one period, and the PDL are each tested. Panel B of Table 4 reveals that the composite factor for All sentiment, APC1, is significant in all specifications, adding as much as 10.7% to the adjusted R-squared. Once again, the coefficients for APC1 are negative, but the negative eigenvector indicates a positive relationship. The result appears to be driven in the short-run by the sentiments of Households, as HPC1 is significant contemporaneously, at one lag, and with the PDL specification, increasing the adjusted R-squared by as much as 11.4%. The sentiment of Businesses appears to have more effect at longer lags since only the PDL of BPC1 is significant, adding 5.7% to the adjusted R-squared. Both now-casting and forecasting of GDP growth are aided by the addition of sentiment data to the CQM model, since both the contemporaneous and lagged sentiment factors are statistically significant. The results suggest that macroeconomic forecasters should not hesitate to incorporate sentiment measures in their efforts to predict future GDP growth.

Section 5 Sentiment and Stock Returns

Do the sentiment factors have any predictive power for aggregate excess stock returns? In order to investigate this question, a baseline model is presented that controls for the composite macroeconomic factor and momentum, i.e., lagged stock returns. If sentiment is nothing more than a reflection of recent stock returns and macroeconomic information, then the sentiment-augmented model should not have any incremental predictive power over the baseline model. The baseline equation is estimated as:

$$(R_{i,t} - Rf_t) = c + \beta_1 (R_{i,t-1} - Rf_{t-1}) + \beta_2 M1_{t-1} + \varepsilon_t \quad (9)$$

The results of the baseline model are presented in Panel A of Table 5. Cumulative three-month (one quarter), six-month (two-quarters), and nine-month (three quarters) excess returns (i.e., the gross return minus the risk-free rate, Rf_t) are examined for the S&P500 index (SPQ), the Russell 1000 Growth index (R1GQ), the Russell 1000 Value index (R1VQ), the Russell 2000 Growth index (R2GQ), and the Russell 2000 Value index (R2VQ), for a total of 15 test portfolios (five stock indexes and three time horizons, Q1, Q2, and Q3.) The Russell 1000 indexes contain large-capitalization stocks, whereas the Russell 2000 indexes contain small-capitalization stocks.

Next, the baseline model is augmented with the composite sentiment factors to determine whether or not sentiment has any incremental predictive power. In this specification, the *first three* principal components of the sentiment surveys are utilized, relying on the arguments of Stone (1947). The augmented model controls for lagged excess returns of the relevant portfolio and the lagged composite macroeconomic factor. The inclusion of a composite macroeconomic factor in a model that tests the ability of sentiment to forecast stock returns efficiently addresses the concerns of researchers such as Brown and Cliff (2005), Lemmon and Portniaguina (2006), and Verma and Verma (2007), who hypothesized that sentiment may be made redundant by macroeconomic and financial information. If the lagged sentiment factors have any incremental ability to predict stock returns, then the *increment* to the adjusted R-squared should be positive. The sentiment-augmented model is estimated as:

$$(R_{i,t} - Rf_t) = c + \beta_1 (R_{i,t-1} - Rf_{t-1}) + \beta_2 M1_{t-1} + \beta_3 S1_{j,PDL} + \beta_4 S2_{j,PDL} + \beta_5 S3_{j,PDL} + \varepsilon_t \qquad \text{for } j = 1, 2, 3 \quad (10)$$

The results are presented in Panels B, C, and D of Table 5 for the sentiment of the All, Business, and Household groups, respectively. A fixed lag of one period and the polynomial distributed lag are both

tested, and both specifications have predictive power, but the results for the polynomial distributed lag are more robust. The robustness of the PDL specification indicates that the sentiment factor possesses non-linearity. Due to space limitations, only the results of the PDL are reported.

Panel B of the Table 5 reveals that the sentiment factors of All respondent groups have some modest predictive power, mostly, but not exclusively, for small-capitalization stocks. Large-capitalization value stocks have some limited predictability. The sentiment factors of All survey respondents show significant predictive power for small-capitalization stocks. The increments to the adjusted R-squared for the Russell 2000 Growth and Value indexes range from 3.6% for the cumulative two-quarter return on the Russell 2000 Growth index to 23.3% for the cumulative three-quarter return on the Russell 2000 Value index.

