<u>SENTIMENT: ON THE PREDICTIVE POWER OF SEARCH, UNCERTAINTY THROUGH THE BUSINESS CYCLE, AND ABNORMAL STOCK RETURNS</u>

by

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Sentiment: On the Predictive Power of Search, Uncertainty through the Business Cycle, and Abnormal Stock Returns

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by

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DEDICATION

In memory of Stephen E. DuBravac, 1944-2013.

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Anatole France, the French poet and novelist, once wrote, “Nine-tenths of education is encouragement.” I am grateful for the considerable encouragement that I have received throughout this endeavor. I thank my advisor, Dr. Tyler Cowen, and committee members Drs. Alex Tabarrok and Garett Jones. I thank the Consumer Electronics Association for 10 wonderful years and hopefully many more to come. I thank Nick (age 10), Ryan (8), and Gavin (6) for incessantly inquiring, “How many words did you write today, Dad?” Encouragement was my source of motion when I had no time, of energy when I had no sleep, and of momentum when my motivation waned.

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ABSTRACT

SENTIMENT: ON THE PREDICTIVE POWER OF SEARCH, UNCERTAINTY THROUGH THE BUSINESS CYCLE, AND ABNORMAL STOCK RETURNS

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Sentiment reveals itself in many diverse forms. Public opinion can be measured in how a populace votes on proposed referendums or the type of products an individual buys at the neighborhood grocery store. In recent years, there has been growing interest in examining and understanding the link between measures of sentiment and real economic activity. This dissertation extends both our understanding on the tendency of assorted economic agents as well as the relationship between opinion and real economic activity.

In the last few years, the online search giant Google has made aggregations of web queries available to researchers. These indexes provide broad summations of what consumers search for online, reveal relative interest across available alternatives, and provide insights into the collective inclination of economic agents. In the first dissertation paper, *Exactly What Does Google Know: Can What We Search for Online Predict Real Upstream Variables?* I examine the ability of aggregated web queries to predict real variables. However, in a unique innovation relative to prior research, my approach

examines real variables that are upstream from the point at which consumers make purchases. My empirical results confirm that indexes of online search queries can be useful in predicting the shipment of consumer electronics products from manufacturers to retailers. These results are robust across a swath of consumer electronic devices. However, my results also show that in most cases, indexes of search queries do not outperform a unique and previously untested indicator that measures consumer opinion toward spending on consumer electronics products using a probabilistic survey approach. Across the six categories of consumer electronics devices examined, the median of the mean absolute error (MAE) improves by 4.4 percent when I include a search query index and by 6.85 percent when I include the probabilistic survey approach. Across all device classes tested, the MAE improved with the inclusion of both the probabilistic survey index and a search query index, suggesting that both measures of sentiment add predictive power.

Overall the results of the first paper are consistent with the premise that the digitization and aggregation of new data streams, such as online search queries, offer promising new ways to improve the predictability of real variables. The results also show that well-tuned surveys using probabilistic questions can add predictive accuracy. Finally, the research opens a new vein of investigation wherein measures of consumer sentiment can successfully be applied to a subset of real variables further up the supply chain.

In the second paper, *Where Are the Bulls? Exploring Optimism and Uncertainty through the Business Cycle*, I use household micro-level data to explore whether and (if so) how household expectations vary systematically across individual characteristics and within cohorts sharing like demographics. My specific focus is an examination of how expectations changed over the course of the business cycle from January 2007 to December 2013, one of the most economically volatile periods in the history of the United States.

I find that individual demographic and socioeconomic characteristics influence sentiment. Namely, income, education, and age are positively correlated with future expectations, whereas home ownership is negatively associated with expectations during the sample period. I also find that gender and race are statistically significant in explaining individual expectations while marital status and presence of children in the home do not have a statistically significant relationship with expectations.

Most importantly, I find that the influences of demographic and socioeconomic characteristics on sentiment break down during severe economic declines, resulting in crowd behavior. An important new finding of this study was that time influenced expectations during the most recent business cycle, but only after the start of the recession. I find that expectations were statistically influenced by time dummies with the largest coefficients in (a) the third quarter of 2011 (following the Arab Spring), (b) the third quarter of 2010 (following the downgrading of Greek government debt to junk bond status in April 2010 and broader concerns that the financial impact would spread across Europe), and (c) the fourth quarter of 2008 (the apex of the recession and uncertainty following the collapse of Lehman Brothers on September 15, 2008).

The overarching goal was to explore and detail what, if any, demographic characteristics play a role in explaining the expectations held by individuals, how those expectations differ across cohorts of the population, and how both sentiment and the explanatory power of one's own characteristics can change over the business cycle.

In the third paper, *Today's Keynote: Do CEO Presentations Lead To Positive Abnormal Stock Returns?* I examine the degree to which capital markets dissect the implicit information in public addresses by CEOs of publicly traded companies and how this analysis in turn impacts stock prices. I look specifically at keynote addresses delivered at the International Consumer Electronics Show (CES), the largest annual trade event in the United States. I examine whether there is a pattern of abnormal stock returns around two key dates: the initial announcement of the keynote and its delivery.

I find that CEO keynotes at the International CES and their prior announcements correspond with statistically insignificant price moves in all but a few select cases. This is also the case when keynotes are taken collectively as a single group.

This dissertation explores the impact and inner workings of sentiment by considering three important questions. First, how successful, and therefore useful, is consumer sentiment at predicting movement in real variables? Second, how does consumer sentiment change as the underlying environment changes, and what role do individual characteristics play in determining the change? Finally, how does sentiment within the financial market community contribute to abnormal stock fluctuations?

I. EXACTLY WHAT DOES GOOGLE KNOW: CAN OUR ONLINE SEARCHES PREDICT REAL UPSTREAM VARIABLES?

Never make predictions, especially about the future. – Casey Stengel

The economic downturn of 2007-2009 highlighted the need to incorporate real-time information into the business decision-making process. Historically, the only real-time variables available to researchers were survey-based approaches, but recent work with search engine queries has provided a second alternative. To date, most research exploring the application of real-time variables has focused on broad macroeconomic variables such as gross domestic product (GDP), unemployment, or other economic series data. This is especially the case for work incorporating search engine queries.

In the present work I expand this nascent research in three ways. First, I explore the ability of search engine queries to predict more narrowly defined data series than have been previously explored. Namely, I examine monthly U.S. shipments for a number of consumer electronics devices. While early research has suggested that search engine queries offer an improvement on alternative measures of consumer sentiment, very little research has looked at this question for more narrowly defined product classes. Second, because the data series that I examine are manufacturer-to-retailer shipments and not retail sales, I apply search engine query data to a heretofore unexamined question. Individuals typically use search engines to research near-term purchases, but can this search behavior also help to explain data series that are upstream of the consumer's decision? Finally, I assess whether forecasts using an index of search engine queries outperform previously untested survey-based indicators of technology-specific consumer sentiment. While early research has shed light on the performance of search query data relative to survey data, thus far the literature is devoid of research comparing search query data to probabilistic survey questions, which have generally been shown to perform better than ordinal-response consumer surveys. Moreover, the existing literature consists of examinations of broad-based surveys and does not include comparisons between search engine queries and granular surveys, like those made in this paper.

The inclusion of search query data is premised on the hypothesis that web searches reveal economically useful information about an individual's future intention and that this information can be used to inform our understanding of supply-and-demand considerations. Research to date has focused primarily on examining how search queries improve the predictability of demand. Virtually no research thus far has looked at the ability of search queries to inform our understanding of the supply side.

Wu and Brynjolfsson (2013, p. 4) remarked, "This new use of technology [i.e., obtaining information from search engines] is not a mere difference in degree, but a fundamental transformation of how much is known about the present and what can be known about the future." But what of the decisions made by economic agents that are somewhat removed from the actual web query? Technology is fundamentally changing our knowledge of the behavior of economic agents, and it makes intuitive sense there is good model fit when searching precedes the transaction in question. This fact has been documented in prior studies. But what of the business decisions that might be taking place in advance of or simultaneously with the search process? What of the business decisions undertaken by separate economic agents when one decision is taking place on the supply side and one on the demand side? This research sheds needed light on the question of timing between detached economic decisions and dispersed economic agents. Goel et al. (2010), in their survey of the research in this area, noted that search data are easy to acquire and can help in making forecasts, but may not provide dramatic increases in predictability. I extend that existing research and examine to what degree if any search data can improve the predictability within the realm of this extension.

In the following paper, estimates based on Google search inquiries are compared to several alternatives. These alternatives include a benchmark autoregressive model alongside models containing consumer sentiment metrics obtained through consumer surveys. Relying on the Diebold-Mariano test of predictive accuracy, the forecasts presented herein conclude the null hypothesis cannot be rejected, suggesting the addition of search engine queries alone does not add sufficient predictive power. However, including indices of search engine inquiries together with other indices of consumer sentiment does improve the predictability of the models tested according to Diebold-Mariano tests.

In the next section I will review the literature on forecasting using measures of consumer sentiment. Then I will explain the data utilized in this research, the empirical approach taken, and the results.

The Predictive Power of Consumer Sentiment Metrics

With consumer spending representing two-thirds of the U.S. economy, analysts are keenly interested in finding ways to measure consumer sentiment on an ongoing basis and to augment more traditional model-based approaches of forecasting. The academic literature is filled with studies examining the predictive power of such tools as the University of Michigan Index of Consumer Sentiment (ICS) and the Conference Board Consumer Confidence Index (CCI). Most of these studies have found that consumer sentiment has at least modest and statistically significant predictive powers,[1] although some studies have provided less conclusive results (see for example Al-Eyd et al. (2009), Desroches & Gosselin (2002), and Roberts & Simons (2001)).

Recently various scholars[2] have begun to examine the characteristics of search engine query indexes and testing these aggregations as a tool to enhance predictability. The earliest studies were by Cooper et al. (2005), who examined cancer media coverage and cancer search activity, and Ettredge et al. (2005), who found an association between aggregate search data and future unemployment statistics. Later studies within this research vein found frequency of search queries could be used to detect influenza outbreaks (Ginsberg et al., 2009; Polgreen et al., 2008);[3] predict initial unemployment claims, automobile demand, and vacation destinations (Choi & Varian, 2009a, 2009b);

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[1] See for example Fair (1971), Mishkin (1978), Carroll et al. (1994), Matsusaka & Sbordone (1995), Howrey (2001), Gelper et al. (2007), Batchelor & Dua (1998), Bram & Ludvigson (1998), Slacalek (2003), Ludvigson (2004), and Haugh (2005).

[2] See for example Choi & Varian (2009a, 2009b), Askitas & Zimmermann (2009), Suhoy (2009), D'Amuri (2009), D'Amuri & Marcucci (2009), Ginsberg et al. (2009), Avar (2009), Efron et al. (2009), Tierney & Pan (2012), Pan et al. (2010), Della Penna & Huang (2009), Goel et al. (2010), Kholodilin et al. (2009), Vosen & Schmidt (2011), and Wu & Brynjolfsson (2013).

[3] Several additional studies have used search data to examine topics within epidemiology, including Corley et al. (2009), Hulth et al. (2009), Pelat et al. (2009), Vadivia & Monge-Corella (2010), and Wilson & Brownstein (2009).

and gauge consumer sentiment (Radinsky et al., 2009; Della Penna & Huang, 2009; Preis et al., 2010).

Suhoy (2009), Askitas and Zimmermann (2009), and D'Amuri and Marcucci (2009) used search query data to examine unemployment in Israel, the United States, and Germany respectively. In addition, such data were used by Baker and Fradkin (2011) to examine job searches in light of unemployment payment extensions, by Vosen and Schmidt (2011) to examine consumption metrics, by Wu and Brynjolfsson (2013) to forecast housing prices and sales, by Lindberg (2011) to study retail sales, and by Guzman (2011) to predict inflation.

Researchers are still at the initial stages of understanding the nature of online searches. For example, Shimshoni et al. (2009) found that the use of many search terms is predictable using simple seasonal decomposition. For the most part, however, these early studies have found that models including relevant search query indexes tend to outperform models excluding these predictive variables for a myriad of categories, from regional influenza occurrence to unemployment rates, jobless claims, and real estate activity.

My work differs from these preceding studies in two key aspects. First, none of the previous research in this vein has examined a time series as narrowly defined as the ones reviewed here. Thus this study answers the question whether search inquiries can improve the predictability of narrowly defined time series within a specific category of consumer durables. Second, all the previous studies concerned with consumer behavior looked at sales to the end market consumer, whereas my data series involves searches upstream from the final consumer. Using shipments of certain consumer electronics devices from manufacturers to retailers and distributors, I examine a data series that precedes sales to end users by four to six weeks. I provide new evidence on the ability of search inquiries to forecast variables that are one step removed from the actual consumers and their web searches. This is the first study that tests whether consumer web searches can reverberate upstream and predict orders and shipments one step removed from the consumer. Up to now, the studies using search data have been primarily concerned with short-term forecasting or nowcasting (i.e., contemporaneous forecasting) of real variables. I answer the question whether search queries can forecast real variables earlier in the process.

The first of these two differentiating aspects will add generally to the body of research; the second will provide particularly valuable insights into the applicability of search data, because it will help to determine whether real economic agents, such as manufacturers and retailers, can use approaches based on upstream search data to frame business decisions such as setting appropriate production and inventory levels. Moreover, this research also provides a type of horse race, I provide alternative model specifications using a standard autoregressive approach and thereby pit potentially useful predictive variables against one another.

Data

Monthly Device Shipments from Manufacturers to Retailers

Monthly shipments of several consumer electronics devices are tracked by the Consumer Electronics Association's (CEA) CE Market Metrics data program. CEA has maintained statistics on the shipment of consumer technology products for more than 80 years. On a monthly basis, it collects shipment figures from individual device manufacturers and aggregates them to calculate total industry shipment volume. These data are also unique in that they capture actual unit volume shipments from manufacturers. These are sales upstream from the end consumer market. I know of no published research seeking to find correlations or ascertain predictive ability between online search query data and data one step removed from the end consumer.

Table 1. *Summary Statistics for Monthly Device Shipments from Manufacturers to Retailers*

Series	N	Mean	Standard Deviation	Variance	Skewness	Kurtosis	Max	Min	25%	50%	75%
Flat Panel Televisions	120	2,002,051	1,172,866	1.38E+12	0.104	2.443	5,128,665	113,650	1,043,458	2,150,433	2,780,071
LCD Televisions	120	1,761,712	1,099,576	1.21E+12	0.207	2.592	4,922,989	71,017	815,811	1,921,721	2,477,165
Plasma Televisions	120	240,339	115,078	1.32E+10	0.367	2.688	530,661	27,464	164,966	220,631	319,832
DVD Players	120	1,390,473	624,664	3.90E+11	0.598	2.426	3,060,478	493,183	879,107	1,290,028	1,861,913
MP3 Players	120	2,698,667	1,618,336	2.62E+12	1.173	4.842	9,134,354	368,795	1,623,094	2,475,132	3,296,171
Digital Cameras	120	2,363,547	1,236,645	1.53E+12	0.936	3.492	6,360,195	438,858	1,408,028	2,215,757	3,032,685

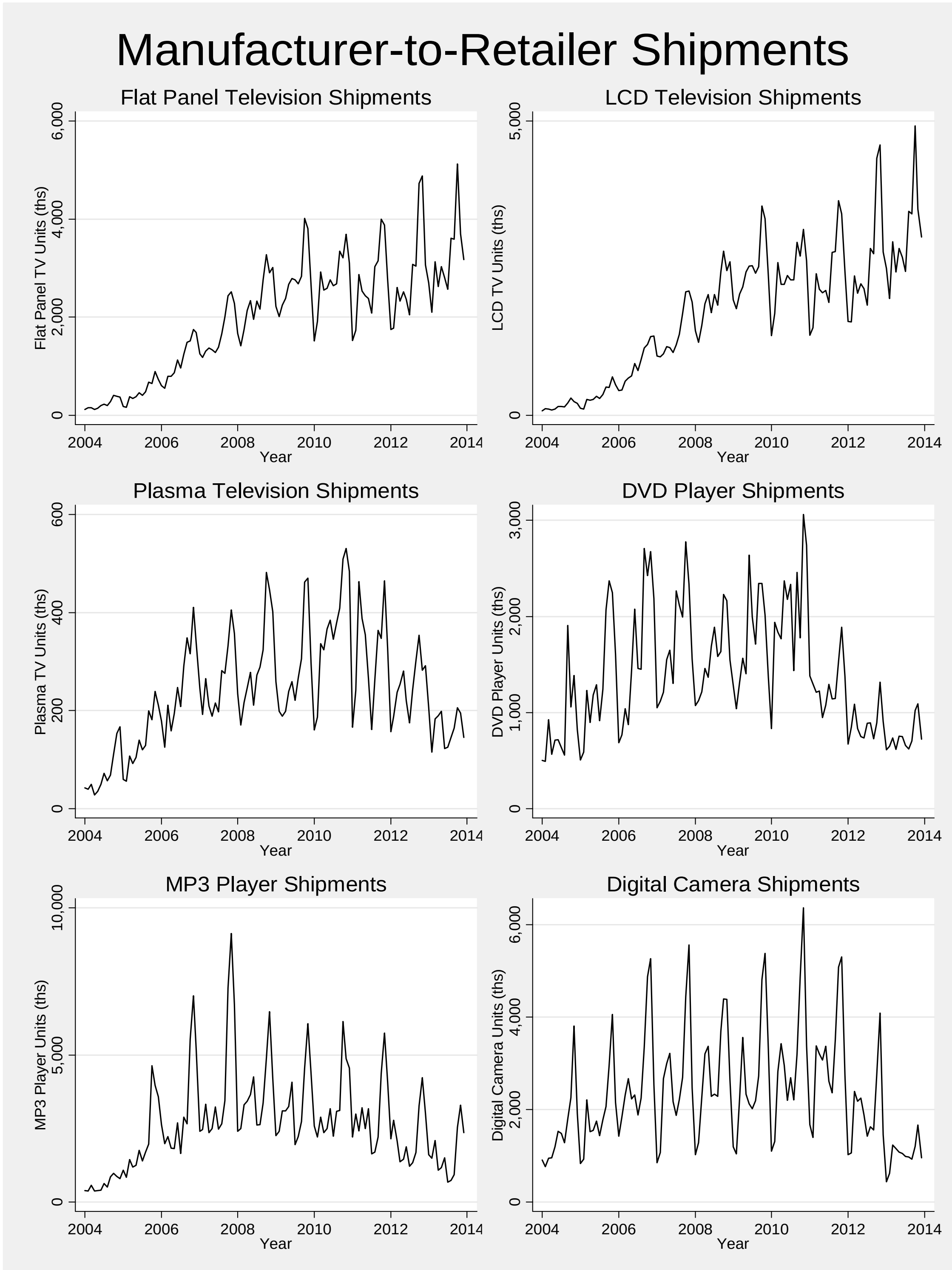

Figure 1. Monthly manufacturer-to-retailer shipments, 2004-2013. *Source:* Consumer Electronics Assocation.

Index of Probabilistic Consumer Expectations

Because I am modeling a more narrowly defined variable (shipments of consumer electronics devices) than economy-wide macroeconomic variables, ideally a corresponding survey-based variable with a focus on technology consumption should be used in alternative model specifications. Luckily, a new and unique survey-based approach looking at consumer interest in purchasing consumer technology exists.

In 2005, CEA, in partnership with CNET, began testing a measure of consumer sentiment through a survey of individuals in CNET's Tech First Panel. Beginning in January 2007, CEA and CNET began using a similar series of questions on a monthly basis through a random-digit-dial phone survey. These questions gauge consumer sentiment on the broader economy in general and on technology specifically. They have become known collectively as the CEA Consumer Sentiment Indexes and are designed to improve on weaknesses of the ICS and CCI by asking consumers about their expectations in the form of subjective probabilities. In modeling choice, economists typically assume that individuals with access to only partial information will form probabilistic expectations to fill the voids and allow them to maximize expected utility. Manski (2004, page 1329) argued that researchers would be better served to "measure expectations in the form called for by modern economic theory; that is, subjective probabilities."

A simple example of a probabilistic expectation question is as follows: What do you think is the percent chance that it will rain tomorrow? Survey respondents then respond with an answer between zero percent and 100 percent. Manski (2004) highlights three compelling advantages to subjective probabilistic questioning:

1. Probability provides a well-defined, absolute numerical scale for responses; responses may therefore be interpersonally comparable.
2. Researchers can use the algebra of probability (Bayes Theorem, the Law of Total Probability, etc.) to examine the internal consistency of a respondent's expectations around different events.
3. When probability has a frequentist interpretation, one can compare elicited subjective probabilities with known event frequencies and reach conclusions about the correspondence between subjective beliefs and frequentist realities.

Economists began eliciting probabilistic expectations in the early 1990s. Guiso et al (1992) used probabilistic expectation questions inserted in the Bank of Italy Survey of Household Income and Wealth to explore the effect earnings uncertainty has on savings and wealth accumulation. Hurd and McGarry (1995), using the Health and Retirement Study, found that respondents' reported probabilities aggregated close to life table values and covaried appropriately with known risk factors. For example, smokers give lower probabilities of living to a certain age than nonsmokers, men give lower probabilities than women, and those in higher socio-economic classes give higher probabilities of survival. Hurd and McGarry (2002) went on to show that subjective survival probabilities predicted actual survival; members of the panel who survived from the first wave in 1992 to the second survey wave in 1994 reported probabilities approximately 50 percent greater at baseline than those who died between the survey waves.

Dominitz and Manski (1997) used probabilistic questions from the Survey of Economic Expectations to study cross-sectional variations in income expectations.

Dominitz, Manski, and Heinz (2003) subsequently used the same survey to explore perceptions of Social Security benefits, and Manski and Straub (1999) used it to study perceptions of job security. Researchers have also used probabilistic expectations to measure expectations of equity returns (Dominitz & Manski, 2005), income expectations of emigrants (McKenzie et al, 2007), and portfolio choice among retirees (Dominitz & Manski, 2007).

Despite a myriad of studies that have leveraged probabilistic questioning to explore consumer expectations, no study has used this methodology to measure consumer expectations on a continuous basis until the advent of the CEA Consumer Sentiment Indexes.

The CEA survey approach addresses three factors raised by academic research about the effectiveness of consumer surveys. First, surveys lacking probabilistic questions, such as the ICS and CCI, inhibit respondents from expressing uncertainty. The CEA Consumer Sentiment Indexes attempt to overcome this shortfall. Dominitz and Manski (2003, page 4) illustrated the importance of the difference as follows:

> Consider, for example, the question: "Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?" How do respondents interpret the phrase "better off financially?" Do different respondents interpret the phrase in the same way? How do respondents who are uncertain of their future prospects answer the question?

Following Dominitz and Manski's recommendations, the CEA Consumer Sentiment Indexes designed questions to "elicit interpersonally comparable expectations of well-defined events." Importantly, the questions elicit expectations in the form called for by modern economic theory; that is, in the form of subjective probabilities (see Dominitz & Manski, 2003, p. 6). In other words, as opposed to asking consumers if they will be "better off," "worse off," or "about the same," this survey allows respondents to indicate a range of uncertainty in their response by inviting them to give their subjective probabilistic expectations.

Second, as Dominitz and Manski (2003) found, attitudinal research tends to show less volatility when the questionnaire asks about topics relative to the respondent as opposed to broader, more removed topics. For example, respondents show less volatility in their responses when asked about their own financial outlook than when asked about general business financial conditions. Both the ICS and the CCI include questions about broad, ambiguous topics like "business conditions," while the CEA indexes are derived largely from questions on the respondent's subjective perceptions of his or her own situation. The risk for both the University of Michigan and the Conference Board is that month-to-month changes in the index are driven by spurious volatility in the responses to questions about large events for which the respondents are uncertain in their reply because of the distance of the question from their own personal experiences.

