Affect and Expectations

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Abstract

In this paper we examine the relationship between emotional affect and expectations about economic variables, using new panel survey data from the Michigan Survey of Consumers. Affect is measured with questionnaire on happiness. We find little correlation between aggregate happiness and expectations. We do find a correlation at the individual level; however, we find that this correlation is entirely or almost entirely due to individual fixed effects. Happier people are more optimistic, but swings in happiness probably do not cause swings in optimism. We also find that differences in happiness between different political or demographic groups are not associated with differences in expectations between the groups. These results cast doubt on the notion that business cycles and asset price movements are driven by national mood swings ("animal spirits"). However, our finding that happier people are more optimistic is troubling for the Rational Expectations Hypothesis, since rational agents' expectations should not have fixed effects that depend on their individual psychological traits.

1 Introduction

John Maynard Keynes coined the term "animal spirits" when he wrote:

> Even apart from the [economic] instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism... whether moral or hedonistic or economic. Most, probably... our decisions to do something positive ... can only be taken as the result of animal spirits – a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.

How much of this "spontaneous optimism" is "hedonistic" in nature? This is an important question. If expectations can be changed by swings in emotional affect – surges of happiness, waves of fear – then the Rational Expectations Hypothesis is false, and much of macroeconomics must involve the study of human psychology. Some prominent economists have claimed that emotion is a key determinant of both expectations and behavior. For instance, a January 2010 New York Times column by Robert Shiller was entitled, "Stuck in Neutral? Reset the Mood" (Shiller 2010). In that article, Shiller made explicit references to "post-boom pessimism," "malaise," "negative 'mood,"' "irrational exuberance," and the "hearts and minds" of consumers. These ideas echoed the arguments in Shiller and George Akerlof's book Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism (Princeton University Press, 2009). We call this the "affective animal spirits" hypothesis.

The notion that emotion has large effects on expectations is consistent with a substantial psychological and decision sciences literature showing that emotional state affects judgment in a number of ways. For instance, Johnson and Tversky (1983) found that "experimental manipulations of affect induced by report of a tragic event produced a pervasive increase in [subjects'] estimates of the frequency of many risks and other undesirable events." A number of other studies and experiments have yielded a similar result (see Section II). Since estimates of probability risk play a central role in economic decision-making, this psychology literature gives us reason to suspect that "affective animal spirits" are at work in the economy.

However, despite psychologists' findings, and despite the popularity of the idea in the press, little attempt has been made by economists to study the link between emotional affect and economic expectations. This paper represents a first attempt to fill that gap. We use survey data on affect and on economy-related expectations to study the link between the two. Our data come from the Michigan Survey of Consumers, a large and widely used survey that contains a number of questions about expectations for the economy, some of which are used to construct the much-studied Index of Consumer Sentiment. Our measure of emotional affect comes from a questionnaire that we included in the survey from 2005 to 2010, asking four questions relating to positive and negative emotional states.

Because each survey respondent in our sample is contacted twice (at an interval of six months), we have panel data. This allows us to disentangle the effects of three postulated components of mood – national or average mood, an individual's fixed effect, and an individual's six-month change in self-reported mood. We are thus able to ask at least three different questions:

1. Does the national mood affect the average person's expectations about the economy?

2. Are people who are happier in the long term also more optimistic in the long term?

3. Are fluctuations in affect at the 6-month frequency associated with fluctuations in expectations at that frequency?

Our answer to these questions are: 1) Not that we can tell, 2) Yes, and 3) Probably not, and if so, not very much. We find no measurable relationship between national mood and national expectations. We do find a significant correlation between individual fixed effects in mood and expectations; happier people are indeed more optimistic. However, we find only a very small, and possibly nonexistent relationship between changes in mood and changes in expectations. We also investigate whether differences in the happiness of demographic or political groups (Democrats and Republicans, the old and the young, etc.) can account for differences in the economic expectations of these groups, but find little or no such effect.

