# BIASED ASSESSMENT OF COMOVEMENT

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**Abstract**

I document a systematic bias in the assessment of comovement: individuals assess a moderate relationship between two variables regardless of the actual strength of the relationship between them. In a survey of finance professionals, participant-assessed betas of different financial and macroeconomic variables with the stock market exhibit compression towards moderate values. In an empirical setting, electricity futures exhibit moderate comovement with gas futures despite persistent heterogeneity in the comovement of gas and electricity in the spot market. Trading against this bias generates annualized excess returns of 7.3 percent and a annualized Sharpe ratio of 1.14. Finally, professional forecasters also exhibit this bias, leading to predictable errors in macroeconomic forecasts. JEL Codes: G12, G40. Total word count: 18,769.

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# 1 Introduction

The assessment of comovement plays a central role in belief formation and decision-making: forecasts are based on assessed relationships between variables; in consumption-based asset pricing models, risk is determined by the comovement of an asset's returns with the marginal utility of consumption; and the comovement between hidden actions and observable outcomes is central to the optimal contracting problem. Assessments of comovement are traditionally assumed to be unbiased estimates based on available data. However, in this paper, I find that individuals consistently mis-estimate comovement across several settings: a survey of finance professionals; commodity futures prices; and professional macroeconomic forecasts. In each setting, individuals assess a moderate relationship between two variables regardless of whether the actual relationship is strong, moderate, or weak. This pattern of compression generates predictable errors in asset prices, predictable errors in forecasts, and distorts perceptions of risk.

The pattern of compression I document in assessments of comovement is most consistent with categorical thinking (Barberis and Shleifer (2003); Mullainathan (2002); Mullainathan et al. (2008)) and a form of inattention proposed in Gabaix (2019). Gabaix (2019) proposes that individuals will extrapolate low auto-correlated variables like stock returns and underreact to higher autocorrelated variables such as inflation if their subjectively assessed autocorrelation anchors on a common autocorrelation and only adjusts partially towards the true autocorrelation of the forecasted variable. In my study of how individuals assess relatedness, my findings are consistent with anchoring on a moderate beta and adjusting only partially towards the true beta of the two variables being evaluated. Combining this framework with a form of categorical thinking places structure on the common anchor: if individuals think about relationships in coarse categories such as "Negatively related", "Not related", or "Positively related", then a wide spectrum of positively (negatively) related variables will have the same mental representation as "positively related" ("negatively related"). If the prior within each category is the average comovement of each pair in the category, then this will lead to over-estimation of weakly positively related variables and under-estimation of strongly positively related variables. This pattern is consistent with my findings across each experimental and empirical settings.

In this paper, I measure relatedness using betas since this provides a straight-forward way to measure the relationship between two variables in my empirical settings where I do not control the data-generating processes and where I cannot elicit beliefs by asking individuals directly. In terms of betas, I express this bias as:

$$\beta^{assessed} = (1-\rho)\,\beta^{rational} + \rho\beta^{c,anchor} \tag{1}$$

An individual's subjective assessed beta, $\beta^{assessed}$, is a weighted combination of the rational beliefs beta based on an individual's information set, $\beta^{rational}$, and the anchor beta representative of the mental category, $\beta^{c,anchor}$, where $c \in \{positively\ related,\ negatively\ related,\ unrelated\}$, and $0 \leq \rho \leq 1$. Intuitively, it is more natural to think about relationships, such as the relationship between stock market returns and GDP growth or rainfall and crop growth, in broad categories such as "positively related" rather than in terms of a specific beta, correlation, or covariance number. However, storing relationships in these coarse categories will result in a wide spectrum of relationships being compressed into the same mental representation. When an individual is faced with a task that requires an assessment of comovement, such as adjusting a forecast or determining the sensitivity of one asset price to another, these coarse mental representations will moderate their observable response towards the compressed anchor beta.

The pairs of variables I study have intuitive positive associations and can be categorized in the "positively related" group - I take this categorization as given though this determination is an interesting avenue to explore in future work. If two variables have a rational beliefs beta below (above) the common anchor, then assessments of comovement will be biased upward (downward) and this will generate the compression that I find empirically. In the context of Equation 1, in each setting, I will construct measures of assessed comovement, $\beta^{assessed}$, and of rational beliefs about comovement based on historical data, $\beta^{rational}$, and compare the two measures. With true measures of assessed and benchmark comovement, this comparison would be a sufficient test of assessments of comovement. In practice, the measures I construct are imperfect characterizations. The challenge in each setting is to address the limitations of each measure which I approach by testing whether deviations of assessed comovement from the benchmark, $\beta^{rational} - \beta^{assessed}$, predict pricing errors in the specific pattern predicted by the bias. I summarize my results and discuss the empirical methodology in more detail below.

First, I motivate my study with a survey of finance professionals. To begin, I recruit a sample of 400 survey participants who currently work in the financial sector. I present each participant with a randomly selected macroeconomic variable or an individual stock drawn from the largest 25 constituents of the S&P

500 by market capitalization. The macroeconomic variables are listed in Table AI in the Appendix. These include personal consumption, local house prices, and wages. Then I present the participant with different hypothetical United States stock market return scenarios and elicit beliefs about the growth rate or individual stock return in each scenario. I aggregate participant responses and calculate the assessed beta for each variable from a regression of average participant growth rates on the corresponding stock market return across all scenarios. I compare the assessed betas against trailing historical betas from a regression of actual growth rates or returns on the S&P 500 index return. I find that individuals assess a moderate beta between individual stock returns and the market return regardless of actual beta and that individuals over-estimate the low comovement between the stock market's return and the growth rates of macroeconomic variables. These findings suggest that biased assessment of comovement may distort perceptions of risk away from traditional measures of risk based on historical data. While only indicative, the distortions in perceptions of risk generated by biased assessment of comovement are consistent with a higher equity premium than implied by the historical comovement between market returns and consumption growth and a flat relationship between average returns and historical CAPM betas. This survey evidence motivates the study of assessments of comovement in two empirical settings where individuals have strong incentives to form accurate assessments of comovement.

I design a framework for testing assessments of comovement empirically and study two settings: commodity futures prices and macroeconomic forecasts. The two settings I study are special in that they provide: many pairs of variables $(X, Y)$ where I can measure actual comovement between $X$ and $Y$; a way to separately measure assessed comovement based on measures of expectations, $\mathbb{E}X$ and $\mathbb{E}Y$, provided in each setting; and strong incentives for individuals to form accurate beliefs about comovement. My design uses many dependent variables, $Y_1, ..., Y_N$, paired with the same independent variable, $X$, and studies how individuals assess the relation $Y_i \sim X$ for each $Y_i$.[1] I measure the actual comovement between each pair of variables by calculating the beta from a regression of historical realizations of $Y_i$ on $X$. I take a similar approach to estimate the assessed comovement between each pair of variables by measuring the comovement of expectations, $\mathbb{E}X$ and $\mathbb{E}Y$, using futures prices or forecast data. I characterize beliefs about comovement by comparing assessed betas to historical betas.

[1] This many-to-one structure allows me to rule out certain channels such as simultaneity, simple forms of over-confidence, and biases on beliefs about $X$, which would generate uniform upward or downward shifts in measures of assessed comovement but not the pattern of compression observed in the data.

In general, there are a number of concerns with constructing measures of assessed comovement and benchmark comovement using this approach. Historical comovement and the comovement of rational forecasts can differ for many reasons including: a systematic relationship between the non-forecastable components of $X$ and $Y$; certain patterns of information flow to traders or forecasters; rational inattention; and noise in the estimation of historical relationships. I develop a separate approach to test these channels. My empirical design tests whether errors, in prices or in forecasts, are predictable based on the difference between my measure of assessed comovement and the historical benchmark. I discuss this test in more detail in the context of my first empirical setting.

My first empirical setting is the electricity and natural gas markets. In a more standard setting such as equity markets, historical firm betas confound fundamental comovement with investor assessments of comovement, making it difficult to construct separate measures of assessed and benchmark comovement. Power and gas are traded in the futures and spot markets across the United States and offer natural measures of assessments of comovement and benchmarks, using data from the futures and spot markets respectively. More importantly, electricity and natural gas markets have a well-defined economic relationship. Natural gas is an input in the production of power, so persistent regional characteristics, such as geographic variation in the mixture of power plants (between natural gas and other forms of production) and the structure of the transmission grid therefore create predictable differences in the relationship between electricity and natural gas in each region. In the spot market, I document this heterogeneous relationship between electricity and gas returns by calculating the daily electricity return beta with respect to gas returns in each different region around the United States. I show that the strengths of these relationships in each geography vary persistently over time: regions with high (low) spot market betas tend to continue to have high (low) spot market betas in the future. However, I find that assessed comovement, measured using futures market betas, is moderate regardless of the historical strength of the association measured in the spot market. Futures betas are approximately 0.5 regardless of the historical spot beta in the contract settlement location.

This compression could be driven by rational channels. The spot market comovement between electricity and natural gas may differ from the futures market comovement under rational beliefs if: factors that drive spot market comovement are not forecastable; through rational inattention if the benefits of accurately estimating the strength of the relationship do not outweigh the costs; through differences in the spot and futures market that cause the spot betas and futures betas to rationally differ; or if historical spot betas are estimated with noise and electricity traders rationally shrink historical spot market betas towards a common prior when determining the appropriate response to a movement in gas futures prices. I test these channels in several ways. First, I shrink historical spot market betas towards the cross-sectional average spot market beta using a standard rational Bayesian shrinkage estimator. I find a flat relationship between futures betas and these shrunken spot market betas. Next, I show that historical spot market betas predict spot market betas in the future - the relationships in the spot market are predictable and persistent over time. Finally, I show that futures pricing errors are predictable based on the difference between assessed comovement and the historical benchmark in a pattern consistent with biased assessments of comovement towards moderate values. This predictability should not arise if the compressed futures betas are driven by non-forecastable components of spot market betas or differences in the spot and futures market that cause futures and spot betas to rationally differ. I implement this test in a trading strategy and show that investors can earn significant returns by trading against this compression. This is difficult to reconcile with the rational inattention channel.

Specifically, I construct a trading strategy that, following a positive gas futures return, goes long electricity futures contracts with a high historical spot beta with gas and shorts electricity futures contracts with a low historical spot beta with gas (and takes opposite positions following a negative gas futures return). If beliefs about comovement are biased towards moderate values, then following a positive (negative) gas futures return, electricity futures with a strong spot market relationship with natural gas will not increase enough (not decrease enough). Similarly, electricity futures with a weak relationship with natural gas will increase too much (decrease too much). These mispricings will eventually correct since futures prices will converge to the spot price as the settlement period approaches. The trading strategy generates annualized excess returns of 7.3 percent with a Sharpe ratio of 1.14. The Fama French 3-factor and 5-factor adjusted alphas are around 7 percent and both are significant at the 1 percent level. The profitability and high Sharpe ratio of the strategy are difficult to reconcile with the compressed futures market betas being driven by non-forecastable spot market comovement or differences in the spot market and futures market that cause rational deviations in the futures market beta from the spot market beta. The trading strategy returns are not driven by loadings on common risk factors or commodity specific risk factors.

Finally, I study assessments of comovement in a setting where I can measure beliefs directly using macroeconomic forecasts collected in the Philadelphia Federal Reserve's Survey of Professional Forecasters (SPF).

In this setting, my goal is to test how accurately forecasters assess the comovement of different macroeconomic quantities with economic conditions proxied for by Nominal Gross Domestic Product (NGDP). First, I show that cross-sectional differences in actual comovement between different macroeconomic variables and NGDP growth are persistent and predictable. However, I find that forecasters' assessed comovement of macroeconomic variable growth rates with NGDP growth are compressed towards moderate values relative to actual historical comovement. This pattern may arise due to non-forecastable components of growth rates or rational Bayesian shrinkage. To investigate these channels, I construct a test analogous to the trading strategy in the commodities setting and test whether the compression in forecast betas generates predictable errors in forecasts. Following an upward forecast revision to the NGDP growth, if beliefs about the comovement of macroeconomic growth rates with nominal GDP are biased towards moderate values, then forecasts for macroeconomic variables with low (high) actual comovement with GDP will move up too much (little). Therefore, on average realized growth will be lower (higher) than forecasts. Similar intuition predicts forecast errors following a downward revision of nominal GDP forecasts. I find that forecast errors are predictable in this manner. These results suggest that professional forecasters also exhibit bias in the assessment of comovement towards moderate values.

This paper most closely relates to research on categorical thinking (Barberis and Shleifer (2003); Mullainathan (2002); Mullainathan et al. (2008)) and the form of inattention proposed by Gabaix (2019). This paper also relates to the broader behavioral finance literature on biased beliefs.[2] Within this literature, extrapolative belief formation and underreaction of beliefs comprise two major areas of study. To reconcile these two areas, researchers have studied why beliefs sometimes over-react and other times under-react. Studies have shown how forms of overconfidence can match patterns of over- or under-reaction found in the data as well as generate speculative bubbles (Griffin and Tversky (1992); Odean (1998); Daniel et al. (1998); Barber and Odean (2001); Scheinkman and Xiong (2003); Gervais et al. (2003); Malmendier and Tate (2005, 2008); Ben-David et al. (2013)). Landier et al. (2017) present experimental evidence that beliefs exhibit both overreaction and underreaction. Their results provide experimental support for the idea that assessments of autocorrelation exhibit compression towards moderate values. Bordalo et al. (2018) provide

[2]A detailed discussion of the literature is provided in Barberis (2018). Work in this area has studied extrapolation of returns (e.g. Cutler et al. (1990); De Long et al. (1990); Hong and Stein (1999); Barberis et al. (2015); Glaeser and Nathanson (2017); DeFusco et al. (2017); Liao and Peng (2018)) and the extrapolation of fundamentals (e.g. Barberis et al. (1998); Choi and Mertens (2006); Alti and Tetlock (2014); Hirshleifer et al. (2015)). In the underreaction literature, Coibion and Gorodnichenko (2015) document underreaction in inflation forecasts. Bouchaud et al. (2019) show evidence of sticky beliefs in earnings forecasts and show how this can generate the profitability premium.

evidence that macroeconomic forecasts actually exhibit overreaction at the individual level but underreaction at the consensus level. Shue and Townsend (2018) show how non-proportional thinking about stock prices can generate both over- and underreaction. Researchers have shown that noise in perceptions caused by limited information processing capacity can generate both the value function and the compression in the probability weighting function proposed in the prospect theory of Kahneman and Tversky (1979). This can generate patterns of over- and under-reaction as well as distortions in perceptions of payoffs based on recently observed outcomes Woodford (2012); Khaw et al. (2018); Frydman and Jin (2018); Enke and Graeber (2019). My paper contributes to the literature on over- and underreaction by showing how patterns of over-reaction and under-reaction may arise from biased assessments of comovement between two variables.

There is a large body of experimental evidence on the assessment of covariation. The psychology literature can broadly be divided into two approaches: the first approach studies how individuals assess correlations when shown data (Jennings et al. (1982) ); the second approach studies how individuals assess correlations based on intuitive beliefs without seeing data.[3] In the former, researchers show experimental participants data in the form of numbers, charts, graphs, or pictures and elicit beliefs about correlation between two data series. The literature finds that participants consistently under-estimate correlations even when the correlations in the data become quite high. Results in the finance literature are generally consistent with the findings in psychology – researchers present experimental participants with numbers or graphs of data and document that individuals struggle to detect patterns or features in the data which often leads to underestimation of correlation (e.g. Kroll et al. (1988); Kallir and Sonsino (2009); Eyster and Weizsacker (2010); Enke et al. (2013); Ungeheuer and Weber (2016); Chinco et al. (2019)). The other approach in the psychology literature examines the assessment of covariation based on internal theories or beliefs. In these studies, participants are asked to provide estimates of comovement between two real-world variables, such as SAT scores and first semester GPA, without being shown any data. The findings in these studies are opposite of the findings in the data-driven literature in psychology and finance - individuals consistently

[3] Chapman and Chapman (1969) show that psychodiagnosticians routinely report associations between symptom statements and projective test protocols where none exist. In studies by Golding and Rorer (1972) and Hamilton and Rose (1980), individuals are asked to provide estimates for the correlation between two real world variables such as SAT scores and freshman year grade point average. The individuals are not shown any data so their estimates are driven by their own intuition or theory about the relatedness of the two variables. In these settings, individuals tend to over-estimate correlations relative to the real world correlations. These findings provide evidence that the perception of covariation is influenced by pre-existing theories or conceptual similarity - if two variables are related in an individual's mind by an internal model or theory, the individual may infer illusory correlation when none exists in reality. Nisbett and Ross (1980) explain these results by suggesting that "a priori theories of expectations may be more important to the assessment of covariation than are the actually observed data configurations."

over-estimate low correlations (Nisbett and Ross (1980)). These differences will arise to the extent that the data-driven literature findings are driven by pattern recognition and data processing capabilities, while the intuitive beliefs literature is driven by how individuals internalize and store mental representations of relatedness once a connection has been established. My paper studies the second channel, the role of intuitive beliefs in the assessment of comovement, and my findings are consistent with the patterns of over-estimation of low comovement documented in this area of psychology literature.

The paper is organized as follows. In Section 2, I provide motivation for studying assessments of comovement by documenting the bias in a survey of finance professionals. In Section 3, I develop a framework for testing beliefs about comovement empirically and study commodity asset prices. In Section 4, I follow the same approach to test professional forecasters' assessments of comovement between different components of the macroeconomy. Section 5 concludes.