Third, as Dominitz and Manski (2003) further noted, qualitative questions have a higher Spearman rank correlation than probabilistic questions, suggesting that qualitative surveys provide more overlapping information on consumer expectations than probabilistic questions. Conversely, probabilistic questions provide more distinct information. Dominitz and Manski (2003) found that the rank correlation of all pairs of the qualitative variables in the ICS survey ranged from 0.72 to 0.93. Data from the CEA Indexes survey exhibit significantly lower Spearman rank correlations (DuBravac, 2008). This result suggests that each question within the CEA Indexes captures unique information distinct from other questions asked in the survey and included as part of the index calculations. This finding is especially meaningful for the two questions used in deriving the CEA Index of Consumer Technology Expectations.

Each month the CEA surveys a sample of 1,000 individuals, weighted to be representative of the total U.S. population.[4] The survey asks several subjective probability questions regarding respondents' outlook on the state of the U.S. economy and spending on consumer technologies.[5] From these results, two indexes are derived: the CEA Index of Consumer Expectations (ICE) and the CEA Index of Consumer Technology Expectations (ICTE).

The ICTE is derived as follows:

$$\text{ICTE}_t = \sum\left(\frac{\sum_{i=1}^{n} cc3a}{n} + \frac{\sum_{i=1}^{n} cc3b}{n}\right)$$

Question cc3a (referred to in this equation) reads, "What do you think is the PERCENT CHANCE that you will purchase any consumer electronics product in the next 12 months?" Question cc3b reads, "What do you think is the PERCENT CHANCE that you will spend MORE on consumer electronics products in the next 12 months compared to

[4] See Appendix Table A2 for a list of the weights.
[5] See Appendix Table A3 for a full list of the questions asked in the CEA-CNET survey.

the last 12 months?" For more information on the CEA Consumer Sentiment Indexes see DuBravac (2008).

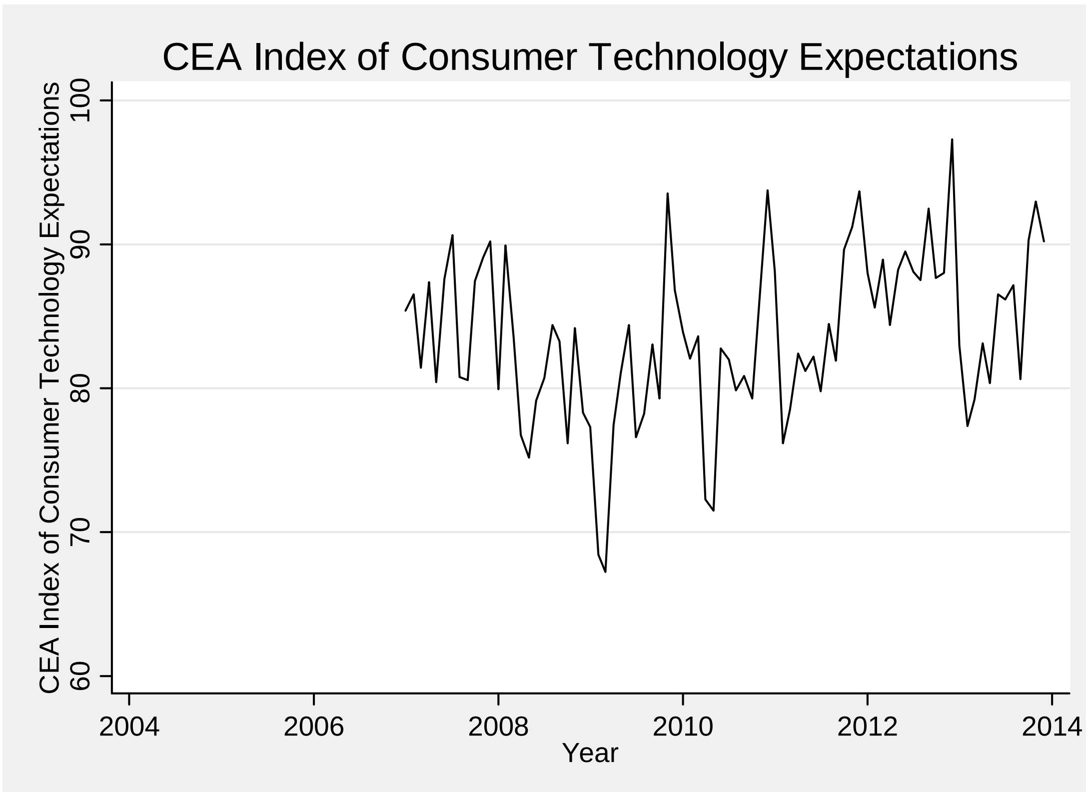

Figure 2. CEA Index of Consumer Technology Expectations, 2007-2013. *Source:* Consumer Electronics Association.

Table 2. *Summary Statistics for CEA Index of Consumer Technology Expectations*

N	Mean	Standard Deviation	Variance	Skewness	Kurtosis	Max	Min	25%	50%	75%
84.0	83.6	5.8	33.3	-0.3	3.2	97.3	67.2	79.9	83.4	87.8

Online Search Query Data

In 2006 Google launched Google Trends,[6] an instrument to analyze aggregated web search terms used on the Google web search platform. Google Trends analyzes a percentage of all Google web searches to determine the relative number of searches performed for a given search term, compared to the total number of Google searches done over the same time.[7] Google Trends produces an index of the search query in question relative to the overall search volume conducted through Google; it does not provide a raw, absolute number of search queries.

Google Trends data are normalized by region to make comparisons across regions possible. If Trends data were not normalized then regions with the highest search volume would always be ranked highest. For example, users in France and Canada may have the same Google Trends number for a given search term if they equally like the search term relative to all search terms within their region. The same Google Trends number does not mean that both countries have the same number of total searches for a given term.

Google Trends data begin with January 2004 and are available in weekly intervals since then. Google classifies each search query into one of 27 top-level categories and 241 second-level categories through natural language processing methods. One can retrieve search query data across all web searches or within a given category. These categories include groupings like “Beauty and Fitness,” “Computers and Electronics,” and “Shopping.” Each of these categories has numerous subcategories. When filtering

[6] In August 2008, Google launched Google Insights for Search, an advanced service for displaying search trends data; in September 2012 Google merged Google Insights for Search into Google Trends.
[7] Google excludes low-volume search terms and duplicate searches from a given user over a short period of time.

results by category, one will receive only search data related to the given search term within that specific category. For example, retrieving search results for the term “iPod” in the Shopping category will exclude news searches for the term “iPod.” Category search term retrievals are essentially a segmentation of the search term. If the keyword being examined is broad or applies to multiple industries or niches, then broad web search results will include all search cases. For example, retrieving search data for the terms “Black Friday,” even using quotation marks, will obtain searches related to the shopping day after Thanksgiving in the United States, commonly referred to by this name, but could also include searches for Rebecca Black’s song “Friday.” Filtering by category can help to focus the search results retrieved.

Google Trends data are available for user-specified phrases or for any of the predefined categories. In this study I test both predefined search data category indicators and my own set of phrases related to various consumer electronics-related demand, such as “digital camera,” “MP3 player,” “DVD player,” “LCD TV,” “iPod,” and “television.” I use the category or phrase that provides the best model fit as measured by minimizing mean absolute error (MAE).

Because this study encompasses only data on device shipments within the United States, I utilize U.S. search queries only. An example of Google Trends data is provided in Figure 3 below, which shows search query data for the search term “iPod” within the “Shopping” category, using the monthly average of the weekly search index as explained in the next section. Several elements are evident in the graphical depiction of the data. First, searches for “iPod” are highly seasonal, with the peak each year occurring in the fourth quarter of the calendar. This fact comes as no surprise, given the popularity of giving and receiving iPods during the holiday season. Second, relative searches for "iPod" peaked in 2005 and 2006 and trailed downwards from there.

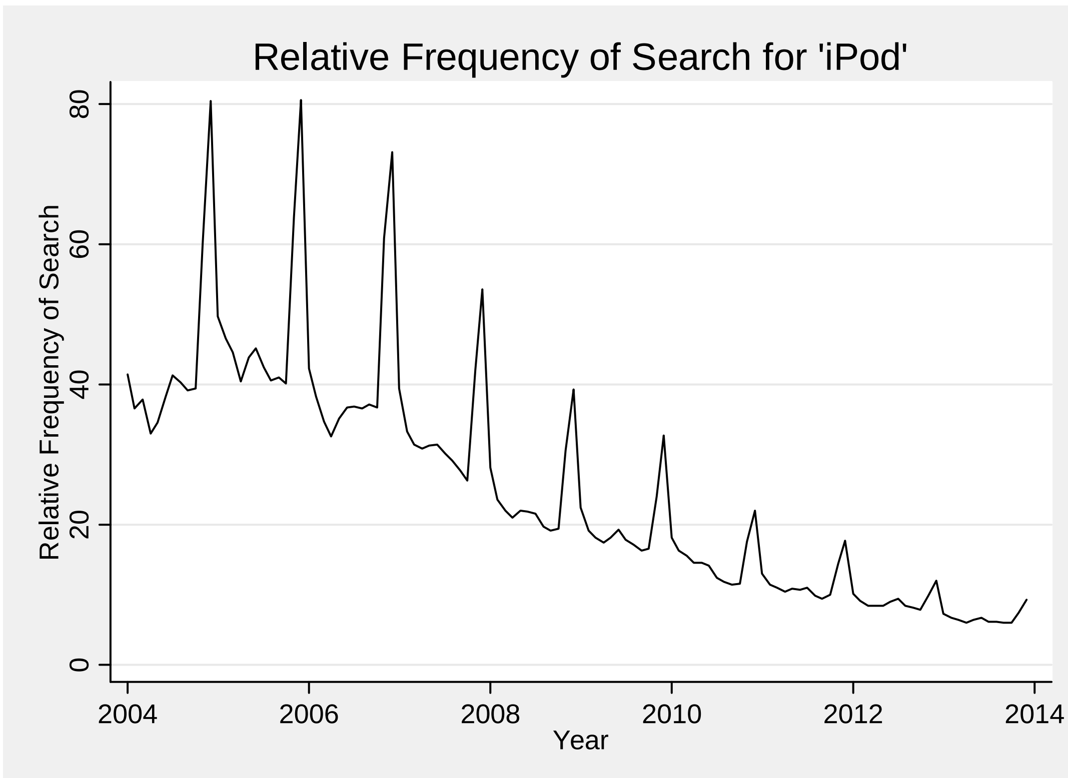

Figure 3. Example of Google Trends data: Web queries for the term "iPod." *Source:* Google Trends (www.google.com/trends).

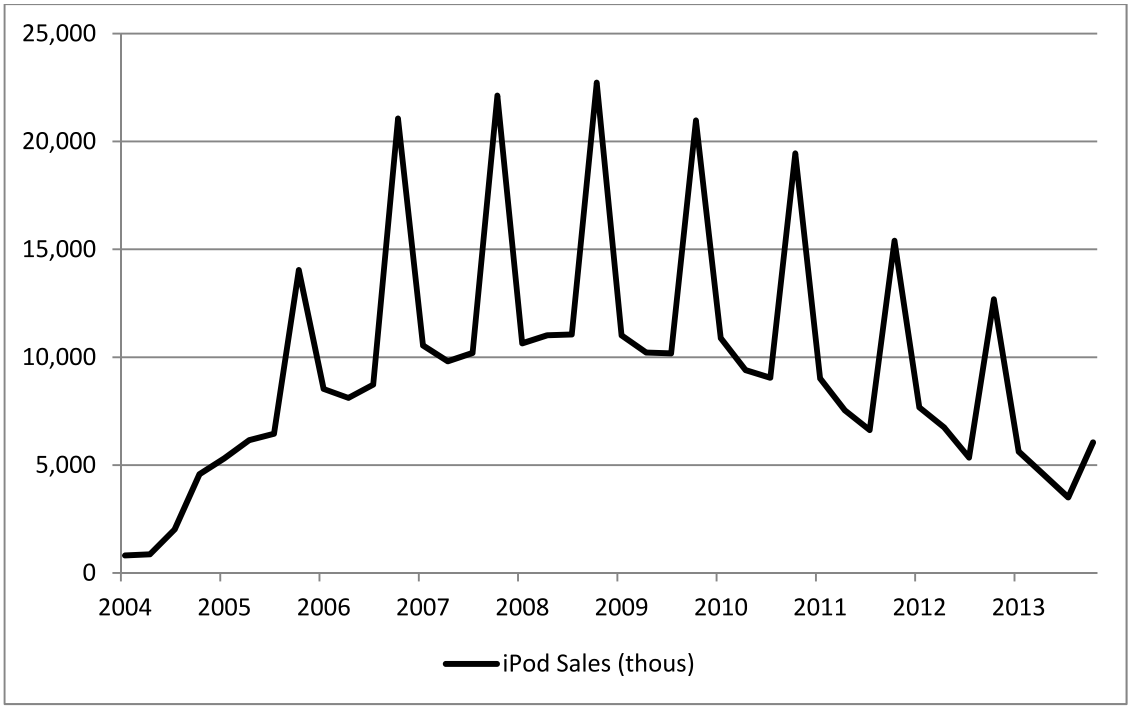

Figure 4. iPod Sales, 2004-2013. *Source:* Apple financial statements.

Constructing Google Search Indices

Google Trends provides data at weekly frequencies, whereas the CEA shipment data are published at monthly intervals. As a result, Google search data series need to be collapsed into monthly intervals. The data are first interpolated to daily frequency by applying a cubic spline methodology, due to the irregular overlapping of weeks and months, they are then aggregated to monthly frequencies.

Stifel Nicholas Retail's Real-time Expenditure Analysis and Detail Survey

Beginning in September 2003, Stifel Nicholas (Stifel), a full-service brokerage and investment banking firm based in St. Louis, Missouri, began a bimonthly survey of consumers, called the Real-time Expenditure Analysis and Detail Survey or READ. Initially inspired by conversations with Dr. Richard Curtin and those responsible for the

ICS survey, Stifel uses a third party to administer the survey to a random sample of 600 families every month (in two waves of 300 families each). Stifel surveys various topics related to what consumers are buying, where they are buying it, and why they chose a specific retailer. In each wave since the inception of the survey, Stifel has asked, “Do you plan to purchase an HDTV within the next year?”

We collapse this data series to monthly intervals, as we did with Google search queries, and use this new monthly series as an additional alternative model specification for predicting flat-panel television shipments, LCD television shipments, and plasma television shipments, respectively.

Empirical Approach

Google Trends data and device shipment data are available from January 2004 to December 2013, whereas the ICTE began in January 2007. The overlap of the two time frames from 2007 through 2013 permits 84 monthly observations. However, because I include twelve-month lags of the ICTE, I am left with 72 monthly observations in my model estimates. I estimate parsimonious autoregressive models of consumer electronic shipments as follows:

Baseline: $\log(C_{t+h}) = intercept + \alpha_1 \log(C_{t-1}) + \alpha_2 \log(C_{t-12}) + \varepsilon_{t+h}$

Alternative model: $\log(C_{t+h}) = intercept + \alpha_1 \log(C_{t-1}) + \alpha_2 \log(C_{t-12}) + \beta S_t^k + \varepsilon_{t+h}$

where C_t is the number of televisions sold in month t and h is the forecast horizon ($h = 0$ for “nowcasts” and 1 for forecasts looking one month ahead). S is the measure of consumer sentiment (either ICTE or a Google Trends series). The variable ε_{t+h} is an error term. This model is a simple seasonal autoregressive model (seasonal AR model).

In this paper I am focusing on a series of single-matrix explanatory variables. I use a simple baseline model together with simple alternative models to ascertain the econometric significance of these new data rather than applying sophisticated modeling prowess. Much of the previous work in this arena (see for example Choi & Varian 2009a, Choi & Varian 2009b, and Wu & Brynjolfsson, 2013) has found that simple models perform equally well as or even outperform more sophisticated nonlinear and multivariate models.

In the next section I provide empirical results for the following fitted models:

Baseline as outlined above:

$$\log(C_{t+h}) = intercept + \beta_1 \log(C_{t-1}) + \beta_2 \log(C_{t-12}) + \varepsilon_{t+h}$$

Alternative model using ICTE:

$$\log(C_{it+h}) = intercept + \beta_1 \log(C_{it-1}) + \beta_2 \log(C_{it-12}) + \beta_3 ICTE_t + \beta_4 ICTE_{t-12} + \beta_3 ICTE(C_{t-1}) + \beta_4 ICTE(C_{t-12}) + \varepsilon_{t+h}$$

Alternative model using STIFEL:

$$\log(C_{it+h}) = intercept + \beta_1 \log(C_{it-1}) + \beta_2 \log(C_{it-12}) + \beta_3 STIFEL_{t-1} + \varepsilon_t$$

Alternative model using an index of search data:

$$\log(C_{it}) = intercept + \beta_1 \log(C_{it-1}) + \beta_2 \log(C_{it-12}) + \beta_3 Search_t + \beta_4 Search_{t-1} + \varepsilon_t$$

where *Search* corresponds to an index of search terms. I test numerous search queries, using multiple categories as well as phrases, and include the search index that provides the best model fit as measured by minimizing mean absolute error (MAE). I also test multiple and different lag options. Ultimately I chose to include both the current and one-period lag in the model because they generally provided the best fit and appear to be the most relevant. Higher-order lags did not generally add much predictive power. Ostensibly, consumers are making searches relevant to consumer electronics devices that they plan to buy within a fairly narrow window of time after the search. While some major purchases such as residential housing might frequently present a longer time gap between research and purchase, that is not likely to be the case with consumer electronics devices, and the econometrics data appear to support that thesis.

I also fit a model that uses a search index as well as the consumer sentiment index. For each prediction, I calculate the mean absolute error (MAE) to compare the competing model specifications. The mean absolute error is the deviation from the actual value:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|PE_t|$$

where $\mathrm{PE}_t = \log(\hat{y}_t) - \log(y_t) \approx \frac{y_t - \hat{y}_t}{y_t}$.

Results

Flat-Panel Television Shipments

As outlined in the previous section, I begin by fitting flat-panel television shipments to a parsimonious seasonal autoregressive (AR) model, which serves as a baseline model (see Model 1 of Table 3 below).[8] I then compare this baseline AR model

[8] I tested a number of different baseline model specifications, including the addition of seasonality dummies, to control for time-specific changes. However, despite the fact that shipments of consumer

to several alternative model specifications. As explained in the prior section, I use the MAE to compare accuracy across alternative model predictions. The first alternative model specification (Model 2 of Table 3) uses a conventional survey-based indicator that I obtained from Stifel Nicholas's question regarding consumers' intentions to purchase "an HDTV within the next year." The second alternative model specification (Model 3 of the table) uses the ICTE. Model 4 uses an index of Google search query rankings to provide another alternative model specification. Finally, Model 5 includes both the ICTE and an index of Google search query rankings as independent variables.

I tested a number of alternative specifications for including online consumer search inquiries. Google Trends allows for predefined categories that contain all queries within a given category, or one can create user-defined categories by specifying phrases that consumers might search for. For flat-panel television shipments, a user-defined index of searches for the term "television" within the shopping category provided the best fit. The results for Models 4 and 5 in Table 3 use this index.

The baseline seasonal AR model shows that past shipments of flat-panel televisions are highly correlated with current-month shipments and explain a large proportion of variance in the dependent variable. For a 10% increase in flat-panel televisions shipped last month, we expect shipments to be 1.5% higher this month. For every 10% increase in flat-panel television shipped in the same month a year earlier, we expect television shipments to be 6% higher.

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electronics do exhibit strong seasonality trends, I found that the inclusion of seasonality dummies does not generally improve model fit. The best fit is provided by the pure and simply seasonal AR model with one-period and 12-period lags.

Table 3. *Linear Regression to Predict Flat-Panel Television Shipments*

Dependent variable: log (flat-panel television shipments)

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
Intercept	3.522	1.068***	3.361	1.130***	3.396	1.022***	4.260	1.179***	4.046	1.087***
Shipments_{t-1}	0.158	0.079**	0.145	0.081*	0.096	0.085	0.217	0.080***	0.156	0.080*
Shipments_{t-12}	0.608	0.073***	0.625	0.075***	0.661	0.073***	0.511	0.075***	0.562	0.073***
Stifel_{t-1}			0.455	0.461						
CTE_t					-0.005	0.003*			-0.004	0.003
CTE_{t-12}					0.008	0.004**			0.008	0.004**
Television_t							0.004	0.003	0.003	0.003
Television_{t-1}							-0.008	0.003**	-0.008	0.003**
MAE	.1214		.1174		.1104		.1161		.1031	
	N = 72		N = 72		N = 72		N = 72		N = 72	
	Adj. R2 = .689		Adj. R2 = .693		Adj. R2 = .720		Adj. R2 = . 726		Adj. R2 = .754	

*$p < .1$; **$p < .05$; ***$p < .01$. Huber-White robust standard errors are shown in parentheses.
Note: "Television" refers to an index derived from search engine queries based on the word "television," as explained in the prior section.

Adding Stifel's measure of HDTV purchasing expectations increases the adjusted R^2 slightly, and the model specification appears to provide a slightly more accurate prediction judging by the lower MAE; however, the variable by itself is not statistically significant.

In Model 3 I include contemporaneous and lagged values for the ICTE. Both contemporaneous and 12-month lagged values are statistically significant, and, as Table 3 highlights, the model provides a superior fit relative to both the baseline model and Model 2, which includes the Stifel measure of anticipated HDTV purchasing. Model 3 shows that a one-unit increase in the prior-month ICTE lowers current shipments of flat panel televisions by 0.5%. Conversely, a one-unit increase in year-ago ICTE results increases current-month shipments of flat-panel televisions by 1%.

In Model 4 I include contemporaneous and lagged values for an index of online search queries. As the table highlights, the contemporaneous value is not significant; this result is consistent for several of the consumer electronic devices analyzed. Previous research has shown that contemporaneous search inquiry indices are statistically significantly positively correlated with present economic outcomes (see for example Choi & Varian 2009a, Choi & Varian 2009b, and D'Amuri & Marcucci, 2009). The present results indicate that lagged variables of search inquiry indices often provide more predictive power. This finding makes intuitive sense because we are predicting shipments of devices from manufacturers to retailers. Within consumer electronics, most retailers have fine-tuned their supply chain dynamics and inventory management to turn inventory around roughly 12 times a year. In other words, most retailers are seeking to hold inventory for a month or less. This pattern creates about a one-month lag between the dates when devices are shipped to retailers and when they are ultimately sold to consumers.

It is common for retailers and manufacturers to work through a series of rolling forecasts that dictate shipments from manufacturers to retailers over the subsequent 12 months. The current-period shipments were likely decided and obligated in a previous period, so no contemporaneous events can impact those commitments. It makes intuitive sense that current-month shipments should be statistically significantly correlated with prior-month online consumer searches[9] because it takes manufacturers and retailers about a month to respond to changes in demand.

At this point it is worth noting that the MAE for Model 4 is superior to the baseline seasonal AR model, but not to the model that includes the index derived from probabilistic survey questions regarding technology purchases. This is also true for most of the consumer electronic device shipments that I modeled.

Model 5 includes both indices of search queries as well as the index derived from probabilistic survey questions regarding technology purchases. As Table 3 shows, the MAE for Model 5 is 0.1031, or roughly a 15% improvement over the baseline model, and this finding is significant at the $p < 0.01$ level.

LCD Television Shipments

Table 4 shows regression results for LCD television shipments. Model 1 of provides results for the simple seasonal autoregressive (AR) model. As the results make clear, the data are well explained by a simple seasonal AR model. For a 10% increase in LCD televisions shipped last month, one can expect LCD television shipments to be 2.1% higher this month. For every 10% increase in LCD television shipped in the same month a year prior, LCD television shipments are expected to be 5.5% higher. These results are nearly consistent with those for flat panel televisions; this finding again makes sense since the bulk of the flat-panel television shipments during the sample period are LCD televisions.

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[9] It is possible that online consumer search inquiries are correlated with other variables that are measured by retailers and manufacturers and subsequently used to influence shipments. For example, retailers could monitor store traffic or current sales of a product and report this information to manufacturers, consequently influencing shipments.

As with the models predicting flat-panel television shipments, I also tested the Stifel survey variable. While the variable does not prove to be independently statistically significant, it does add generally to the predictive power of the baseline model. The model provides a higher adjusted R^2 as well as a lower MAE.