Panel C of Table 5 presents the results for the sentiment factors of the Business group. The Business sentiment factors show predictive power for all five of the major stock market averages. The sentiment-augmented equation for the cumulative three-quarter return on the S&P500 index is improved by 4.8% relative to the baseline equation. The increments to the adjusted R-squared for the Russell indexes range from an improvement of 1.4% for the cumulative three-quarter return of large-capitalization growth stocks to 14.5% for the cumulative three-quarter return of large-capitalization value stocks. Note that the significant coefficients in Panel C are positive. Table 2 reveals that the eigenvector of the third principal component of Business sentiment is mostly negative, and loads heavily on FED, the Philadelphia Federal Reserve Business Outlook Survey, which has a negative coefficient. This suggests that Business sentiment inversely anticipates the excess return on large-capitalization value and small-capitalization growth stocks. One possible interpretation is that business managers have a keen sense of the pulse of the economy. If managers detect improved business conditions, they may become more optimistic about future economic growth and respond to survey questions accordingly. As their optimism rises, their level

of risk aversion declines, and thus they demand lower returns on their investments, creating a negative relation between changes in Business sentiment and future aggregate excess stock returns.

The results for the sentiment of Households are presented in Panel D of Table 5. The Household sentiment factors display significant predictive power for all portfolios except the large-capitalization growth stocks. The improvements to the adjusted R-squared range from 0.6% for the one-quarter return on the S&P500 to as much as 36.5% for the cumulative three-quarter return on small-capitalization value stocks. Note that the significant coefficients in Panel D are negative, and occur mostly for HPC2. Table 2 reveals that HPC2, the second principal component of Household sentiment, has mostly positive elements on the eigenvector, with the positive elements loading most heavily on the University of Michigan Index of Consumer Sentiment - Current Conditions Preliminary (MCP) and the Conference Board Consumer Confidence Index - Present Situation (CBP). The combination of the positive loadings on the principal component with the negative coefficient in the regression suggests a negative relation between changes in these surveys and subsequent excess returns. However, note that HPC2 also loads *negatively* (and heavily) on all three of the Union Bank of Switzerland/Gallup Indexes of Investor Optimism – Headline, Personal Financial, and Economic (UBS, UBP, and UBE). The combination of the negative loadings on the principal component with the negative coefficient in the regression suggests a positive relation between changes in the Union Bank of Switzerland/Gallup surveys and subsequent excess returns.

One interpretation could be that this dichotomy is consistent with systematic overreaction by naïve investors such as that postulated by De Bondt and Thaler (1989), with an associated subsequent return reversal. This explanation is plausible given that the respondent groups of the University of Michigan and Conference Board surveys are households of ordinary consumers, who may not be particularly adept at interpreting economic data or anticipating stock market trends. Conversely, the respondents to the Union Bank of Switzerland/Gallup surveys are *investor* households, with a minimum of $10,000 in

investable assets. The minimum asset requirement of the Union Bank of Switzerland/Gallup surveys may act as a filtering mechanism, creating a strategic universe of respondents who are sophisticated in financial matters, pay attention to economic trends, and correctly anticipate the direction of the stock market.

Section 6 Conclusion

The economic magnitude of the predictability demonstrated in this chapter is significant. Consider the GDP growth regressions in Table 3. Panel C shows that the one-period lag specification for the All sentiment factor, APC1, has a coefficient of -0.232. From Table 1, note that the standard deviation of APC1 is 2.634. Multiplication of the coefficient and the standard deviation indicates that a one-standard deviation rise (decline) in APC1 predicts a decline (rise) of -0.611% in the following quarter's GDP growth. Similarly, from Panel D, a one-standard deviation rise (decline) in the Business sentiment factor, BPC1, predicts a decline (rise) of -0.205% in GDP growth over the following quarter.

Next, consider the excess stock returns regressions presented in Table 5. Panel B shows the results for the All sentiment factor, APC2. In the regression for R1VQ1, the one-quarter excess return on the Russell 1000 Value index, APC2 has a coefficient of -0.444. The standard deviation of APC2, given in Table 1, is 1.746. Multiplication of the regression coefficient and the standard deviation indicates that a one-standard deviation rise (decline) in APC2 predicts a decline (rise) of -0.775% in the following quarter's excess return on a broad portfolio of large-capitalization value stocks from its unconditional mean. In the regression for R2GQ3, the cumulative three-quarter excess return on the Russell 2000 Growth index, APC3 has a coefficient of -3.620. Table 1 shows that the standard deviation of APC3 is 1.386. This implies that a one-standard deviation rise (decline) in APC3 predicts a decline (rise) of -5.017% in the following nine-month's excess return on a broad portfolio of small-capitalization growth stocks from its