## 2 Motivating Evidence from a Survey

I study how investment professionals assess the comovement between individual stocks and stock market returns, and between the macroeconomy and stock market returns in a survey setting. I find that assessments of comovement exhibit a pattern of compression towards moderate values: participants over-estimate the low comovement between stock market returns and growth rates of macroeconomic variables and estimate a moderate beta between individual stock returns and the market regardless of actual beta.

### 2.1 Overview

I conduct a survey through the firm Qualtrics on a set of investment professionals.[4] Participants are shown a consent form and an overview of the survey including compensation and expected duration. Qualtrics includes two screening questions to limit participation to individuals who work in the financial sector and who manage money on behalf of other people. Next, I ask participants to provide estimates for stock returns or macroeconomic growth rates under different aggregate stock market return scenarios. Individuals answer ten questions in total. Finally, participants provide basic demographic information about themselves and exit the survey. Expected completion time is 30 minutes.

[4] An overview of the background and statistics is provided in section 6.1.1 of the Appendix.

## 2.2 Design

Participants are shown the name of a large publicly traded firm randomly drawn from the top 25 largest constituents of the S&P 500 by market capitalization at the end of 2017 and asked about their familiarity with the firm. Individuals read the following description:

> Standard & Poor's 500, also known as the S&P 500, is an American stock market index consisting of 500 large firms. The S&P 500 index can be considered representative of the overall United States stock market.

Individuals are presented with 9 different monthly U.S. stock market return scenarios and asked to provide beliefs about the return of the firm in each scenario. The scenarios are an S&P 500 monthly return of: -50 percent; -20 percent; -10 percent; -5 percent; 0 percent; 5 percent; 10 percent; 20 percent; 50 percent. I include a description of each scenario in terms of the value of a \$100 investment in the S&P 500.[5] I ask individuals to provide an estimate for the dollar value of a \$100 investment made in the firm over the same month. The question text is:

> The monthly S&P 500 return is 10 percent. In other words, an investment of \$100 in the S&P 500 at the beginning of the month would be worth \$110 at the end of the month. What do you think an investment of \$100 in Microsoft stock at the beginning of this same month would be worth at the end of the month? (Please express your answer in dollars)

The structure is the same for questions about macroeconomic variables. I show individuals the name and a description of a macroeconomic variable randomly drawn from a set of 16 variables.[6] I ask participants to provide beliefs about the growth rate of the variable under the same set of monthly S&P 500 return scenarios. I provide an initial level for the macroeconomic variable at the beginning of the market return scenario month and ask participants to provide estimates for the level of the variable at the end of the month. For example, to solicit estimates of housing market returns I ask individuals:

> If the average house price in the United States was \$100,000 on average at the end of the previous month, what do you think the average house price in the United States will be at the end of the

[5] I frame the scenarios and elicit answers in dollars to address concerns that individuals may have difficulty understanding the concept of growth rates or returns.

[6] The 16 macroeconomic variables used in the survey are listed in Table AI in the Appendix.

current month when the United States stock market return is 5 percent? (Please provide a dollar amount)

Individuals make estimates for 5 randomly selected firms and 5 randomly selected macroeconomic variables. I remove participants from the sample who: completed the entire survey in under 8 minutes, submitted responses with implausible values (negative stock price estimates), or clicked through the survey (left many questions blank or submitted "1" for every answer).

## 2.3 Results

I analyze the firm stock price questions and the macroeconomic variable questions using the same procedure. For each participant $i$ who answered questions about firm or macroeconomic variable $j$, I convert the dollar estimates under the different market return scenarios $k$ into returns:

$$r_{j,k}^{i} = log\left(\frac{Value_{j,k}^{i}}{InitialValue_{j}}\right) \tag{2}$$

where $Value_{j,k}^{i}$ is the response of participant $i$ about her belief of the end of month value of variable $j$ in market return scenario $k$ given the start of the month value $InitialValue_{j}$ provided in the problem description. I aggregate across individuals to obtain average expected returns for each stock (or growth rates for each macroeconomic variable) under each market return scenario:

$$r_{j,k} = \frac{1}{N_j}\sum_{i} r_{j,k}^{i} \tag{3}$$

where $N_j$ is the number of participants who submitted responses about variable $j$. I calculate the average assessed beta of variable $j$ with respect to the stock market by regressing the average expected returns $r_{j,k}$ on the corresponding aggregate stock market monthly return in the given scenario denoted by $r_k^{mkt}$.

$$r_{j,k} = \alpha_j + \beta_j^{experimental} r_k^{mkt} + \epsilon_k \tag{4}$$

Next, I regress the actual monthly time-series of every variable $j$ on actual S&P 500 monthly returns over the longest sample for which data are available to obtain actual betas with respect to the market. Figure I plots the survey assessed betas $\beta_j^{assessed}$ on the y-axis against the historical betas $\beta_j^{historical}$ on the x-axis for each macroeconomic variable $j$ and for 5 portfolios of firms sorted based on actual betas. I divide the firms into quintiles based on actual betas and calculate the average of the survey betas and historical betas within each quintile. For macroeconomic variables that have a very weak relationship with the stock market, participants assess a moderate relationship which leads to significant over-estimation the low betas. For stocks, individuals assess a moderate beta regardless of the actual beta of the firm.

**[Figure I: Assessed versus Historical Beta]**

## 2.4 Discussion

Participants assess moderate comovement between the stock market and different variables regardless of the historical comovement between these variables.

**Misperception of Risk** In traditional asset pricing models, comovement with risk factors determines risk and expected returns. However, if assessments of comovement are biased towards moderate values, then high and low beta assets will have similar perceived riskiness and average realized portfolio returns may not line up with portfolio beta. In the survey, there is a flat relationship between assessed beta and historical beta - if asset returns correspond to this perceived risk, this will generate a pattern consistent with the flat relationship documented empirically between average portfolio returns and CAPM beta (Fama and French (2004)).

Survey participants over-estimate the low comovement between the stock market and macroeconomic variables such as consumption growth and labor income growth. This over-estimation has implications for household stock market participation decisions. The excess market return over the risk-free rate is large enough that households would need an implausibly high risk aversion to match the low allocation rate to the stock market in the U.S.[7] Heaton and Lucas (2000) discuss the role of background risk in which human capital returns are correlated with the stock market so that individuals effectively hold a large position in the stock market through their human capital, which reduces their optimal holdings in the stock market. However, the empirical correlation between labor income and the stock market is very low.[8] Survey participants assess a moderate relationship between wage growth and the S&P 500 return despite the actual relationship being

[7] There are many potential reasons for the low investment in the stock market, such as lack of sophistication, lack of funds, or low levels of trust (Choi and Robertson (2017)).

[8] Heaton and Lucas (2000) calculate the correlation of quarterly aggregate wage income growth with the CRSP value weighted market return to be -0.07.

close to zero. Biased assessments of comovement substantially alter the perceived risk of the stock market and can potentially help to explain the low allocation of wealth to the stock market in the data. Similarly, participants' over-estimation of the low comovement between stock market returns and consumption growth make the stock market appear much riskier from the perspective of consumption-based asset pricing models. Based on survey participant responses, the assessed beta of consumption growth with respect to S&P 500 returns from the survey results ranges from 0.10 to 0.4, which is approximately 20x higher than the actual beta. The distortion of perceived risk is consistent with an equity premium that appears too large based on historical measures of risk.

**Motivating Evidence** This evidence, while only indicative, highlights implications for perceptions of risk in asset pricing and motivates the study of assessments of comovement in empirical settings. In the next section, I discuss my empirical approach for testing assessments of comovement within the setting of electricity and natural gas markets.

# 3 Assessment of Comovement and Asset Prices

The U.S spot and futures markets for electricity and gas provide a natural setting for studying assessments of comovement. Electricity and natural gas markets have a well-defined economic relationship - natural gas is an input in the production of power. Persistent, physical constraints govern both electricity prices and the relationship with local natural gas prices in every region: in regions with many natural gas plants, changes in gas price are shifters for the local supply curve of power and the comovement between electricity and gas spot prices will be high; in regions where most of the generation comes from nuclear, coal, or hydro-electric generation, the sensitivity of power to gas prices will be weak. I measure these relationships using spot market pricing data by calculating the daily electricity spot market return beta with respect to gas returns in each different region around the U.S. I show that the strengths of these relationships in each geography vary persistently over time. Investors trade futures contracts that settle based on the spot price of electricity (or gas) in a specific location. I measure investor beliefs about the comovement between electricity and natural gas in each different location by calculating the futures market return beta for each electricity futures contract and the associated gas futures contract. I find evidence consistent with a bias in the assessment of comovement towards moderate values. The perceived strength of the relationship between electricity and natural gas, measured using futures market betas, is moderate and similar across all contracts regardless of the spot market relationship. I discuss the potential problems with using futures betas and spot betas to measure assessed and benchmark comovement. To address these concerns, I develop a second test based on predicting errors in futures prices and show that trading against this compression generates significant profits. The strategy yields annual returns of 7.3 percent with a Sharpe ratio of 1.14 with statistically significant 3-factor and 5-factor alphas of around 7 percent annually.

I provide a brief overview of the electricity and gas markets in the following subsection. Then I describe the measures of assessed and benchmark comovement and provide an initial characterization of assessments of comovement. I discuss the potential problems with this comparison and describe the second part of my empirical design.

## 3.1 Background

Wholesale electricity markets allow speculators (such as banks and hedge funds) and hedgers (such as power plants and consumer entities) to buy and sell electricity at different geographic locations in a spot market and a futures market. Liquid day-ahead futures markets exist in New England (ISONE), New York (NYISO), the mid-Atlantic (PJM), and the Midwest (MISO). The size of electricity contracts are typically measured in megawatts (MW), which is a unit for measuring power. One feature of the electricity market is that electricity is non-storable so the standard storage arbitrage relationship between spot and futures prices does not hold. However, just as in other commodities markets, electricity futures prices reflect market expectations of future spot prices with a potential risk premium component. Similarly, natural gas can be bought or sold in both the spot market and futures market for delivery at various locations around the U.S.

I acquire data from several organizations. Spot market electricity data comes from NYISO, PJM, ISO-NE, and MISO.[9] Electricity futures data are end of day prices on the Chicago Mercantile Exchange (CME) and the Intercontinental Exchange (ICE). Spot gas data comes from Bloomberg and Natural Gas Intelligence. Gas futures data comes from the U.S. Energy Information Administration (EIA), CME, and ICE. The futures data span the period from 2009 to 2018. The spot data span from the early 2000s to 2018 with the start period varying by geographic region. Additional commodities data comes from Bloomberg and

[9] These are organizations formed at the recommendation of the Federal Energy Regulatory Commission which coordinate, control, and monitor the operation of the electrical power system in a designated geographic region in the U.S.

SummerHaven.

### 3.1.1 Electricity Markets

**Spot** The spot price of power is the market clearing price which matches generator supply with consumer demand. Each day, power generators submit offers to sell power, and demand (entities which consume power) submits bids to buy power. The spot price of electricity is calculated at the hourly level as the market clearing price. In an unconstrained world, the price of power would be the same at all locations. However, there are physical constraints that impact the transfer of power from generation to demand – power lines will melt if too much power is transferred across them, and dissipation of power increases with transmission distance. These constraints lead to variation in the price of power across locations. The price of power at a given location is determined by the incremental cost of supplying an additional megawatt to the location. This also drives heterogeneity in the relationship between electricity and gas spot prices since in some regions the incremental megawatt often comes from local natural gas power plants, while in other regions it may often come from local coal, nuclear, or hydroelectric power plants.

**Futures** Futures contracts that settle on the spot price of power are traded by speculators, generators, and consumers. In an electricity futures contract, the buyer of the contract agrees to pay a fixed price at a future date in exchange for power to be delivered over a designated future period. Electricity futures contracts are cash settled, meaning the seller pays the buyer the spot price and receives the fixed price over the settlement period rather than delivering actual power to the buyer. An electricity futures contract is defined by location, settlement period, and class. The location determines the geographic region over which the spot price of power will be calculated. The settlement period specifies the calendar period over which the spot price of power will be calculated. Settlement periods are typically months of the year. Finally, the class determines the time of day over which the price of power will be calculated.[10] The size of the contract, measured in MW, determines the scaling factor in the settlement calculation.[11] I restrict the study

[10] There are three main classes: onpeak, which includes hours ending 0800 to 2300 Monday through Friday; offpeak, which is all other hours; and around-the-clock (ATC), which is a 7x24 contract (all hours of every day).

[11] For example, as of June 4th, 2017, a trader may take a 50 megawatt long position in New York City, September 2019 onpeak futures for \$40/MWh. At the time of trade, no cash is sent between parties but a small fraction of the notional value of the contract must be deposited as an initial margin with the exchange. At any time before the settlement period begins in September 2019, either party could enter into an offsetting position at that day's market price and effectively close their position. They would make profits (or losses) equal to the difference in their original purchase (sale) price and their new sale (purchase) price. If they hold to settlement, then the buyer will receive the spot price of power in New York City from

to monthly onpeak futures contracts as offpeak contracts are less liquid. Table **AII** in the Appendix shows the set of tradeable electricity locations across the U.S. used in this paper.

### 3.1.2 Natural Gas Markets

**Spot** Natural gas can be bought and sold for immediate or near-term delivery in the spot market. Similar to the electricity markets, natural gas can be purchased for delivery at a number of different locations. The standard delivery location is Henry Hub in southern Louisiana. Natural gas is moved across pipelines from Henry Hub to delivery points across the U.S. The spot price of natural gas at these delivery points may differ from the spot price at Henry Hub due to transmission and storage constraints. The gas price faced by power plants in a given region is the spot price of gas at the nearest delivery point which can differ substantially from the spot price at Henry Hub. I use EIA defined mappings (in Table AIII in the Appendix) to match each electricity location to its associated gas location.

**Futures** Henry Hub is the designated delivery point for the standard NYMEX gas futures contract. In this futures contract, the buyer agrees to pay a fixed price at a future date in exchange for gas to be delivered at Henry Hub over the monthly delivery period of the contract. There are also basis futures contracts that pay the difference between the spot price at a specified delivery point and the spot price at Henry Hub at the time of delivery. These contracts can be bought in conjunction with a Henry Hub futures contract to construct a futures contract for delivery at different locations across the country.[12] I use basis gas futures contracts to construct futures prices of gas deliverable in the local area corresponding to each electricity region.

## 3.2 Measuring Assessed and Benchmark Comovement

The strength of relationship between electricity and gas varies predictably across regions due to persistent characteristics of geography such as the composition of power plants and the structure of the electricity

September 1, 2019 to September 30, 2019 during the hours ending 0800 to 2300 Monday through Friday multiplied by the contract size of 50MW and pay the fixed price of \$40/MWh multiplied by the number of onpeak hours and the contract size. If the average spot price in New York City during onpeak hours in September 2019 is \$55/MWh then the buyer will receive: $\$1,056,000 = \$55/MWh \times 24$ *Onpeak Days* $\times\, 16$ *Hours/Onpeak Day* $\times\, 50MW$ *Contract Size*) and will pay the fixed price of $\$768,000 = \$40/MWh \times 24$ *Onpeak Days* $\times\, 16$ *Hours/Onpeak Day* $\times\, 50MW$ *Contract Size* with a net profit of \$288,000.

[12] Gas futures contracts expire three business days prior to the first calendar day of the delivery month. When the cash settled contracts expire, the buyer of the futures receives the difference between the price of the futures contract at expiry and the fixed price. Natural gas futures prices are quoted in dollars per million British thermal units (mmBtu).

transmission grid. I measure this geographic heterogeneity using location-specific spot prices for electricity and gas to estimate each location's spot market beta from a regression of daily electricity spot market returns on daily gas spot market returns. I measure investor assessments of the regional comovement between electricity and gas by estimating the futures beta from a regression of daily electricity futures returns on daily gas futures returns.

In the context of Equation 1 (repeated below as Equation 5), the historical spot market beta measures $\beta^{rational}$ and the futures market beta measures $\beta^{assessed}$. If futures betas and spot market betas are appropriate measures and assessed comovement is rational, corresponding to $\rho = 0$, then futures betas and historical spot market betas should line up. The challenge and the focus of this paper is to determine to what extent the futures and spot market betas are appropriate measures of assessed and rational comovement.

$$\beta^{assessed} = (1 - \rho)\, \beta^{rational} + \rho \beta^{c,anchor} \tag{5}$$

**Benchmark Comovement** I measure the relationship between electricity and natural gas in each location by estimating the historical daily spot market return beta between electricity and natural gas at each different location and season[13]. I estimate spot return sensitivity, $\beta^{spot}_{i,m}$, of electricity daily spot market returns on gas daily spot market returns during month $m$ for location $i$ for each $i, m$ pair:

$$r^{spot}_{i,t,m} = \alpha_{i,m} + \beta^{spot}_{i,m} r^{spot}_{g(i),t,m} + \epsilon_{i,t,m} \tag{6}$$

$r^{spot}_{i,t,m}$ is the daily spot electricity return[14] in location $i$, day $t$, and settlement month $m$, and $r^{spot}_{g(i),t,m}$ is the daily spot gas return of the gas used by power plants in location $i$.

**Assessed Comovement** I measure investor beliefs about the relationship between electricity and natural gas across different locations and seasons using the beta of daily electricity and gas futures returns. To obtain the futures beta for each contract, I construct two series: daily futures returns of electricity in the two months leading up to the start of the settlement period and daily futures returns of the local natural gas in the two months leading up to the settlement period. Futures returns are defined as: $r^{futures}_{i,t,m} = log\left(\frac{F_{i,t,m}}{F_{i,t-1,m}}\right)$ where

[13] Throughout this section I refer to the month of the year (January, February, ..., December) as the "calendar month" or the "season." I refer to specific months such as January 2017 or March 2009 as the "settlement month" or "settlement period".