Model 3 in Table 4 includes contemporaneous and lagged values for the ICTE. In the case of LCD television shipments, only the lagged values of ICTE are statistically significant, but the model does provide incremental accuracy. The MAE improves from 0.1289 to 0.1201, an improvement of 6.8%, and is significant at the $p < 0.01$ level.

I again tested several search query series, finding that the search phrase "Televisions" in the shopping category provided the best fit. As the results for Model 4 show, inclusion of these series helps to explain incremental variance in the dependent variable. As I noted for flat-panel televisions, the contemporaneous search inquiry index is not independently statistically significant.

Finally, I estimated a model that includes both contemporaneous and lagged values of both ICTE and a search query index. This model provided the highest degree of accuracy, lowering the MAE from 0.1289 for the baseline model to 0.1112, an improvement of 13.7% that is significant at the $p < 0.01$ level.

Table 4. *Linear Regression to Predict LCD TV Shipments*

Dependent variable: log (LCD television shipments)

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
Intercept	3.363	1.078***	3.193	1.135***	3.368	1.046***	3.960	1.168***	3.869	1.072***
Shipments_{t-1}	0.214	0.079***	0.197	0.083**	0.132	0.093	0.286	0.078***	0.203	0.087**
Shipments_{t-12}	0.562	0.072***	0.582	0.076***	0.616	0.075***	0.463	0.073***	0.514	0.072***
Stifel_{t-1}			0.548	0.504						
CTE_{t}					-0.004	0.003			-0.002	0.003
CTE_{t-12}					0.009	0.004**			0.010	0.004**
Television_{t}							0.003	0.003	0.002	0.003
Television_{t-1}							-0.009	0.003***	-0.008	0.003***
MAE	.1289		.1247		.1201		.1234		.1112	
	N=72		N=72		N=72		N=72		N=72	
	Adj. R2=.6797		Adj. R2=.6848		Adj. R2=.7106		Adj. R2=.7197		Adj. R2=.7504	

* $p < .1$; ** $p < .05$; *** $p < .01$. Huber-White robust standard errors are shown in parentheses.
Note: “Television” refers to an index derived from search engine queries based on the word “television.”

Plasma Televisions

Table 5 shows regression results for plasma television shipments. Model 1 provides results for the baseline seasonal autoregressive (AR) model. For a 10% increase in plasma televisions shipped last month, one can expect unit volume this month to increase by 5%. Plasma television shipments are predicted to increase by 4.7 percent for each additional 10% increase in unit shipped in the same month a year prior.

Again, as in the previous two cases, I tested the Stifel survey variable, which is significant at $p < .1$. The model provides a higher adjusted R^2 as well as a lower MAE and accordingly is about 3% more accurate than the baseline model.

Model 3 in Table 5 includes contemporaneous and lagged values for the ICTE. Both variables are statistically significant, and the model provides incremental accuracy. The MAE is 0.1837, a 6.9% increase from the baseline AR model.

The search query index that provided the best fit for plasma television shipments was the search phrase "plasma" in the shopping category. As the results for Model 4 indicate, both contemporaneous and lagged values of the index are statistically significant. However, while inclusion of this series helps to explain incremental variance in the dependent variable from the baseline model, it did not improve explanatory power or accuracy over inclusion of the ICTE.

Finally, I estimated a model that includes both contemporaneous and lagged values of both ICTE and the search query index. As Model 5 in Table 5 demonstrates, this model provided the highest degree of accuracy, lowering the MAE from 0.1973 for the baseline model to 0.1718. This is an improvement of 12.9% and is significant at the $p < 0.01$ level.

DVD Player Shipments

Table 6 shows regression results for four competing models of DVD player shipments. Model 1 of Table 6 provides results for the same baseline seasonal autoregressive (AR) model as presented for each of the data series. A 10% increase in DVD players shipped last month results in an expected increase in current-month unit volume of 5.7%. DVD player shipments are predicted to increase by 3.8% for each additional 10% increase in unit shipped in the same month from a year prior.

Table 5. *Linear Regression to Predict Plasma TV Shipments*

Dependent variable: log (plasma television shipments)

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
Intercept	0.146	1.263	0.931	1.428	0.894	1.274	1.391	1.376	2.410	1.415*
Shipments_{t-1}	0.508	0.082***	0.489	0.079***	0.499	0.075***	0.455	0.096***	0.458	.0819***
Shipments_{t-12}	0.477	0.109***	0.457	0.113***	0.562	0.105***	0.424	0.116***	0.487	0.104***
Stifel_{t-1}			-1.296	0.697*						
CTE_{t}					-0.011	0.005**			-0.011	0.006*
CTE_{t-12}					-0.009	0.005*			-0.011	0.005**
Plasma_{t}							0.018	0.008**	0.020	0.008***
Plasma_{t-1}							-0.012	0.007*	-0.016	0.007**
MAE	.1973		.1913		.1837		.1893		.1718	
	N=72		N=72		N=72		N=72		N=72	
	Adj. R2=.5650		Adj. R2=.5812		Adj. R2=.6238		Adj. R2=.5885		Adj. R2=.6544	

* $p < .1$, **$p < .05$, ***$p < .01$. Huber-White robust standard errors are shown in parentheses.
Note: “Plasma” refers to an index derived from search engine queries based on the word “plasma.”

Model 2 in Table 6 includes contemporaneous and lagged values for the ICTE. Neither variable is statistically significant by itself, but predictive accuracy is improved slightly. The MAE of 0.1824 represents nearly a 1% increase in accuracy from the baseline AR model.

The search query index that provided the best fit for DVD player shipments was the search phrase “TV” within the shopping category. While it is interesting that this phrase performed better than search phrases like “DVD Player,” it does make intuitive sense since DVD players attach to TVs. As the results for Model 3 indicate, contemporaneous values of the search index are statistically significant but the lagged value of the index are not. Inclusion of this series helps to explain incremental variance in the dependent variable from the baseline model and also provides improved explanatory power. DVD player shipments are the only category of consumer electronics examined where the model that includes search query data provides improved accuracy over inclusion of the ICTE.

Finally, I estimated a model that included both contemporaneous and lagged values of both ICTE and the search query index. As Table 6 demonstrates, this model (Model 4) provided the highest degree of accuracy, lowering the MAE from 0.1839 for the baseline model to 0.1759, an improvement of 4.4% that is significant at the $p < 0.01$ level.

Table 6. *Linear Regression to Predict DVD Player Shipments*

Dependent variable: log (DVD player shipments)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
intercept	0.398	1.056	1.693	1.640	2.239	1.385	4.470	1.891**
Shipments$_{t-1}$	0.579	0.068***	0.560	0.080***	0.478	0.100***	0.479	0.106***
Shipments$_{t-12}$	0.388	0.086***	0.381	0.090***	0.345	0.092***	0.289	0.095***
CTE$_t$			-0.007	0.004			-0.008	0.004*
CTE$_{t-12}$			-0.004	0.007			-0.009	0.007
"TV"$_t$					0.019	0.009**	0.025	0.010**
"TV"$_{t-1}$					-0.010	0.006	-0.017	0.006***
MAE	.1839		.1824		.1759		.1727	
	N = 72		N = 72		N = 72		N = 72	
	Adj. R2 = .6654		Adj. R2 = .6802		Adj. R2 = .6959		Adj. R2 = .7241	

*$p < .1$, **$p < .05$, ***$p < .01$. Huber-White robust standard errors are shown in parentheses.
Note: "TV" refers to an index derived from search engine queries based on the word "TV."

MP3 Players

Table 7 provides results for four competing models of MP3 player shipments. Model 1 of this table provides results for the baseline seasonal autoregressive (AR) model. A 10% increase in MP3 players shipped last month results in an expected increase in current-month unit volume of 2.9%. Current MP3 player shipments are expected to increase 7.9 percent for each 10% increase in units shipped during the same month from the prior year. Both variables are significant, and the baseline model explains 78 percent of the variance in MP3 player unit shipments.

Model 2 in Table 7 includes contemporaneous and lagged values for the ICTE. The model is improved and accuracy also increases. The MAE of 0.1649 is a 4.9% increase in accuracy from the baseline seasonal AR model.

The search query index that provided the best fit for MP3 player shipments was the search phrase “MP3 player” within the shopping category. The search phrase “iPod” also performed well, but was narrowly beaten out by the term “MP3 player.” As the results for Model 3 in Table 7 indicate, inclusion of search query data improves the accuracy of the model by 4.5% over the baseline AR model but does not improve the model over inclusion of the ICTE.

The final model that I estimated includes both contemporaneous and lagged values of both the ICTE and the search query index. As Model 4 in Table 7 demonstrates, this model provides the most explanatory power and the highest degree of accuracy. The MAE is lowered to 0.1634 from the baseline model MAE of 0.1734, an improvement of 5.8% that is significant at the $p < 0.01$ level.

Table 7. *Linear Regression to Predict MP3 Player Shipments*

Dependent variable: log (MP3 player shipments)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
intercept	-1.591	1.049	-0.721	0.956	-0.561	1.270	-0.095	1.146
$\mathbf{Shipments_{t-1}}$	0.297	0.056***	0.285	0.055***	0.249	0.064***	0.268	0.070***
$\mathbf{Shipments_{t-12}}$	0.802	0.073***	0.834	0.070***	0.777	0.092***	0.803	0.090***
$\mathbf{CTE_t}$			-0.005	0.004			-0.004	0.004
$\mathbf{CTE_{t-12}}$			-0.009	0.004***			-0.010	0.004***
"MP3 Player"$_t$					0.008	0.010	0.006	0.009
"MP3 Player"$_{t-1}$					-0.001	0.006	-0.003	0.005
MAE	.1734		.1649		.1656		.1634	
	N = 72		N = 72		N = 72		N = 72	
	Adj. R2 = .7838		Adj. R2 = .8028		Adj. R2 = .7888		Adj. R2 = .8043	

*$p < .1$, **$p < .05$, ***$p < .01$. Huber-White robust standard errors are shown in parentheses.
Note: "MP3 Player" refers to an index derived from search engine queries based on the word "MP3 Player."

Digital Cameras

The final consumer electronics durable item tested was digital camera unit shipments. The results of my four competing models are presented in Table 8 Model 1 provides results for the baseline seasonal autoregressive model. A 10% increase in digital cameras shipped last month results in an expected increase in current-month unit volume of 3.7%. A 10% increase in digital cameras shipped in the same month a year ago increases current monthly shipments by 7.5%. Here again, we see that the parsimonious model fits the data well, explaining 75% of the variance in digital camera unit shipments.

Model 2 in Table 8 includes contemporaneous and lagged values for the ICTE. The model is improved and accuracy also increases. The adjusted R^2 improves to 0.83. The MAE of 0.1723 marks a 20.5% increase in accuracy from the baseline seasonal AR model, the largest improvement in model accuracy found for any of the consumer electronic devices examined.

The search query index that provided the best fit for digital camera unit shipments was the category index of “Camera and Photo Equipment” in the shopping category. This was the only instance when a category index outperformed any search phrase. As the results for Model 3 in Table 8 highlight, inclusion of search query data improves the accuracy of the model by 7.2% over the baseline AR model but is significantly less accurate than the model with inclusion of the ICTE.

The final model estimated for digital cameras includes both contemporaneous and lagged values of both the ICTE and the search query index. As Model 4 in Table 8 demonstrates, this model provides the most explanatory power and the highest degree of accuracy. For all consumer electronic device shipments that I tested, this model outperformed all other models in both explanatory power as well as accuracy as measured by MAE. The MAE for digital cameras was lowered to 0.1634, an improvement of 24.2% from the baseline AR model and an improvement of 4.6% over the model specification that includes only the ICTE.

Table 9 summarizes the results for the six consumer electronic cases outlined above. As the results show, only a single device class (DVD players) has a lower MAE for the inclusion of a search query index. For all other devices, the ICTE provides a greater increase in accuracy over the baseline model that includes neither predictor.

Table 8. *Linear Regression to Predict Digital Camera Shipments*

Dependent variable: log (digital camera shipments)

	Model 1		Model 2		Model 3		Model 4	
Regressor	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.	Beta	Robust Std. Err.
Intercept	-2.115	1.094*	-0.054	1.047	-1.512	1.133	0.753	1.021
$Shipments_{t-1}$	0.378	0.062***	0.379	0.048***	0.170	0.087*	0.240	0.076***
$Shipments_{t-12}$	0.759	0.081***	0.809	0.078***	0.876	0.109***	0.828	0.087***
CTE_t			-0.018	0.005***			-0.011	0.005**
CTE_{t-12}			-0.016	0.005***			-0.017	0.004***
Camera and Photo Equip. Shopping $Category_t$					0.009	0.005	0.010	0.005**
Camera and Photo Equip. Shopping $Category_{t-1}$					0.004	0.004	-0.001	0.003
MAE	.2167		.1723		.2012		.1643	
	N = 72		N = 72		N = 72		N = 72	
	Adj. R2 = .7533		Adj. R2 = .8298		Adj. R2 = .8039		Adj. R2 = .8529	

*$p < .1$; **$p < .05$; ***$p < .01$. Huber-White robust standard errors are shown in parentheses.

Table 9. *Summary of MAE for Predicting Present Manufacturing Shipments for a Number of Consumer Electronics Products*

	MAE baseline	**MAE ICTE**	**MAE Search**	**MAE % Improvement for ICTE over baseline**	**MAE % Improvement for Search over baseline**
Flat Panel Televisions	.1214	.1104	.1161	-9.1%	-4.4%
LCD Televisions	.1289	.1201	.1234	-6.8%	-4.3%
Plasma Televisions	.1973	.1837	.1893	-6.9%	-4.1%
DVD Players	.1839	.1824	.1759	-0.8%	-4.4%
MP3 Players	.1734	.1649	.1656	-4.9%	-4.5%
Digital Cameras	.2167	.1723	.2012	-20.5%	-7.2%

Conclusions and Implications

Search query data open up an entirely new and exciting class of information to researchers, offering great potential to record unprompted consumer intentions. The results of this paper paint a more nuanced view of these new data.

I found that inclusion of search query data does improve baseline predictions of manufacturer-to-retailer unit shipments for a number of consumer electronics product classes. But I also found that search query data alone are inferior to a unique consumer sentiment index based on probabilistic surveys of consumers and their intentions to buy technology broadly. Only in the single case of DVD players does the inclusion of search variables outperform the probabilistic-based sentiment index as measured by MAE.

Moreover, the results do not show conclusively that online search patterns and behaviors are correlated with contemporaneous shipments of consumer electronics products from manufacturers to retailers. This paper provides the first known test of the ability of search query data to predict manufacturing shipments of a product, as opposed to sales of a product within a consumer channel level. These results could suggest that search query data are best suited for economic transactions where consumer research on the Internet precedes the transaction, as opposed to those where the transaction in question takes place in advance of the search.

Search query data have proved to be effective in predicting a number of contemporaneous variables and can provide incremental forecast accuracy. However, the results of this study suggest that they are less useful than other alternatives when utilized to forecast decisions happening upstream from the search. When combined with other measures of consumer sentiment, however, search queries do add to our ability to explain data series such as the shipment of consumer electronics products.

This research vein is new and nascent. A large and still underresearched area of study involves deciphering and splitting supply and demand signals. Wu and Brynjolfsson (2013, page30) indicated difficulty in extricating supply and demand signals in search queries. As they noted, they “found no set of queries that can consistently identify shifts in the supply curve. However, because of the fine-grained nature of the search terms, [they] are hopeful that indices can be created to precisely tease out a shift in the demand curve from a shift in the supply curve.”

From my analysis of consumer electronic device trends, I find no strong evidence that online search patterns and behaviors provide a more reliable predictor than other available alternatives. Taken in conjunction with other measures of sentiment, though, these measures do appear to add some predictive power and outperform baseline seasonal AR models or AR models that rely solely on these alternative metrics.

The customizable nature of online search queries leaves open a host of opportunities for researchers. Because one can craft uniquely defined indices using one’s own set of word phrases, the possibilities are truly infinite. One can use these hand-crafted indices to attempt to measure both the supply and the demand side of diverse market segments.

With respect to consumer electronics, one could create indices for extremely granular product classes and segments. For example, strategists, engineers, or product managers could use search query data to monitor changing preferences over time and make adjustments for product feature sets, colors, or other defining attributes. More fine-grained predictions should improve resource allocation, supply chain dynamics, and profitability margins for both manufacturers and retailers because they will be more closely aligned with current consumer behaviors. The real-time nature and availability of search data allow manufacturers and retailers to respond quickly to changing preferences. For example, Google Trends provides weekly reports on the volume of queries, broken down into regional analyses at the country, state, and even city levels. This information could enable national retailers to improve their cross-store assortment.

Researchers can use these so-called "nanodata" that monitor changing micro-behaviors to make informed predictions about the level and direction of contemporaneous and future economic activities. This is a nascent field where explorations are taking place to examine where search queries indices can be used to improve the predictive nature of forecasting models.

Certain markets are likely to be more amenable to the use of search query data, whereas some markets will not benefit from the inclusion of search query data or other real-time high frequency data series. My results suggest that unit shipment volume to retailers is possibly one area where search query data can be helpful, but perhaps not as helpful as other traditional alternatives.

My results may also indicate that search data perform best, in terms of adding meaningful predictive power, in markets not well explained by variables traditionally used to fit the model. In the present study, the data are well explained by a simple seasonal autoregressive model. This research shines valuable light on which potential markets are not well positioned for the inclusion of nanodata to improve predictability. Markets will vary in the time horizon of predictability, depending on the lag from consumer online searches to actual consumer activity. The results of this study indicate measures of consumer online activity does a poor job of helping to explain shipments into a specific consumer channel. As more analysts and firms begin to take note of available high-frequency behavioral data, however, we might expect to see this relationship improve to the point that lagged variables of online consumer activity will indeed add to the predictability of upstream economic events such as manufacturing shipments to retailers.

The use of search data is still in its infancy. There is a continued need to improve understanding as to how to integrate this data source into our existing research approaches and how to decipher the implications of these “digital traces.”

II. WHERE ARE THE BULLS? EXPLORING OPTIMISM AND UNCERTAINTY THROUGH THE BUSINESS CYCLE

Life is largely a matter of expectation. — Horace

Expectations play a pivotal role in a myriad of financial applications, from risk aversion to asset valuation to asset allocation. Market participants have long looked for ways to capture and quantify the expectations held by others. For example, the Survey of Professional Forecasters was started in 1968 when the American Statistical Association, in conjunction with the National Bureau of Economic Research, began conducting a quarterly survey of macroeconomic forecasts for the United States economy. The University of Michigan began its Index of Consumer Sentiment (ICS) through a series of annual surveys of consumers initiated in the late 1940s; it then moved to quarterly surveys in 1952 and to monthly surveys in 1978.[10] Many other metrics have been derived to quantify the expectations held by individuals.

As discussed in the first paper of this dissertation, in recent years researchers have become increasingly interested in measuring individual expectations by asking respondents for replies in probabilistic terms. A simple example of a probabilistic expectations question is "What do you think is the percent chance that it will rain tomorrow?" Subjects then respond with an answer between zero and 100%.

[10] See Curtin (1982) and Linden (1982)

Using the same unique dataset from the Consumer Electronics Association as was utilized in the first paper, I explore optimism and pessimism in the US. Specifically, I explore and detail consumer expectations through the business cycle. In the previous essay I examined an index derived from these microlevel data; in this essay I will use the actual underlying microdata. I will argue that (a) individual demographic and socioeconomic characteristics influence sentiment; (b) these individual influences on sentiment break down during severe economic declines, resulting in crowd behavior; and (c) it is important to understand how individual sentiment changes during the business cycle. The overarching goal is to explore and detail what, if any, demographic characteristics play a role in explaining the expectations held by individuals, how those expectations differ across cohorts of the population, and how both sentiment and the explanatory power of one's own characteristics can change over the business cycle.

Using household microlevel data allows the exploration of whether and, if so, how household expectations vary systematically across the population while controlling for individual characteristics such as age, income, race, education, employment, and household situation. These results will shed vital light on the inclinations of individuals. My specific focus is an examination of how expectations changed over the course of the business cycle from January 2007 to December 2013, one of the most economically volatile periods in U.S. history.

Thus far, most empirical research analyzing micro-level sentiment indicators has focused on inflation expectations. For example, Bryan and Venkatu (2001a, 2001b) found that inflation predictions differ according to socioeconomic and demographic characteristics. Others (Lombardelli & Saleheen, 2003; Palmqvist & Stromberg, 2004; Ranchhod, 2003) found similar results in other countries.

Souleles (2004) suggested that demographic and socioeconomic differences in sentiment exist because of time-varying, group-specific shocks. For example, during an economic downturn some segments of the population may be more harmed than others.

Doms and Morin (2004) explored how aggregate sentiment indicators are influenced by news reports on the economy. They found that media coverage effects are very short-lived. However, little work has been done to examine the micro-foundations of these results. Mankiw and Reis (2002) and Mankiw et al. (2003) suggested that information disseminates through the economy slowly. If this is true, one might expect to find that media coverage impacts sentiment expectations in different ways, and with different lag times, for various demographic and socioeconomic groups.

Mankiw et al. (2003) indicated that inflation expectations reflect partial though incomplete updating in response to macroeconomic news. They argued that expectations are updated in a staggered fashion and that establishment or adjustment of expectations will therefore vary with macroeconomic conditions. But few have explored the cross-sectional variation of expectations.

This study adds to the body of literature in several ways. First, I examine whether within-group variance of opinion was highest at the start of the recession, whether it declined as the economic downturn became more publicized, and whether any decline occurred systematically across different demographic and socioeconomic cohorts. For example, if individuals update their expectations in a staggered fashion, then uncertainty of expectations should be highest at turning points in the business cycle, such as when publicity of the downturn remains low. As cumulative publicity increases, individuals update their beliefs and over time the variance of disagreement should decline. Second, I examine whether certain segments of the population update their beliefs more rapidly than others. One might expect certain segments of the population (say, the cohort of college-educated individuals) to update beliefs more quickly than others, presumably because they are more attuned to news and information or have more at stake (for example if they own financial assets with valuations correlated to the performance of the economy).

Finally, I examine how changes in consumer sentiment are explained by changes in asset prices. The existence of disruptions in the financial markets during the survey period also allows me to test whether these financial disruptions impacted households in a systematic way. Understanding how the repricing of risk during this period—beginning in the credit markets and spreading through the real estate and equity markets—impacted household sentiment will help policymakers to prescribe the correct course of action during similarly unstable economic times in the future. This research is also relevant to financial market participants. General finance theory relies on the belief there is no heterogeneity of expected returns because investors rely on a single valuation model. Behavior finance theory, of course, does not posit this belief. This research also contributes indirectly to the nascent but growing body of literature on the economics of happiness.[11]

The goal of this paper is to document how expectations differ both within and across demographic and socioeconomic groups and to determine what might motivate these differences. I begin by discussing the unique aspects of the dataset used. Next I document the diversity of expectations across both the population and the business cycle, with a focus on detailing how within-group expectations changed over the business cycle from 2007 to 2013. I then provide new evidence on individual beliefs, based on the dataset used. Drawing on the data for this time period, I show how value changes of financial instruments across the business cycle impacted expectations and how the predictive power of individual characteristics broke down during this time of economic malaise.

Data

The Consumer Electronics Association (CEA) began surveying consumers in January 2007 as a way of eliciting expectations regarding future economic activity. Each month, CEA surveys a representative sample of 1,000 individuals in the United States. The survey asks several probability questions regarding both people's outlook and their perception of the current state of the U.S. economy. This study focuses on one of the eight probability questions contained in the survey:[12]

[11] See for example, MacKerron (2010), Kahneman and Krueger (2006), Stevenson and Wolfers (2008a), and Stevenson and Wolfers (2008b).
[12] See Appendix Table A2 for a list of all questions asked in the survey.