These findings throw cold water on the idea that swings in mood, either of the nation or of individuals, cause large swings in expectations about the economy. If macroeconomic variables (consumption, investment) or financial markets are driven by the mood of the nation, the effect does not appear to operate via altered expectations as proposed by Keynes. Similarly, the well-documented effect of events like recessions and elections on happiness also does not seem to work by altering expectations. However, the finding that happiness and expectations are correlated for individuals over the long term is subtly troubling for the Rational Expectations Hypothesis, which cannot be true if expectation are driven by psychological traits.

The plan of the paper is as follows. Section II reviews the economics literature on survey measures of consumer confidence, the psychology literature on affect and expectations, and some other relevant papers about self-reported affect. Section III introduces the survey data, reintroducing the Survey of Consumers and explaining our added questionnaire on affect. Section IV presents our analysis of the data, including our national-level, individual-level, and subgroup-level analyses. In Section V we discuss our results. We argue that our results hold true not only for the types of affect measured in our survey (happiness and sadness), but for any emotion that is correlated with these. We also discuss the relevance of our results for the fields of macroeconomics, finance, and psychology. Section VI concludes.

2 Literature

2.1 Consumer sentiment

The Michigan Survey of Consumer Sentiment asks people many questions about their expectations for future economic conditions and their evaluation of recent economic conditions. Five of these questions (see Table 1) are averaged to create the Index of Consumer Sentiment, which is also called "consumer confidence" (we will use the two terms interchangeably unless otherwise specified). Many studies have explored the use of consumer confidence for forecasting macroeconomic variables. Matsusaka and Sbordone (1995) find that the Index of Consumer Sentiment Granger-causes U.S. GNP, and that consumer sentiment accounts for 13 to 26 percent of the variance in U.S. output. Heim (2009) finds that consumer confidence is systematically related to future consumption of nondurable goods. Dees and Brinca (2011) find that large changes in consumer confidence give good out-of-sample predictions of changes in future consumption. Acemoglu and Scott (1994) find that an alternative measure of consumer confidence in the United Kingdom predicts future consumption, rejecting a simple version of the Permanent Income Hypothesis. For an overview of studies of the use of consumer confidence in forecasting consumer spending, see DesRoches and Gosselin (2002).

There is also a literature on using consumer confidence to forecast asset prices. Fisher and Statman (2002) find that consumer confidence predicts subsequent returns for the Nasdaq and for small-cap stock indices. Chen (2011), using a Markov switching model of "bull" and "bear" markets, finds that large drops in consumer confidence forecast an increased likelihood of a switch to a "bear" market. However, Christ & Bremmer (2003) find that stock prices Granger-cause consumer confidence but not vice versa.

Do these results imply that the Index of Consumer Sentiment can be regarded as a measure of "autonomous" expectations, i.e. optimism or pessimism that is unrelated to economic fundamentals? Not necessarily. As DesRoches and Gosselin (2002) note, some studies find that once economic fundamentals are taken into account, consumer confidence loses much of its predictive power. Barsky and Sims (2008) examine the shapes of empirical impulse responses of macroeconomic variables to innovations in consumer confidence, and compare these to the shapes of impulse responses in a New Keynesian DSGE model. They find that impulse responses for confidence shocks are similar to the impulse responses to shocks to news about future productivity in the DSGE model, but not similar to impulse responses to shocks to sentiment itself. This implies that swings in consumer confidence reflect information about economic fundamentals rather than autonomously moving "animal spirits." In other words, this strand of research finds that consumer confidence may reflect expectations, but not expectations that move spontaneously, as Keynes, Shiller, and others postulate. As we will see, this interpretation agrees with our own findings in this paper. However, note that this literature only examines changes in consumer confidence, and does not deal with the long-term level of confidence. This, too, will bear on our results.

2.2 Affect and expectations

A number of psychology experiments have established a link between individuals' emotional affect and their assessments of probability and risk. One study already mentioned was Johnson and Tversky (1983). Nygren et al. (1996) found that when positive affect was induced in experimental subjects, their estimates of the probabilities of favorable events increased. Lerner and Keltner (2001) found that fear and anger have substantial but opposite effects on risk perception. Wright and Bower (1992) found that happier people are more optimistic. Mayer et al. (1992) found that people are likely to perceive "mood-congruent events" – i.e., events that would tend to cause a mood similar to their current mood – were perceived to be more probable. Ambady and Gray (2002) found that negative affect (sadness) impaired certain kinds of social judgments. Perhaps most intriguingly, behavioral economists Eduardo Andrade and Dan Ariely (2009), using a series of dictator and ultimatum games, found that short-lived changes in emotional state had a persistent effect on decision-making long after the emotion had passed.