[14] Spot returns are defined as $r^{spot}_{i,t,m} = log\left(\frac{p_{i,t,m}}{p_{i,t-1,m}}\right)$ where $p_{i,t,m}$ is the spot price at the end of day $t$, for location $i$, during settlement month $m$.

$F_{i,t,m}$ is the futures price at the end of day $t$, for location $i$, with settlement month $m$. I run the following regression separately for each $i$ and $m$:

$$r_{i,t,m}^{futures} = \alpha_{i,m} + \beta_{i,m}^{futures} r_{g(i),t,m}^{futures} + \epsilon_{i,t,m} \tag{7}$$

where $r_{i,t,m}^{futures}$ is the daily electricity futures return of location $i$, with settlement period $m$, in day $t$; $r_{g(i),t,m}^{futures}$ are the gas daily futures returns of the gas hub $g\left(i\right)$ which delivers gas to power plants in location $i$, with settlement period $m$, at the end of day $t$. I obtain sensitivity estimates, $\beta_{i,m}^{futures}$, which are the futures sensitivity of electricity returns to gas returns for each location-settlement month combination.

### 3.2.1 Strengths and Weaknesses of the Measures

The main challenge of empirical settings compared to experimental ones, is that I do not construct the data-generating processes and cannot directly ask financial market participants about their assessments of comovement. My benchmark measure comes from historical comovement between electricity and gas in each region in the spot market and my measure of beliefs comes from the return comovement of the corresponding futures contracts. I employ a many-to-one design where I compare many electricity contracts to one gas location. The mappings between electricity locations and corresponding gas supply location are defined by the EIA. This design rules out biases or frictions that would affect gas futures returns since these would generate upward or downward shifts in the beta of every associated electricity contract but not a pattern of compression. However, there are several potentially serious shortcomings of extracting measures of benchmark and assessed comovement in the method described above. I present a stylized example to illustrate the strengths of these measures and also the potential problems. The central questions are: why are the futures beta and historical spot market betas appropriate measures of investor assessments of comovement and a benchmark and, in particular, should there be any relationship between contract futures betas and historical spot market betas?

Consider the following example. The log spot price of electricity in location $i$, day $t$, is given by $p_t^{e,i}$ and is a function of two factors: a common factor that drives demand for both electricity and gas, $d_t$, and spot gas price $p_t^g$.

$$p_t^{e,i} = \eta^i d_t + \gamma^i p_t^g \tag{8}$$

$\gamma^i$ is the location specific loading of electricity spot prices on local gas spot prices and is invariant across time. Inuitively, $\gamma^i$ is higher for locations with many natural gas power plants since changes in spot gas price are supply curve shifters for local power, and $\gamma^i$ is lower in locations with few or no natural gas plants (all nuclear or coal) since changes in spot gas price will not affect the supply curve of power in that region. $\eta^i$ is the sensitivity of power price in region $i$ to $d_t$ which could be any factor that drives electricity and gas spot prices such as weather conditions. $\eta^i$ may be higher for cities where the demand for electricity comoves strongly with changes in temperature.

In this example, there is one spot gas location which provides gas to the many electricity regions $i$. Empirically, I use the EIA defined mappings which match each gas location with many local electricity locations. Log spot gas price is:

$$p_t^g = \eta^g d_t + o_t \tag{9}$$

where $p_t^g$ is the spot price of gas on day $t$, $\eta^g$ is the loading on common factor, $d_t$, and $o_t$ is a factor that is unrelated to spot electricity prices outside of its effect on spot gas prices. $o_t$ and $d_t$ are exogenous AR(1) processes:

$$o_t = \rho_o o_{t-1} + \epsilon_t^o \tag{10}$$

$$d_t = \rho_d d_{t-1} + \epsilon_t^d \tag{11}$$

To highlight the potential problem with using historical spot market betas as a benchmark for futures betas, in this example, I assume that $\rho_o = 1$ and $\rho_d = 0$. Electricity spot market returns are:

$$r_t^{e,i} = \eta^i \epsilon_t^d + \gamma^i r_t^g \tag{12}$$

and gas spot market returns are:

$$r_t^g = \eta^g \epsilon_t^d + (\rho_o - 1)\, o_{t-1} + \epsilon_t^o \tag{13}$$

Then the spot beta is:

$$\beta_{spot}^i = \gamma^i + \eta^i \eta^g \frac{V\left(\epsilon_t^d\right)}{V\left(r_t^g\right)} \tag{14}$$

Next, I derive the futures beta. I ignore risk premia variation for simplicity. At the end of the section, I provide several tests and discuss the potential patterns of risk premia variation. Under risk neutrality, futures prices are set as:

$$f_{t,T}^j = logF_{t,T}^j = log\mathbb{E}_t\left(P_T^j\right) = \mathbb{E}_t\left(p_T^j\right) + \frac{1}{2}Var_t\left(p_T^j\right) \tag{15}$$

where $f_{t,T}^j$ is the futures price of commodity $j$ as of date $t$ for delivery at date $T$, $P_T^j$ is the spot price of commodity $j$ as of delivery date $T$, and $p_T^j$ is the logged spot price. Assuming constant conditional volatility, electricity futures returns are:

$$r_{t,T}^{e,i} = \eta^i\left(\mathbb{E}_t d_T - \mathbb{E}_{t-1} d_T\right) + \gamma^i\left(\mathbb{E}_t p_T^g - \mathbb{E}_{t-1} p_T^g\right) \tag{16}$$

And similarly, gas futures returns are:

$$r_{t,T}^g = \eta^g\left(\mathbb{E}_t d_T - \mathbb{E}_{t-1} d_T\right) + \left(\mathbb{E}_t o_T - \mathbb{E}_{t-1} o_T\right) \tag{17}$$

The futures beta from a regression of daily electricity futures returns on daily gas futures returns is[15]:

$$\beta_{futures}^i = \gamma^i + \eta^i \eta^g \frac{\rho_d^{2(T-t)} V\left(\epsilon_t^d\right)}{V\left(r_{t,T}^g\right)} \tag{18}$$

The location-specific loading on gas, $\gamma^i$, should be reflected in both spot and futures betas. If $\gamma^i$ is the sole source of heterogeneity in betas then futures betas should correspond to the historical spot market beta after accounting for estimation error and time-variation in betas (I discuss these issues and the associated tests

[15] The change in expectations of $o_t$ and $w_t$ are given by $\mathbb{E}_t o_T = \rho_o^{T-t} o_t$ and $\mathbb{E}_{t-1} o_T = \rho_o^{T-t+1} o_{t-1}$ so $\mathbb{E}_t o_T - \mathbb{E}_{t-1} o_T = \rho_o^{T-t} o_t - \rho_o^{T-t+1} o_{t-1} = \rho_o^{T-t}\left(\rho_o o_{t-1} + \epsilon_t^o\right) - \rho_o^{T-t+1} o_{t-1} = \rho_o^{T-t}\epsilon_t^o$. Similarly, $\mathbb{E}_t d_T - \mathbb{E}_{t-1} d_T = \rho_d^{T-t}\epsilon_t^d$

I run to address them in Subsection 3.3). This captures the intuition behind using these measures to test assessments of comovement. However, the component of spot market betas driven by loadings on the common factor, $d_t$, will not necessarily translate into futures betas. In the stylized example, the autocorrelation of the $d_t$ process is assumed to be 0 ($\rho_d = 0$ ), so $\beta^i_{futures} = \gamma^i$. In general, if $\rho \approx 0$ then for $T-t$ large, $\rho_d^{T-1} \approx 0$ and $\beta^i_{futures} \approx \gamma^i$. This highlights a problem of my approach to constructing measures of benchmark and assessed comovement: if all regions share a common $\bar{\gamma}$ so that the heterogeneity observed in spot betas is driven by geographic heterogeneity in $\eta^i$, then there will be a flat relationship between futures betas and spot betas even if beliefs about comovement are rational. In general, this issue will arise if: the factors driving spot market comovement are not forecastable; or if the structure of information arrival to traders reduces the volatility of forecasts compared to the volatility of the forecasted processes. For example, if forecasts for the common factor don't fluctuate at long horizons, such as month-ahead weather forecasts which don't vary from day to day, then this component of spot market betas will not map into futures market betas. I design a separate test to address these issues and document the results in subsection 3.4.

In the next subsection, I present an initial characterization of assessed comovement compared to benchmark comovement and document a pattern of compression. To address the issues described in this subsection, I develop a new design to test whether the compression in futures betas relative to historical spot betas generates predictable errors in futures prices in the pattern predicted by biased assessments of comovement towards moderate values. I present these sets of results below.

### 3.3 Comparison of Assessed Comovement with Benchmark

I compare the futures beta of each location and settlement month combination, $\beta^{futures}_{i,m}$, against the average of the past three years spot market betas, $\beta^*_{i,m} = \frac{1}{3}\left(\beta^{spot}_{i,m-12} + \beta^{spot}_{i,m-24} + \beta^{spot}_{i,m-36}\right)$, for the same location $i$ in the same calendar month in previous years. I run the following regression:

$$\beta^{futures}_{i,m} = \alpha + \delta\beta^*_{i,m} + \epsilon_{i,m} \tag{19}$$

where $\beta^{futures}_{i,m}$ is the futures beta for location $i$ in month $m$ estimated from Equation 7 and $\beta^*_{i,m}$ is the average of the betas for location $i$ in the same calendar month for the previous three years. The parameter $\delta$ measures the relationship between futures market beta and spot market beta. Column 1 of Table I documents results from the regression specified in Equation 19. The slope of the best fit line, $\delta$, is -0.013 and the intercept, $\alpha$, is 0.463. Figure II plots the futures beta on the y-axis and the historical spot beta on the x-axis. Each point represents a location-settlement month futures and historical beta pair.

For each contract (location-season) pair, electricity futures beta with respect to gas futures is approximately 0.5 regardless of the underlying strength of the relationship between electricity and gas measured in the historical spot market. The assessed comovement between electricity and natural gas is compressed towards moderate values relative to the historical strength of relationship. I examine the rational channels that could contribute to this compression such as: estimation error in the historical spot market betas; time-variation in the strength of relationship between electricity and gas, or more generally, limited power of historical spot market betas to predict future relationships between electricity and gas; differences in the spot and futures markets that cause the rational futures betas to differ from historical spot betas. I address the first two channels below. To study the third channel, I develop a separate design discussed in the last section.

**[Table I: Beta Comparison Regression Results]**

**[Figure II: Futures Beta versus Historical Spot Beta]**

#### 3.3.1 Estimation Error in Spot Beta

One concern is that volatility in spot prices can add significant estimation error in spot betas, which will lead to attenuation bias in the estimated relationship between futures market betas and historical spot market beta. I shrink the spot market beta in each location towards the cross-sectional average spot market beta across all locations in the U.S. in each season using Vasicek's method. The degree to which I shrink towards the cross-sectional average is determined by the ratio of the standard error of the estimated location-season spot market beta and the standard deviation of the cross-sectional spot market betas:

$$\beta_{i,m}^{spot,vasicek} = \frac{se\left(\beta_{i,m}^{spot}\right)^2}{sd\left(\beta_{j,m}^{spot}\right)^2 + se\left(\beta_{i,m}^{spot}\right)^2}\bar{\beta_m} + \frac{sd\left(\beta_{j,m}^{spot}\right)^2}{sd\left(\beta_{j,m}^{spot}\right)^2 + se\left(\beta_{i,m}^{spot}\right)^2}\beta_{i,m}^{spot} \tag{20}$$

where $\beta_{i,m}^{spot}$ is the spot market beta of location $i$ in settlement month $m$, $se\left(\right)$ denotes the standard error of the beta estimation, and $sd\left(\right)$ denotes the standard deviation of cross-sectional betas across all locations in settlement month $m$, $\bar{\beta_m} = \frac{1}{J}\sum_j \beta_{j,m}^{spot}$.

I regress futures betas on the average of the past three years Vasicek shrunken spot market betas:

$$\beta_{i,m}^{futures} = \alpha + \delta \bar{\beta}_i^{spot,vasicek} + \epsilon_{i,m} \tag{21}$$

where $\beta_{i,m}^{futures}$ is the futures beta for location $i$ in month $m$ estimated from Equation 7 and $\bar{\beta}_i^{spot,vasicek} = \frac{1}{3}\left(\beta_{i,m-12}^{spot,vasicek} + \beta_{i,m-24}^{spot,vasicek} + \beta_{i,m-36}^{spot,vasicek}\right)$ for the same location $i$ in the same calendar month in previous years.

Column 2 of Table I documents results from the regression specified in Equation 21. The slope of the best fit line, $\delta$, is -0.012 and the intercept, $\alpha$, is 0.461. Figure III plots the futures beta on the y-axis and the historical Vasicek spot beta on the x-axis. Each point represents a location-settlement month futures and historical beta pair.

The flat relationship between futures betas and spot market betas persists using Vasicek shrunken spot market betas. In general, the relationship between futures market betas and spot market betas is flat which is difficult to reconcile with attenuation bias which would generate a weaker but still positive relationship between futures and spot market betas.

**[Figure III: Futures Beta versus Historical Vasicek Beta]**

### 3.3.2 Are Spot Market Betas Informative About Future Relationships?

A second concern is that the historical spot market betas are uninformative about the future strength of relationship between electricity and natural gas. For example, if the relationship between electricity and natural gas in each region varied unpredictably over time, this can generate cross-sectional heterogeneity in spot market betas that should not result in cross-sectional heterogeneity in rational futures market betas. I test whether the spot market betas in each location are persistent across time by comparing the the spot beta, $\beta_{i,m}^{spot}$, against the spot beta for the same location in the same calendar month in prior years, $\beta_{i,m-12}$, $\beta_{i,m-24}$, $\beta_{i,m-36}$. I run the following regression:

$$\beta_{i,m}^{spot} = \alpha + \delta_{spot} \overline{\beta}_{i,m}^{spot} + \epsilon_{i,m} \tag{22}$$

Column 3 of Table I documents the regression results. The slope of the best fit line is positive and significant with a point estimate of 0.349 that is significant at the 1 percent level.[16] The adjusted R-squared of the regression of current beta on past beta is 0.08. Figure IV plots $\beta_{i,m}^{spot}$ on the y-axis against average trailing historical spot betas, $\overline{\beta}_{i,m}^{spot}$, on the x-axis. There is a positive relationship between historical trailing beta and current beta indicating that the estimated historical relationship between electricity and natural gas is informative about the future strength of relationship. Locations with a strong relationship between electricity and gas spot returns continue to have strong relationships and similarly for locations with weak relationships.

**[Figure IV: Current Spot Beta versus Historical Spot Beta]**

## 3.4 Predicting Pricing Errors

Without fully specifying the electricity and gas spot price processes to include all common factors driving prices, it is difficult to address the concerns outlined in subsection 3.2.1 using the futures beta and spot beta comparison approach. To address these issues, I use an approach where I test whether futures pricing errors are predictable using the difference between observed futures betas and historical spot market betas. The approach is based on the idea that if the compressed futures betas are rational, then it should not be possible to predict errors in these futures prices using information contained in the historical spot market betas. On the other hand, if the compressed futures market betas are driven by a bias in the assessment of comovement towards moderate values, this will generate predictable errors in electricity futures prices based on the difference between the spot beta and futures beta and prior gas futures returns.

I construct a trading strategy that, following a positive gas futures return, goes long electricity futures contracts where the high historical spot beta exceeds the futures beta with gas and shorts electricity futures contracts where the historical spot beta is smaller than the futures beta (and takes opposite positions following a negative gas futures return). If assessments of comovement are biased towards moderate values, following a positive (negative) gas futures return, electricity futures with a strong relationship with natural gas will not increase enough (not decrease enough). Similarly, electricity futures with a weak relationship with natural gas will increase too much (decrease too much). This mispricing will eventually correct since futures prices converge to the spot price as the settlement period approaches. If the compressed futures

[16] Column 4 of Table I documents the results using Vasicek betas. The results are similar.

market betas are driven by biased assessments of comovement towards moderate values then the strategy will be profitable, but if the compressed futures betas are rational, then the strategy will not be profitable.

### 3.4.1 Trading Strategy

To implement this intuition, I develop a trading strategy in the electricity futures market based on difference between futures beta and spot beta for each location. Figure V provides an example of the trading strategy. Table AIII in the Appendix shows the EIA defined mappings between gas locations and electricity regions. There are four main gas locations: Algonquin Citygate in New England; Transco Zone 6 in New York; TETCO-M3 in the Mid-Atlantic; and Chicago Citygate in the Midwest. The strategy trades prompt month electricity futures contracts that settle on the spot price of electricity in location $i \in I_r$ where $I_r$ denotes the set of all electricity locations within gas region $r$ where $r \in \{Algonquin, Transco\ Zone\ 6, TETCO-M3, Chicago\ Citygate\}$. The strategy takes offsetting long short positions within each gas location (long positions in electricity locations mapped to Algonquin Citygate are offset by short positions in locations also mapped to Algonquin Citygate).