1. What do you think is the percent chance that you will be BETTER OFF financially in the next 12 months?

While the CEA dataset is relatively new, it does have multiple advantages over other consumer sentiment surveys. First, the CEA survey obtains probabilistic expectations which, as explained previously, may provide superior results relative to traditional survey methodologies in measuring individual expectations. Second, the survey captures expectations of 1,000 individuals each month, rather than the 500 individuals surveyed by the ICS, thereby enabling greater segmentation analysis. While the survey is not panel in nature, given the relatively large number of individuals interviewed each month and the relatively short time span between surveys, it resembles panel data.[13] As a result, broad cohort analysis is possible because of the information collected about a host of demographic and expectational variables.

Diversity of Expectations and Within-Group Expectation Changes

The CEA sentiment dataset provides a host of demographic details for each observation. In this section I document how an individual's beliefs depend upon these demographic details and how within-group expectations change over the business cycle. Expectations as well as within-group expectation differences are influenced by gender, education, children, income, age, employment status, and asset ownership.

In this section I concentrate specifically on expectations of one's own financial well-being. Previous studies have found that attitudinal research tends to show less

[13] A key distinction between panel data and time-series cross-sectional data is that, in the former, the number of observations (N) are typically drastically larger than the unit of time (T). Furthermore, the units in a panel (individuals) are sampled from a large population, while the units measured in traditional time-series cross-sectional data normally come from a smaller population (e.g., countries over time). My dataset has a large N and relatively small T, thus more closely resembling panel data.

variance when individuals are questioned about topics specific to themselves as opposed to broad topical questions (Dominitz & Manski, 2003). Consequently, I focus on the question "what do you think is the percent chance that you will be BETTER OFF financially in the next 12 months?" I measure within-group disagreement by examining the cross-sectional standard deviation[14] of expectations across socioeconomic demographic details.

Aggregate (Mean) Expectation

Aggregate expectations of personal financial well-being during the sample period, from 2007 to 2013, were relatively stable and actually increased slightly over the entire sample horizon (see Figure 5). However, across the sample period, average expectations showed strong volatility. After generally rising during 2007 and the first half of 2008, expectations fell notably during the recession and remained below average for most of 2009 and 2010. An improvement in aggregate expectations in the latter half of 2011 was followed by a subsequent decline in 2012; more favorable attitudes resumed in 2013.

Within-group variation in expectations across the entire population rose steadily during the sample period (see Figure 6). Within-group disagreement generally declined as aggregate expectations declined. Most of the periods of highest disagreement of expectations occurred when expectations were more optimistic than average.

[14] Stevenson and Wolfers (2008b) used variance to measure dispersion of happiness but pointed out that other measures of dispersion such as standard deviation, Gini coefficient, interquartile range, and 90-10 ratio would be a monotonic function of variance. Kalmijn and Veenhoven (2005) assessed different approaches to quantifying happiness dispersion and concluded by endorsing the use of standard deviation.

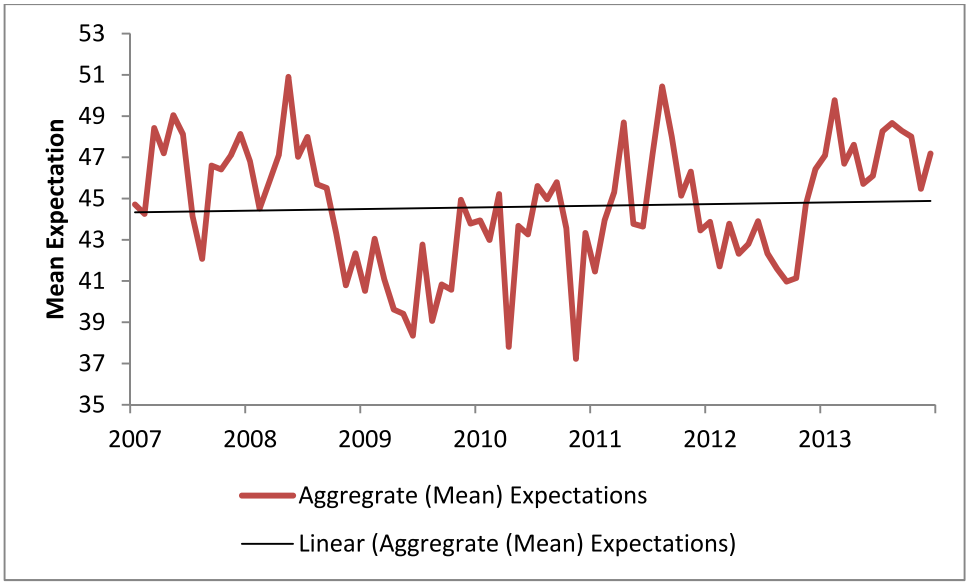

Figure 5. Average percent chance that respondents will feel better off financially in the next 12 months. *Source*: CEA surveys, 2007-2013. Author's calculations.

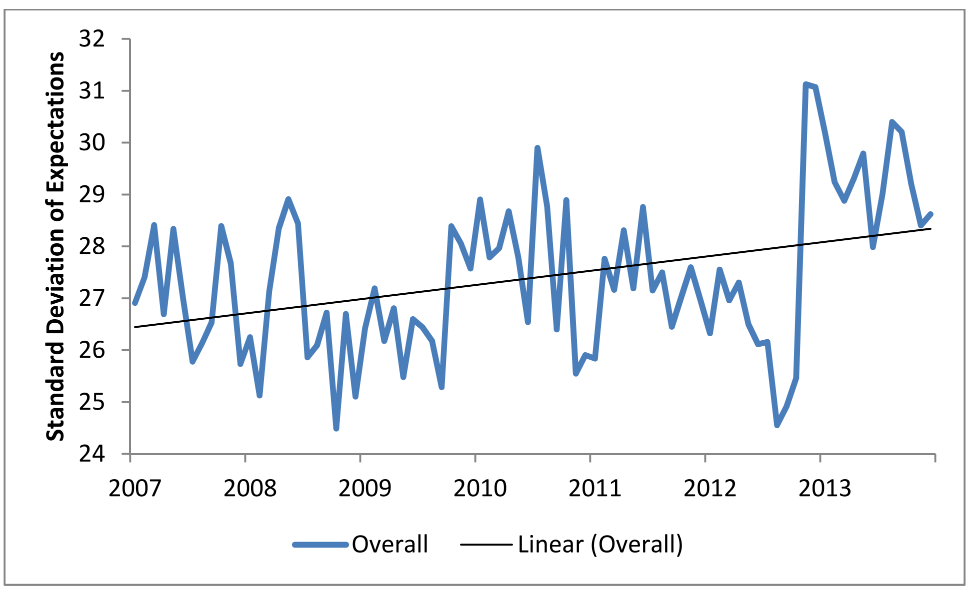

Figure 6. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months. *Source*: CEA surveys, 2007-2013. Author's calculations.

Gender

Men are more optimistic than women across the entire time horizon, and expectations for both cohorts declined heading into and following the recession (see Figure 7). While men were more optimistic about their own financial well-being over the next 12 months during the sample period, there was also more within-group disagreement about those expectations, as measured by the cross-sectional standard deviation (see Figure 8).

Prior to the start of the recession there was greater within-cohort uncertainty about expectations among men compared to women, but that within-cohort disagreement narrowed over the sample period as the disagreement of expectations among women increased over the time horizon, closing the gap between men and women. Tests of homoscedasticity across gender were generally rejected.[15]

Education

Expectations of being better off financially are positively correlated with education achievement levels. During the sample period, expectations declined across all education cohorts (see Figure 9), although they fell slightly more for the least educated cohort. Despite an apparently close relationship, as displayed in Figure 9, the means of the cohort with some college education and that with a college degree were not statistically equivalent according to an adjusted Wald test.

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[15] I test for homoscedasticity across each socioeconomic variable, following Levene (1960), whose method is robust to nonnormality of the error distribution. I also test for homoscedasticity across each variable, using two variants proposed by Brown and Forsythe (1974). Both of these variants use more robust estimators of central tendency (e.g., median rather than mean and the 10 percent trimmed mean in place of the mean). For gender, the more strict use of median in place of mean does suggest homoscedasticity.

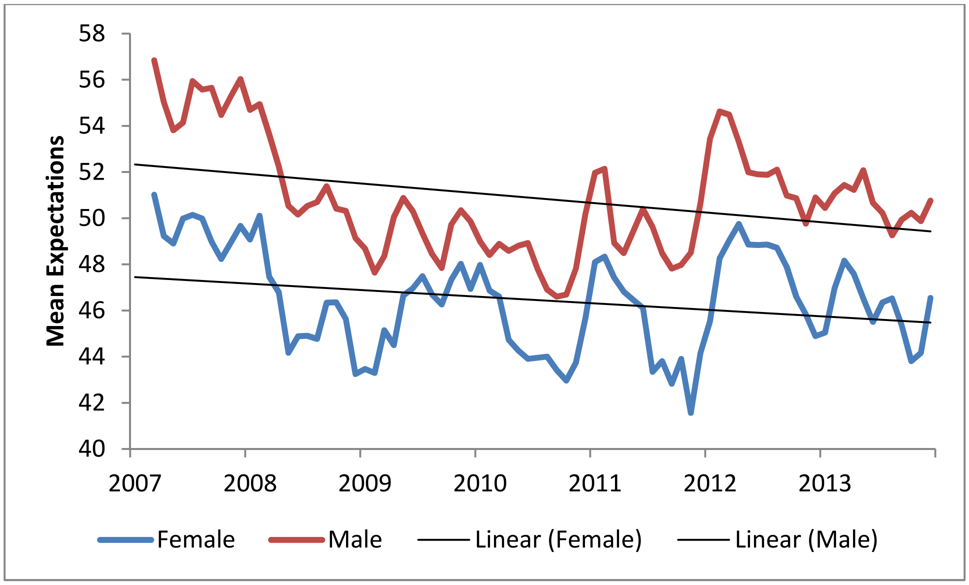

Figure 7. Percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by gender. *Source*: CEA surveys, 2007-2013. Author's calculations.

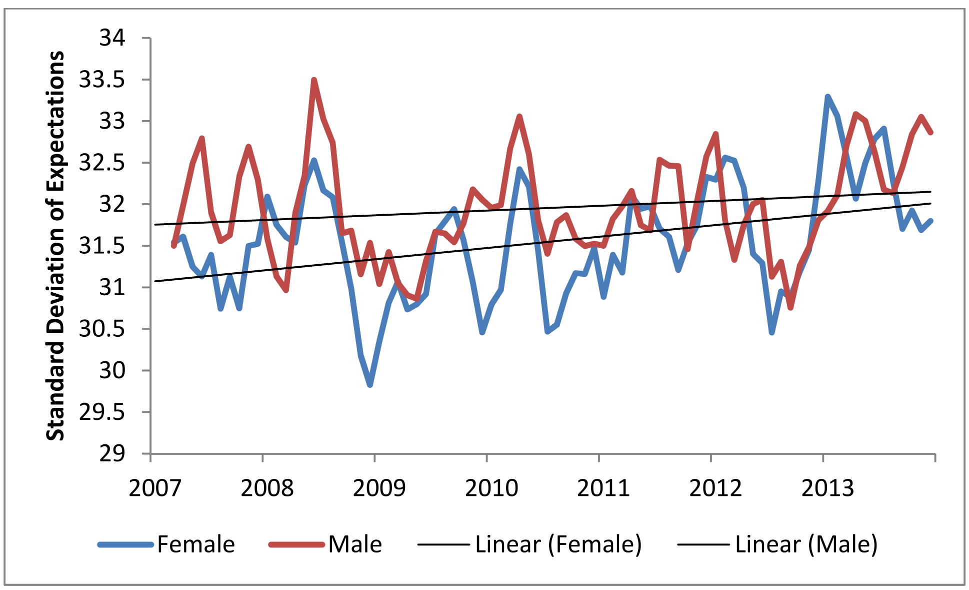

Figure 8. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by gender. *Source*: CEA surveys, 2007-2013. Author's calculations.

Prior to the recession, the group with a high-school diploma or less showed the highest within-group disagreement of expectations (see Figure 10). The within-group disagreement increased slightly for this cohort across the sample period, but it increased more for the cohorts with higher education. By the end of the sample period, the group with some college education showed nearly as much within-group disagreement of expectations as the cohort with a high-school diploma or less. The cohort with a college degree or more in education also showed an increase in within-group disagreement of expectations during the sample period. Test statistics rejected the null hypothesis of equal variability among the three groups.

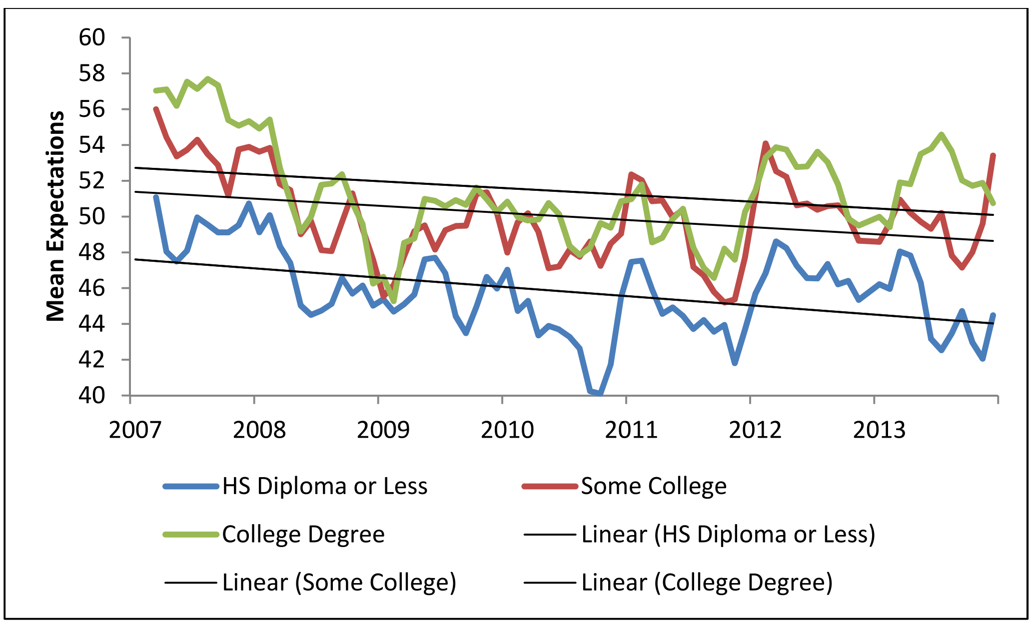

Figure 9. Percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by education. *Source*: CEA surveys, 2007-2013. Author's calculations.

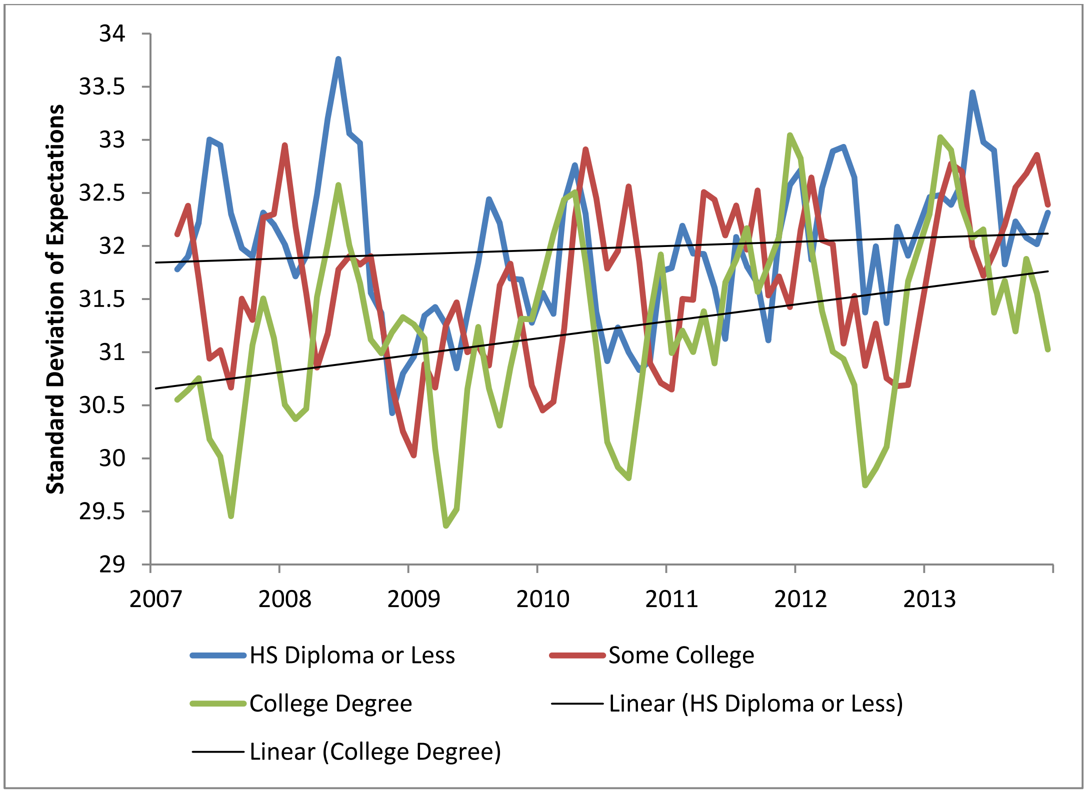

Figure 10. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by education. *Source*: CEA surveys, 2007-2013. Author's calculations.

Individuals with Children

Individuals with children were generally more optimistic, though expectations for both cohorts declined over the sample period (see Figure 11). The adjusted Wald tests rejected the null hypothesis of statistically equivalent means. The cohort without children showed a larger within-group variance of expectations, but neither group exhibited a significant increase in within-group disagreement of expectations during the sample period. I failed to reject the null of heteroskedasticity across the two cohorts.

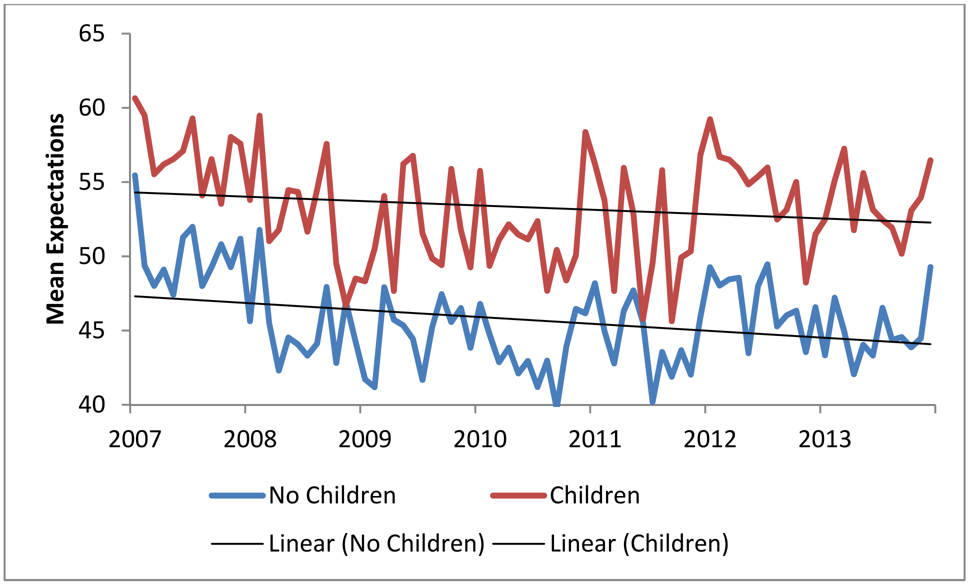

Figure 11. Percent chance that respondents will feel better off financially in the next 12 months, by whether the respondent has children. *Source*: CEA surveys, 2007-2013. Author's calculations.

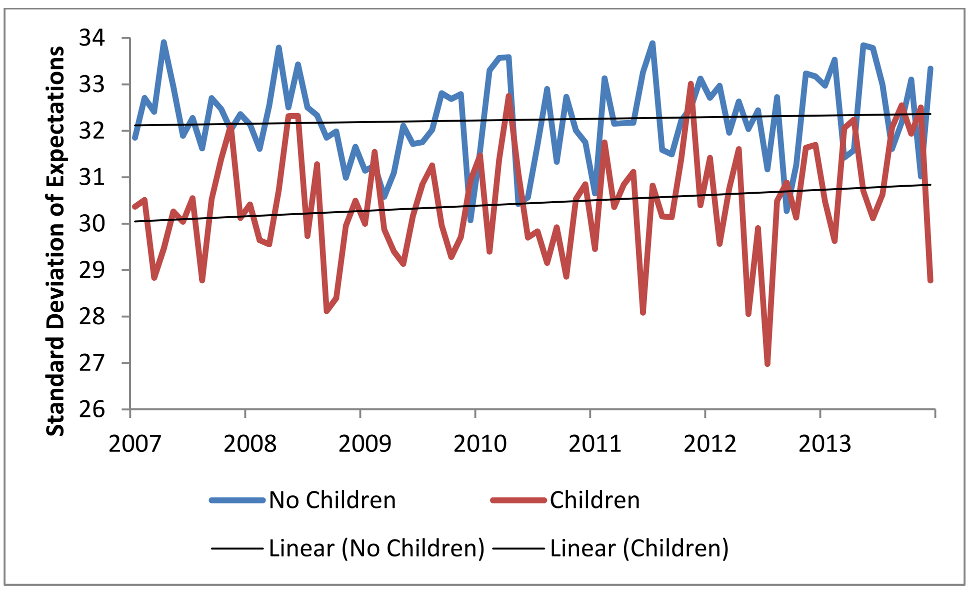

Figure 12. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months, by whether the respondent has children. Source: CEA surveys, 2007-2013. Author's calculations.

Income

Cohorts with lower income levels had lower expectations of being better off financially over the next 12 months. Moreover, expectations of being better off financially over the next 12 months declined for all income cohorts over the same period (see Figure 13). The null hypothesis of statistically equivalent means across income cohorts was not rejected.

Those in the lowest income cohort showed the highest within-group variance of expectations at the start of the recession, but this variance declined slightly during the sample period, while the within-group expectations for the cohorts with higher incomes actually increased during and after the recession (see Figure 14). The null hypothesis of heteroskedasticity across the two cohorts was not rejected.

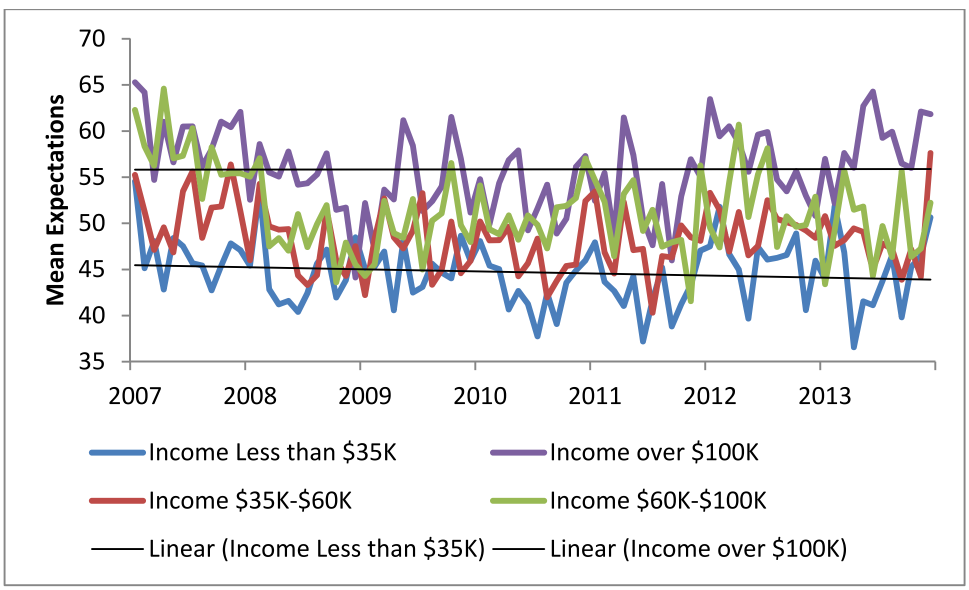

Figure 13. Percent chance that respondents will feel better off financially in the next 12 months, by income. *Source*: CEA surveys, 2007-2013. Author's calculations.