unconditional mean. Conversely, in the same regression for R2GQ3, Panel C shows that the Business sentiment factor, BPC3, has a regression coefficient of 4.575. Multiplication of the coefficient for BPC3 with its standard deviation of 1.017 obtained from Table 1 indicates that one-standard deviation rise (decline) in BPC3 predicts a rise (decline) 4.653% in the following three-quarter's excess return on a broad portfolio of small-capitalization growth stocks from its unconditional mean.

Turning to the Household sentiment factors in Panel D, one can observe that in the regression for the cumulative three-quarter excess return on the Russell 1000 Value index, HPC2 has a coefficient of -2.378. The standard deviation of HPC2, given in Table 1, is 1.218. Multiplication of the regression coefficient with the standard deviation indicates that a one-standard deviation rise (decline) in HPC2 predicts a decline (rise) of -2.896% in the following nine-month's excess return on a broad portfolio of large-capitalization value stocks from its unconditional mean. In the regression for the cumulative three-quarter excess return on the Russell 2000 Value index, HPC2 has a coefficient of -4.590. Multiplying by the standard deviation of HPC2 implies that a one-standard deviation rise (decline) in HPC2 predicts a decline (rise) of -5.591% in the following three-quarter's excess return on a broad portfolio of small-capitalization value stocks from its unconditional mean.

The results presented herein shed new light on the question of whether or not sentiment surveys are relevant to forecasting economic growth and stock returns, and whether they contain information that is orthogonal to macroeconomic and financial data. One important benefit of survey data is that they are readily available on a high-frequency basis. Thus, researchers have at their disposal an important and relatively under-exploited tool for forecasting economic quantities and asset prices, as well as measuring expectations of different population groups. I have shown that sentiment surveys have significant predictive power for both GDP growth and excess stock returns, and that the result is robust to the inclusion of information pertaining to the macroeconomic environment and momentum. Additionally,

while the sentiment surveys share some common predictive signals, the sentiments of different respondent universes can be distinguished, and have non-identical predictive power. Furthermore, the findings reject the conventional wisdom that sentiment affects only small-capitalization stocks. The results suggest that it would behoove researchers to incorporate sentiment in their forecasting models of economic growth and stock returns.

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TABLE 1 - DESCRIPTIVE STATISTICS

Sentiment changes and the first principal component of All, Business, and Household Sentiment
QUARTERLY AVERAGE DATA - 41 Observations

	Mean	Median	Std. Dev.	AC1	AC3	AC12
ISM - ISM Purchasing Managers Index	-0.066	-0.539	2.134	0.071	-0.202	-0.196
NPM - NAPM Chicago Business Barometer	0.047	0.000	3.161	-0.268	0.102	0.073
FED - Philadelphia Fed Business Outlook Survey	-0.098	0.016	1.192	0.038	-0.003	0.062
MIP - Michigan Preliminary ICS - Headline	-0.088	0.209	2.207	-0.328	0.114	0.027
MCP - Michigan Preliminary ICS - Current Conditions	-0.027	-0.029	1.808	-0.297	0.137	-0.176
MXP - Michigan Preliminary ICS - Expectations	-0.136	0.115	3.065	-0.409	0.091	0.009
CBH - Conference Board CCI - Headline	-0.044	0.097	3.662	-0.288	-0.237	0.042
CBX - Conference Board CCI - Expectations	-0.104	0.398	4.879	-0.444	-0.268	0.147
CBP - Conference Board CCI - Present Situation	0.016	0.146	3.552	0.267	0.057	-0.066
UBS - UBS/Gallup Investor Optimism - Headline	-0.390	-0.223	21.180	-0.487	-0.058	-0.020
UBP - UBS/Gallup Investor Optimism - Personal	5.794	0.139	43.312	-0.236	-0.040	-0.050
UBE - UBS/Gallup Investor Optimism - Economic	4.098	0.508	24.297	-0.037	-0.054	-0.035
HMI - NAHB/WF Builders Index - Headline	-0.345	0.000	3.129	0.193	0.097	-0.205
HM6 - NAHB/WF Builders Index - Next 6 Months	-0.213	0.000	3.339	-0.103	0.118	-0.092
HMP - NAHB/WF Builders Index - Present Conditions	-0.388	0.000	3.175	0.230	0.052	-0.190
HMT - NAHB/WF Builders Index - Traffic	-0.330	0.647	3.708	0.070	0.149	-0.250
APC1 - All Sentiment Principal Component 1	0.000	-0.290	2.634	-0.256	-0.047	-0.105
APC2 - All Sentiment Principal Component 2	0.000	0.342	1.746	0.118	0.075	-0.034
APC3 - All Sentiment Principal Component 3	0.000	0.193	1.386	-0.119	-0.009	0.007
BPC1 - Business Sentiment Principal Component 1	0.000	-0.491	1.948	0.149	0.099	-0.204
BPC2 - Business Sentiment Principal Component 2	0.000	-0.063	1.280	-0.161	0.017	-0.039
BPC3 - Business Sentiment Principal Component 3	0.000	-0.074	1.017	0.078	-0.089	0.030
HPC1 - Household Sentiment Principal Component 1	0.000	-0.070	2.429	-0.342	-0.057	-0.002
HPC2 - Household Sentiment Principal Component 2	0.000	0.203	1.218	0.117	0.009	0.043
HPC3 - Household Sentiment Principal Component 3	0.000	-0.020	0.946	-0.329	-0.009	-0.214