At the end of month $t$, I examine all electricity futures prices, $F^{e}_{i,t+2,t}$, where $i$ is the settlement location and $t+2$ is the settlement month. For each of these futures contracts, I construct $\hat{\beta}^{\Delta}_{i,m} = \hat{\beta}^{spot}_{i,m} - \hat{\beta}^{futures}_{i,m}$, where $\hat{\beta}^{spot}_{i,m}$ is estimated using the daily spot beta between electricity and gas returns in location $i$ in the same calendar month as settlement period $m$ but in the previous three calendar years (average of the 3 betas), and $\hat{\beta}^{futures}_{i,m}$ is estimated using daily returns of electricity and gas futures of the contract for location $i$ settling in month $m$ over the all trading days in month $t$. $r^{gas}_{i,t+2,t}$ is the return from the first trading day in month $t$ to the last trading day of month $t$ of the gas futures contract with settlement period $t+2$, delivering to location $i$. For each location $i \in I_r$, I create an indicator variable, $\mathbb{I}_{\beta^{\Delta}_{i,m} > Median\left(\beta^{\Delta}_{i,m}\right), \forall i \in I_r}$. For each gas region, I divide electricity futures contracts into two groups based on the difference between the spot market beta and futures market beta. I enter into a long position in the electricity futures contract for location $i$ if $r^{gas}_{i,t+2,t} > 0$ and $\mathbb{I}_{\beta^{\Delta}_{i,m} > Median\left(\beta^{\Delta}_{i,m}\right), \forall i \in I_r} = 1$ or if $r^{gas}_{i,t+2,t} < 0$ and $\mathbb{I}_{\beta^{\Delta}_{i,m} > Median\left(\beta^{\Delta}_{i,m}\right), \forall i \in I_r} = 0$. I take a short position otherwise. I hold the positions until the end of month $t+1$, earning a return on each position of $r_{i,t+1} = log\left(\frac{F_{i,t+2,t+1}}{F_{i,t+2,t}}\right)$. I calculate the equal weighted average of all position returns to obtain monthly returns of the trading strategy.

**[Figure V: Trading Strategy Example]**

The annualized return of this strategy is 7.3 percent with a standard deviation of 6.6 percent, yielding an annualized Sharpe ratio of 1.14. The strategy returns aggregated to the gas location level are each positive. I run the same strategy restricting available assets to the most liquid locations. The annualized return of this strategy is 12.1 percent with a standard deviation of 9.2 percent and a Sharpe ratio of 1.32. I regress the monthly returns of the baseline strategy on the Fama French 3 factors and the Fama French 5 factors. The strategy yields an annualized 3-factor alpha of 7.1 percent, significant at the 1 percent level, and an annualized 5-factor alpha of 7.7 percent, also significant at the 1 percent level. For the liquid strategy, the annualized 3-factor alpha is 11.8 percent, significant at the 5 percent level and the annualized 5-factor alpha is 12.7 percent, also significant at the 5 percent level. Summary statistics for each trading strategy are reported in Table II. Output from the regression of monthly returns onto the Fama French 3-factor and 5-factor models are reported in Table **III**. Figure **VI** shows the monthly time-series cumulative returns of both specifications. Strategy returns are earned over the full 10 year trading period.

**[Table II: Trading Strategy Summary Statistics]**

**[Table III: Trading Strategy Fama French Regression Results]**

**[Figure VI: Trading Strategy Cumulative Return]**

The compression in futures betas compared to historical spot market betas and the profitability of the trading strategy are consistent with biased assessments of comovement towards moderate values and are difficult to reconcile with the alternative channels discussed above.

#### 3.4.2 Risk Premia

The trading strategy returns cannot be explained by standard risk models such as the CAPM, Fama French 3-factor model, or the Fama French 5-factor model. I test whether the trading strategy returns are explained by loadings on commodity specific factors. I regress the monthly strategy returns on an equal-weighted portfolio constructed to capture the average return of a broad set of commodities.[17] Next, I construct a proxy for the "market return" of electricity futures contracts by equal weighting long positions in prompt month electricity futures contracts across all locations in the U.S. I regress the monthly strategy returns on these factors. Both regression specifications follow:

[17] Data from AQR "Commodities for the Long Run: Index Level Data, Monthly

$$r_t^{strategy} = \alpha + \beta r_t^{factor} + \epsilon_t \tag{23}$$

where $r_t^{strategy}$ is the monthly trading strategy return, $r_t^{factor}$ is either the return of an equal-weighted basket of commodity futures long positions or the equal-weighted market portfolio of prompt month electricity futures contracts. The trading strategy returns are not driven by loadings on short-term commodity futures returns. The annualized strategy alphas are 7.3 percent and 7.5 percent respectively and significant at the 1 percent level. Columns 3 and 4 of Table III show the results for the baseline strategy.

In traditional hedging demand channels in the commodities literature, hedging demand from power plants who are naturally long power price, or load-entities who are naturally short power price could generate location specific risk premia based on the composition of generation and load-entities in a region. However, location-specific risk premia won't explain the strategy returns since the strategy goes both long or short the same location based on whether the previous gas futures return was positive or negative. While there are potentially more complex patterns of risk premia variation, I now turn to a setting without risk premia where I can measure beliefs directly and document a similar pattern of compression.

# 4 Assessment of Comovement and Forecasts

In this section, I study assessments of comovement using growth forecasts for different macroeconomic variables. This allows me to measure beliefs directly without concerns about distortions from risk premia fluctuations. I study whether analysts correctly assess the comovement between different macroeconomic quantities and overall economic conditions which I proxy for using Nominal Gross Domestic Product (NGDP). Intuitively, stronger economic conditions are associated with higher consumption growth, more housing starts, greater investment growth, and greater industrial production growth which I find in the forecast data. However, forecasters assess moderate comovement between macroeconomic growth rates and NGDP growth regardless of the historical comovement which generates a similar pattern in growth forecast errors.

Forecast data comes from the Federal Reserve Bank of Philadelphia, which conducts the Survey of Professional Forecasters (SPF). SPF participants are professional forecasters trained in economics and statistics. Each quarter, participants are asked to provide forecasts of a number of U.S. macroeconomic variables at the end of the current quarter and for the next 4 quarters after that. Each participant makes forecasts about many different macroeconomic variables, so I can measure the within-analyst comovement of macroeconomic growth forecasts. I construct a panel of analyst forecasts for 12 macroeconomic variables.[18] These variables are described in Table AIV in the Appendix. I obtain the actual realizations of these variables from the National Income and Product Accounts (NIPA) tables from the Bureau of Economic Analysis (BEA) and from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.

The empirical tests in this section have the same structure as those in the electricity and natural gas section: first, I compare assessed comovement of macroeconomic growth rates with NGDP growth rates against trailing historical comovement; second, I show that macroeconomic growth rate forecast errors are predictable based on the assessed comovement between the variable and NGDP and revisions to NGDP forecasts.

## 4.1 Initial Characterization of Assessed Comovement

**Benchmark Comovement** I construct a benchmark measure of comovement using the historical beta of quarterly growth rates between each macroeconomic variable and NGDP. At each quarter $t$, for each macroeconomic variable $j$, I calculate the lookback beta, $\beta^{lb}_{j,t}$, from the regression of actual quarterly growth rates of macroeconomic variable $j$ from quarters $t-19$ to $t$ on contemporaneous NGDP growth rates shown in Equation 24.

$$g_{j,t-k} = \alpha + \beta^{lb}_{j,t} g_{NGDP,t-k} + \epsilon_{t-k} \; k \in \{0, 1, ..., 19\} \tag{24}$$

where $g_{j,t-k}$ is the quarterly growth rate of macroeconomic variable in quarter $t-k$ and $g_{NGDP,t-k}$ is the quarterly growth rate of Nominal Gross Domestic Product in quarter $t-k$.

To see how macroeconomic betas vary over time, I divide the historical sample into two halves and for each macroeconomic variable, I calculate the beta with respect to NGDP in the second half and compare to the beta in the first half. Figure VII plots the second half beta on the y-axis and the first half beta on the x-axis. I plot the best fit line and the 45° line for reference. The best fit line has a positive slope and

[18] AAA Corporate Bond Yield (BOND), Housing Starts (HOUSING), Nominal GDP (NGDP), GDP Price Index (PGDP), Real Personal Consumption Expenditures (RCONSUM), Real Federal Government Consumption and Gross Investment (RFED-GOV), Real Nonresidential Fixed Investment (RNRESIN), Real Residential Fixed Investment (RRESINV), Real State and Local Government Consumption and Gross Investment (RSLGOV), Treasury Bill Rate (TBILL), Treasury Bond Rate (TBOND), and Civilian Unemployment Rate (UNEMP).

with the exception of HOUSING, the betas generally line up along the regression line indicating a persistent comovement with NGDP across long samples.

**[Figure VII: Persistence of Macroeconomic Betas]**

**Lookback Betas versus Future Betas** Next, I compare each lookback beta, $\beta^{lb}_{j,t}$, to the beta calculated using future realized growth rates. For each lookback beta, $\beta^{lb}_{j,t}$, I calculate a corresponding lookahead beta, $\beta^{la}_{j,t}$, from the regression of actual quarterly growth rates of macroeconomic variable $j$ from quarters $t+1$ to $t+5$ on contemporaneous NGDP growth rates shown in Equation 25. The time horizon is chosen to be equivalent to the horizon of analyst forecasts.

$$g_{j,t+k} = \alpha + \beta^{la}_{j,t} g_{NGDP,t+k} + \epsilon_{t+k} \; k \in \{1,2,3,4,5\} \tag{25}$$

where $g_{j,t+k}$ is the quarterly growth rate of macroeconomic variable in quarter $t+k$ and $g_{NGDP,t+k}$ is the quarterly growth rate of Nominal Gross Domestic Product in quarter $t+k$.

Finally, I estimate the persistence of cross-sectional differences in beta in Equation 26:

$$\beta^{la}_{j,t} = \delta^{la} \beta^{lb}_{j,t} + \mu_t + \epsilon_{j,t} \tag{26}$$

where $\beta^{la}_{j,t}$ is the lookahead beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 25, $\beta^{lb}_{j,t}$ is the lookback beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 24, and $\mu_t$ are quarter fixed effects. Column 1 of Table IV shows the regression results. The coefficient $\delta^{la}$ is 0.603 and significant at the 1 percent level indicating that past beta is strongly persistent. These results suggest that the comovement of different macroeconomic variable growth rates with respect to NGDP is stable over long horizons and exhibits persistent differences in the cross-section.

**[Table IV: Beta Comparison Regression Results]**

Figure VIII plots the lookahead beta, $\beta^{la}_{j,t}$, on the y-axis against the lookback beta, $\beta^{lb}_{j,t}$ on the x-axis. The black $y=x$ line and blue best-fit lines are plotted for reference. The positive relationship between lookahead beta and lookback beta indicates a persistent strength in relationship between a macroeconomic variable's growth rate and NGDP growth.

**[Figure VIII: Lookahead Beta versus Trailing Historical Beta]**

**Assessed Comovement** At each point in time, an analyst provides beliefs about the path of growth for different macroeconomic variables over the next five quarters. I measure assessed comovement between macroeconomic variables and NGDP using the comovement of the forecasted growth rates. During quarter $t$, each analyst $i$ provides forecasts for the level of each macroeconomic variable, $j$, at the end of quarters $t,\ t+1,\ t+2,\ t+3\ t+4$. The analyst knows the $t-1$ value of the macroeconomic variable from the NIPA release version available at time $t$. For growth variables, I construct the analyst's quarterly growth rate forecasts as:

$$\mathbb{E}_t^i\left(g^j_{t+k-1\to t+k}\right) = log\left(\frac{\mathbb{E}_t^i\left(x_{j,t+k}\right)}{\mathbb{E}_t^i\left(x_{j,t+k-1}\right)}\right) \tag{27}$$

where $g^j_{t+k-1\to t+k}$ denotes the growth rate of macroeconomic variable $j$ from quarter $t+k-1$ to quarter $t+k$, $\mathbb{E}_t^i\left(g^j_{t+k-1\to t+k}\right)$ is the forecast analyst $i$ made at time $t$ for this growth rate, $\mathbb{E}_t^i\left(x_{j,t+k}\right)$ is analyst $i$'s forecast in quarter $t$ of macroeconomic variable $j$'s level $k$ quarters out. The notation $\mathbb{E}_t^i\left(x_{j,t-1}\right)$ denotes the actual value of the macroeconomic variable at the end of the previous quarter from the NIPA release version available at the time of forecast. For level variables,[19] I set $\mathbb{E}_t^i\left(g^j_{t+k-1\to t+k}\right)$ equal to the level forecast $\mathbb{E}_t^i\left(x_{j,t+k}\right)$ divided by 100, so that a level forecast of unemployment of 4 percent in quarter $t+2$ is represented as 0.04.

I construct the measure, $\beta_{j,t}$, of assessed comovement of macroeconomic variable $j$ with NGDP using forecasts made as of quarter $t$. I estimate the assessed beta, $\beta_{j,t}$, by regressing growth rate (or adjusted level) forecasts for macroeconomic variable $j$ made in quarter $t$ on contemporaneous growth rate forecasts of NGDP. In my baseline measure, $\beta_{j,t}$ is estimated from a pooled regression across all analyst forecasts made in quarter $t$ for macroeconomic variable $j$. So, if in quarter $t$, 20 analysts each make 5 quarterly growth rate forecasts for quarterly consumption growth from quarters $t+1$ to $t+5$, I estimate $\beta_{Consumption,t}$ based on the regression of the $20\times 5 = 100$ quarterly consumption growth rate forecasts regressed on the corresponding NGDP growth rate forecasts. The regression specification is:

$$\mathbb{E}_t^i\left(g^j_{t+k-1\to t+k}\right) = \alpha_{j,t} + \beta_{j,t}\mathbb{E}_t^i\left(g^{NGDP}_{t+k-1\to t+k}\right) + \epsilon_{i,j,t,k}\ \forall j,t \tag{28}$$

[19] AAA Corporate Bond Yield, Treasury Bill Rate, Treasury Bond Rate, and Civilian Unemployment Rate

where $\mathbb{E}_t^i\left(g_{t+k-1\to t+k}^j\right)$ is the quarterly growth rate forecast for quarter $t+k$, for macroeconomic variable $j$, made by analyst $i$, at quarter $t$ and $\mathbb{E}_t^i\left(g_{t+k-1\to t+k}^{NGDP}\right)$ is the corresponding NGDP quarterly growth rate forecast.

As robustness, I also construct a measure of assessed comovement using the comovement of revisions of annual growth forecasts which I label $\beta_{j,t}^{rev}$. Section 6.2 in the Appendix describes the construction of this measure.

#### 4.1.1 Comparison of Assessed Comovement with Benchmark

I compare the assessed beta of macroeconomic variable growth rates with respect to NGDP growth rates against the trailing historical beta. At each quarter, $t$, I calculate the assessed comovement between each macroeconomic variable, $j$, and NGDP growth using growth rate forecasts, $\beta_{j,t}$ estimated from Equation 28. I compare the forecast betas with historical actual betas, $\beta_{j,t}^{lb}$, from the regression of macroeconomic variable growth rates on contemporaneous NGDP growth over the trailing 20 quarters from Equation 24.

Figure IX plots $\beta_{j,t}$ on the y-axis against $\beta_{j,t}^{lb}$ on the x-axis where each point is a forecast beta and trailing historical beta for a macroeconomic variable, $j$, and forecast quarter date, $t$, combination. The black 45° line and the blue best fit line are also displayed. There is a positive relationship between forecast beta and historical beta.

**[Figure IX: Assessed Beta versus Trailing Historical Beta]**

I regress assessed betas, $\beta_{j,t}$, on trailing historical betas, $\beta_{j,t}^{lb}$ :

$$\beta_{j,t} = \delta^f \beta_{j,t}^{lb} + \mu_t + \epsilon_{j,t} \tag{29}$$

where $\beta_{j,t}$ is the forecast beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 28, $\beta_{j,t}^{lb}$ is the lookback beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 24, and $\mu_t$ are quarter fixed effects. This is the same structure as Equation 26 where I compare the lookahead beta, $\beta_{j,t}^{la}$, to the lookback beta.

Column 2 of Table IV shows the regression results from Equation 29. The coefficient $\delta^f$ is 0.296 and significant at the 1 percent level, indicating that forecast comovement is positively related to past comovement. Comparing with the regression results from Equation 26, the coefficient from the regression of lookahead beta on past beta, $\delta^{la}$, is 0.603 compared to the coefficient of forecast beta on past beta, $\delta^{f}$, of 0.233. Analyst macroeconomic growth rate forecasts covary moderately with NGDP growth forecasts despite differences in historical comovement that persist into the forecast period.

The initial characterization of assessed betas versus historical betas suffers from some of the same issues discussed in the electricity and natural gas setting. The comovement of analyst forecasts will be compressed relative to historical comovement due to factors such as non-forecastable components of macroeconomic growth rates.[20] To address this issue, I follow the empirical design outlined in the electricity and natural gas section and test whether forecast errors are predictable based on the difference between historical betas and forecast betas.

## 4.2 Predicting Forecast Errors

I test whether annual growth forecast errors are predictable using the two measures of assessed comovement and revisions to annual NGDP forecasts. If the assessed comovement with NGDP is biased towards moderate values, then analysts will adjust forecasts for low comovement variables and high comovement to a similar degree so that the NGDP forecast revision interacted with the assessed beta will predict forecast error with a positive coefficient.

I define $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t} - \beta_{j,t}$ as the difference between $\beta^{lb}_{j,t}$, the lookback beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 24, and $\beta_{j,t}$, the forecast beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 28. I construct the average annual forecast revision to NGDP from quarter $t-1$ to $t$ as $FR^{NGDP}_{t-1\to t} = \frac{1}{N_t}\sum_i \left(\mathbb{E}^i_t\left(g^{NGDP}_{t\to t+4}\right) - \mathbb{E}^i_{t-1}\left(g^{NGDP}_{t\to t+4}\right)\right)$ where $N_t$ is the number of analysts making forecasts about annual NGDP in quarter $t$. I construct average annual forecast error for each macroeconomic variable $j$ as of each quarter $t$ as $FE_{j,t} = \frac{1}{N_t}\sum\left(g^{j}_{t\to t+4} - \mathbb{E}^i_t\left(g^{j}_{t\to t+4}\right)\right)$ where $N_t$ is the number of analysts making annual growth forecasts for macroeconomic variable $j$ as of quarter $t$.