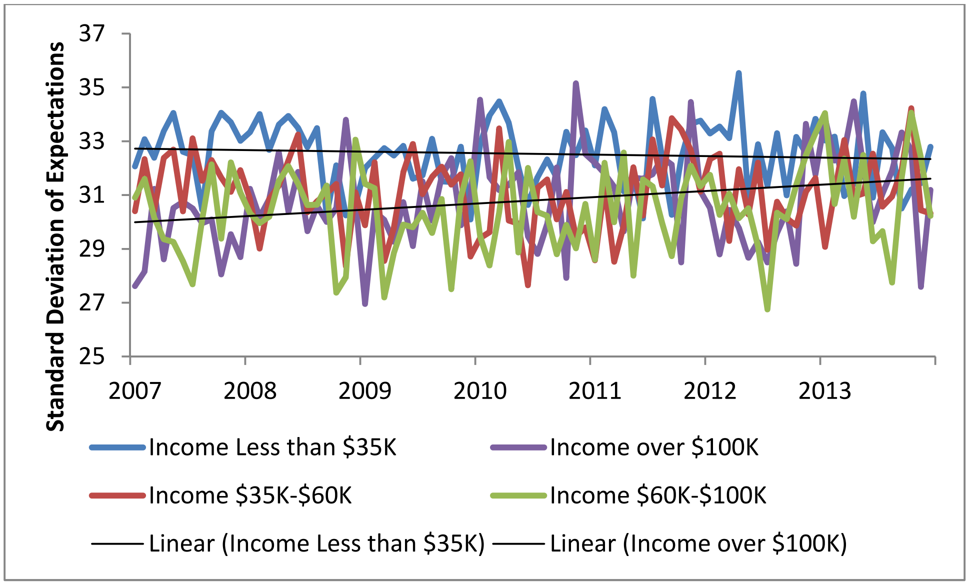

Figure 14. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months, by income. *Source*: CEA surveys, 2007-2013. Author's calculations.

Age

Expectations for financial health over the next 12 months were negatively correlated with age (see Figure 15). The younger the age cohort, the stronger the expectations for financial well-being. Despite both increases and decreases in expectations over the sample period, this negative correlation between age and expectations continued throughout the entire sample period. The adjusted Wald test confirmed that means across income cohorts were not statistically equivalent.

Disagreement within a cohort, however, was positively correlated with age (see Figure 16). That is, the older the cohort, the stronger the disagreement between individuals within the cohort group. The null hypothesis of groupwise heteroskedasticity was not rejected.

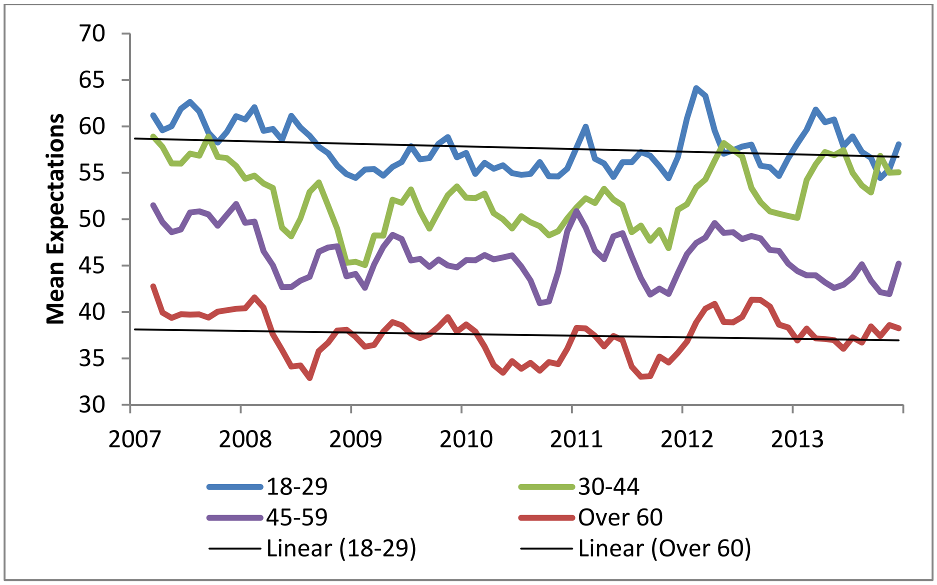

Figure 15. Percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by age. *Source*: CEA surveys, 2007-2013. Author's calculations.

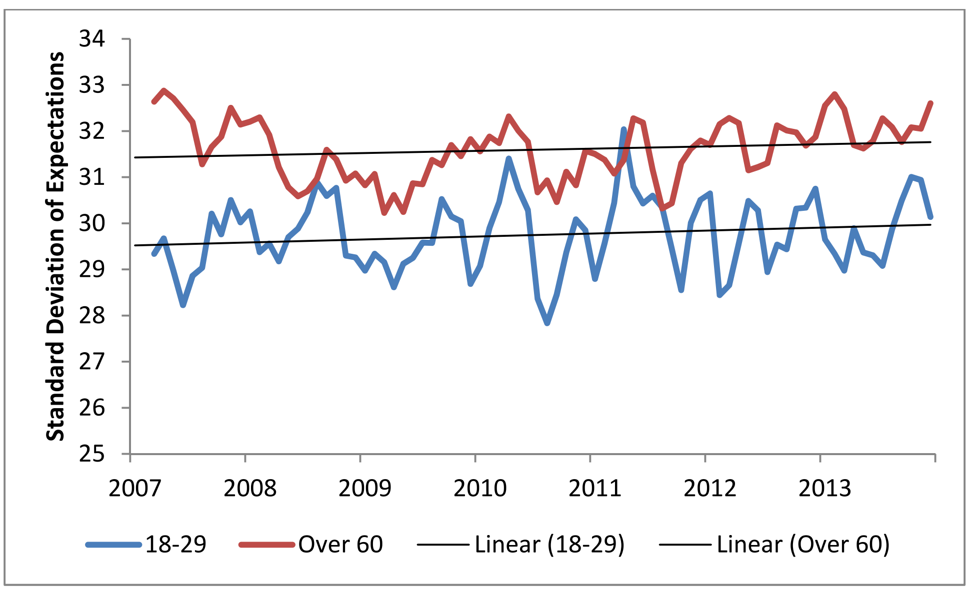

Figure 16. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by age. *Source*: CEA surveys, 2007-2013. Author's calculations.

Employment

Prior to the onset of the 2007-2008 recession, expectations among those fully employed were higher than those among people who were not employed[16] (see Figure 17). Expectations of retirees were always lower than those of other cohorts. By the most severe period of the recession in late 2008, expectations of employed persons and others converged; in 2013 they diverged again. The adjusted Wald test rejected the null hypothesis that the means are statistically the same.

Within-group disagreement among the employed cohort increased slowly over the sampling period, while disagreement among the non-employed cohort decreased. By the end of the sample period, within-group disagreement as measured by the cross-sectional standard deviation was slightly higher among the non-employed cohort than among the employed cohort. I failed to reject the null hypothesis of groupwise heteroskedasticity.

Marital Status

Expectations for personal financial well-being over the next 12 months declined generally for both the married cohort and for those not married (see Figure 18). The adjusted Wald test confirmed that mean expectations for both cohorts were not statistically equivalent.

[16] Those not employed include students, self-classified homemakers, and others not currently employed, along with those looking for work.

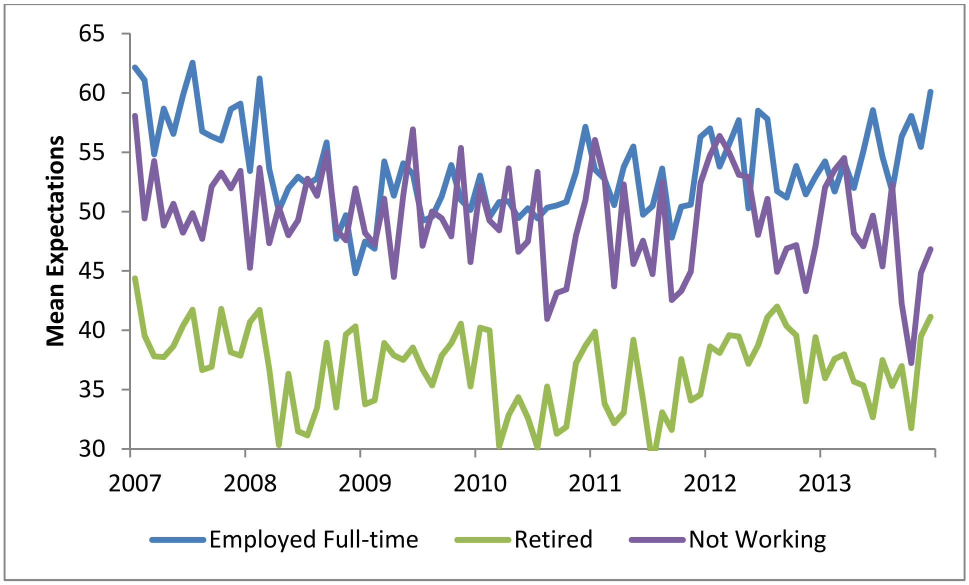

Figure 17. Percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by employment status. *Source*: CEA surveys, 2007-2013. Author's calculations.

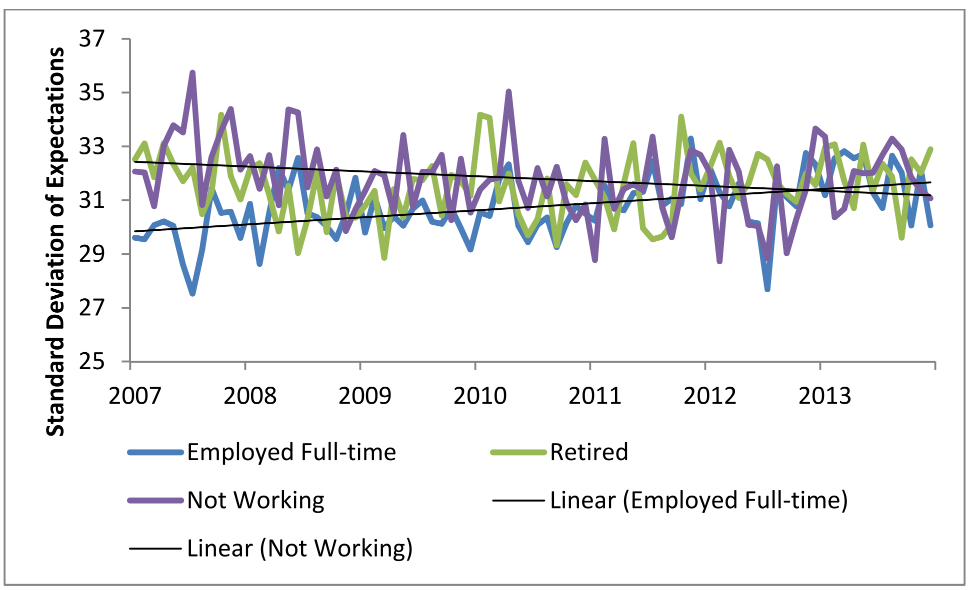

Figure 18. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by employment status. *Source*: CEA surveys, 2007-2013. Author's calculations.

Individuals who were not married showed slightly more within-group disagreement before the recession (see Figure 19). Over the sample period, however, the married cohort saw an increase in within-group disagreement, closing the gap with the non-married cohort. I failed to reject the null hypothesis of groupwise heteroskedasticity.

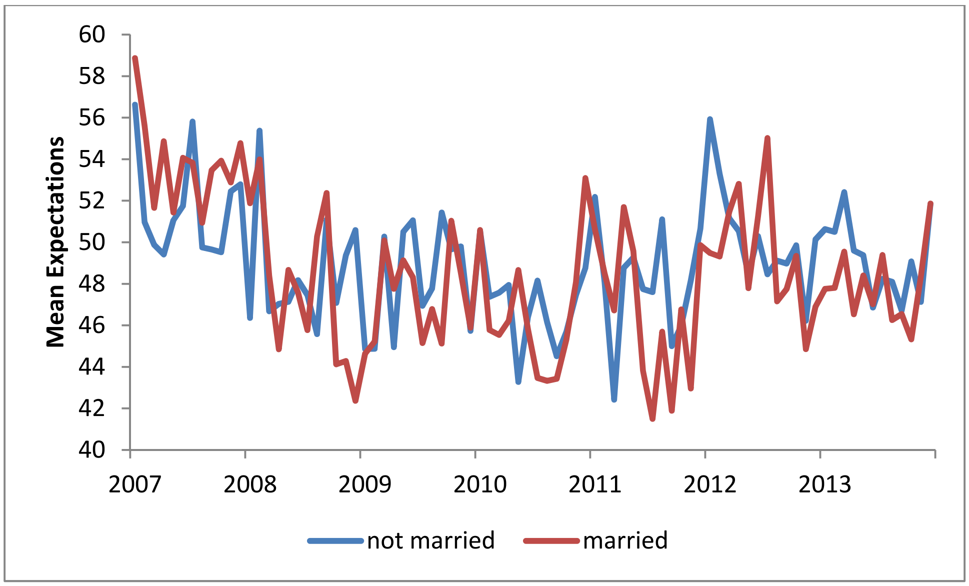

Figure 19. Percent chance that respondents will feel better off financially in the next 12 months, by marital status. *Source*: CEA surveys, 2007-2013. Author's calculations.

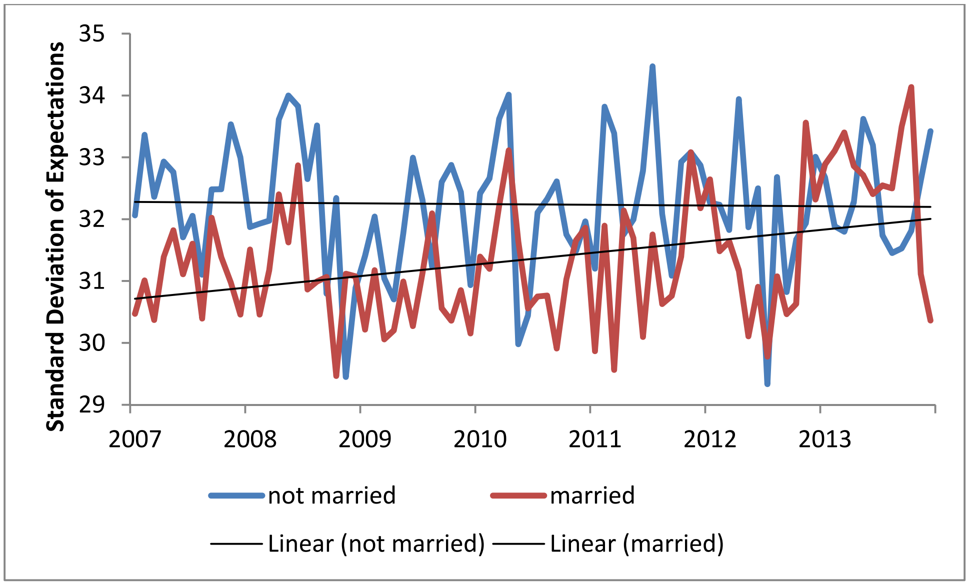

Figure 20. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months, by marital status. *Source*: CEA surveys, 2007-2013. Author's calculations.

Race

Mean expectations for Whites and Hispanics increased over the sample horizon, while mean expectations for Blacks and the collective category of Other Races declined (see Figure 21). Whites had the highest mean expectations over the sample period (57.493), followed by Hispanics (53.098), Other Races (48.773), and African Americans (46.546). The adjusted Wald test rejected the null hypothesis of statistically equivalent means.

Within-group differences of expectations changed little over the sample horizon (see Figure 16). The Other Races cohort exhibited the highest within-group difference of expectations, followed by African Americans, Caucasians, and finally Hispanics.

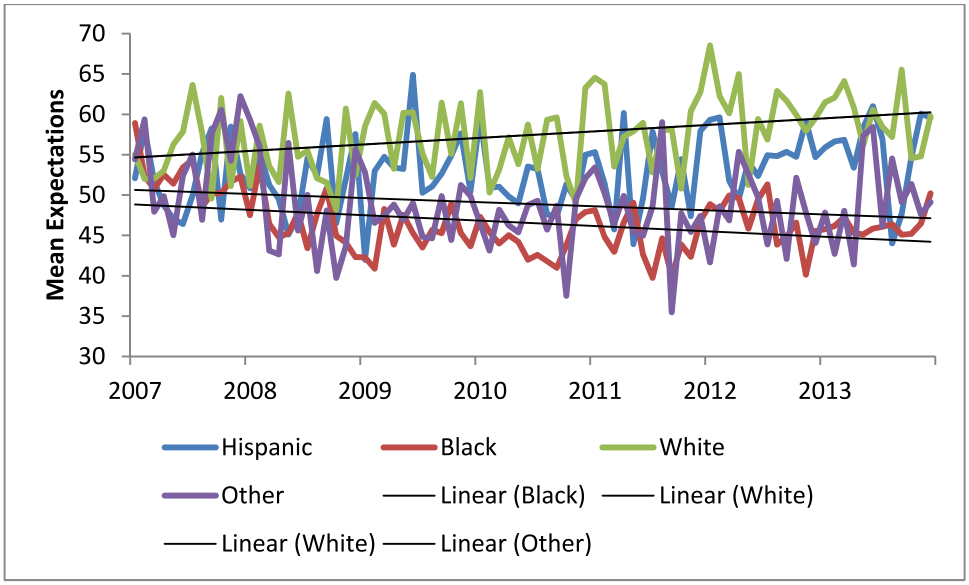

Figure 21. Percent chance that respondents will feel better off financially in the next 12 months, by race. *Source*: CEA surveys, 2007-2013. Author's calculations.

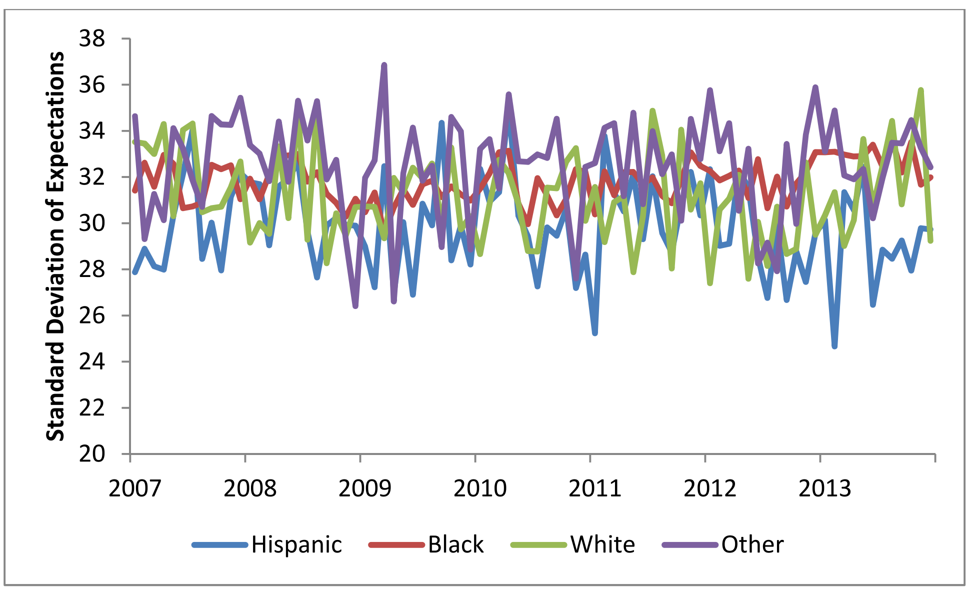

Figure 22. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months, by race. *Source*: CEA surveys, 2007-2013. Author's calculations.

Homeownership

Prior to the onset of the 2007-2008 recession, homeowners and renters held comparable expectations about their financial well-being over the ensuing 12 months (see Figure 23). This situation changed in 2008, when expectations held by homeowners fell below expectations of renters, and the new relationship continued through the sample period. Expectations among renters actually improved over the time horizon while expectations among homeowners declined.

In a similar fashion, within-group disagreement of expectations increased for homeowners over the same period, eclipsing the level of within-group disagreement among those who did not own homes (see Figure 24).

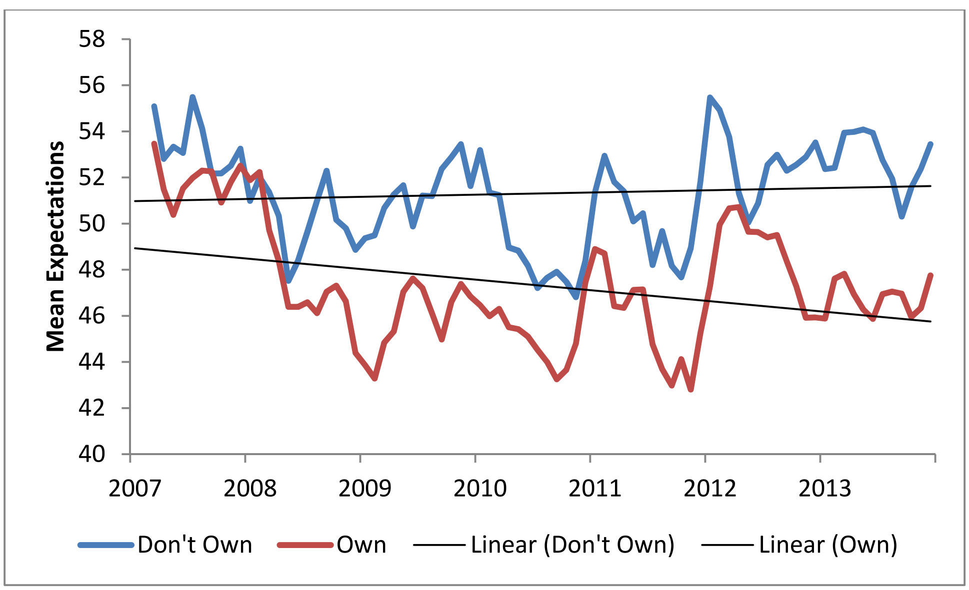

Figure 23. Percent chance that respondents will feel better off financially in the next 12 months (three-month moving average), by homeownership status. *Source*: CEA surveys, 2007-2013. Author's calculations.

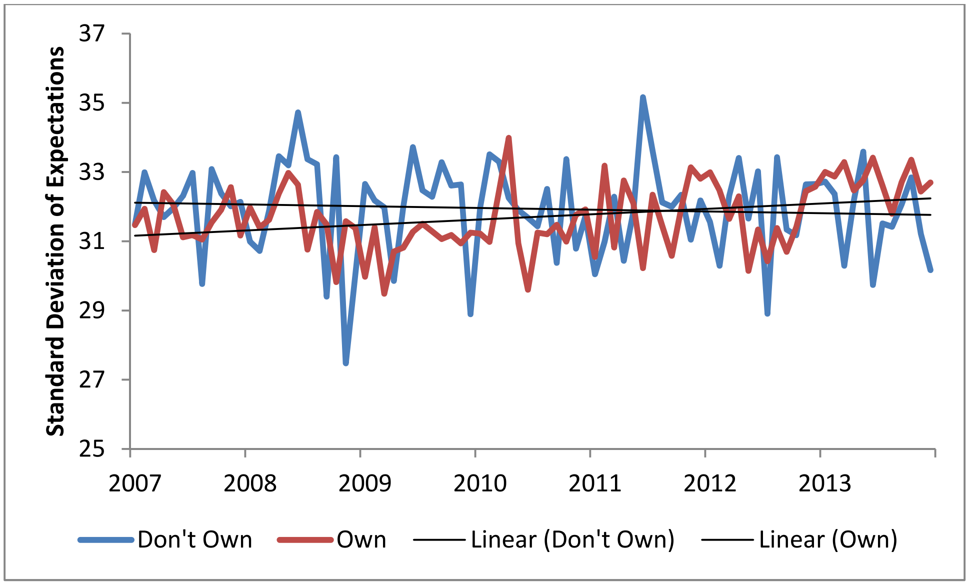

Figure 24. Cross-sectional standard deviations of percent chance that respondents will feel better off financially in the next 12 months, by homeownership status. *Source*: CEA surveys, 2007-2013. Author's calculations.