Macroeconomic variables lagged according to data reporting lags

	Mean	Median	Std. Dev.	AC1	AC3	AC12
NEW_ORDERS(t-2)	0.014	-0.064	1.648	-0.352	0.267	-0.124
UNFILLED_ORDERS(t-2)	0.136	0.058	1.212	0.233	0.285	-0.045
HOUSING_STARTS(t-1)	-0.029	-0.403	6.009	-0.424	-0.063	-0.146
CONSTRUCTION(t-2)	0.271	0.365	1.077	0.200	0.208	-0.097
BUILDING_PERMITS(t-1)	0.041	-0.193	3.514	-0.274	0.009	0.063
HOURLY_EARNINGS(t-1)	0.065	0.069	0.271	0.190	-0.094	-0.091
AVG_WEEKLY_HOURS(t-1)	-0.017	0.000	0.251	-0.457	0.083	-0.005
CPI(t-1)	0.212	0.186	0.254	0.246	-0.083	-0.142
PPI(t-1)	0.187	0.222	0.577	0.108	0.187	-0.182
RETAIL_SALES(t-1)	0.205	0.208	1.075	-0.370	-0.061	-0.067
TRADE-WEIGHTED_EXCHANGE_RATE(t-1)	-0.192	-0.131	1.178	0.306	0.002	-0.088
MONEY_SUPPLY(t-1)	0.300	0.308	0.399	0.300	0.142	0.000
CONSUMER_CREDIT(t-2)	0.326	0.282	0.394	0.276	0.074	0.074
INVENTORY_SALES_RATIO(t-2)	-0.024	0.000	0.816	-0.329	0.117	-0.151
NET_GOV_RECEIPTS(t-1)	-0.360	-1.214	3.249	-0.264	0.356	0.820
UNEMPLOYMENT_RATE(t-1)	-0.006	0.000	0.126	-0.101	0.184	0.015
TIPS-IMPLIED_INFLATION(t-1)	-0.006	0.003	0.222	0.291	-0.110	-0.016
FED_FUNDS_RATE(t-1)	0.000	0.003	0.182	0.666	0.500	0.019
PRIME_RATE(t-1)	0.000	0.000	0.177	0.708	0.531	0.036
CORPORATE_BOND_RATE(t-1)	-0.015	-0.040	0.166	0.178	-0.104	-0.146
TBILL_3M(t-1)	-0.002	0.012	0.199	0.453	0.426	0.110
EXPORT_IMPORT_RATIO(t-2)	0.016	-0.001	0.195	0.008	0.000	-0.005
TBOND_YIELD_1YEAR(t-1)	-0.005	0.000	0.201	0.445	0.305	-0.042
TBOND_YIELD_10YEAR(t-1)	-0.014	-0.043	0.216	0.161	0.008	-0.169
TBOND_YIELD_20YEAR(t-1)	-0.015	-0.050	0.185	0.125	-0.012	-0.214
30-YR_FIXED_MORTGAGE(t-1)	-0.013	-0.020	0.127	0.533	0.021	-0.269
DISPOSABLE_PERSONAL_INCOME(t-1)	0.258	0.284	0.725	-0.185	-0.154	0.026
INDUSTRIAL_PRODUCTION(t-1)	0.211	0.243	0.541	0.078	0.186	0.088
NON-FARM_EMPLOYMENT(t-1)	0.103	0.119	0.131	0.649	0.617	0.309
MANUFACTURING_AND_TRADE_SALES(t-1)	0.226	0.278	0.739	-0.358	0.128	-0.074