This literature strongly motivates our hypothesis that self-reported happiness and sadness affect economic expectations.

2.3 Happiness

Survey measures of affect are common in the economics literature. The most widespread survey measure of affect, and thus the closest we have to a standard measure, is self-reported happiness, which has been widely used by economists for a variety of purposes (see DiTella and MacCulloch (2006) for a survey). Our own survey measure of affect uses two questions about happiness and two about sadness, and thus fits squarely into the happiness literature. For this reason, we refer to our composite index of affect valence (positivity) as "happiness."

There is significant evidence that happiness contains a large individual fixed effect. Psychologists who study happiness have found it to have both "trait" (individual fixed-effect) and "state" (transitory, event-dependent) properties, with the former probably explaining more of the variance in the data than the latter (Stones, et. al. 1995). In other words, it is likely that each person has her own fairly stable long-term baseline level of happiness, with day-to-day events causing fluctuations around this mean. This conclusion is supported by studies that show that genetics have strong predictive power for an individual's happiness (Weiss, Bates, & Luciano 2008). The economics literature agrees with this two-component model of happiness; a study by Kimball, Ohtake and Tsutsui (forthcoming) found that innovations to happiness caused by outside events disappear in a matter of days, as happiness reverts to the individual's mean level. In general, the conclusion that happiness contains a stable "trait" component and a volatile "state" component is robust. This is central to our analysis, since we decompose happiness into a "persistent" component and a "transitory" component.

Although few or no economists have studied the causal impact of happiness on economic outcomes, there is a literature on the effect of economic variables on happiness. This is important because happiness is often used as an "alternative" indicator of economic performance. For example, Wolfers (2003) finds that high unemployment, high macroeconomic volatility, and (to a lesser extent) high inflation lower perceived well-being. Additionally, DiTella, MacCulloch, and Oswald (2001) find that changes in self-reported happiness are strongly correlated with changes in GDP, even after accounting for other real economic variables (and for individual fixed effects). Our results in the current study are first and foremost about effects of happiness on the economy, but as we will see they also have relevance for this literature.

3 Data

Our data are survey data from the Survey of Consumer Sentiment, from August 2005 through January 2011. The Survey contains a number of questions regarding expectations regarding the future state of the economy, as well as questions regarding evaluation of the economy's present and past performance. Henceforth we refer to these simply as "expectation variables" unless other wise noted. A full list of all such questions used in this paper is available in Table 1, and descriptive statistics for the expectation variables are given in Table 2. In particular, five of these questions are averaged to produce the variable known as “consumer confidence”; these five questions appear first in Tables 1 and 2 and are highlighted in bold. Each expectation variable is normalized to a 0-100 scale, with more positive values signaling better expectations about or evaluations of the economy.

The Survey also contains a number of demographic variables, which we will use when we estimate group happiness.

Beginning in August 2005, we added to the survey four questions regarding respondents' emotional state in the previous week. These questions are listed at the bottom of Table 1. Wee asked questions regarding both negative and positive emotions. Responses to all questions were normalized to a 100-point scale, with “No” responses to the negative-emotion questions (e.g. “Much of the time during the past week, you felt sad. Would you say yes or no?”) being given positive values. There were four possible answers for each question, so that each answer can have a value of 0, 25, 50, or 100. Survey respondents' answers to these four questions are highly correlated; these correlations are listed in Table 3.

All four of our affect questions related to positive or negative affect. To simplify things, we average a person's four responses to produce a “happiness index” that measures the person's overall emotional valence (happiness or sadness). Henceforth we refer to this index simply as “happiness.” Because this is our only measure of affect, we will use the terms “happiness” and “affect” interchangeably until we discuss other possible emotional states in Section (4.3.5).