Evidence Regarding the Ability of Demographic and Socioeconomic Variables to Explain Differences in Sentiment across the Business Cycle

In this section I evaluate expectations of financial well-being more formally. My approach thus far has focused on assessing trends within and between groups by analyzing time series of expected financial well-being (mean and dispersion). However, averages can mask underlying heterogeneity across socioeconomic and demographic subcohorts. I therefore extend my analysis here to include changes over time within and between demographic groups, in order to examine which groups are most impacted by changes over the business cycle. The empirical results in this section yield estimates of difference in expectations both between demographic and socioeconomic groups and over time.

Empirical Approach

In this section I describe my approach to characterizing how demographic and socioeconomic attributes impact the expectations of individuals. I begin with the following regression:

(1) $P_{i,t} = \alpha_t + \beta_t X_{i,t} + \varepsilon_{i,t}$

where *i* denotes an individual response and *t* denotes a time period. $X_{i,t}$ is a vector of covariates of self-reported independent variables[17] including gender, children, educational attainment, age, income, marital status, and employment status. In the next section I also allow these variables to vary (interact) with time. $P_{i,t}$ represents the expectations of individual *i* at time period *t*.

Using binary variables, one can see the equivalent of the fixed-effects model. Equation (1) above becomes:

(2) $P_{i,t} = \beta_O + \beta_1 X_{1,i,t} + \cdots + \beta_k X_{k,i,t} + \gamma_2 E_2 + \cdots + \gamma_n E_n + \varepsilon_{i,t}$

where E_n is the entity *n*. Because there are binary (dummy) variables, *n*-1 entities are included in the model; γ is the coefficient of the binary regressors (entities).

We can add time effects to the fixed-effects model above to have a time and entity fixed-effects model. Equation (2) above becomes:

(3) $P_{i,t} = \beta_O + \beta_1 X_{1,i,t} + \cdots + \beta_k X_{k,i,t} + \gamma_2 E_2 + \cdots + \gamma_n E_n + \delta_2 T_2 + \cdots +$

$\delta_n T_n + \varepsilon_{i,t}$

where T_n is time as a binary (dummy) variable, so there are *t*-1 time periods. δ_n is the coefficient for the binary time regressors.

[17] See Appendix Table A2 for a full list of available independent variables.

Because the sample period of seven years is relatively short, I assume that there is no risk that changes in proportions of the population in each group will impact the level of optimism for that group. Moreover, throughout the sample period there have been no fundamental shifts in the way or the order in which questions were asked, so there is no need to account for any changes in measurement that might affect responses and subsequently results.

In a cross-section of individuals, it is likely that some of the observed differences in responses will reflect lack of knowledge as opposed to deeply seated beliefs. For example, Vissing-Jorgensen (2002) found that individuals with high levels of financial assets showed less uncertainty than individuals with fewer assets. My interest in this study is to examine what might explain increases or declines in expectations across cohorts and through time during the business cycle.

Fixed-effects models work best for data that contain within-cluster variation and for which variables obviously change over the time horizon used for estimation. I specifically chose to use a time fixed-effects model because I believed that the recession of 2007-2008 represented a special event that affected the outcome variable.

Empirical Results

In the case of time-series cross-sectional data, the interpretation of the beta coefficients is that for a given observation, as X varies across time by one unit, P changes (increases or decreases) by β units. Because we have good within-cluster variation and also had substantial change over the sample period, a fixed-effects model works well.

Table 10, regression 1 shows that homeownership, gender, age, income, and race all influenced expectations of financial well-being. Employment status and educational attainment generally influenced expectations of financial well-being, and marital status and presence of children were not statistically significant explanatory variables. The control group was single Caucasian women between the ages of 45 and 59, inclusive, who had at least a four-year college degree, had annual income between $60,000 and $100,000, had no children living at home, and were employed full-time. This control group had probability expectations of being better off financially over the next 12 months of 56.15 across the sample time horizon (equal to the constant in regression 1).

Table 10, regression 1 shows that men had probabilistic expectations 3.3 percentage points higher than women when controlling for other variables. Younger individuals were more optimistic by a sizable margin; individuals under 35 had expectations 11.92 percentage points higher. As I explained in the previous section, expectations were positively related to income. Individuals with annual income over $100,000 had expectations six percentage points higher than the control group. Owing a home lowered expectations of financial well-being by 1.53 percentage points. This relationship is likely driven by the fact that home prices dropped significantly during the time period studied. Expectations of employed individuals were higher than those of people who were retired or not working, but not statistically different than those of part-time workers. Likewise, expectations were higher for those with higher levels of education, though there is not a statistical difference between those with a college degree and those with some college. Caucasians are the most optimistic ethnic group, with

Table 10. *Determinants of One-Year Expectations of Being Financially Better Off*

Dependent variable: Percent chance that respondents will be better off financially in the next 12 months

	Regression 1		Regression 2	
Regressor	Beta	Robust Std. Error	Beta	Robust Std. Error
Constant	58.142	0.542***	62.931	0.779***
Homeownership	-1.527	0.304***	-1.394	0.304***
Male	3.319	0.224***	3.355	0.223***
Married	0.170	0.253	0.291	0.253
Children	-0.431	0.292	-0.351	0.291
Age (18-34)	11.919	0.382***	11.749	0.382***
Age (35-44)	5.000	0.376***	4.874	0.374***
Age (60+)	-3.413	0.327***	-3.257	0.326***
Income <$35K	-4.904	0.320***	-4.847	0.320***
Income $35K-$60K	-1.339	0.306***	-1.340	0.305***
Income > $100K	6.213	0.320***	5.934	0.320***
Working Part-Time	-1.155	0.425***	-1.274	0.424***
Retired	-6.449	0.341***	-6.426	0.340***
Not Currently Employed	-3.149	0.349***	-3.159	0.348***
High School Graduate or Less	-3.605	0.281***	-3.683	0.281***
Some College	-0.873	0.281***	-0.822	0.281***
African American	-10.500	0.393***	-10.543	0.394***
Hispanic	-7.240	0.576***	-7.332	0.577***
Other Ethnicity	-10.074	0.593***	-10.268	0.593***
Time Dummy (2Q2007)			-1.417	0.802*
Time Dummy (3Q2007)			-1.008	0.802
Time Dummy (4Q2007)			-1.160	0.813
Time Dummy (1Q2008)			-3.588	0.805***
Time Dummy (2Q2008)			-6.726	0.815***
Time Dummy (3Q2008)			-5.936	0.810***
Time Dummy (4Q2008)			-7.958	0.807***
Time Dummy (1Q2009)			-6.865	0.801***
Time Dummy (2Q2009)			-4.512	0.807***
Time Dummy (3Q2009)			-5.064	0.811***
Time Dummy (4Q2009)			-4.469	0.810***
Time Dummy (1Q2010)			-5.606	0.813***
Time Dummy (2Q2010)			-6.465	0.806***
Time Dummy (3Q2010)			-8.288	0.800***
Time Dummy (4Q2010)			-5.440	0.820***
Time Dummy (1Q2011)			-5.970	0.807***
Time Dummy (2Q2011)			-5.646	0.812***
Time Dummy (3Q2011)			-10.232	0.802***
Time Dummy (4Q2011)			-7.299	0.822***

	Regression 1		Regression 2	
Regressor	Beta	Robust Std. Error	Beta	Robust Std. Error
Time Dummy (1Q2012)			-3.239	0.810***
Time Dummy (2Q2012)			-4.059	0.803***
Time Dummy (3Q2012)			-3.493	0.809***
Time Dummy (4Q2012)			-6.027	0.815***
Time Dummy (1Q2013)			-4.627	0.819***
Time Dummy (2Q2013)			-5.020	0.813***
Time Dummy (3Q2013)			-4.797	0.819***
Time Dummy (4Q2013)			-3.274	0.820***
Root MSE	30.718		30.639	
	N = 79,448		N = 79,448	
	Adj. R2 = 0.0884		Adj. R2 = 0.0934	

**p* < .1, ***p* < .05, ****p* < .01. Huber-White robust standard errors are shown in parentheses.

expectations 7.24 to 10.5 percentage points higher than other racial groups when controlling for other demographic details.

Table 10, regression 2, adds time dummies for each of 27 quarters, with the control being the first quarter of 2007. I note first that expectations for the first quarter of 2007 were not statistically different from those during the subsequent three quarters of that year. The recession officially began in December 2007. According to the Bureau of Labor Statistics, as of December 2007 the national unemployment rate was 5 percent and had been at or below that number for the previous 30 months. Starting in the first quarter of 2008 however, expectations were statistically influenced by time dummies. The largest coefficients can be found in (a) the third quarter of 2011 (following the Arab Spring), (b) the third quarter of 2010 (following the downgrading of Greek government debt to junk bond status in April 2010 and broader concerns that the financial impact would spread across Europe), and (c) the fourth quarter of 2008 (the apex of the recession and uncertainty following the collapse of Lehman Brothers on September 15, 2008).

Results specific to the inclusion of time dummies highlight several noteworthy points. First, beliefs were impacted by a number of events and not just by the onset of the recession. Second, even following the official end of the recession, volatile economic events continued to severely impact expectations. Finally, in addition to domestic issues, it is evident that geopolitical concerns following the U.S. recession negatively impacted individuals' expectations regarding their own future financial well-being.

Comparisons of regressions 1 and 2 show that the coefficients are generally comparable across the two models, with a few exceptions. Once I control for time, the difference in expectations between those who are working full-time and those working part-time become statistically significant and the coefficient nearly doubles. The same is true for education where, when I control for time, expectations held by those with at least a four-year college degree are statistically higher than the expectations for those with less than a four-year college degree. I interpret these results to suggest that the economic opportunities for part-time workers and those with less than a four-year college degree diminished as the recession worsened and during the subsequent, shallow economic recovery. Once I control for time, the impact of the recession on the expectations of people with a college education and full-time employment becomes more apparent. A joint F-test of the cluster time dummies rejects the null hypothesis that all quarters' coefficients are jointly equal to zero. In other words, time fixed effects add explanatory power.

Exploring Expectations with Financial Asset Prices

In the previous section I showed how expectations of one's own financial well-being are influenced by demographic and socioeconomic descriptors. In this section I show how these expectations are influenced by the inclusion of asset valuations.

I begin by controlling for equity market returns as measured by the Standard and Poor's 500 index. As Table 11, regression 1 illustrates, prior month returns on the S&P 500 have a statistically significant though perhaps not especially meaningful impact on expectations of financial well-being. A one-percentage-point increase in the S&P 500 over the prior month increases expectations of financial well-being over the next 12 months by 0.08 percentage points.[18] Moreover, when controlling for changes in equity prices, the coefficients of the other included variables are comparable to regression results in Table 10.

In regression 3 of Table 11, I include time dummies as I did in regression 2 of the previous section. Similar to the previous section, dummy variables for the 2007 quarters prior to the onset of the recession are not statistically meaningful, with the exception of the second quarter. The coefficient for the three-month return on the S&P 500 is slightly stronger than that observed in regression 1. A 1% change in the S&P 500 over the prior three months increases expectations by nearly one-tenth of a percentage point – still a small effect compared to other explanatory variables.

[18] Results are robust to changes in the specified measure of the S&P 500 index's return, namely, whether one uses value-weighted or equally weighted monthly returns and whether or not one includes dividend distributions.

Table 11. *Determinants of One-Year Expectations of Being Financially Better Off with Financial Asset Prices*

Dependent variable: Percent chance that respondents will be better off financially in the next 12 months

	Regression 1		Regression 2		Regression 3	
Regressor	Beta	Robust Std. Error	Beta	Robust Std. Error	Beta	Robust Std. Error
Constant	58.063	0.542***	62.932	0.779***	62.786	0.780***
Homeownership	-1.524	0.304***	-1.394	0.304***	-1.402	0.304***
Male	3.315	0.224***	3.355	0.223***	3.355	0.223***
Married	0.167	0.253	0.291	0.253	0.293	0.253
Children	-0.427	0.292	-0.351	0.291	-0.352	0.291
Age (18-34)	11.924	0.382***	11.749	0.382***	11.755	0.382***
Age (35-44)	5.020	0.376***	4.873	0.374***	4.874	0.374***
Age (60+)	-3.417	0.327***	-3.257	0.326***	-3.257	0.326***
Income <$35K	-4.932	0.320***	-4.847	0.320***	-4.853	0.320***
Income $35K-$60K	-1.340	0.306***	-1.340	0.305***	-1.343	0.305***
Income > $100K	6.255	0.320***	5.934	0.320***	5.931	0.320***
Working Part-Time	-1.135	0.425***	-1.274	0.424***	-1.283	0.424***
Retired	-6.444	0.340***	-6.426	0.340***	-6.421	0.340***
Not Currently Employed	-3.136	0.349***	-3.159	0.348***	-3.160	0.348***
High School Graduate or Less	-3.587	0.281***	-3.683	0.281***	-3.680	0.281***
Some College	-0.870	0.281***	-0.822	0.281***	-0.819	0.281***
African American	-10.488	0.393***	-10.543	0.394***	-10.549	0.394***
Hispanic	-7.236	0.576***	-7.332	0.577***	-7.335	0.577***
Other Ethnicity	-10.071	0.593***	-10.268	0.593***	-10.277	0.593***
S&P 500 Monthly Return	9.081	2.242***	-0.380	2.938		
S&P 500 Quarterly Return					9.385	2.813***
Time Dummy (2Q2007)			-1.410	0.804*	-1.813	0.811**
Time Dummy (3Q2007)			-1.006	0.802	-0.726	0.806
Time Dummy (4Q2007)			-1.165	0.813	-1.098	0.813
Time Dummy (1Q2008)			-3.601	0.811***	-2.459	0.873***

	Regression 1		Regression 2		Regression 3	
Regressor	Beta	Robust Std. Error	Beta	Robust Std. Error	Beta	Robust Std. Error
Time Dummy (2Q2008)			-6.730	0.815***	-6.652	0.815***
Time Dummy (3Q2008)			-5.947	0.814***	-4.973	0.860***
Time Dummy (4Q2008)			-7.988	0.842***	-5.416	1.111***
Time Dummy (1Q2009)			-6.879	0.807***	-5.318	0.923***
Time Dummy (2Q2009)			-4.494	0.820***	-5.786	0.892***
Time Dummy (3Q2009)			-5.046	0.821***	-6.134	0.872***
Time Dummy (4Q2009)			-4.462	0.811***	-4.868	0.818***
Time Dummy (1Q2010)			-5.600	0.815***	-5.739	0.814***
Time Dummy (2Q2010)			-6.480	0.816***	-6.226	0.810***
Time Dummy (3Q2010)			-8.275	0.807***	-8.123	0.801***
Time Dummy (4Q2010)			-5.428	0.825***	-6.231	0.853***
Time Dummy (1Q2011)			-5.964	0.808***	-6.640	0.831***
Time Dummy (2Q2011)			-5.646	0.812***	-5.707	0.812***
Time Dummy (3Q2011)			-10.251	0.816***	-9.168	0.864***
Time Dummy (4Q2011)			-7.285	0.828***	-7.468	0.823***
Time Dummy (1Q2012)			-3.225	0.817***	-3.906	0.833***
Time Dummy (2Q2012)			-4.063	0.804***	-3.879	0.805***
Time Dummy (3Q2012)			-3.487	0.810***	-3.707	0.811***
Time Dummy (4Q2012)			-6.029	0.815***	-5.933	0.815***
Time Dummy (1Q2013)			-4.615	0.824***	-5.192	0.836***
Time Dummy (2Q2013)			-5.017	0.813***	-5.385	0.820***

	Regression 1		Regression 2		Regression 3	
Regressor	Beta	Robust Std. Error	Beta	Robust Std. Error	Beta	Robust Std. Error
Time Dummy (3Q2013)			-4.791	0.821***	-4.964	0.821***
Time Dummy (4Q2013)			-3.262	0.825***	-3.891	0.841***
MSE	30.715		30.639		30.637	
	N = 79,448		N = 79,448		N = 79,448	
	Adj. R2 = 0.0886		Adj. R2 = 0.0934		Adj. R2 = 0.0936	

**p* < .1, ***p* < .05, ****p* < .01. Huber-White robust standard errors are shown in parentheses.

How the Predictive Power of Explanatory Variables Deteriorates During Periods of Economic Malaise

In this section I show how the predictive power of individual characteristics breaks down during periods of economic malaise. In a previous section I showed how employment situation and income can impact one's beliefs regarding one's financial well-being; here I show that these relationships no longer hold true during severe economic decline and uncertainty.

Numerous factors drive our perceptions of and expectations for the future. In the previous sections I have shown how beliefs differ according to demographic and socioeconomic characteristics. I also showed how the expectations within these cohorts changed as we entered and subsequently exited an economic recession. In this section I allow these demographic variables to change with time. In this way I can measure how they influence expectations as one moves through the business cycle.

As Table 12, regression 1 illustrates, the demographic descriptors show similar coefficients to those calculated in regressions shown earlier in this paper (see Tables 10 and 11). Regression 1 of Table 12, however, provides a measure of employment that is allowed to vary over time. The dummy variable equals 1 if the observation is employed full-time and zero otherwise. The results show that, for most months in my sample, the coefficient on this dummy variable is positive and significant. This is true for all months except for five months where the coefficient either experiences a sign change (two months) or loses significance (four months; in one case there was both a sign change and a loss of statistical significance). These five months start with the fourth quarter of 2008 and continue through the subsequent four quarters of 2009. The coefficient for this dummy variable is also depicted graphically in Figure 25. A joint F-test of the cluster interactive dummies rejects the null hypothesis that all quarters' coefficients are jointly equal to zero. In other words, they add explanatory power.

Regression 2 of Table 12includes a dummy variable that equals 1 when annual income is over $50,000 and zero otherwise. As with regression 1 of the results are comparable to previous results shown in earlier tables. The coefficients for other explanatory variables are significant and of similar magnitude to the results in earlier tables. However, when household income is allowed to vary over time an interesting result surfaces. As in regression 1, the coefficients are large, positive, and statistically significant for most months. The dummy variable for income breaks down in the same period of time. In the fourth quarter of 2008 and continuing into 2009, the interactive term either loses statistical significance or dips to a much lower magnitude. Similarly, a joint F-test of the cluster interactive dummies for regression 2 rejects the null hypothesis that all quarters' coefficients are jointly equal to zero.

I interpret these results as suggesting that in the depth of the recession, individual expectations collapse and individual demographic characteristics have less explanatory power. Prior research shows correlations tend to move higher in times of economic crisis (See for example Asgharian et al. (2013), Corsetti et al. (2011), and Erb et al. (1994)). A similar phenomenon appears to take place with personal beliefs about one's own future financial well-being. During times of severe economic delay, individual expectations are less explained by individual demographic details.

Table 12. *Determinants of One-Year Expectations of Being Financially Better Off Using Time-Dependent Explanatory Variables*

Dependent variable: Percent chance that respondents will be better off financially in the next 12 months

	Regression 1		Regression 2	
Regressor	Beta	t-stat	Beta	t-stat
Constant	60.942	0.770***	60.553	0.816***
Homeownership	-1.567	0.303***	-1.317	0.332***
Male	3.189	0.222***	3.354	0.248***
Married	0.292	0.250	0.628	0.279**
Age (18-34)	12.220	0.368***	12.384	0.400***
Age (35-44)	5.010	0.355***	4.793	0.387***
Age (60+)	-4.762	0.285***	-5.002	0.320***
Income < $35K	-4.802	0.320***		
Income $35K-$60K	-1.352	0.305***		
Income > $100K	6.068	0.319***		
High School Graduate or Less	-3.722	0.280***	-4.012	0.313***
Some College	-0.842	0.281***	-1.084	0.313***
African American	-10.482	0.393***	-10.060	0.426***
Hispanic	-7.187	0.577***	-7.180	0.632***
Other Ethnicity	-10.196	0.592***	-9.243	0.671***
Time Dummy (2Q2007)	-4.643	0.992***	-9.594	1.316***
Time Dummy (3Q2007)	-3.680	0.980***	-10.390	1.269***
Time Dummy (4Q2007)	-3.183	1.004***	-8.239	1.314***
Time Dummy (1Q2008)	-5.210	0.972***	-9.643	1.288***
Time Dummy (2Q2008)	-8.585	0.975***	-12.893	1.266***
Time Dummy (3Q2008)	-7.749	0.965***	-12.008	1.300***
Time Dummy (4Q2008)	-6.844	0.955***	-8.212	1.292***
Time Dummy (1Q2009)	-7.161	0.963***	-9.477	1.178***
Time Dummy (2Q2009)	-5.401	0.950***	-9.750	1.205***
Time Dummy (3Q2009)	-4.989	0.981***	-8.556	1.222***
Time Dummy (4Q2009)	-4.564	0.981***	-7.840	1.185***
Time Dummy (1Q2010)	-7.178	0.962***	-10.441	1.178***
Time Dummy (2Q2010)	-8.422	0.958***	-12.662	1.179***
Time Dummy (3Q2010)	-10.530	0.922***	-14.706	1.169***
Time Dummy (4Q2010)	-8.083	0.970***	-12.322	1.224***
Time Dummy (1Q2011)	-8.043	0.943***	-11.119	1.175***
Time Dummy (2Q2011)	-8.428	0.951***	-12.804	1.182***
Time Dummy (3Q2011)	-13.203	0.930***	-16.128	1.163***
Time Dummy (4Q2011)	-9.203	0.983***	-12.349	1.218***
Time Dummy (1Q2012)	-5.648	0.943***	-14.710	1.612***
Time Dummy (2Q2012)	-7.033	0.933***	-17.477	1.623***
Time Dummy (3Q2012)	-4.982	0.942***	-12.551	1.606***
Time Dummy (4Q2012)	-8.232	0.947***	-14.154	1.679***
Time Dummy (1Q2013)	-5.990	0.963***	-12.388	1.560***

	Regression 1		Regression 2	
Regressor	Beta	t-stat	Beta	t-stat
Time Dummy (2Q2013)	-8.126	0.954***	-16.916	1.565***
Time Dummy (3Q2013)	-6.944	0.974***	-15.939	1.613***
Time Dummy (4Q2013)	-7.235	0.981***	-13.319	1.586***
Working Full-time Dummy (2Q2007)	6.974	1.138***	5.363	1.314***
Working Full-time Dummy (3Q2007)	5.923	1.140***	5.037	1.301***
Working Full-time Dummy (4Q2007)	4.467	1.172***	3.499	1.365***
Working Full-time Dummy (1Q2008)	3.543	1.151***	2.612	1.316**
Working Full-time Dummy (2Q2008)	3.875	1.187***	3.438	1.377**
Working Full-time Dummy (3Q2008)	3.720	1.172***	4.142	1.327***
Working Full-time Dummy (4Q2008)	-2.573	1.155**	-0.869	1.302
Working Full-time Dummy (1Q2009)	0.589	1.137	0.574	1.280
Working Full-time Dummy (2Q2009)	1.549	1.167	1.532	1.367
Working Full-time Dummy (3Q2009)	-0.090	1.160	-1.077	1.311
Working Full-time Dummy (4Q2009)	0.200	1.154	-0.281	1.308
Working Full-time Dummy (1Q2010)	3.441	1.178***	4.021	1.359***
Working Full-time Dummy (2Q2010)	4.144	1.155***	3.097	1.303**
Working Full-time Dummy (3Q2010)	4.961	1.155***	4.129	1.353***
Working Full-time Dummy (4Q2010)	5.706	1.195***	4.902	1.386***
Working Full-time Dummy (1Q2011)	4.428	1.174***	3.724	1.365***
Working Full-time Dummy (2Q2011)	6.229	1.183***	5.059	1.338***
Working Full-time Dummy (3Q2011)	6.519	1.157***	7.664	1.317***
Working Full-time Dummy (4Q2011)	4.002	1.198***	3.248	1.405**
Working Full-time Dummy (1Q2012)	5.220	1.180***	2.865	1.512*
Working Full-time Dummy (2Q2012)	6.673	1.159***	4.217	1.466***
Working Full-time Dummy (3Q2012)	2.715	1.175***	2.183	1.441
Working Full-time Dummy (4Q2012)	4.356	1.200***	3.761	1.489**
Working Full-time Dummy (1Q2013)	2.841	1.201***	3.085	1.458**
Working Full-time Dummy (2Q2013)	6.914	1.177***	6.596	1.490***
Working Full-time Dummy (3Q2013)	4.922	1.195***	5.531	1.490***
Working Full-time Dummy (4Q2013)	8.832	1.184***	8.724	1.500***
Income >50K Dummy (2Q2007)			9.572	1.401***
Income >50K Dummy (3Q2007)			10.418	1.351***
Income >50K Dummy (4Q2007)			9.214	1.431***
Income >50K Dummy (1Q2008)			8.189	1.386***
Income >50K Dummy (2Q2008)			8.042	1.409***
Income >50K Dummy (3Q2008)			6.677	1.393***
Income >50K Dummy (4Q2008)			2.078	1.359
Income >50K Dummy (1Q2009)			3.616	1.286***
Income >50K Dummy (2Q2009)			6.383	1.372***
Income >50K Dummy (3Q2009)			6.422	1.320***
Income >50K Dummy (4Q2009)			5.816	1.313***
Income >50K Dummy (1Q2010)			4.852	1.350***
Income >50K Dummy (2Q2010)			8.661	1.306***
Income >50K Dummy (3Q2010)			7.053	1.334***