TABLE 2 - PRINCIPAL COMPONENTS AND EIGENVECTORS - SENTIMENT

SENTIMENT - FIRST THREE PRINCIPAL COMPONENTS

Sample: 1997Q1-2007Q2; Quarterly average data includes 41 observations

All Sentiment (APC)				**Business Sentiment (BPC)**				**Household Sentiment (HPC)**			
	Comp 1	Comp 2	Comp 3		Comp 1	Comp 2	Comp 3		Comp 1	Comp 2	Comp 3
Eigenvalue	6.770	2.975	1.874	Eigenvalue	3.702	1.600	1.009	Eigenvalue	5.757	1.448	0.873
Variance Prop.	0.423	0.186	0.117	Variance Prop.	0.529	0.229	0.144	Variance Prop.	0.640	0.161	0.097
Cumulative Prop.	0.423	0.609	0.726	Cumulative Prop.	0.529	0.757	0.902	Cumulative Prop.	0.640	0.801	0.898
Eigenvectors:				Eigenvectors:				Eigenvectors:			
Variable	Vector 1	Vector 2	Vector 3	Variable	Vector 1	Vector 2	Vector 3	Variable	Vector 1	Vector 2	Vector 3
ISM	-0.169	-0.061	-0.215	ISM	-0.156	0.635	-0.296				
NPM	-0.117	-0.127	-0.249	NPM	-0.068	0.713	-0.045				
FED	-0.010	-0.077	0.550	FED	0.060	-0.211	-0.942				
MIP	-0.326	-0.125	0.236					MIP	-0.370	0.241	0.330
MCP	-0.224	0.047	0.376					MCP	-0.240	0.369	0.538
MXP	-0.315	-0.189	0.137					MXP	-0.366	0.145	0.188
CBH	-0.333	-0.181	0.119					CBH	-0.382	0.166	-0.329
CBX	-0.329	-0.193	0.065					CBX	-0.382	0.027	-0.041
CBP	-0.184	-0.095	0.242					CBP	-0.205	0.438	-0.671
UBS	-0.330	-0.170	-0.144					UBS	-0.379	-0.201	-0.052
UBP	-0.286	-0.129	-0.343					UBP	-0.295	-0.533	-0.036
UBE	-0.253	-0.130	-0.364					UBE	-0.327	-0.491	-0.031
HMI	-0.222	0.467	-0.017	HMI	-0.514	-0.079	-0.005				
HM6	-0.225	0.413	0.107	HM6	-0.466	-0.183	-0.123				
HMP	-0.187	0.481	-0.035	HMP	-0.498	-0.060	0.016				
HMT	-0.242	0.398	-0.109	HMT	-0.488	-0.010	0.092				

TABLE 3 - REGRESSING GDP GROWTH ON LAGGED GDP GROWTH, LAGGED MACROECONOMIC FACTOR, AND LAGGED SENTIMENT FACTOR

Dependent variable is GDP gowth. Estimation method is Ordinary Least Squares. For one-period lag, sample period is 1997Q2-2007Q2, with 41 observations. For polynomial distributed lag, sample period is 1997Q4-2007Q1, with 38 observations. Newey-West HAC standard errors and covariance matrix with lag truncation = 3 is employed throughout. T-statistics given in parentheses with significance level indicated by * = significant at 10%, ** = 5%, *** = 1%. Increment is the difference between adjusted R-squared of sentiment-augmented regression and adjusted R-squared of baseline specification of GDP growth regressed on lagged GDP growth and lagged macroeconomic factor only.