I run a pooled regression of forecast errors for each macroeconomic variable $j$ at each quarter $t$ on $\beta^{\Delta}_{j,t}$, NGDP forecast revisions $FR^{NGDP}_{t-1\to t}$, and the interaction term:

$$FE_{j,t} = \alpha + \delta_1\beta^{\Delta}_{j,t} + \delta_2 FR^{NGDP}_{t-1\to t} + \delta_3 FR^{NGDP}_{t-1\to t}\times\beta^{\Delta}_{j,t} + \epsilon_{j,t} \tag{30}$$

[20] Section 6.3 in the Appendix discusses how non-forecastable components of growth rates can generate compression.

where $FR^{NGDP}_{t-1\to t}$ is the average forecast revision of annual NGDP across all analysts from quarter $t-1$ to $t$, $\beta^{\Delta}_{j,t}$ is the difference between trailing historical beta and analyst forecast beta, and $FE_{j,t}$ is the average annual growth rate forecast error across all analysts for macroeconomic variable $j$. Observations in this regression are at the quarter, macroeconomic variable level. Table V documents the results of the regression specified in Equation 30. The first column shows the output using $\beta_{j,t}$ as the measure of assessed comovement and the second column shows the results using the forecast revision beta, $\beta^{rev}_{j,t}$, as the measure of assessed comovement. The cross-term $\delta_3$ is positive in both cases and significant at the 5 percent level for the $\beta_{j,t}$ measure. Forecast errors follow a pattern consistent with compression of forecast betas towards moderate values.

**[Table V: Forecast Error on Assessed Beta and NGDP Revision]**

**Robustness** I run an additional test that is independent from choices in forecast beta measure construction. I run the regression specification from Equation 30 replacing $\beta^{\Delta}_{j,t}$ with the trailing historical beta, $\beta^{lb}_{j,t}$.[21] Column 3 of Table V documents the results of the regression. The cross-term $\delta_3$ is positive and significant at the 5 percent level. This result is consistent with biases in the assessment of comovement towards moderate values.

Table VI documents the predictability results from a number of robustness specifications. I show the coefficient, $\delta_3$, on the cross-term from the regression specified in Equation 30 along with the standard error. Results for the three different measures of beta are shown in the different columns of the table: $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t} - \beta_{j,t}$; $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t} - \beta^{rev}_{j,t}$; and $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t}$. I use different lookback windows to construct $\beta^{lb}_{j,t}$ from 12 quarters, 20 quarters, 28 quarters. I winsorize the $\beta^{\Delta}_{j,t}$ and the $FR^{NGDP}_{t-1\to t} \times \beta^{lb}_{j,t}$ variables at the 1 percent, 5 percent, and 10 percent levels to remove the effect of extreme values. Additionally, run the tests using $log\,(1 + FE_{j,t})$ as the dependent variable. For the forecast beta specifications, the cross-term is positive for 20 out of the 20 robustness checks and significant for 8 out of the 20. For the trailing beta specification, the coefficient remains positive for 10 out of the 10 robustness tests and significant for 9 out of the 10.

**[Table VI: Forecast Error Robustness]**

[21] The intuition is that following an upward (downward) revision to NGDP, if analysts assess moderate comovement of all components of the macroeconomy, then they will adjust both low beta variable and high beta variable forecasts up (down) similarly. On average, this will lead to realizations that are higher (lower) than forecasts for high (low) beta variables.

### 4.3 Discussion

Professional forecasts of different macroeconomic variables exhibit a similar pattern of compression in assessments of comovement. Forecasters assess a moderate comovement between different macroeconomic variables and GDP growth which generates predictable errors in their forecasts. This bias can arise if individuals believe that different components of the macroeconomy tend to move together - when the economy is growing, production is also growing, housing starts are high, and investment is increasing. However, if individuals think about these variables as being "positively related' with strong economic conditions and not in terms of specific beta numbers such as 0.45 or 1.56, then this can lead to distortions in their forecasts. Anchoring on a moderate prior and adjusting only partially towards the data they observe based on historical regressions will generate the compression between forecast betas and historical trailing betas and the pattern of forecast errors I document in this setting.

# 5 Conclusion

Traditionally, economists have assumed that beliefs about comovement are unbiased estimates based on available data. In this paper, I test this assumption across a number of settings and document evidence that assessments of comovement are systematically biased towards moderate values: individuals assess a moderate relationship between two variables regardless of whether the actual relationship is strong, moderate, or weak. Equation 1 (repeated as Equation 31 below) provides a framework for thinking about this bias.

$$\beta^{assessed} = (1-\rho)\,\beta^{rational} + \rho\beta^{c,anchor} \tag{31}$$

An individual's subjective assessed beta, $\beta^{assessed}$, is a weighted combination of the rational beliefs beta based on an individual's information set, $\beta^{rational}$, and the anchor beta representative of the mental category, $\beta^{c,anchor}$, where $c \in \{positively\ related,\ negatively\ related,\ unrelated\}$, and $0 \leq \rho \leq 1$. Individuals think about relationships in coarse categories so that a wide spectrum of relationships are compressed into the same mental representation. When required to assess the relationship between a pair of variables, the individual uses available data but only adjusts partially away from the common anchor of the associated mental category. This partial adjustment will generate compression in assessed comovement relative to rational benchmark comovement and generate the patterns of errors in prices and forecasts that I document in this paper.

Table VII summarizes the results of the paper. In each setting, I regress assessed betas on benchmark betas in the regression below:

$$\beta^{assessed} = \alpha + \delta\beta^{rational} + error$$

With accurate measures of assessed and benchmark comovement, then the rational benchmark corresponds to estimates of $\alpha = 0$ and $\delta = 1$. The compression documented in this paper corresponds to a moderate, positive $\alpha$ and a $\delta$ less than 1. In each setting, individuals anchor on a moderate positive beta and only partially adjust their assessments of comovement towards the comovement observed in the data. To address potential issues with my measures of assessed and benchmark comovement, I develop a separate empirical design. I show that the compression in assessed betas generates errors in asset prices and in forecasts in the particular pattern predicted by biased assessements of comovement towards moderate values.

**[Table VII: Summary of Results]**

There are many settings in economics where individuals need to assess the relationship between two variables: making forecasts, extracting information from a signal, assessing risk, and making investment decisions. In this paper, I document how this bias can distort asset prices, forecasts, and perceptions of risk. While the objective of this paper is to establish initial facts and characterize the pattern of beliefs of comovement, examining potential mechanisms behind the bias, such as categorical thinking and forms of inattention, presents an interesting avenue for future studies.

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# 6 Appendix

## 6.1 Survey

### 6.1.1 Survey Background Information

The survey ran in October 2018 on two groups: approximately 200 individuals who work in the financial sector; and approximately 200 individuals who work in the financial sector and manage money on behalf of other people. Participants are adults in the U.S. who complete the survey remotely using their own computers or mobile devices.

Individuals are asked to provide estimates for individual stock returns or macroeconomic variable growth rates under different aggregate U.S. stock market return scenarios. The goal is to measure the assessed covariation between financial and macroeconomic variables where associations may already be formed. At the end of each survey, individuals are asked some basic demographic information and questions to test their financial literacy. Qualtrics manages the payment to each participant. I pay Qualtrics $7.00 per individual for the 200 financial sector participants and $35.00 per individual for the 200 individuals who work in the financial sector and manage money on behalf of other people.

## 6.2 Constructing Forecast Revision Beta

For each macroeconomic variable, $j$, in each quarter $t$, for each analyst $i$, I construct the forecast revision of annual growth forecasts as:

$$FR^j_{i,t-1\to t} = \mathbb{E}^i_t\left(g^j_{t\to t+4}\right) - \mathbb{E}^i_{t-1}\left(g^j_{t\to t+4}\right) \tag{32}$$

I use annual forecast revisions to match the horizon of forecast errors in empirical tests which I will describe later. I construct the measure $\beta^{rev}_{j,t}$ of assessed comovement of macroeconomic variable $j$ with NGDP using forecasts revisions from quarter $t-1$ to quarter $t$. I estimate the assessed beta, $\beta^{rev}_{j,t}$, by regressing annual forecast revisions for macroeconomic variable $j$ from quarter $t-1$ to $t$ on contemporaneous annual forecast revisions of NGDP. In my baseline measure, $\beta^{rev}_{j,t}$, is estimated from a pooled regression across all analyst forecast revisions made in quarter $t$ for macroeconomic variable $j$. So, if in quarter $t$, 20 analysts each revise annual growth rate forecasts for consumption growth, I estimate $\beta^{rev}_{Consumption,t}$ based on the regression of the 20 annual consumption growth rate forecast revisions on the corresponding annual NGDP growth rate forecast revisions. The regression specification is:

$$FR^{j}_{i,t-1\rightarrow t} = \alpha_{j,t} + \beta^{rev}_{j,t} FR^{NGDP}_{i,t-1\rightarrow t} + \epsilon_{i,j,t,k} \; \forall j,t \tag{33}$$

where $FR^{j}_{i,t-1\rightarrow t}$ is the annual growth rate forecast revision, for macroeconomic variable $j$ made by analyst $i$ from quarter $t-1$ to $t$ and $FR^{NGDP}_{i,t-1\rightarrow t}$ is the corresponding NGDP annual growth rate forecast revision.

## 6.3 Non-Forecastable Component of Growth Rates

Suppose that the growth rate of macroeconomic variable $j_1$ evolves according to:

$$g_{j_1,t+1} = \alpha_{j_1} + \beta_{j_1} w_t + \gamma_{j_1} \delta_{t+1} \tag{34}$$

where $\alpha$ is a constant, $\beta$ is the loading on shocks $w$ which comprise the forecastable component of growth rate, and $\gamma$ is the loading on shocks $\delta$ which comprise the non-forecastable component of growth rate. Rational forecasts of the growth rate of macroeconomic variable $j_1$ in $t+1$ made at time $t$ are:

$$E_t\left(g_{j_1,t+1}\right) = \alpha_{j_1} + \beta_{j_1} w_t \tag{35}$$

The $\beta$ of variables $g_{j_1}$ and $g_{j_2}$ is given by:

$$Cov\left(g_{j_1,t}, g_{j_2,t}\right) = Cov\left(\alpha_{j_1} + \beta_{j_1} w_t + \gamma_{j_1}\delta_{t+1}, \alpha_{j_2} + \beta_{j_2} w_t + \gamma_{j_2}\delta_{t+1}\right) = \beta_{j_1}\beta_{j_2}\Omega + \gamma_{j_1}\gamma_{j_2}\Gamma \tag{36}$$

where $\Omega = Cov\left(w_t, w_t\right)$ and $\Gamma = Cov\left(\delta_t, \delta_t\right)$. Comovement of rational forecasts is given by:

$$Cov\left(E_t\left(g_{j_1,t+1}\right), E_t\left(g_{j_2,t+1}\right)\right) = \beta_{j_1}\beta_{j_2}\Omega \tag{37}$$

The comovement of the non-forecastable components of growth will drive differences between historical comovement and rational forecast comovement.

## 6.4 Figures

Figure AI: **United States Electricity Map**

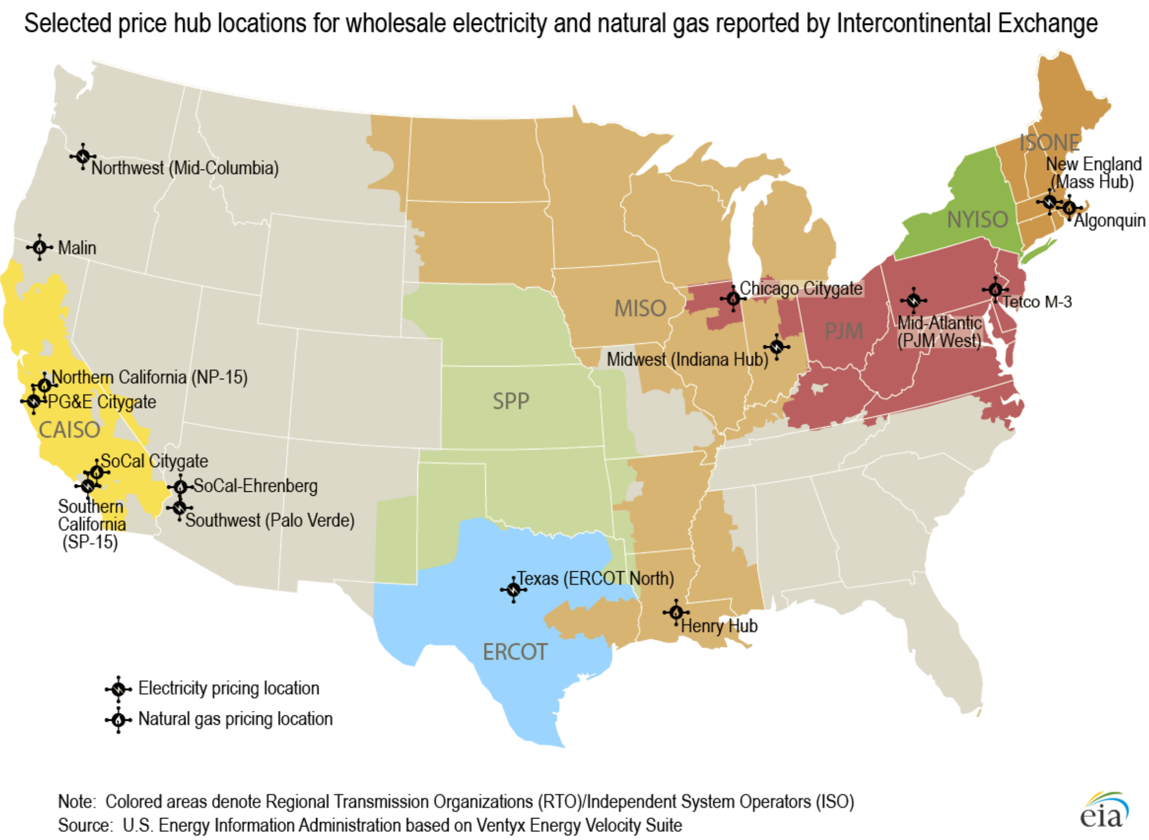


Figure AI shows the different electricity regions across the United States. Each of the highlighted region are overseen by Independent System Operators (ISOs) - organizations formed at the direction of the Federal Energy Regulatory Commission (FERC) to coordinate, control, and monitor the electric grid over a designated geography. Source: EIA

## 6.5 Tables

Table AI: **Macroeconomic Variables**

| Name | Description |
|---|---|
| Chinese Stock Market | Shanghai Stock Exchange Composite Index |
| Durable | Durable goods consumption in the United States |
| Durable (Own) | Participant's own durable goods consumption |
| Nondurable | Nondurable goods consumption in the United States |
| Nondurable (Own) | Participant's own nondurable goods consumption |
| Services | Services consumption in the United States |
| Services (Own) | Participant's own services consumption |
| European Stock Market | STOXX Europe 600 stock market index |
| FTSE | FTSE 100 stock market index |
| Housing | Average house price in the United States |
| Housing (Local) | Average housing price in participant's neighborhood |
| Inflation | Inflation rate in the United States |
| Inflation (Own) | Inflation faced by participant |
| Japanese Stock Market | Nikkei 225 stock market index |
| Probability of Losing Job | Probability that the average worker in the United States will lose his or her job |
| Wages | Average wages for workers in the United States |

Table AI shows the list of macroeconomic variables potentially shown to participants in the survey. Individuals are asked to provide estimates for the growth rates (returns or levels) of these variables under various S&P 500 return scenarios.

Table AII: **Electricity Zones**

| ISO | Region | Zone Name | Secondary Name | Zone ID | Futures Start |
|---|---|---|---|---|---|
| ISONE | New England | Massachusetts Hub | masshub | 4000 | December 2008 |
| | | Maine | me | 4001 | February 2012 |
| | | New Hampshire | nh | 4002 | February 2012 |
| | | Connecticut | ct | 4004 | February 2012 |
| | | Rhode Island | ri | 4005 | January 2016 |
| | | Se Massachusetts | sema | 4006 | February 2012 |
| | | West Central Massachusetts | wcma | 4007 | February 2012 |
| | | Ne Massachusetts | nema | 4008 | February 2012 |
| MISO | | Illinois Hub | illinois hub | 1005 | March 2011 |
| | | Indiana Hub | indiana hub | 1006 | October 2009 |
| NYISO | New York | Zone A | west | 61752 | December 2008 |
| | | Zone B | genese | 61753 | July 2017 |
| | | Zone C | centrl | 61754 | June 2011 |
| | | Zone E | mhk vl | 61756 | July 2017 |
| | | Zone F | capitl | 61757 | June 2011 |
| | | Zone G | hud vl | 61758 | December 2008 |
| | | Zone I | dunwod | 61760 | July 2017 |
| | | Zone J | nyc | 61761 | December 2008 |
| | | Zone K | longil | 61762 | July 2017 |

**Electricity Zones Continued**

| ISO | Region | Zone Name | Secondary Name | Zone ID | Futures Start |
|---|---|---|---|---|---|
| PJM | Mid-Atlantic | Eastern Hub | eastern hub | 51217 | February 2010 |
| | | Western Hub | western hub | 51288 | October 2009 |
| | | Aeco Zone | aeco | 51291 | April 2012 |
| | | Bge Zone | bge | 51292 | January 2011 |
| | | Dpl Zone | dpl | 51293 | April 2012 |
| | | Jcpl Zone | jcpl | 51295 | February 2010 |
| | | Meted Zone | meted | 51296 | July 2011 |
| | | Peco Zone | peco | 51297 | January 2011 |
| | | Pepco Zone | pepco | 51298 | January 2010 |
| | | Ppl Zone | ppl | 51299 | January 2011 |
| | | Penelec Zone | penelec | 51300 | April 2012 |
| | | Pseg | pseg | 51301 | October 2009 |
| | | Pepco Dc | pepco dc | 338268 | July 2017 |
| | | Pepco Md | pepco md | 338269 | July 2017 |
| | | Aps Zone | aps | 8394954 | April 2012 |
| | | Aep Zone | aep | 8445784 | March 2015 |
| | | Comed Zone | comed | 33092371 | March 2011 |
| | | Aep Dayton Hub | aep-dayton hub | 34497127 | February 2010 |
| | | Duquesne Zone | duq | 37737283 | July 2011 |
| | | Atsi Zone | atsi | 116013753 | June 2014 |

Table AIII: **Natural Gas Points and Electricity Regions**

| Region | Gas Point | Electricity Point |
|---|---|---|
| New England | Algonquin Citygate | Massachusetts Hub (ISONE) |
| New York City | Transco Zone 6-NY | NYC Zone J (NYISO) |
| Mid-Atlantic | TETCO-M3 | Western Hub (PJM) |
| Midwest | Chicago Citygate | Illinois Hub (MISO) |

Table AIII shows the gas point and main electricity zone associated with each geographic region.