	Regression 1		Regression 2	
Regressor	Beta	t-stat	Beta	t-stat
Income >50K Dummy (4Q2010)			8.287	1.385***
Income >50K Dummy (1Q2011)			5.922	1.354***
Income >50K Dummy (2Q2011)			8.638	1.332***
Income >50K Dummy (3Q2011)			3.720	1.300***
Income >50K Dummy (4Q2011)			6.756	1.403***
Income >50K Dummy (1Q2012)			4.254	0.603***
Income >50K Dummy (2Q2012)			4.843	0.584***
Income >50K Dummy (3Q2012)			3.263	0.576***
Income >50K Dummy (4Q2012)			2.557	0.610***
Income >50K Dummy (1Q2013)			2.507	0.587***
Income >50K Dummy (2Q2013)			3.712	0.603***
Income >50K Dummy (3Q2013)			3.695	0.610***
Income >50K Dummy (4Q2013)			2.799	0.608***
MSE	30.65		30.63	
	N=79,579		N=63,577	
	Adj. R2= 0.0932		Adj. R2= 0.0944	

**p* < .1, ***p* < .05, ****p* < .01. Huber-White robust standard errors are shown in parentheses.

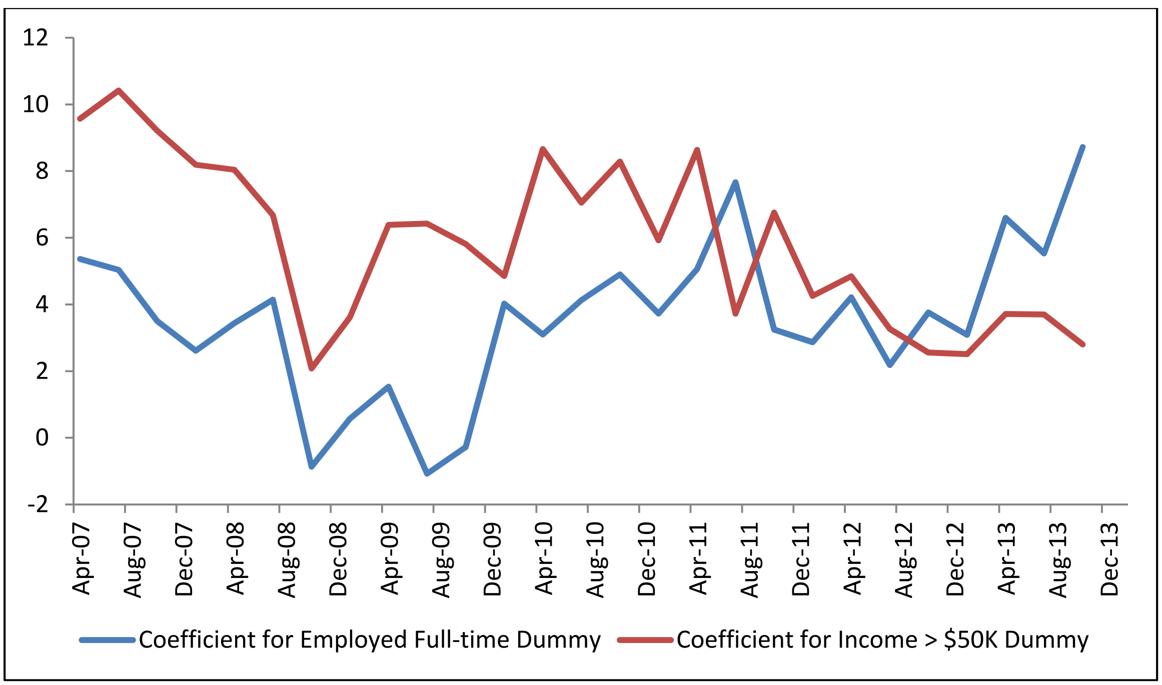

Figure 25. Coefficients for two dummy variables interacted with time. *Source*: CEA surveys, 2007-2013. Author's calculations.

Conclusion

As Vissing-Jorgensen (2002) pointed out, “Less is known about disagreement concerning aggregate stock-market returns and how investor beliefs begin to differ.” This paper seeks to explore how these changes in beliefs evolve, specifically over the business cycle, and what might explain them. My primary empirical objective was to describe the data, and my secondary empirical objective was to suggest possible causal links. I explored three questions: (a) how group expectations changed as the economy deteriorated, (b) whether demographic or socioeconomic characteristics alone can explain the difference in expectations held by different demographic or socioeconomic cohorts, and (c) how the predictive power of demographic and socioeconomic characteristics changes through the business cycle. My work parallels the literature on income inequality and happiness inequality. The mapping between subjective experience and responses to subjective well-being questions remains poorly understood (Kahne & Krueger, 2006), and my findings contribute to the much broader literature on trends in well-being and particularly inequality.

I provided new insights into the differences in expectation that exist across demographic groups and documented how these expectations of financial well-being fluctuated across the business cycle. I began by showing mean expectations and increases and decreases in within-group disparity by demographic characteristics. I found that, during my sample period, men had higher average expectations of future financial well-being but women experienced a larger increase over time of within-group disagreement about well-being expectations than men. I found that progressively higher levels of education were correlated with more optimistic expectations and also that, during the sample period, college-educated individuals experienced an increase in within-group disagreement of expectations (vis-à-vis those with less than a college degree). My results found that household income was correlated with greater expectations of financial well-being, but those with higher incomes also experienced an increase in within-group disparity of expectations, compared to those with lower incomes, during the sample period. I found that having children or being married did not statistically impact expectations of being better off financially, but married individuals did appear to experience a larger increase in within-group expectation disagreement than unmarried individuals during the sample period. Younger individuals had statistically higher expectations, but within-group expectations changed consistently across age cohorts. Homeownership appeared to positively influence expectations until the recession hit, at which point owning a home led to lowered expectations. I also found that individuals owning a home showed an increase in within-group disparity of expectations when compared to renters. Despite findings in inequality research showing closure of race gaps, my research found that race did influence expectations of future well-being. Caucasians had statistically higher expectations, though within-group expectation differences did not change significantly for any race group during the sample period.

These results broadly show that demographic characteristics impact expectations of financial well-being. They appear to be consistent with the work of Souleles (2004), who suggested that demographic and socioeconomic differences in sentiment exist because some segments of the population might be more harmed by economic downturns than others.

My results also show that considering asset prices can to help explain expectations; this relationship suggests that individuals pay attention to situational factors that could impact their future financial well-being. An important new finding of this study was that time influenced expectations during the most recent business cycle, but only after the start of the recession. Moreover, I also found that the influence of time on expectations outweighed other variables such as employment status and income levels (when these variables are allowed to interact with time). Consistent with the work of Mankiw and Reis (2002) and Mankiw et al. (2003), who suggested that information disseminates through the economy slowly, I found that the influence of time broke down the impact of employment status and income on expectations about a year after the recession officially began, and that this effect extended a year beyond the end of the recession. Consistent with Mankiw et al. (2003), expectation updates appear to occur in a staggered fashion.

While my work extends our understanding of expectations of well-being and the characterization of differences both across groups and within groups through the business cycle, future research is warranted as to what creates differences in expectations among demographically similar individuals and why these differences widen and contract through the business cycle.

III. TODAY'S KEYNOTE: DO CEO PRESENTATIONS LEAD TO POSITIVE ABNORMAL STOCK RETURNS?

Each January, the largest technology event in the United States—and, by some measures, in the world—is held in Las Vegas. The International Consumer Electronics Show, known now as the International CES, has represented for more than 50 consecutive years the Mecca for technology introductions ranging from the VCR to HDTVs. Each year, a select number of CEOs are invited to serve as CES keynotes and are given the stage before more than 150,000 of the technology industry's most influential individuals. Within this group are thousands of reporters and investment analysts including portfolio managers, sell-side and buy-side equity analysts, and other institutional investors. The CEOs utilize this stage to introduce new products, services, and offerings and to lay out their vision for the future. According to the results of the Most Valued Conferences Survey conducted by global public relations and public affairs firm Burson-Marsteller, CEOs receive an average of 3.4 speaking requests per week, or 175 per year. While the World Economic Forum was listed as the most sought-after opportunity among CEOs, the Consumer Electronics Show was ranked ninth.

It is generally believed that CEOs wield incredible influence over their companies, not solely through operational control but also by their ability to persuade the broader public to invest in the financial assets of the firm. By successfully encouraging support of their debt and equity in the financial markets, CEOs create an atmosphere wherein they can more easily—and often more cheaply—borrow money in the financial markets. With advantageous access to capital markets, companies can expand their businesses at a favorable cost relative to their peers.

There has been significant research into how announcements impact stock prices. Some of the earliest research in this vein focused on the informational content of dividends and corresponding announcements to dividend changes. Miller and Modigliani (1961) showed that a firm's dividend policy does not affect its value in a perfect market with no personal or corporate taxes. Miller and Modigliani's dividend irrelevance proposition spurred significant research into the information content of dividends and their subsequent announcements. Although early examinations of dividend announcements concluded that the information content of dividend announcements conveyed little value (Watts, 1973), other studies found significant abnormal returns surrounding dividend change announcements (Petit, 1972).[19] The value of a firm is simply the sum of discounted future cash flows; therefore, it should come as no surprise that finance markets incorporate changes in dividend policy into the price of the stock.

Research has also explored the impact that other announcements have had on stock values. For example, strategic alliance announcements in the U.S. result in positive abnormal returns on announcement day (Brook et al., 2005; Chan et al., 1997; Gleason et al.; 2003), suggesting that unexpected alliances create value.

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[19] For more on the informational content of dividends, see Penman, 1983; Healy and Palepu, 1988; Leftwich and Zmijewski, 1994; DeAngelo et al., 1996; Benartzi et al., 1997; Nissim and Ziv, 2001; Grullon et al., 2005; and summaries by Allen and Michaely, 2002; Brav et al., 2005.

Research has also found that announcements of CEO turnover impact financial market asset prices but with mixed results. Bonnier and Bruner (1989) and Weisbach (1988) found positive price moves from turnover announcements, Khanna and Poulsen (1995) reported negative price moves, and both Reinganum (1985) and Warner et al. (1988) found statistically insignificant price moves. Consistent with prospect theory, the framing of information can even influence investor response. For example, Henry (2008) found that the tone and length of earnings press announcements impacted the response by investors.

I extend this literature by examining the relationship between the CEO and the market's value of the firm with respect to three main questions: (1) Is there a relationship between delivering a keynote at CES and stock returns? (2) If so, what is the impact on the firm's stock price when the CEO keynotes CES? (3) Does this relationship manifest itself at the time of the announcement of the keynote or at the time of the actual keynote?

There are several hypotheses to explain why speaking at the International CES would lead to abnormal stock returns. First, keynotes at CES have become a venue for product announcements, but CES has also long been a platform for broader company announcements. Take for example, this story from the June 7, 1982 *Wall Street Journal*:

> Atari, Lucasfilm in Joint Video-Game Venture
>
> Warner Communications Inc.'s Atari unit and Lucasfilm Ltd., producer of such movies as *Raiders of the Lost Ark* and *Star Wars*, plan a joint venture to make video games and other home-entertainment products.
>
> The venture, announced at the annual Consumer Electronics Show here, is the first of its kind between a video-game and home-computer maker like Atari and a movie company. Other movie studios are said to be in discussions to license some classic films and coming movies for video-game cartridges.

Media coverage of the event itself also suggests the power of CES. With the decline of the Comdex trade show, CES is essentially the only major technology show. Seeds of major trends are often planted at the show. Here is another example from the January 12, 2004, *Wall Street Journal*:

> Last week, Apple Computer Inc. and H-P blindsided the computer and consumer-electronics industries by announcing that H-P would resell Apple's iPod music player and provide a link to Apple's iTunes online music store on its personal computers. The final agreement was hammered out between Apple Chief Executive Steve Jobs and Carly Fiorina, H-P's chief executive, late the night before *it was announced at the Consumer Electronics Show in Las Vegas on Thursday*. Financial terms of the relationship weren't disclosed.

Media coverage over a long period of time clearly suggests that the financial markets would wisely look to CES, but of course anecdotal evidence is not enough. I propose an empirical approach to measure the impact of the release of new information on stock returns, looking specifically at occasions when company CEOs have spoken at CES. This essay contributes to the current economic literature by adding to our understanding of three key issues: (1) announcement effects, (2) abnormal stock returns and the efficiency of capital markets, and (3) financial market event studies.

I begin by describing the dataset utilized. Next I explain the event-study methodology employed. Empirical results are then presented, followed by concluding remarks.

Sample Construction

The Consumer Electronics Association provided data on CEO keynotes, including, for each keynote, the dataset including the company and the day on which the keynote took place at the International CES. For keynotes after 1998, the dataset also includes when the announcement of the keynote was first publicly made. The sample for this study contains firms that keynoted CES from 1992 to 2012. The sample period consists of 77 keynotes. The sample is reduced by three firms that were privately held at the time of their respective keynote and six firms that did not have equity publicly traded in US financial markets, leaving a total of 68 observations over a 21-year time frame.[20]

For each company I obtained daily closing prices from the Center for Research in Security Prices (CRSP) for the periods comprising January 1992 through December 2012 inclusively. Through CRSP I also obtained daily value-weighted returns (including distribution) for the S&P 500 Index and for the NASDAQ index.

Empirical Approach

I employ standard event-study methodology in this examination to ascertain the reaction of investors to CEO keynotes at CES (the event). Event-study methodology assumes that capital markets are efficient and therefore internalize new information (in this case, announcement of keynotes or the content of keynotes when delivered) through the repricing of assets. In other words, investors examine new information as it is released, determine if the new information has any bearing on future company cash flows, and bid up (or down) the price of the company's common equity in line with the direction and magnitude of cumulative company cash flows. Event studies involve the following steps: (1) identification of the events and specification of the event window,[21] (2) selection of the firms to include within the sample, (3) prediction of a "normal" base

[20] The full list is available in the Appendix.
[21] The event window is typically some day before the event, the day of the event (day 0), and several days after the event.

case scenario during the event window had the event not occurred, (4) estimation of aberrations within the event window, defined as the difference between the "normal" predicted scenario and what actually occurred, and (5) assessment of any abnormalities for statistical significance.

I begin by estimating a market model[22] for each firm's stock return prior to the event (t = 0). Following MacKinlay (1997), I utilize an estimation period of 150 days (t = –164 to t = –14)[23] and estimate the following equation for each company:

$$R_{it} = a_i + \beta_i RM_t + \varepsilon_{it}$$

with $E(\varepsilon_{it}) = 0$ and $\mathrm{Var}(\varepsilon_{it}) = \sigma_{e_i}^2$

where R_{it} is the daily return for firm *i* on day *t* and *RM* denotes the daily return for the overall market (value-weighted S&P 500, NASDAQ, etc.) on day *t*. α_i and β_i are firm-specific parameters. The equation above is the market model, which assumes a linear relationship between the return of the security and the return on the market portfolio.[24]

Using the coefficients α_i and β_i, I estimate the returns for each firm *i* over the event window:[25]

$$PR_{it} = a_i + \beta_i RM_t$$

[22] Several methods can be used utilized to estimate market activity. In addition to the market model, common models used to calculate the normal rate of return include the capital asset pricing model (CAPM), mean-adjusted return model, market-adjusted return model, and constant return model (single index model).
[23] Several different estimation periods were tested. Results are robust to specification changes.
[24] I test both the S&P 500 and the NASDAQ as the market portfolio. Results are robust to specification changes.
[25] I tested several competing event window lengths, each of which produced similar empirical results. The results presented here utilize a five-day event window: two days before the event, the event day ($t = 0$), and two days following the event.

where PR denotes the predicted daily return for firm *i* on day *t*. From here I calculate the abnormal returns for firm *i* by subtracting the predicted daily return PR_{it} from the actual daily return R_{it} as follows:

$$AR_{it} = R_{it} - a_i - \beta R_{mt}$$

The abnormal returns will be jointly normally distributed with a zero conditional mean and a conditional variance $\sigma^2(AR_{it})$:

$$\sigma^2(AR_{it}) = \sigma_{e_i}^2 + \frac{1}{L}\left[1 + \frac{(R_{mt} - \bar{R}_m)^2}{\sigma_m^2}\right]$$

where L is the estimation period (ie number of days used for the estimation) and $\bar{R}_m$ is the mean of the market portfolio. When L is large, $\sigma^2(AR_{it}) \xrightarrow{yields} \sigma_{e_i}^2$

In order to draw overall inference on the abnormal returns for each keynote, I aggregate abnormal returns (AAR) as follows:

$$AAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N}$$

For large L, the variance is:

$$VAR(AAR_t) = \frac{\sum_{i=1}^{N} \sigma_{e_i}^2}{N^2}$$

To test if the average abnormal return for each company is statistically different from zero I calculate the following test statistic:

$$\frac{\frac{\sum_{i=1}^{N} AR_{it}}{N}}{\frac{\sum_{i=1}^{N} \sigma_{e_i}^2}{N^2}}$$

If the absolute value of the test statistic above is greater than 1.96, then the average abnormal return for the stock is statistically significant at the 95% level.

Empirical Results

I apply the event-study methodology outlined above to the CEO keynotes delivered at the International CES over a 21-year horizon. I begin by presenting the most disaggregated results (i.e., at the individual keynote level). Table 13 provides the calculated cumulative abnormal returns using both the S&P 500 and the NASDAQ Composite. These results utilize an estimation window of 150 days ($t = -164$ to $t = -14$) and an event window of five days (two days before the event, the event day, and two days after the event). The corresponding test statistic as outlined in the previous section is reported for each keynote.

Table 13. *Cumulative Abnormal Returns for International CES Keynotes, 1992-2012*

CES Year	Company	Cumulative Abnormal Return (using S&P 500)	Test Statistic	Cumulative Abnormal Return (using NASDAQ)	Test Statistic
1992	Apple Inc	0.0696	1.1940	0.0002	0.0060
1993	Intl Business Machines Corp	-0.0164	-0.1489	-0.0127	-0.1099
1994	AT&T Inc	-0.0747	-0.6704	-0.0434	-0.3113
1995	Sony Corp	-0.0019	-0.0663	-0.0159	-0.4470
1996	Compaq Computer Corp	-0.0076	-0.0564	0.0592	0.8479
1998	Sun Microsystems Inc	0.0406	0.4576	0.0353	0.6872
1999	Sony Corp	-0.0790	-1.3896	-0.1200	3.6498**
1999	Cisco Systems Inc	0.0079	0.0572	-0.0333	-0.1978
2000	Microsoft Corp	-0.0116	-0.1437	0.0284	0.3549
2000	3Com Corp	-0.1204	-0.7293	-0.0949	-0.6353
2000	Sun Microsystems Inc	-0.0080	-0.0316	0.0200	0.1312
2000	Realnetworks Inc	-0.0042	-0.0181	0.0811	0.3798
2001	Intel Corp	-0.0087	-0.2143	-0.0646	-0.7664
2002	Microsoft Corp	0.0135	0.1960	-0.0081	-0.2230
2002	Hewlett-Packard	0.0145	0.1486	0.0071	0.0675
2002	Koninklijke Philips Nv	-0.0137	-0.1323	-0.0307	-0.3596
2002	Sprint Corp	0.0069	0.0620	-0.0052	-0.0445
2003	Microsoft Corp	0.0070	0.0935	-0.0022	-0.0552
2003	Intel Corp	0.0170	0.1517	-0.0081	-0.1018
2003	Sony Corp	0.0281	0.4474	0.0147	0.1573
2003	Texas Instruments Inc	-0.0418	-0.2695	-0.0390	-0.2510
2004	Microsoft Corp	0.0149	0.4017	-0.0005	-0.0110
2004	Hewlett-Packard	0.0320	0.2415	0.0057	0.0402
2004	Sprint Corp	0.0482	0.6296	0.0403	0.5092
2005	Intel Corp	-0.0243	-0.4787	0.0096	0.2825
2005	Microsoft Corp	0.0328	0.7980	0.0424	1.0129
2005	Motorola Solutions Inc	0.0190	0.4761	0.0368	0.9479
2005	Hewlett-Packard	-0.0437	-0.6230	-0.0271	-0.3729
2005	Texas Instruments Inc	-0.0668	-1.0623	-0.0474	-0.8194
2006	Microsoft Corp	-0.0107	-0.2551	-0.0162	-0.3435
2006	Intel Corp	0.0287	0.7109	0.0210	0.5410
2006	Sony Corp	0.0186	0.2509	0.0119	0.1536
2006	Google Inc	0.0214	0.4644	0.0021	0.0533
2006	Yahoo Inc	0.0057	0.0762	-0.0112	-0.1519
2007	Disney (Walt) Co	0.0013	0.0422	-0.0012	-0.0367
2007	Motorola Solutions Inc	-0.0894	-0.7034	-0.1086	-0.9873
2007	CBS Corp	-0.0105	-0.2852	-0.0121	-0.3102
2007	Dell Inc	0.0186	0.2120	0.0133	0.1574
2007	Viacom Inc	0.0267	0.5007	0.0230	0.4410
2008	Intel Corp	-0.0898	-0.6704	-0.0620	-0.5316
2008	Panasonic Corp	-0.0436	-0.9488	-0.0185	-0.3906

CES Year	Company	Cumulative Abnormal Return (using S&P 500)	Test Statistic	Cumulative Abnormal Return (using NASDAQ)	Test Statistic
2008	Comcast Corp	0.0298	0.7448	0.0546	2.0048**
2008	General Motors Co	0.0531	0.3412	0.0900	0.5520
2009	Microsoft Corp	0.0148	0.1331	0.0004	0.0042
2009	Ford Motor Co	0.1045	0.7060	0.0946	0.7317
2009	Sony Corp	0.1380	0.8177	0.1163	0.6846
2009	Cisco Systems Inc	-0.0092	-0.1283	-0.0202	-0.4090
2009	Eastman Kodak Co	0.1384	3.6609**	0.1268	5.4924**
2009	Intel Corp	-0.0400	-0.5714	-0.0497	-0.8743
2010	Microsoft Corp	-0.0240	-0.5187	-0.0255	-0.6637
2010	Ford Motor Co	0.1170	1.0059	0.1310	0.9338
2010	Intel Corp	0.0022	0.0516	0.0097	0.2996
2010	Nokia Corp	-0.0033	-0.0801	0.0077	0.1740
2011	Microsoft Corp	0.0115	0.1407	0.0079	0.0993
2011	Verizon Communications Inc	-0.0062	-0.0568	-0.0085	-0.0734
2011	Cisco Systems Inc	0.0391	1.1806	0.0295	0.8312
2011	Ford Motor Co	0.0252	0.4093	0.0202	0.3814
2011	General Electric Co	0.0135	0.5784	0.0121	0.4827
2011	Xerox Corp	-0.0008	-0.0197	-0.0065	-0.1913
2012	Microsoft Corp	0.0166	0.2715	0.0065	0.1233
2012	Intel Corp	0.0025	0.0858	-0.0061	-0.1792
2012	Qualcomm Inc	-0.0170	-0.3695	-0.0325	-0.8477
2012	Ericsson	-0.0130	-0.2422	-0.0276	-0.4943

** = significant at the .05 level.

As the results in Table 13 highlight, there is only one keynote (Kodak 2009) with statistically significant abnormal returns when the market model is estimated using the S&P 500 and only three keynotes (Sony 1999, Comcast 2008, Kodak 2009) with statistically significant abnormal returns when the market model is estimated using the NASDAQ Composite. In 63 CEO keynote events at the International CES over the 21-year span from 1992 to 2012, nearly all events have statistically insignificant price moves. Company announcements publicized during the CEO keynote at the International CES appear to have no impact on capital markets in almost all observations.