PANEL A.	**Baseline Model - Lag 1**				**PANEL B.**	**Baseline Model - PDL**			
Variable	**Coeff.**	**t-stat.**	**Adj. R-sq.**		**Variable**	**Coeff.**	**t-stat.**	**Adj. R-sq.**	
GDP(t-1)	-0.007	(-0.036)	0.079		GDP(pdl)	0.219	(4.654***)	0.277	
MPC1(t-1)	0.378	(1.785*)			MPC1(pdl)	-0.002	(-0.059)		
PANEL C.	**Sentiment Augmented Model - Lag 1**				**PANEL D.**	**Sentiment Augmented Model - PDL**			
Variable	**Coeff.**	**t-stat.**	**Adj. R-sq.**	**Increment**	**Variable**	**Coeff.**	**t-stat.**	**Adj. R-sq.**	**Increment**
ALL SENTIMENT					**ALL SENTIMENT**				
GDP(t-1)	-0.007	(-0.037)	0.137	0.058	GDP(pdl)	0.181	(2.775***)	0.270	-0.007
MPC1(t-1)	0.265	(-1.199)			MPC1(pdl)	0.009	(-0.199)		
APC1(t-1)	-0.232	(-2.432**)			APC1(pdl)	-0.066	(-1.065)		
BUSINESS					**BUSINESS**				
GDP(t-1)	-0.018	(-0.093)	0.070	-0.009	GDP(pdl)	0.155	(2.785***)	0.296	0.020
MPC1(t-1)	0.362	(1.712*)			MPC1(pdl)	0.055	(-1.207)		
BPC1(t-1)	-0.133	(-1.199)			BPC1(pdl)	-0.105	(-2.818***)		
HOUSEHOLD					**HOUSEHOLD**				
GDP(t-1)	0.004	(-0.019)	0.141	0.062	GDP(pdl)	0.215	(3.517***)	0.256	-0.021
MPC1(t-1)	0.256	(-1.135)			MPC1(pdl)	-0.003	(-0.084)		
HPC1(t-1)	-0.259	(-2.888***)			HPC1(pdl)	-0.012	(-0.168)		

TABLE 4 - REGRESSING GDP GROWTH ON QUARTERLY AVERAGE CQM FORECASTS AND SENTIMENT FACTOR

Dependent variable is GDP gowth. Estimation method is Ordinary Least Squares. For one-period lag, sample period is 1997Q2-2007Q2, with 41 observations. For polynomial distributed lag, sample period is 1997Q4-2007Q1, with 38 observations. Newey-West HAC standard errors and covariance matrix with lag truncation = 3 is employed throughout. T-statistics given in parentheses with significance level indicated by * = significant at 10%, ** = 5%, *** = 1%. Increment is the difference between adjusted R-squared of sentiment-augmented regression and adjusted R-squared of baseline specification of GDP growth regressed on quarterly average CQM forecasts only.

PANEL A. - BASELINE MODEL

Variable	Coeff.	t-stat.	Adj.R-sq.
C	0.434	(0.523)	0.107
CQM	1.045	(3.520***)	

PANEL B. - SENTIMENT-AUGMENTED MODEL

ALL SENTIMENT					BUSINESS SENTIMENT					HOUSEHOLD SENTIMENT				
Variable	**Coeff.**	**t-stat.**	**Adj.R-sq.**	**Increment**	**Variable**	**Coeff.**	**t-stat.**	**Adj.R-sq.**	**Increment**	**Variable**	**Coeff.**	**t-stat.**	**Adj.R-sq.**	**Increment**
C	0.247	(0.299)	0.123	0.016	C	0.257	(0.304)	0.119	0.012	C	0.294	(0.357)	0.110	0.003
CQM	1.111	(3.721***)			CQM	1.107	(3.673***)			CQM	1.092	(3.652***)		
APC1	-0.147	(-1.793*)			BPC1	-0.188	(-1.569)			HPC1	-0.129	(-1.165)		
C	1.151	(1.334)	0.164	0.058	C	0.530	(0.617)	0.103	-0.004	C	1.208	(1.422)	0.166	0.059
CQM	0.749	(2.397**)			CQM	1.002	(3.356***)			CQM	0.726	(2.284**)		
APC1(t-1)	-0.232	(-2.812***)			BPC1(t-1)	-0.147	(-1.614)			HPC1(t-1)	-0.257	(-3.168***)		
C	1.088	(1.403)	0.214	0.107	C	0.355	(0.404)	0.103	-0.004	C	1.267	(1.801)	0.221	0.114
CQM	0.769	(2.798***)			CQM	1.067	(3.492***)			CQM	0.692	(2.482**)		
APC1	-0.210	(-2.449**)			BPC1	-0.169	(-1.426)			HPC1	-0.237	(-2.119**)		
APC1(t-1)	-0.282	(-3.364***)			BPC1(t-1)	-0.107	(-1.128)			HPC1(t-1)	-0.345	(-3.845***)		
C	0.919	(1.421)	0.188	0.081	C	0.285	(0.345)	0.164	0.057	C	0.937	(1.482)	0.137	0.031
CQM	0.801	(3.019***)			CQM	1.057	(3.589***)			CQM	0.786	(2.763***)		
APC1(pdl)	-0.159	(-2.599**)			BPC1(pdl)	-0.126	(-3.829***)			HPC1(pdl)	-0.143	(-1.959**)		