Table AIV: **SPF Macroeconomic Variables**

| Name | Abbreviation | SPF Description |
|---|---|---|
| AAA Corporate Bond Yield | BOND | Forecasts for the quarterly average and annual average level of Moody's Aaa corporate bond yield. Percentage points. Prior to 1990:Q4, this is the new, high-grade corporate bond yield (Business Conditions Digest variable 116). Quarterly forecasts are for the quarterly average of the underlying daily levels. Annual forecasts are for the annual average of the underlying daily levels. |
| Housing Starts | HOUSING | Forecasts for the quarterly average and annual average level of housing starts. Seasonally adjusted, annual rate, millions. Quarterly forecasts are for the quarterly average of the underlying monthly levels. Annual forecasts are for the annual average of the underlying monthly levels. |
| Nominal GDP | NGDP | Forecasts for the quarterly and annual level of nominal GDP. Seasonally adjusted, annual rate, billions $. Prior to 1992, these are forecasts for nominal GNP. Annual forecasts are for the annual average of the quarterly levels. |
| GDP Price Index | PGDP | Forecasts for the quarterly and annual level of the chain-weighted GDP price index. Seasonally adjusted, index, base year varies. 1992 - 1995, GDP implicit deflator. Prior to 1992, GNP implicit deflator. Annual forecasts are for the annual average of the quarterly levels. |
| Real Personal Consumption Expenditures | RCONSUM | Forecasts for the quarterly and annual level of chain-weighted real personal consumption expenditures. Seasonally adjusted, annual rate, base year varies. Annual forecasts are for the annual average of the quarterly levels. Prior to 1996, fixed-weighted real personal consumption expenditures. |

**SPF Macroeconomic Variables Continued**

| Name | Abbreviation | SPF Description |
|---|---|---|
| Real Federal Government Consumption and Gross Investment | RFEDGOV | Forecasts for the quarterly and annual level of chain-weighted real federal government consumption and gross investment. Seasonally adjusted, annual rate, base year varies. Annual forecasts are for the annual average of the quarterly levels. Prior to 1996, real fixed-weight federal government purchases of goods and services. |
| Real Nonresidential Fixed Investment | RNRESIN | Forecasts for the quarterly and annual level of chain-weighted real nonresidential fixed investment. Also known as business fixed investment. Seasonally adjusted, annual rate, base year varies. Annual forecasts are for the annual average of the quarterly levels. Prior to 1996, fixed-weighted real nonresidential fixed investment. |
| Real Residential Fixed Investment | RRESINV | Forecasts for the quarterly and annual level of chain-weighted real residential fixed investment. Seasonally adjusted, annual rate, base year varies. Annual forecasts are for the annual average of the quarterly levels. Prior to 1996, fixed-weighted real residential fixed investment |
| Real State and Local Government Consumption and Gross Investment | RSLGOV | Forecasts for the quarterly and annual level of chain-weighted real state and local government consumption and gross investment. Seasonally adjusted, annual rate, base year varies. Annual forecasts are for the annual average of the quarterly levels. Prior to 1996, real fixed-weighted state and local government purchases of goods and services. |

**SPF Macroeconomic Variables Continued**

| Name | Abbreviation | SPF Description |
|---|---|---|
| Treasury Bill Rate | TBILL | Forecasts for the quarterly average and annual average three-month Treasury bill rate. Percentage points. Quarterly forecasts are for the quarterly average of the underlying daily levels. Annual forecasts are for the annual average of the underlying daily levels. |
| Treasury Bond Rate | TBOND | Forecasts for the quarterly average and annual average 10-year Treasury bond rate. Percentage points. Quarterly forecasts are for the quarterly average of the underlying daily levels. Annual forecasts are for the annual average of the underlying daily levels |
| Civilian Unemployment Rate | UNEMP | Forecasts for the quarterly average and annual average unemployment rate. Seasonally adjusted, percentage points. Quarterly forecasts are for the quarterly average of the underlying monthly levels. Annual forecasts are for the annual average of the underlying monthly levels. |

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# 7 Tables & Figures

Figure I: **Assessed versus Historical Beta**

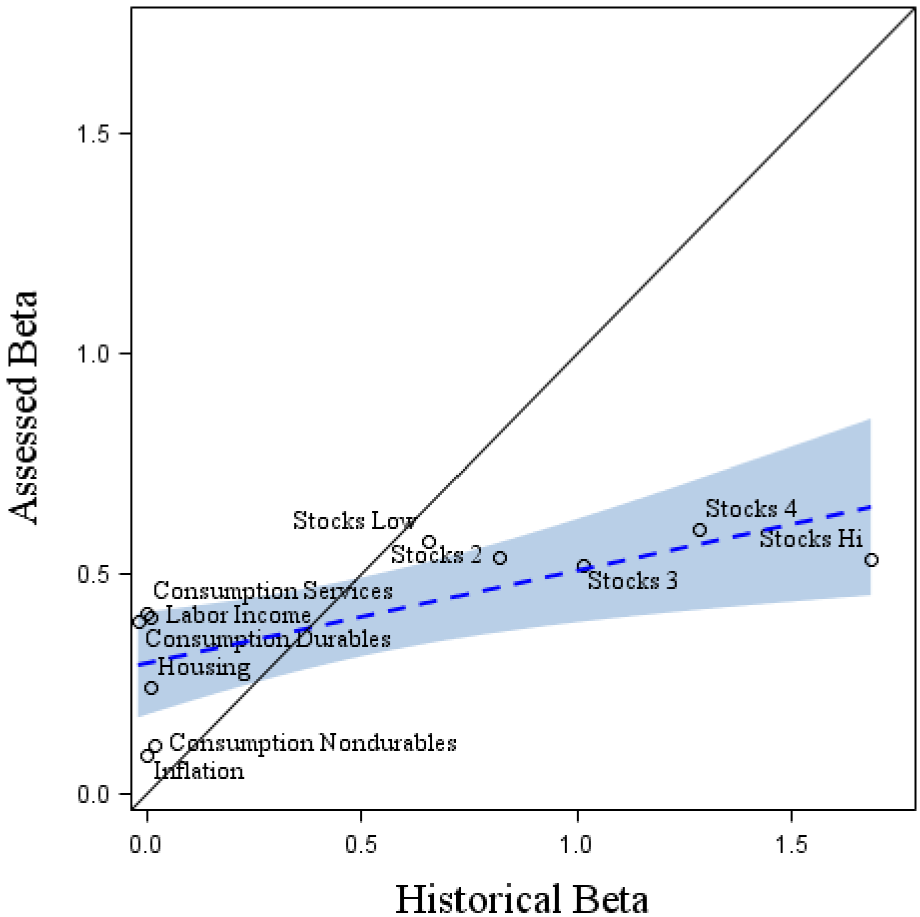


Figure I presents results from the survey on the assessment of the comovement between different macroeconomic and financial variables and the stock market. For each variable, $j$, the figure plots the participant assessed beta, $\beta_j^{assessed}$, obtained from the regression specified in Equation 4, against the actual historical beta, $\beta_j^{historical}$, obtained from a regression of variable $j$ on the S&P 500 return. For the firm betas, I divide the firms into quintiles based on historical betas and plot the average of the assessed beta and historical betas within each quintile.The best fit line in blue and the 45° line in black are plotted for reference.

Figure II: **Futures Beta versus Historical Spot Beta**

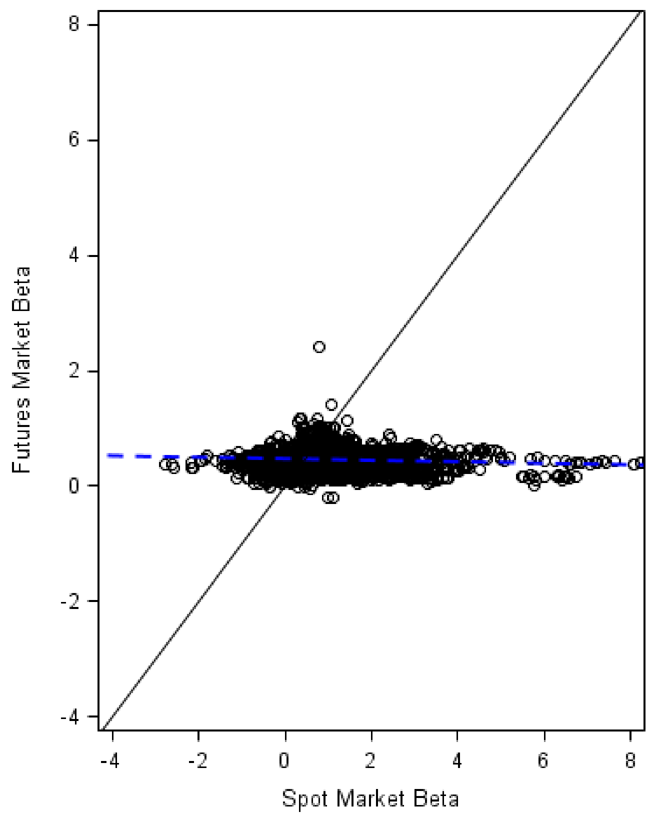


Figure II plots the the futures beta of each location-settlement month combination, $\beta_{i,m}^{futures}$, against the average of the past three years spot market betas, $\overline{\beta}_{i,m} = \frac{1}{3}\left(\beta_{i,m-12}^{spot} + \beta_{i,m-24}^{spot} + \beta_{i,m-36}^{spot}\right)$, for the same location $i$ in the same calendar month in previous years.

I calculate the futures beta, $\beta_{i,m}^{futures}$, by running the following regression separately for each $i$ and $m$:

$$r_{i,t,m}^{futures} = \alpha_{i,m} + \beta_{i,m}^{futures} r_{g(i),t,m}^{futures} + \epsilon_{i,t,m}$$

where $r_{i,t,m}^{futures}$ is the daily electricity futures return of location $i$, with settlement period $m$, in day $t$; $r_{g(i),t,m}^{futures}$ are the gas daily futures returns of the gas hub $g(i)$ which delivers gas to power plants in location $i$, with settlement period $m$, at the end of day $t$.

I analogously estimate spot return beta, $\beta_{i,m}^{spot}$, of electricity daily spot market returns on gas daily spot market returns during month $m$ for location $i$ for each $i, m$ pair:

$$r_{i,t,m}^{spot} = \alpha_{i,m} + \beta_{i,m}^{spot} r_{g(i),t,m}^{spot} + \epsilon_{i,t,m}$$

$r_{i,t,m}^{spot}$ is the daily spot electricity return in location $i$, day $t$, and settlement month $m$, and $r_{g(i),t,m}^{spot}$ is the daily spot gas return of the gas used by power plants in location $i$. The regression best fit line in blue and the $45^{\circ}$ line in black are plotted for reference.

Figure III: **Futures Beta versus Historical Vasicek Beta**

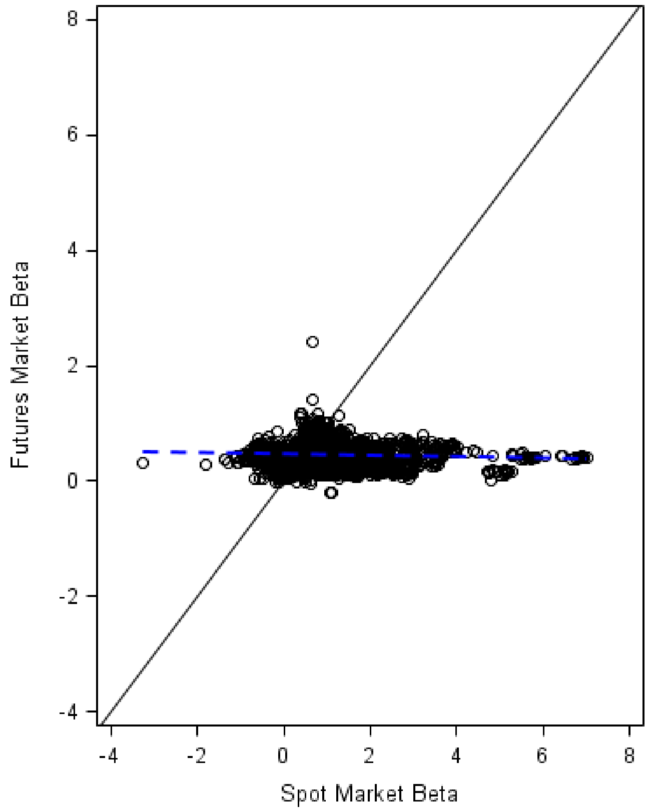


Figure III plots the the futures beta of each location-settlement month combination, $\beta_{i,m}^{futures}$, against the average of the past three years Vasicek spot market betas, $\bar{\beta}_{i}^{spot,vasicek} = \frac{1}{3}\left(\beta_{i,m-12}^{spot,vasicek} + \beta_{i,m-24}^{spot,vasicek} + \beta_{i,m-36}^{spot,vasicek}\right)$, for the same location $i$ in the same calendar month in previous years.

I calculate the futures beta, $\beta_{i,m}^{futures}$, by running the following regression separately for each $i$ and $m$:

$$r_{i,t,m}^{futures} = \alpha_{i,m} + \beta_{i,m}^{futures} r_{g(i),t,m}^{futures} + \epsilon_{i,t,m}$$

where $r_{i,t,m}^{futures}$ is the daily electricity futures return of location $i$, with settlement period $m$, in day $t$; $r_{g(i),t,m}^{futures}$ are the gas daily futures returns of the gas hub $g(i)$ which delivers gas to power plants in location $i$, with settlement period $m$, at the end of day $t$.

Vasicek betas, $\beta_{i,m}^{spot,vasicek}$, are estimated from:

$$\beta_{i,m}^{spot,vasicek} = \frac{se\left(\beta_{i,m}^{spot}\right)^2}{sd\left(\beta_{j,m}^{spot}\right)^2 + se\left(\beta_{i,m}^{spot}\right)^2}\bar{\beta_m} + \frac{sd\left(\beta_{j,m}^{spot}\right)^2}{sd\left(\beta_{j,m}^{spot}\right)^2 + se\left(\beta_{i,m}^{spot}\right)^2}\beta_{i,m}^{spot}$$

where $\beta_{i,m}^{spot}$ is the spot market beta of location $i$ in settlement month $m$, $se\left(\right)$ denotes standard error of the beta estimation, $sd\left(\right)$ denotes the standard deviation of cross-sectional betas across all locations in settlement month $m$, $\bar{\beta_m} = \frac{1}{J}\sum_j \beta_{j,m}^{spot}$. The regression best fit line in blue and the 45° line in black are plotted for reference.