In additional to testing for statistically significant abnormal stock returns during the event window of the keynote, I also test if there are statistically significant abnormal stock returns during a five-day event window around the public announcement of the keynote. While the International CES is held during the second week of January each year, the CEO keynotes are regularly announced months in advance. Testing for statistically significant abnormal returns during the event window surrounding the announcement of the impending CEO keynote tells us if financial market participants are anticipating a forthcoming announcement that will impact future cash flows (Table 14). As the results in Table 14 highlight, there is only one keynote announcement (Microsoft 2002) with statistically significant abnormal returns when the market model is estimated using the S&P 500 and only one keynote announcement (Microsoft 2003) with statistically significant abnormal returns when the market model is estimated using the NASDAQ Composite. In 52 CEO keynote announcement events over the 14-year span from 1999 to 2012 for which announcement dates were available, nearly all events have statistically insignificant price moves—similar to the results presented for the event window surrounding the actual CEO keynote. Announcing the upcoming keynote does not appear to be viewed as material by the capital markets and, statistically insignificant abnormal returns are observed in almost all instances.

Table 14. *Cumulative Abnormal Returns for International CES Keynote Announcements, 1999-2012*

CES Year	Company	Cumulative Return (using S&P 500)	Test Statistic	Cumulative Return (using NASDAQ)	Test Statistic
1999	Sony Corp	0.0381	0.3442	0.0362	0.3947
1999	Cisco Systems Inc	0.0301	0.5543	0.0488	0.6629
2000	Microsoft Corp	0.0156	0.2155	0.0182	0.3202
2000	3Com Corp	0.0047	0.0846	0.0098	0.1432
2000	Sun Microsystems Inc	0.0722	0.7300	0.0353	0.4071
2000	Realnetworks Inc	-0.0467	-0.2619	-0.1165	-0.6340
2001	Intel Corp	-0.0343	-0.5864	-0.0442	-0.9332
2002	Microsoft Corp	-0.0831	-1.9628**	-0.0207	-0.5206
2002	Hewlett-Packard Co	0.0045	0.0408	-0.0106	-0.2298
2002	Koninklijke Philips Nv	-0.0618	-0.4565	-0.0768	-0.6920
2002	Sprint Corp	0.0163	0.1931	0.0092	0.0958
2003	Microsoft Corp	0.1224	1.4046	0.1264	2.3628**
2003	Intel Corp	-0.0329	-0.2547	-0.0547	-0.5524
2003	Sony Corp	-0.0251	-0.1788	-0.0189	-0.1493
2003	Texas Instruments Inc	0.1682	1.3752	0.0459	0.4582
2005	Microsoft Corp	-0.0142	-0.6339	-0.0108	-0.4944
2005	Intel Corp	-0.0257	-0.4139	-0.0077	-0.2006
2005	Motorola Solutions Inc	0.0137	0.2793	0.0098	0.2741
2005	Hewlett-Packard Co	0.0035	0.0750	0.0510	0.2472
2005	Texas Instruments Inc	0.0783	0.3705	0.0076	0.2569
2006	Microsoft Corp	-0.0316	-1.6132	-0.0276	-1.4554
2006	Intel Corp	-0.0294	-0.6492	-0.0241	-0.6218
2006	Sony Corp	0.0568	1.1480	0.0627	1.2350
2006	Yahoo Inc	-0.0010	-0.0331	0.0019	0.0370
2006	Google Inc	0.0024	0.0443	0.0035	0.1193
2007	Motorola Solutions Inc	-0.0271	-0.4842	-0.0063	-0.1303
2007	Disney (Walt) Co	-0.0032	-0.1277	0.0055	0.2412
2007	CBW Corp	-0.0196	-0.4415	-0.0216	-0.4741
2007	Viacom Inc	0.0029	0.0571	0.0003	0.0053
2008	Panasonic Corp	-0.0497	-0.7397	-0.0506	-0.7274
2008	Intel Corp	0.0278	1.0115	0.0216	0.6512
2008	General Motors Co	-0.0239	-0.2809	-0.0269	-0.2948
2008	Comcast Corp	0.0012	0.0220	-0.0050	-0.0938
2009	Microsoft Corp	-0.0128	-0.4972	0.0033	0.2341
2009	Sony Corp	-0.0191	-0.6298	-0.0050	-0.1410
2009	Ford Motor Co	0.0431	0.3624	0.0667	0.5138
2009	Cisco Systems Inc	-0.0332	-0.3757	-0.0399	-0.5228
2009	Eastman Kodak Co	-0.0404	-0.3637	-0.0076	-0.0844
2009	Intel Corp	0.0171	0.1600	0.0081	0.0807
2010	Microsoft Corp	-0.0092	-0.1054	-0.0026	-0.0358

CES Year	Company	Cumulative Return (using S&P 500)	Test Statistic	Cumulative Return (using NASDAQ)	Test Statistic
2010	Intel Corp	-0.0205	-0.4641	-0.0130	-0.3087
2010	Ford Motor Co	-0.0032	-0.0185	-0.0060	-0.0341
2010	Nokia Corp	0.0201	0.2375	0.0235	0.2887
2011	Microsoft Corp	0.0214	0.2689	0.0266	0.3117
2011	Verizon Communications Inc	0.0143	0.5040	0.0178	0.5026
2011	Xerox Corp	-0.0372	-0.5375	-0.0330	-0.4649
2011	Cisco Systems Inc	-0.1402	-0.3894	-0.1366	-0.3938
2011	General Electric Co	0.0014	0.0360	0.0046	0.1097
2011	Ford Motor Co	0.0432	0.9333	0.0440	0.6501
2012	Microsoft Corp	0.0224	0.4460	0.0138	0.3047
2012	Qualcomm Inc	-0.0137	-0.5126	-0.0032	-0.1125
2012	Intel Corp	-0.0059	-0.1035	-0.0006	-0.0115

Note: ** = significant at the .05 level.

Testing Across All Observations as a Group

In addition to examining the average abnormal return for each CES keynote as a single event, I also calculate the cumulative abnormal returns for all CES keynotes treated as a single group. Along with estimating disaggregated results by individual keynote and keynote announcement events, I also test if all keynote events as a single group exhibit statistically significant abnormal returns. I perform the same test for keynote announcement events as a whole.

Results for these estimates are presented in Table 15. Testing across all observations as a single group fails to produce statistically significant abnormal returns. Consistent with the results from the previous section, CEO keynotes at CES as a single group do not exhibit statistically significant abnormal returns. In other words, there appears to be no discernable financial market reaction to CEO keynotes at CES over the last 20 years. Similar results are produced when examining International CES keynote announcements as a single group. Given that only a few individual CES keynotes exhibited statistically significant abnormal returns, it is not surprising that testing cumulative abnormal returns for companies treated as a single group also reveals no statistical significance in abnormal returns.

Table 15. *Cumulative Abnormal Returns for All CES Keynotes Treated as a Single Group*

Market Portfolio Used to Estimate Market Model	Event Group	Average Cumulative Abnormal Returns	Robust Standard Errors
S&P 500	CES Keynote	0.0015	0.0057
NASDAQ Composite	CES Keynote	0.0011	0.0060
S&P 500	CES Keynote Announcement	0.0001	0.0063
NASDAQ Composite	CES Keynote Announcement	-0.0001	0.0056

Conclusion

I investigated two questions. First, do investors reward companies prior to CEO keynotes at CES by bidding their stock higher because of some anticipation that the company will have new influential technology to release during the keynote? Second, do investors reward companies after CEO keynotes at CES by bidding their stock higher because the announcements lived up to investor expectations?

One possible reason to expect positive abnormal stock returns from CES keynote appearances is that there exists private insider information regarding future products and offerings. I tested this possibility by examining abnormal stock returns in the window following public announcement of the CES keynote and in the window encompassing the actual keynote. If investors perceive the announcement of the CES keynote as a signal of private information about forthcoming technology, then positive abnormal return should be observed around these announcements. Furthermore, if investors are excited about technologies announced during the CES keynote, positive abnormal returns should be observed following the actual keynote. Of course the opposite also holds; if investors do not perceive the technologies announced during CES keynote to be game-changing announcements or if the announcements do not live up to investor expectations, then negative abnormal returns should be observed following the actual keynote.

Do CEO keynotes at the International CES provide access to unique and material information relevant to the performance and outlook of the company, and do investors and traders correspondingly price this new information into the equity of the company? I have investigated these questions by examining a sample of 68 cases where CEOs keynoted the International CES during a 21-year sample period (1992 to 2012).

The empirical results presented in this paper find only a few select cases where a company's common equity exhibited statistically significant abnormal returns in the window around a CEO's keynote at CES. Similarly, the empirical results presented in this paper show only one or two cases where a company's common equity exhibited statistically significant abnormal returns in the window around the announcement of a CEO's keynote at CES. I find limited evidence that CEOs are providing material information and that investors are in turn pricing this new information into the marketplace. By and large, there appears to be little evidence of statistically meaningful abnormal financial returns following either the announcement of a keynote at the International CES or the keynote itself.

The lack of statistically significant abnormal returns for either of these two time windows could be explained in several ways. First, perhaps financial market participants simply aren't watching the CES keynotes for material information and thus are not pricing this new information into the price of the stock in the days leading up to and preceding the keynote. Given the vast media coverage and the large number of overall attendees that attend CES each year, including a large number of professional investors, financial analysts, and portfolio managers, I find this potential explanation unsatisfactory. A second possible explanation is that the International CES is just too big and relevant information is overlooked. The International CES has become the largest annual trade show in the country, attracting over 150,000 attendees each year and encompassing over 1.8 million net square feet of exhibit space. More than 20,000 new products are launched at the International CES each year, all in the course of four days. Therefore, perhaps there are simply too many competing announcements at the event and these competing announcements consequently pull some of the attention of capital market participants away from the keynote, causing capital market participants not to fully consider information revealed during the keynote presentation of a CEO. Under this scenario, any relevant information released during the keynote might be priced into the market, but not immediately within the window utilized in this examination. This explanation is also unsatisfactory because it would require less than efficient markets. A final possible explanation is that companies participating in CES, especially those whose CEO is invited to keynote, begin sharing information about products and other company announcements in the weeks leading up to the International CES in order to take full advantage of the exposure received at CES. Under this scenario, any new information would be priced into the price of the company's common equity as the information became available and would not be captured in the estimation window, which encompasses the days around the keynote.

My examination of CEO keynotes at CES differs from previous studies examining announcement effects. The literature is full of studies finding statistically significant abnormal stock returns around company specific announcements, but little work has been done in examining specific platforms used to disseminate that information. Moreover, to the best of my knowledge no studies have looked for the presence of statistically significant abnormal stock returns from public speeches. These results provide evidence that CEOs do not use keynote opportunities to provide a drastically different view of company perspectives or objectives.

APPENDIX

Table A1. *List of Weights*

Variable	N	Sum of Weight	Mean	Std. Dev	Variance	Skewness	Kurtosis
Gender (Male = 1, Female = 0)	84782	83983.8375	.4857428	.4997996	.2497997	.057052	1.003255
Children (Living in the Home = 1)	83462	82605.6042	.3857654	.4867785	.2369533	.4693523	1.220292
Education (= 1 if High School Diploma or less, = 2 if some college, = 3 if four-year college degree or more)	84782	83983.8375	1.852338	.8720338	.760443	.1339779	1.628865
Employment (1 = Employed full-time or self-employed, 2 = employed part-time, 3 = retired, 4 = not working	84385	83541.9385	2.181491	1.234939	1.525075	.3516565	1.465719
Home Ownership (= 1 if Own, = 0 if Renting)	81481	79317.8699	.7073733	.4549713	.2069989	-.9115942	1.831004
Married (Married or Living as Married = 1, = 0 if not married)	83325	82535.4562	.5148167	.4997834	.2497835	-.0592927	1.003516
Age	80661	83976.8351	2.436262	1.183382	1.400394	-.0590258	1.640142
Race	80661	83976.8351	2.131971	.7093776	.5032166	.9742781	4.418377
Income	65550	69491.3191	2.286706	1.140368	1.300438	.2669179	1.645657

Table A2. *List of Available Independent Variables and Corresponding Survey Question Asked in the CEA Survey*

Variable	Survey Question	Response Range
Gender		Male Female REFUSED/NO RESPONSE
Head of household	Do you consider yourself one of the heads of your household?	YES NO REFUSED/NO RESPONSE
Current Employment Status	Which of the following best describes your current employment status? Are you…	Employed full-time Employed part-time Self-employed Retired Student Homemaker Or are you not currently employed REFUSED/NR (This question changed over the survey period)
Marital Status	What is your current marital status? Are you …	Married Living as married Single and never married Divorced Separated Widowed REFUSED/NR
Home Ownership	Do you own or rent the dwelling in which you live?	OWN RENT REFUSED/NR
Size of Household	INCLUDING yourself, how many ADULTS 18 years of age and older are currently living in your household?	RECORD NUMBER. RANGE IS 1-10, REFUSED
Children	Are there any children under the age of 18 living in your household?	YES NO REFUSED/NR
Number of Children in the Home	How many children in each of the following age groups are living in your household?	[RECORD NUMBER FOR EACH. RANGE IS 0-10, REFUSED] 6 years of age or younger 7-12 years of age 13-17 years of age

Variable	Survey Question	Response Range
Educational Attainment	What was the last grade in school you completed?	8TH GRADE OR LESS HIGH SCHOOL INCOMPLETE [GRADES 9, 10, 11] HIGH SCHOOL COMPLETE [GRADE 12] SOME COLLEGE, BUT NO DEGREE ASSOCIATE'S DEGREE COLLEGE GRADUATE/BACHELOR'S DEGREE POSTGRADUATE DEGREE, SUCH AS MASTER'S, PH.D., M.D., J.D. REFUSED/NR
Age	What is your age?	[RECORD NUMBER FROM 18-98, AND REFUSED]
Age Range	[IF S8QUAN REFUSED, ASK] S8Please tell me, which of the following ranges best fits your age? [READ LIST]	18-20 21-24 25-29 30-34 35-39 40-44 45-49 50-54 55-59 60-64 65-69 70-74 75 or older REFUSED/NR
Race	Are you Spanish, Hispanic, or Latino?	
Race	Which of the following describe your race? You can select as many as apply. [READ LIST. RECORD AS MANY AS APPLY]	White/Caucasian Black/African-American Asian/Asian-American, or Some other race REFUSED/NR

Variable	Survey Question	Response Range
Household Income	Was your TOTAL household income BEFORE taxes for 2011… [READ LIST UNTIL STOPPED]	Under $25,000 $25,000 but less than $30,000 $30,000 but less than $35,000 $35,000 but less than $40,000 $40,000 but less than $50,000 $50,000 but less than $60,000 $60,000 but less than $75,000 $75,000 but less than $100,000 $100,000 but less than $125,000 $125,000 or more DON'T KNOW/REFUSED/NR
	What do you think is the percent chance that the U.S. economy will be in BETTER shape 12 months from now?	
	What do you think is the percent chance that the U.S. economy will be in WORSE shape 12 months from now?	
	What do you think is the percent chance that you will be BETTER OFF financially in the next 12 months?	
	What do you think is the percent chance that you will be WORSE financially in the next 12 months?	
	What do you think is the percent chance that someone you know will lose their job in the next 12 months?	
	What do you think is the percent chance that you will purchase any consumer electronics product in the next 12 months?	
	What do you think is the percent chance that you will spend MORE on consumer electronics products in the next 12 months compared to the last 12 months?	

Variable	Survey Question	Response Range
	What do you think is the percent chance that you will spend LESS on consumer electronics products in the next 12 months compared to the last 12 months?	

Table A3. *List of All CES Keynotes*

Company	Keynote	Position	Announcement Date	Keynote Date	CES Year
Apple Computers, Inc.	John Sculley	Chairman and CEO		1/9/1992	1992
IBM	Jack Kuehler	President		1/7/1993	1993
AT&T	Robert Kavner	Executive Vice President and CEO		1/6/1994	1994
Sony Corp. of America	Michael P. Schulhof	President and CEO		1/6/1995	1995
Compaq Computer Corp.	Eckhard Pfeiffer	CEO		1/5/1996	1996
Bloomberg Financial Markets	Michael Bloomberg	President and Founder		1/9/1997	1997
HSN, Inc.	Barry Diller	Chairman and CEO		1/8/1998	1998
Sun Microsystems, Inc.	Scott McNealy	Chairman, President and CEO		1/9/1998	1998
Microsoft Corporation	Bill Gates	Chairman, President and CEO		1/10/1998	1998
Forbes Magazine	Steve Forbes	President and CEO, Forbes, Inc.		1/8/1998	1998
Cisco Systems, Inc.	John Chambers	President and CEO	8/19/1998	1/8/1999	1999
Sony Corp. of America	Howard Stringer	President	6/30/1998	1/7/1999	1999
3Com	Eric Benhamou	Chairman and CEO	8/6/1999	1/6/2000	2000
Sun Microsystems, Inc.	Scott McNealy	Chairman and CEO	7/12/1999	1/6/2000	2000
Microsoft Corporation	Bill Gates	Chairman, President and CEO	8/19/1999	1/5/2000	2000
RealNetworks Inc.	Rob Glaser	Chairman and CEO	8/25/1999	1/7/2000	2000
Intel Corporation	Craig Barrett	President and CEO	6/28/2000	1/5/2001	2001
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	8/7/2000	1/6/2001	2001
Palm Inc.	Carl Yankowski	CEO	10/18/2000	1/6/2001	2001
Samsung Electronics Co. Ltd.	Daeje Chin	President and CEO, Digital Media Business	7/16/2001	1/8/2002	2002
Hewlett-Packard Company	Carleton Fiorina	Chariman and CEO	7/23/2001	1/8/2002	2002
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	9/26/2001	1/7/2002	2002
Royal Philips Electronics	Gerard Kleisterlee	President and CEO	9/5/2001	1/9/2002	2002
Sprint Corporation	William T. Esrey	Chairman and CEO	7/23/2001	1/10/2002	2002
Intel Corporation	Craig Barrett	CEO	6/26/2002	1/9/2003	2003
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	6/10/2002	1/8/2003	2003
Sony Corporation	Kunitake Ando	President and COO	7/23/2002	1/9/2003	2003
Texas Instruments Inc.	Tom Engibous	Chairman, President and CEO	7/18/2002	1/10/2003	2003
Panasonic AVC Networks Company	Fumio Otsubo	President	8/30/2003	1/8/2004	2004
Hewlett-Packard Company	Carleton Fiorina	Chairman and CEO	8/30/2003	1/8/2004	2004
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	8/30/2003	1/7/2004	2004
Sprint Corporation	Gary Forsee	Chairman and CEO	8/30/2003	1/9/2004	2004
Hewlett-Packard Company	Carleton Fiorina	Chariman and CEO	9/7/2004	1/7/2005	2005
Intel Corporation	Craig Barrett	CEO	8/5/2004	1/5/2005	2005
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	8/5/2004	1/5/2005	2005

Company	Keynote	Position	Announcement Date	Keynote Date	CES Year
Motorola Inc.	Ed Zander	Chairman and CEO	8/24/2004	1/6/2005	2005
Texas Instruments Inc.	Rich Templeton	President and CEO	10/18/2004	1/7/2005	2005
Google Inc.	Larry Page	Co-Founder and President of Products	11/15/2005	1/6/2006	2006
Intel Corporation	Paul Otellini	CEO	9/2/2005	1/5/2006	2006
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	9/2/2005	1/4/2006	2006
Sony Corporation	Sir Howard Stringer	Chairman and CEO	9/2/2005	1/5/2006	2006
Yahoo! Inc.	Terry Semel	Chairman and CEO	9/2/2005	1/6/2006	2006
CBS Corp.	Leslie Moonves	President and CEO	11/16/2006	1/9/2007	2007
Dell Inc.	Michael Dell	Founder and Chairman	9/2/2006	1/9/2007	2007
Walt Disney Corp	Robert Iger	President and CEO	7/10/2006	1/8/2006	2007
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	7/10/2006	1/7/2006	2007
Motorola Inc.	Ed Zander	Chairman and CEO	7/10/2006	1/8/2006	2007
Viacom	Tom Freston	President and CEO	11/16/2006	1/9/2007	2007
Comcast	Brian L. Roberts	Chairman and CEO	9/4/2007	1/8/2008	2008
General Motors	Rick Wagoner	Chairman and CEO	8/27/2007	1/8/2008	2008
Intel Corporation	Paul Otellini	CEO	7/5/2007	1/7/2008	2008
Microsoft Corporation	Bill Gates	Chairman and Chief Software Architect	7/5/2007	1/6/2008	2008
Panasonic	Toshihiro Sakamoto	President	7/5/2007	1/7/2008	2008
Cisco Systems, Inc.	John Chambers	Chairman and CEO	7/10/2008	1/9/2009	2009
Kodak	Antonio Perez	Chairman and CEO	10/21/2008	1/9/2009	2009
Ford	Alan Mulally	President and CEO	8/29/2008	1/8/2009	2009
Intel Corporation	Craig Barrett	Chairman	7/10/2008	1/9/2009	2009
Microsoft Corporation	Steve Ballmer	CEO	8/29/2008	1/7/2009	2009
Sony Corporation	Sir Howard Stringer	Chairman and CEO	8/29/2008	1/8/2009	2009
Ford	Alan Mulally	President and CEO	9/21/2009	1/7/2010	2010
Hisense	Zhou Houjian	Chairman	9/9/2009	1/8/2010	2010
Intel Corporation	Paul Otellini	President and CEO	7/29/2009	1/7/2010	2010
Microsoft Corporation	Steve Ballmer	CEO	7/29/2009	1/6/2010	2010
Nokia	Olli-Pekka Kallasvio	President and CEO	9/15/2009	1/8/2010	2010
Cisco Systems, Inc.	John Chambers	Chairman and CEO	11/9/2010	1/7/2011	2011
Ford	Alan Mulally	President and CEO	10/8/2010	1/7/2011	2011
Samsung	BK Yoon	President of Visual Display Business and Chief Design Officer	9/15/2010	1/6/2011	2011
Audi	Rupert Stadler	Chairman	10/5/2010	1/6/2011	2011
General Electric	Jeffrey Immelt	Chairman and CEO	11/9/2010	1/7/2011	2011
Microsoft Corporation	Steve Ballmer	CEO	7/8/2010	1/5/2011	2011
Verizon	Ivan Sedenberg	Chairman and CEO	8/4/2010	1/6/2011	2011
Xerox	Ursula Burns	Chairman and CEO	11/9/2010	1/7/2011	2011
Ericsson	Hans Vestberg	President and CEO	9/8/2012	1/11/2012	2012
Mercedes-Benz	Dr. Dieter Zetsche	Chairman of Daimler AG and Head of Mercedes-Benz Cars	9/6/2011	1/10/2012	2012
Intel Corporation	Paul Otellini	President and CEO	10/27/2011	1/10/2012	2012
Microsoft Corporation	Steve Ballmer	CEO	7/6/2011	1/9/2012	2012
Qualcomm	Dr. Paul Jacobs	Chairman and CEO	10/3/2012	1/10/2012	2012

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BIOGRAPHY

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