TABLE 5 - REGRESSING EXCESS RETURNS ON LAGGED RETURNS, LAGGED MACROECONOMIC FACTOR, AND LAGGED SENTIMENT FACTORS (FIRST 3 PRINCIPAL COMPONENTS)

Dependent variable is excess return on portfolio *i* at time *t*. Estimation method is Ordinary Least Squares. For polynomial distributed lag, sample period is 1997Q4-2007Q1, with 38 observations. Newey-West HAC standard errors and covariance matrix with lag truncation = 3 is employed throughout. T-statistics given in parentheses with significance level indicated by * = significant at 10%, ** = 5%, *** = 1%. Increment is the difference between adjusted R-squared of sentiment-augmented regression and adjusted R-squared of baseline specification of excess returns regressed on lagged returns and lagged macroeconomic factor only.

PANEL A. - BASELINE		PANEL B. - ALL (PDL)					PANEL C. - BUSINESS (PDL)					PANEL D. - HOUSEHOLD (PDL)				
INDEX	**Adj. R-sq.**	**APC1(pdl)**	**APC2(pdl)**	**APC3(pdl)**	**Adj. R-sq.**	**Increment**	**BPC1(pdl)**	**BPC2(pdl)**	**BPC3(pdl)**	**Adj. R-sq.**	**Increment**	**HPC1(pdl)**	**HPC2(pdl)**	**HPC3(pdl)**	**Adj. R-sq.**	**Increment**
SPQ1	-0.039	-0.418	-0.233	-0.531	-0.066	-0.028	-0.124	0.251	0.480	-0.118	-0.080	-0.521	-0.903	-0.965	-0.032	0.006
		(-1.216)	(-0.896)	(-1.024)			(-0.385)	(0.311)	(0.656)			(-1.221)	(-1.618)	(-0.729)		
SPQ2	-0.049	-0.307	-0.126	-0.647	-0.117	-0.068	-0.183	-0.066	1.109	-0.111	-0.062	-0.401	-1.283	-1.824	-0.063	-0.014
		(-0.615)	(-0.281)	(-0.651)			(-0.382)	(-0.043)	(0.819)			(-0.658)	(-1.601)	(-0.802)		
SPQ3	-0.021	-0.167	0.427	-0.990	-0.055	-0.034	-0.610	-0.532	2.269	0.027	0.048	-0.225	-1.597	-1.618	-0.057	-0.035
		(-0.317)	(0.455)	(-0.709)			(-0.716)	(-0.284)	(1.364)			(-0.374)	(-1.355)	(-0.574)		
R1GQ1	-0.043	-0.450	-0.069	-0.612	-0.098	-0.055	-0.289	0.508	0.606	-0.117	-0.074	-0.488	-0.675	-0.549	-0.108	-0.065
		(-1.087)	(-0.191)	(-0.976)			(-0.711)	(0.444)	(0.644)			(-1.028)	(-1.238)	(-0.346)		
R1GQ2	-0.032	-0.425	0.255	-0.729	-0.094	-0.062	-0.566	0.211	1.092	-0.095	-0.063	-0.388	-1.016	-1.342	-0.105	-0.073
		(-0.717)	(0.351)	(-0.599)			(-0.767)	(0.101)	(0.641)			(-0.624)	(-1.067)	(-0.511)		
R1GQ3	-0.009	-0.347	1.161	-1.011	-0.023	-0.014	-1.308	-0.269	2.267	0.005	0.014	-0.227	-0.939	-0.338	-0.104	-0.096
		(-0.522)	(0.759)	(-0.594)			(-0.946)	(-0.111)	(1.085)			(-0.369)	(-0.616)	(-0.102)		
R1VQ1	-0.010	-0.404	-0.444	-0.458	0.004	0.014	0.064	0.080	0.368	-0.076	-0.067	-0.580	-1.080	-1.353	0.086	0.096
		(-1.372)	(-2.831***)	(-0.954)			(0.255)	(0.131)	(0.558)			(-1.563)	(-1.869*)	(-1.266)		
R1VQ2	-0.053	-0.196	-0.570	-0.709	-0.066	-0.013	0.228	-0.119	1.195	-0.054	-0.001	-0.411	-1.648	-2.410	0.048	0.101