Figure IV: **Spot Beta versus Historical Spot Beta**

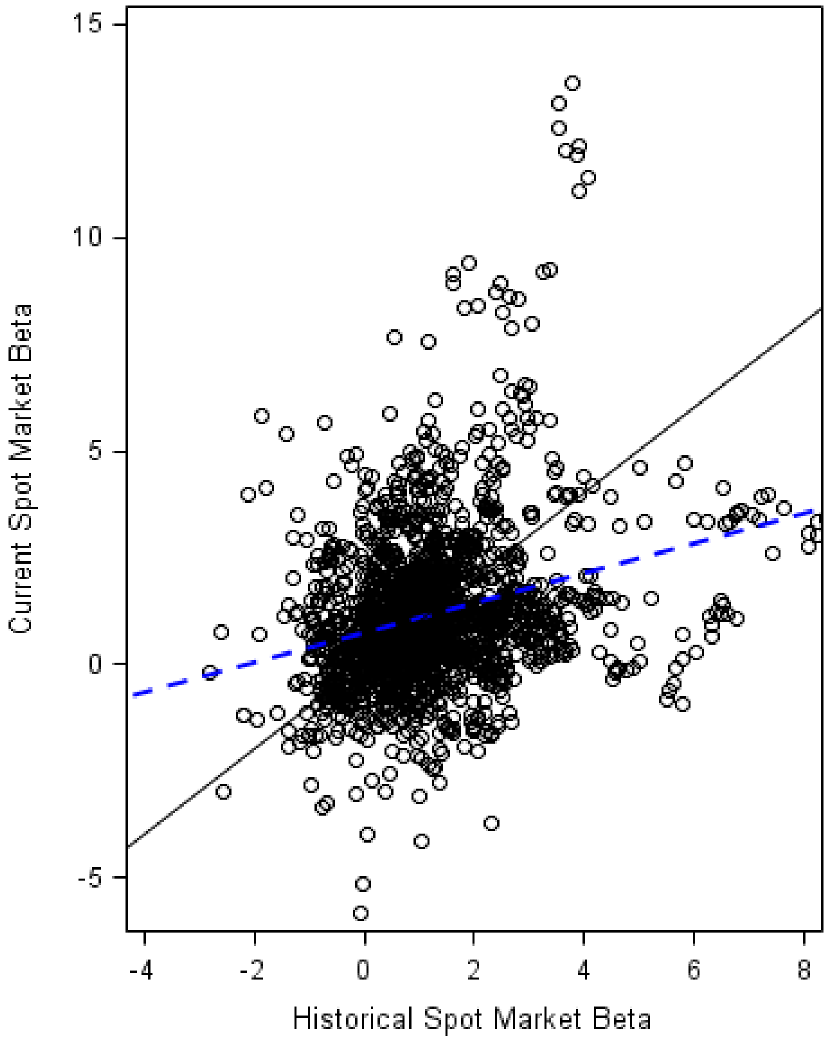


Figure IV shows the spot market beta of each location-settlement month combination, $\beta_{i,m}^{spot}$, compared with the average spot market beta over the past three years, $\overline{\beta}_{i,m} = \frac{1}{3}\left(\beta_{i,m-12}^{spot} + \beta_{i,m-24}^{spot} + \beta_{i,m-36}^{spot}\right)$, for the same location $i$ in the same calendar month. I estimate spot return beta, $\beta_{i,m}^{spot}$, of electricity daily spot market returns on gas daily spot market returns during month $m$ for location $i$ for each $i, m$ pair:

$$r_{i,t,m}^{spot} = \alpha_{i,m} + \beta_{i,m}^{spot} r_{g(i),t,m}^{spot} + \epsilon_{i,t,m}$$

$r_{i,t,m}^{spot}$ is the daily spot electricity return in location $i$, day $t$, and settlement month $m$, and $r_{g(i),t,m}^{spot}$ is the daily spot gas return of the gas used by power plants in location $i$. The regression best fit line in blue and the $45^{\circ}$ line in black are plotted for reference.

Figure V: **Trading Strategy Example**

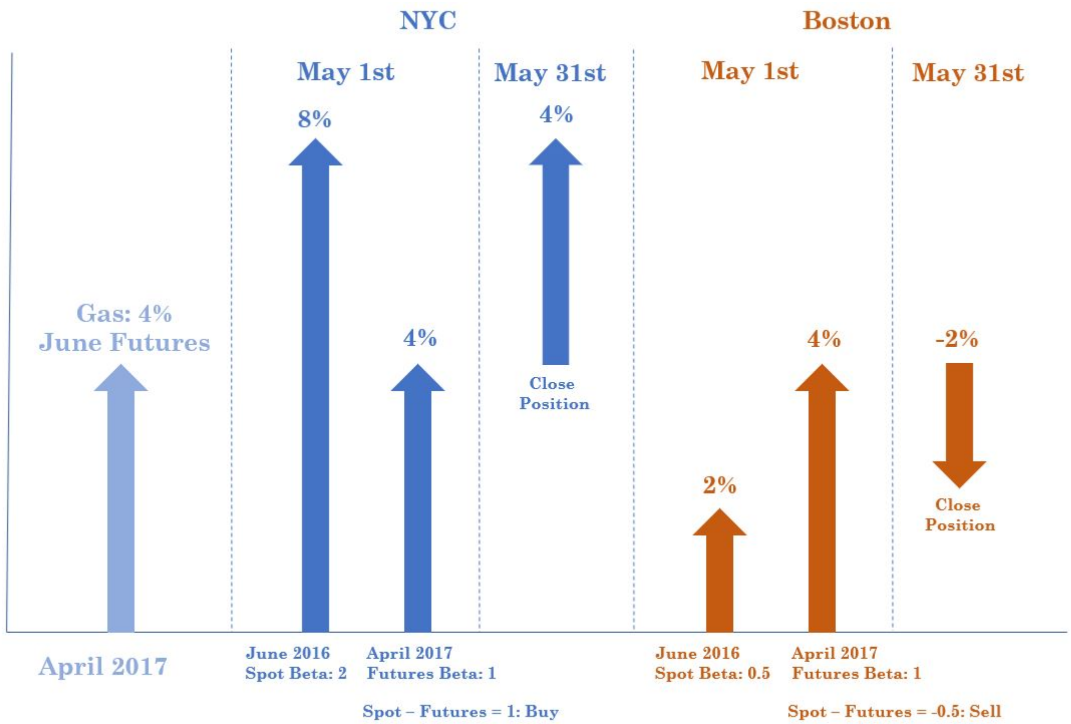


Figure V shows a stylized example of the trading strategy for two electricity futures contracts: a New York City June 2017 futures contract and a Boston June 2017 futures contract. In this example, the date is May 1, 2017. The June 2017 gas futures contract return was 4% from April 1, 2017 to April 30, 2017. The historical spot market beta (calculated using daily spot market returns in June 2016) in New York City is 2.0 and the historical spot market beta in Boston is 0.5. The futures betas of both contracts is 1.0.
Following the 4% June 2017 gas futures return, the NYC electricity futures contract should have increased by 8% based on the strong relationship between NYC electricity and gas in the spot market. If the NYC electricity futures contract only increased by 4%, reflecting the futures beta of 1, then the NYC electricity futures contract will be underpriced and should increase on average as the contract approach its settlement period. Similarly, the Boston electricity futures contract is overpriced and should fall as the contract approaches settlement. The trading strategy is to go long the New York City electricity futures contract and short the Boston electricity futures contract on May 1, 2017 and close out the positions at the end of May before the contracts enter the settlement period.

Figure VI: **Trading Strategy Cumulative Return**

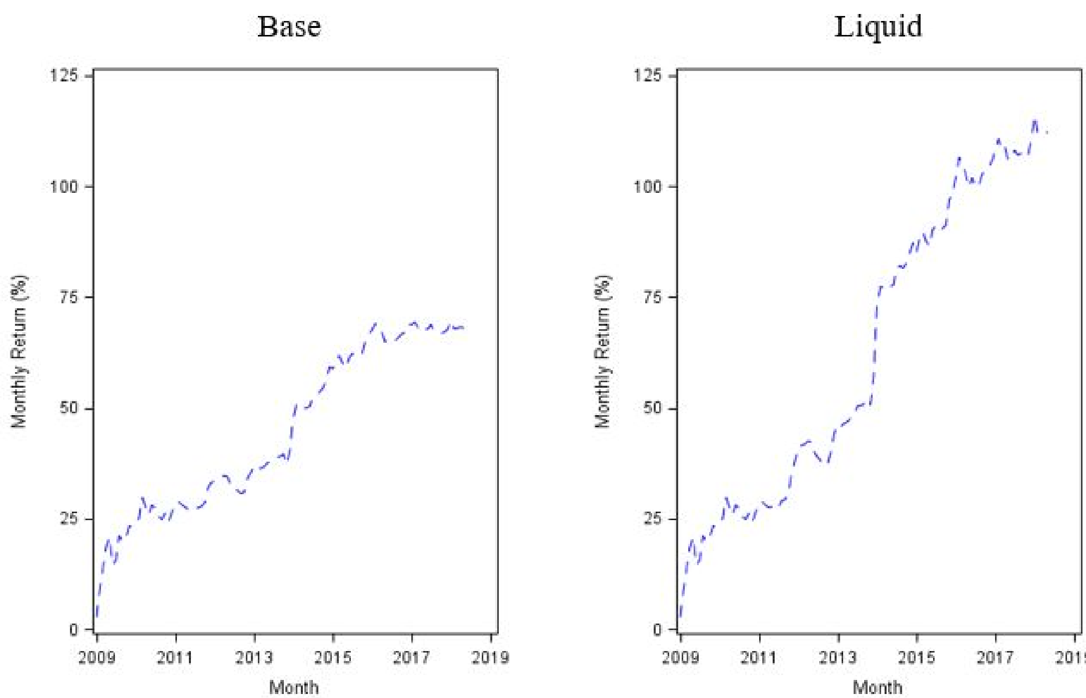


Figure VI shows the cumulative monthly return from January 2009 to May 2018 of the baseline trading strategy and the liquid contract trading strategy.

Figure VII: **Persistence of Macroeconomic Betas**

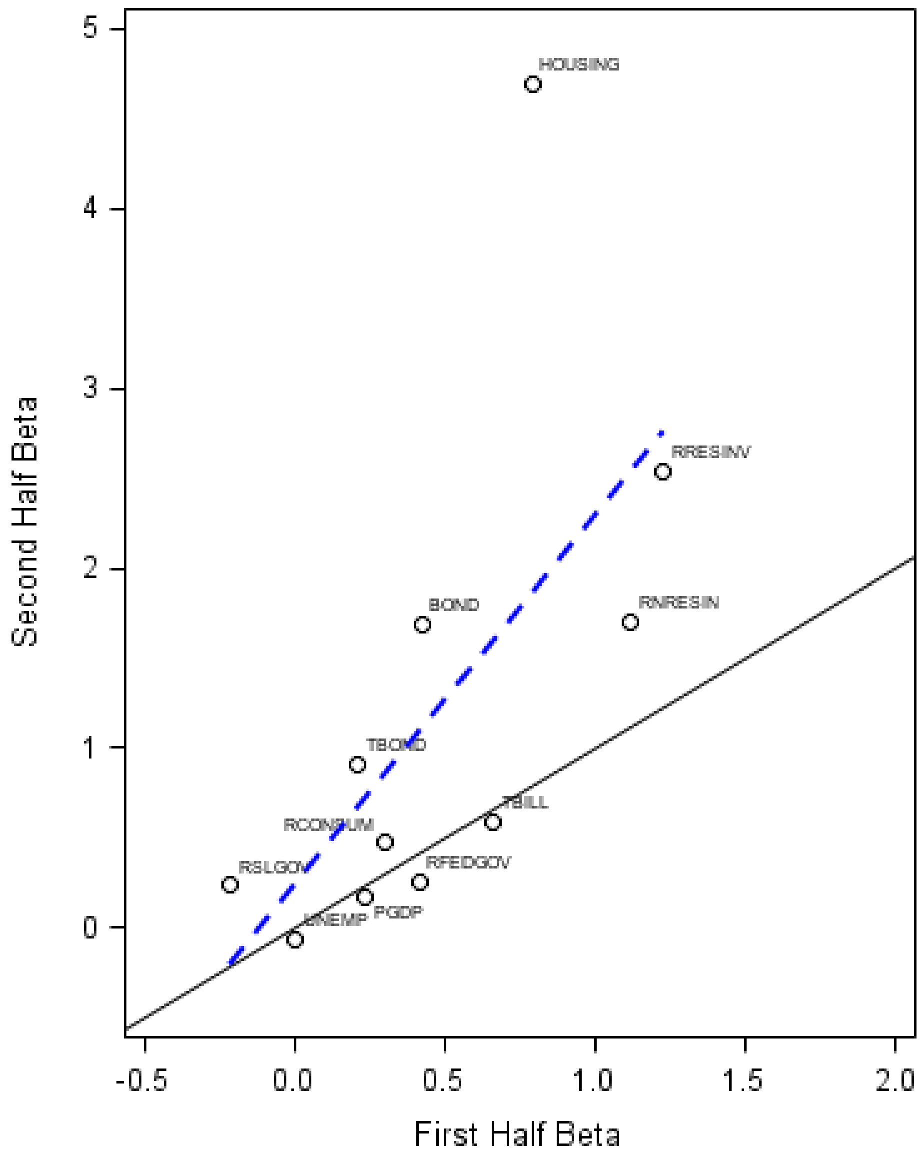


Figure VII plots the second half betas against the first half betas for each macroeconomic variable. The second half betas are calculated from a regression of quarterly macroeconomic variable growth rates on NGDP growth rates using data from the second half of the sample period. First half betas are calculated analogously using data from the first half of the sample period. The regression best fit line in blue and the 45° line in black are plotted for reference.

Figure VIII: **Lookahead Beta versus Trailing Historical Beta**

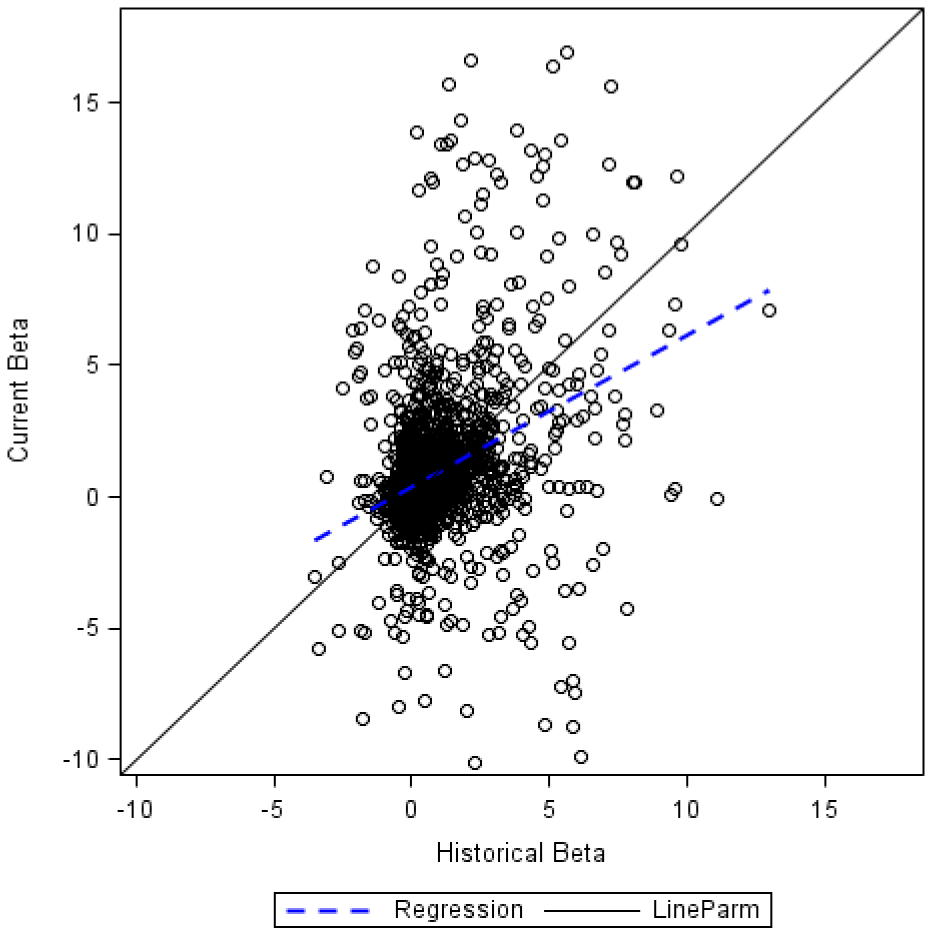


Figure VIII plots the lookahead beta, $\beta^{la}_{j,t}$, on the y-axis against the lookback beta, $\beta^{lb}_{j,t}$ on the x-axis. Each point represents lookback and lookahead values for a macroeonomic variable $j$ as of each quarter $t$. The lookahead beta, $\beta^{la}_{j,t}$, is calculated from the regression of actual quarterly growth rates of macroeconomic variable $j$ from quarters $t+1$ to $t+5$ on contemporaneous NGDP growth rates shown in the equation below:

$$g_{j,t+k} = \alpha + \beta^{la}_{j,t} g_{NGDP,t+k} + \epsilon_{t+k} \; k \in \{1,2,3,4,5\}$$

where $g_{j,t+k}$ is the quarterly growth rate of macroeconomic variable in quarter $t+k$ and $g_{NGDP,t+k}$ is the quarterly growth rate of Nominal Gross Domestic Product in quarter $t+k$.
The lookback beta, $\beta^{lb}_{j,t}$, is calculated from the regression of actual quarterly growth rates of macroeconomic variable $j$ from quarters $t-19$ to $t$ on contemporaneous NGDP growth rates shown in the equation below:

$$g_{j,t-k} = \alpha + \beta^{lb}_{j,t} g_{NGDP,t-k} + \epsilon_{t-k} \; k \in \{0,1,...,19\}$$

where $g_{j,t-k}$ is the quarterly growth rate of macroeconomic variable in quarter $t-k$ and $g_{NGDP,t-k}$ is the quarterly growth rate of Nominal Gross Domestic Product in quarter $t-k$. The regression best fit line in blue and the 45° line in black are plotted for reference.

Figure IX: **Assessed Beta versus Trailing Historical Beta**

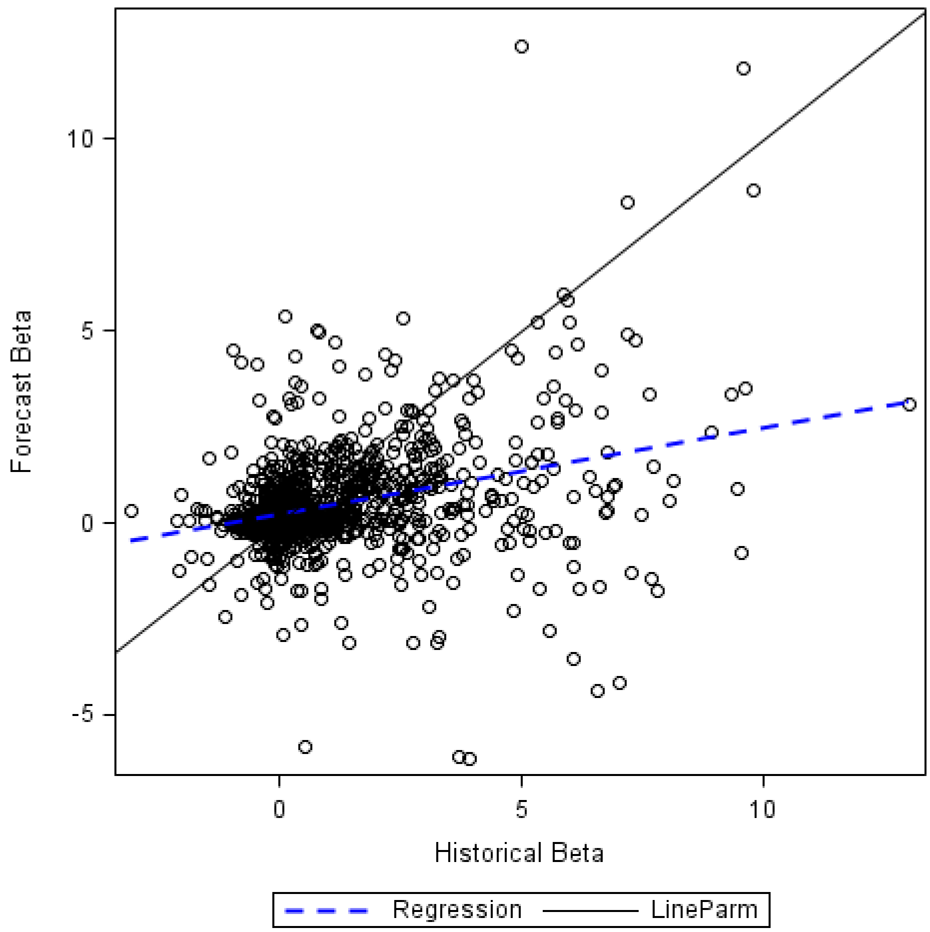


Figure IX plots the analyst forecast beta, $\beta_{j,t}$, on the y-axis against the lookback beta, $\beta^{lb}_{j,t}$ on the x-axis. Each point represents the forecast beta and lookahead beta for a macroeonomic variable $j$ as of each quarter $t$. I calculate the forecast beta, $\beta_{j,t}$ by running the following regression separately for each $j$ and $t$:

$$\mathbb{E}^i_t\left(g^j_{t+k-1\to t+k}\right) = \alpha_{j,t} + \beta_{j,t}\mathbb{E}^i_t\left(g^{NGDP}_{t+k-1\to t+k}\right) + \epsilon_{i,j,t,k}$$

$\mathbb{E}^i_t\left(g^j_{t+k-1\to t+k}\right)$ is the quarterly growth rate forecast for quarter $t+k$, for macroeconomic variable $j$, made by analyst $i$, at quarter $t$ and $\mathbb{E}^i_t\left(g^{NGDP}_{t+k-1\to t+k}\right)$ is the corresponding NGDP quarterly growth rate forecast.

The lookback beta, $\beta^{lb}_{j,t}$, is calculated from the regression of actual quarterly growth rates of macroeconomic variable $j$ from quarters $t-19$ to $t$ on contemporaneous NGDP growth rates shown in the equation below:

$$g_{j,t-k} = \alpha + \beta^{lb}_{j,t} g_{NGDP,t-k} + \epsilon_{t-k} \; k \in \{0, 1, ..., 19\}$$

where $g_{j,t-k}$ is the quarterly growth rate of macroeconomic variable in quarter $t-k$ and $g_{NGDP,t-k}$ is the quarterly growth rate of Nominal Gross Domestic Product in quarter $t-k$. The regression best fit line in blue and the 45° line in black are plotted for reference.

Table I: **Beta Comparison Regression Results**

| | Futures Beta | | Spot Beta | |
|---|---|---|---|---|
| Historical Spot Beta | -0.013*** | | 0.349*** | |
| | (0.003) | | (0.023) | |
| Historical Vasicek Beta | | -0.012*** | | 0.446*** |
| | | (0.003) | | (0.027) |
| Intercept | 0.463*** | 0.461 | 0.708*** | 0.628 |
| | (0.005) | (0.005) | (0.039) | (0.041) |
| Adj. R-Squared | 0.01 | 0.00 | 0.08 | 0.09 |
| Obs | 2735 | 2735 | 2617 | 2617 |

Table I shows the output from four regressions. The first column shows the regression, specified in Equation 19, of the futures beta of each location-settlement month combination, $\beta_{i,m}^{futures}$, on the average of the past three years spot market betas $\overline{\beta}_{i,m} = \frac{1}{3}\left(\beta_{i,m-12}^{spot} + \beta_{i,m-24}^{spot} + \beta_{i,m-36}^{spot}\right)$, for the same location $i$ in the same calendar month in previous years. The second column shows the regression, specified in Equation 21, of $\beta_{i,m}^{futures}$ on the average of the past three years Vasicek spot market betas. The third column shows the regression, specified in Equation 22, of the spot beta of each location-settlement month combination $\beta_{i,m}^{spot}$, on the average of the past three years spot market betas $\overline{\beta}_{i,m} = \frac{1}{3}\left(\beta_{i,m-12}^{spot} + \beta_{i,m-24}^{spot} + \beta_{i,m-36}^{spot}\right)$, for the same location $i$ in the same calendar month in previous years. The fourth column shows $\beta_{i,m}^{spot}$ regressed on the average of the past three years of Vasicek spot market betas. Point estimates are displayed in the table with standard errors in parentheses below. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table II: **Trading Strategy Summary Statistics**

| | All | Liquid |
|---|---|---|
| Return | 7.3 | 12.0 |
| St. Dev. | 6.4 | 9.2 |
| Sharpe Ratio | 1.14 | 1.30 |
| Fama French 3-factor alpha | 7.1 | 11.9 |
| Fama French 5-factor alpha | 7.7 | 12.7 |

Table II shows summary statistics for electricity futures trading strategy in the baseline specification and for the same specification restricted to liquid contracts. The trading strategy returns are from January 2009 to May 2018. All reported values are annualized.

Table III: **Trading Strategy with Factor Models**

| | Baseline | | | | Liquid | | | |
|---|---|---|---|---|---|---|---|---|
| Market | 0.026 | 0.010 | | | 0.022 | -0.002 | | |
| | (0.051) | (0.052) | | | (0.074) | (0.074) | | |
| HML | 0.050 | -0.007 | | | 0.046 | -0.068 | | |
| | (0.073) | (0.089) | | | (0.105) | (0.127) | | |
| SMB | -0.059 | -0.118 | | | -0.059 | -0.161 | | |
| | (0.079) | (0.082) | | | (0.114) | (0.117) | | |
| RMW | | -0.287** | | | | -0.485*** | | |
| | | (0.126) | | | | (0.179) | | |
| CMA | | 0.115 | | | | 0.246 | | |
| | | (0.152) | | | | (0.217) | | |
| CommMkt | | | 0.015 | | | | 0.027 | |
| | | | (0.043) | | | | (0.063) | |
| EMkt | | | | 0.010 | | | | 0.040** |
| | | | | (0.013) | | | | (0.019) |
| Alpha | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.010*** | 0.011*** | 0.010*** | 0.011*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.002) |
| Obs | 112 | 112 | 112 | 112 | 112 | 112 | 112 | 112 |
| Adj. $R^2$ | -0.02 | 0.01 | 0.00 | 0.00 | -0.02 | 0.03 | -0.01 | 0.03 |

Table III shows the output from the regression of monthly trading strategy returns on: the Fama French 3-Factor model; the Fama French 5-Factor model; the equal-weighted return of a broad set of commodities designated as ‘CommMkt‘ (provided by AQR); and the equal-weighted “market portfolio” of prompt month electricity futures contracts designated as EMkt. The first four columns are the baseline trading strategy. The last four columns are the trading strategy restricted to liquid contracts. ***, **, and * denote $p<0.01$, $p<0.05$, and $p<0.1$ respectively.

Table IV: **Assessed versus Historical Beta Regression Results**

| | Current Beta | Assessed Beta |
|---|---|---|
| Historical Beta | 0.603*** | 0.233*** |
| | (0.040) | (0.016) |
| R-Squared | 0.19 | 0.23 |
| N | 2599 | 1603 |

Table IV presents results from two regressions. Column 1 shows the regression, specified in Equation 26, of $\beta^{la}_{j,t}$ on $\beta^{lb}_{j,t}$:

$$\beta^{la}_{j,t} = \delta^{la}\beta^{lb}_{j,t} + \mu_t + \epsilon_{j,t}$$

where $\beta^{la}_{j,t}$ is the lookahead beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 25, $\beta^{lb}_{j,t}$ is the lookback beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 24, and $\mu_t$ are quarter fixed effects.
Column 2 shows the regression, specified in Equation 29, of forecast beta $\beta_{j,t}$, on lookback beta $\beta^{lb}_{j,t}$, including quarter fixed effects:

$$\beta_{j,t} = \delta^{f}\beta^{lb}_{j,t} + \mu_t + \epsilon_{j,t}$$

where $\beta_{j,t}$ is the forecast beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 28, $\beta^{lb}_{j,t}$ is the lookback beta for macroeconomic variable $j$ at quarter $t$ estimated in Equation 24, and $\mu_t$ are quarter fixed effects. Point estimates are displayed with standard errors in parentheses below. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table V: **Forecast Error on Assessed Beta and NGDP Revisions**

| | Forecast Beta | Revision Beta | Trailing Beta |
|---|---|---|---|
| $\alpha$ | -0.005** | -0.004** | 0.000 |
| | (0.002) | (0.002) | (0.002) |
| $\beta^{\Delta}_{j,t}$ | -0.001 | -0.004*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) |
| $FR^{NGDP}_{t-1\to t}$ | 0.224 | 0.161 | -0.492 |
| | (0.304) | (0.311) | (0.325) |
| $FR^{NGDP}_{t-1\to t} \times \beta^{\Delta}_{j,t}$ | 0.724*** | 0.403* | 0.785*** |
| | (0.243) | (0.219) | (0.162) |
| Adj. R-Squared | 0.01 | 0.01 | 0.06 |
| N | 1603 | 1603 | 1603 |

Table V shows the output from the forecast error predictability regressions. Column 1 shows the regression, specified in Equation 30, of forecast errors on $\beta^{\Delta}_{j,t}$, NGDP forecast revisions $FR^{NGDP}_{t-1\to t}$, and the interaction term:

$$FE_{j,t} = \alpha + \delta_1 \beta^{\Delta}_{j,t} + \delta_2 FR^{NGDP}_{t-1\to t} + \delta_3 FR^{NGDP}_{t-1\to t} \times \beta^{\Delta}_{j,t} + \epsilon_{j,t}$$

$\beta^{\Delta}_{j,t}$ is the difference between trailing historical beta and analyst forecast beta. I construct the average annual forecast revision to NGDP from quarter $t-1$ to $t$ as $FR^{NGDP}_{t-1\to t} = \frac{1}{N_t}\sum_i \left(\mathbb{E}^i_t\left(g^{NGDP}_{t\to t+4}\right) - \mathbb{E}^i_{t-1}\left(g^{NGDP}_{t\to t+4}\right)\right)$ where $N_t$ is the number of analysts making forecasts about annual NGDP in quarter $t$. I construct average annual forecast error for each macroeconomic variable, $j$, as of each quarter $t$, as $FE_{j,t} = \frac{1}{N_t}\sum\left(g^j_{t\to t+4} - \mathbb{E}^i_t\left(g^j_{t\to t+4}\right)\right)$ where $N_t$ is the number of analysts making annual growth forecasts for macroeconomic variable $j$ as of quarter $t$. Observations in this regression are at the quarter, macroeconomic variable level.

Column 2 shows the same regression specification using forecast revision betas. The specification is the same except that $\beta^{\Delta}_{j,t}$ is calculated as the difference between the lookback beta and the forecast revision beta: $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t} - \beta^{rev}_{j,t}$. $\beta^{rev}_{j,t}$ is estimated from Equation 33.

Column 3 shows the same regression specification using the lookback beta by itself: $\beta^{\Delta}_{j,t} = \beta^{lb}_{j,t}$. Point estimates are displayed with standard errors in parentheses below. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table VI: **Forecast Error Robustness**

| | | $\beta_{j,t}^{\Delta}=\beta_{j,t}^{lb}-\beta_{j,t}$ | | $\beta_{j,t}^{\Delta}=\beta_{j,t}^{lb}-\beta_{j,t}^{rev}$ | | $\beta_{j,t}^{\Delta}=\beta_{j,t}^{lb}$ | |
|---|---|---|---|---|---|---|---|
| | | $\delta_3$ | s.e. | $\delta_3$ | s.e. | $\delta_3$ | s.e. |
| W $\beta_{j,t}^{\Delta}$ | | | | | | | |
| | 0.01 | 0.717*** | (0.272) | 0.452* | (0.231) | 0.757*** | (0.177) |
| | 0.05 | 0.569* | (0.337) | 0.636** | (0.287) | 0.741*** | (0.215) |
| | 0.10 | 0.308 | (0.423) | 0.631* | (0.382) | 0.827*** | (0.291) |
| W $FR_{t-1\to t}^{NGDP}\times\beta_{j,t}^{\Delta}$ | | | | | | | |
| | 0.01 | 0.806** | (0.353) | 0.367 | (0.309) | 1.324*** | (0.285) |
| | 0.05 | 0.652 | (0.616) | 0.257 | (0.529) | 1.520*** | (0.512) |
| | 0.10 | 0.536 | (0.986) | 0.029 | (0.865) | 1.641* | (0.959) |
| Lookback | | | | | | | |
| | 12 | 0.894*** | (0.232) | 0.515** | (0.204) | 1.145*** | (0.168) |
| | 20 | 0.724*** | (0.243) | 0.403* | (0.219) | 0.785*** | (0.162) |
| | 28 | 0.073 | (0.236) | 0.383 | (0.274) | 0.912*** | (0.178) |
| $log\left(FE_{j,t}\right)$ | | 0.491** | (0.223) | 0.295 | (0.201) | 0.646*** | (0.149) |

Table VI shows the output from the forecast error predictability regressions. Each regression follows the specification from Equation 30. I regress forecast errors on $\beta_{j,t}^{\Delta}$, NGDP forecast revisions $FR_{t-1\to t}^{NGDP}$, and the interaction term:

$$FE_{j,t}=\alpha+\delta_1\beta_{j,t}^{\Delta}+\delta_2 FR_{t-1\to t}^{NGDP}+\delta_3 FR_{t-1\to t}^{NGDP}\times\beta_{j,t}^{\Delta}+\epsilon_{j,t}$$

I construct the average annual forecast revision to NGDP from quarter $t-1$ to $t$ as $FR_{t-1\to t}^{NGDP}=\frac{1}{N_t}\sum_i\left(\mathbb{E}_t^i\left(g_{t\to t+4}^{NGDP}\right)-\mathbb{E}_{t-1}^i\left(g_{t\to t+4}^{NGDP}\right)\right)$ where $N_t$ is the number of analysts making forecasts about annual NGDP in quarter $t$. I construct average annual forecast error for each macroeconomic variable, $j$, as of each quarter $t$, as $FE_{j,t}=\frac{1}{N_t}\sum\left(g_{t\to t+4}^{j}-\mathbb{E}_t^i\left(g_{t\to t+4}^{j}\right)\right)$ where $N_t$ is the number of analysts making annual growth forecasts for macroeconomic variable $j$ as of quarter $t$. Observations in this regression are at the quarter, macroeconomic variable level.

I show the cross-term coefficient estimate, $\delta_3$, standard error, and the adjusted $R^2$ for each different regression specification. The column headers indicate how $\beta_{j,t}^{\Delta}$ is constructed for every regression in the column. So, all regressions in the first column construct $\beta_{j,t}^{\Delta}$ as $\beta_{j,t}^{\Delta}=\beta_{j,t}^{lb}-\beta_{j,t}$. The first three rows of the table show the regression specifications winsorizing $\beta_{j,t}^{\Delta}$ at the 1 percent, 5 percent, and 10 percent levels respectively. The next three rows show the regression results winsorizing the cross-term at the 1 percent, 5 percent, and 10 percent levels. The rows 7 through 9 show the results varying the lookback window used to calculated the lookback beta. The last row shows the results predicting log forecast errors. Point estimates are displayed with standard errors in parentheses below. ***, **, and * denote p<0.01, p<0.05, and p<0.1 respectively.

Table VII: **Summary of Results**

| Setting | $\alpha$ | $\delta$ | Discussion |
|---|---|---|---|
| Macro- & Financial Variables with the Market | 0.30 | 0.21 | Distorts perceptions of risk. The stock market appears riskier than suggested by traditional measures based on historical data. Assessed betas of individual stocks are compressed towards moderate values, generating a flat relationship between perceived risk and historical measures of risk. |
| Asset Prices: Commodity Futures | 0.46 | -0.01 | Generates a systematic mispricing of commodity futures. Trading against this bias is highly profitable. |
| Macroeconomic Forecasts | 0.31 | 0.23 | Generates predictable errors in macroeconomic growth forecasts. |

Table VII summarizes the results of the paper. In each setting, I regress assessed betas on benchmark betas in the regression below:

$$\beta^{assessed} = \alpha + \delta\beta^{rational} + error$$

The measures of assessed beta and benchmark beta are described in each setting. With accurate measures of assessed and benchmark comovement, then the rational benchmark corresponds to estimates of $\alpha = 0$ and $\delta = 1$. The compression documented in this paper corresponds to a moderate, positive $\alpha$ and a $\delta$ less than 1.