		(-0.427)	(-2.384**)	(-0.796)			(0.729)	(-0.101)	(1.051)			(-0.664)	(-2.127**)	(-1.231)		
R1VQ3	-0.014	0.034	-0.314	-1.152	-0.008	0.006	0.081	-0.569	2.345	0.131	0.145	-0.183	-2.378	-2.918	0.130	0.143
		(0.065)	(-0.779)	(-0.929)			(0.185)	(-0.392)	(1.691*)			(-0.286)	(-2.369**)	(-1.226)		
R2GQ1	0.017	-0.618	-0.466	-1.894	0.090	0.073	-0.189	1.311	0.810	-0.011	-0.028	-0.710	-2.392	-0.847	0.103	0.086
		(-1.465)	(-1.498)	(-2.861***)			(-0.448)	(1.059)	(0.677)			(-1.502)	(-3.491***)	(-0.488)		
R2GQ2	-0.035	-0.265	-0.316	-2.569	0.001	0.036	-0.222	1.350	2.270	-0.067	-0.032	-0.293	-3.163	-1.679	0.001	0.036
		(-0.403)	(-0.588)	(-2.107**)			(-0.359)	(0.637)	(1.145)			(-0.399)	(-2.518**)	(-0.538)		
R2GQ3	0.007	0.233	0.698	-3.620	0.129	0.122	-0.886	1.034	4.575	0.094	0.087	0.343	-3.846	-0.526	0.082	0.075
		(0.311)	(0.594)	(-2.306**)			(-0.863)	(0.464)	(1.977*)			(0.434)	(-2.105**)	(-0.129)		
R2VQ1	-0.010	-0.478	-0.770	-1.035	0.087	0.097	0.242	0.513	0.093	-0.065	-0.055	-0.718	-1.955	-1.472	0.170	0.180
		(-1.619)	(-2.281**)	(-1.905*)			(0.711)	(0.642)	(0.116)			(-2.372**)	(-3.203***)	(-1.373)		
R2VQ2	-0.045	0.029	-1.029	-1.809	0.134	0.179	0.619	0.631	1.285	-0.005	0.040	-0.218	-3.169	-2.807	0.207	0.251
		(0.066)	(-2.111**)	(-1.968*)			(1.103)	(0.487)	(1.037)			(-0.387)	(-3.469***)	(-1.645)		
R2VQ3	-0.027	0.580	-0.877	-2.681	0.206	0.233	0.700	0.297	2.721	0.087	0.114	0.351	-4.590	-3.653	0.338	0.365
		(0.886)	(-1.669*)	(-2.081**)			(1.003)	(0.187)	(1.615)			(0.605)	(-3.573***)	(-1.766*)		

SPQ1 is the one-quarter ahead return on the S&P500 index. SPQ2 is the cumulative two-quarter ahead return on the S&P500 index. SPQ3 is the cumulative three-quarter ahead return on the S&P500 index. R1GQ1 is the one-quarter ahead return on the Russell 1000 Growth index. R1GQ2 is the cumulative two-quarter ahead return on the Russell 1000 Growth index. R1GQ3 is the cumulative three-quarter ahead return on the Russell 1000 Growth index. R1VQ1 is the one-quarter ahead return on the Russell 1000 Value index. R1VQ2 is the cumulative two-quarter ahead return on the Russell 1000 Value index. R1VQ3 is the cumulative three-quarter ahead return on the Russell 1000 Value index. R2GQ1 is the one-quarter ahead return on the Russell 2000 Growth index. R2GQ2 is the cumulative two-quarter ahead return on the Russell 2000 Growth index. R2GQ3 is the cumulative three-quarter ahead return on the Russell 2000 Growth index. R2VQ1 is the one-quarter ahead return on the Russell 2000 Value index. R2VQ2 is the cumulative two-quarter ahead return on the Russell 2000 Value index. R2VQ3 is the cumulative three-quarter ahead return on the Russell 2000 Value index.