Each survey respondent was interviewed twice ; the interval between interviews was about 6 months for all respondents. Respondents who answered a question of interest in one of the interviews but not the other were dropped from the sample.[1] Thus, we have a balanced panel. The total number of individual respondents in our data set is 11,986, meaning that the total number of contacts is double that, or 23,972. The minimum monthly number of usable survey contacts in our dataset is

[1] This includes respondents for whom one contact fell outside of the months in which the affect questionnaire was included with the survey.

194 (maximum 421, average 380).

A full explanation of the sampling techniques used to construct the Survey of Consumers is available at http://www.oecd.org/dataoecd/13/42/33650864.pdf. For the purposes of this paper, we treat the sample as perfectly representative of the American adult population.

4 Analysis

4.1 Definitions and Normalizations

For variables measuring affect, we use the symbol x. An individual i's response to affect question q on day t is therefore x_{itq}. q ranges between 1 and 4. The Happiness Index (henceforth, simply "happiness") we call x_{it}, and is defined as the average of the four questions:

$$x_{it} = x_{it1} + x_{it2} + x_{it3} + x_{it4} \tag{1}$$

Variables measuring expectations (or evaluations) of economic conditions are given the symbol y. We have many expectation variables, so we use y_{it} generically, and give results for the specific expectation variables in the tables.

We studentize all variables at the level of the entire sample. Therefore, a happiness value of 1 means "1 unconditional standard deviation above the unconditional mean of happiness." We think this makes our point estimates more intuitive, since it defines swings in affect and expectations in terms of how much these variables tend to swing. When we discuss economic significance, of course, it will be necessary to convert variables back into their absolute levels.

4.2 Aggregate-level analysis

The "affective animal spirits" hypothesis is that swings in the national mood cause swings in expections about the economy, which in turn causes changes in macroeconomic aggregates. Therefore, this hypothesis requires that the national mood be correlated with national expectations. Such a correlation is necessary, though not sufficient, to vindicate the idea of "affective animal spirits." So a first-pass test of our hypothesis is to look for a correlation between these two aggregates. As our measures of aggregate happiness and aggregate expectations, we use the montly averages of the answers to our survey questions. Call these $\overline{x}_{i\tau}$ and $\overline{y}_{i\tau}$, where τ represents a month instead of a day.. We assume for now that these survey averages are perfect proxies for the national averages; in other words, we ignore composition effects for now. This is an assumption we will relax later.

First, a casual look at the data tells us that movements in happiness do not explain much of the movement of expectations. Figure 1 shows the movements of monthly aggregate happiness and aggregate bus12, (an expectation variable representing expectations for business conditions over the next 12 months) over our sample period. Bus12 exhibits large swings, coinciding with the financial crisis of 2008, while happiness basically does not move. Looking at Table 2, we can see that expectations are substantially autocorrelated at one lag, while happiness is not. Table 5 shows autocorrelations for happiness and bus12 at several lags, showing much the same result. Expectations are slow to change, while happiness is quick to change; this makes it unlikely that big movements in happiness will be able to cause big movements in expectations.

But a relationship of some sort may still exist. Assuming that both $\overline{x}_{i\tau}$ and $\overline{y}_{i\tau}$ are stationary (which seems reasonable), we run a 2-variable vector autoregression of $\overline{y}_{i\tau}$ on $\overline{x}_{i\tau}$. We run the VAR once with 2 lags and once with 5 lags.[2] . For all but one of these expectation variables, there is no relationship between aggregate happiness and aggregate expectations at any lag. The one exception is bus12. As shown in Table 6, lagged bus12 has a statistically significant effect on happiness at one, two, three and four lags (the reverse is not true, due to the much greater time-series variance of bus12). In other words, this VAR shows a possible relationship between happiness and lagged expectations at the aggregate level. Our later analysis, which is done at the individual instead of the aggregate level, cannot confirm or reject this result, since individuals are recontacted at a 6-month frequency instead of a 1-month frequency.

However, observe that the VAR coefficients representing the effect of bus12 on happiness *alternate signs* from one lag to the next; the coefficient for 1-month-lagged bus12 is positive, the coefficient for 2-month-lagged bu12 is negative, and so on. This "ringing" effect does not make much logical sense, and may indicate that this is an artifact of the relatively small sample, especially given the lack of significant effects for the other expectation variables. Therefore, taken together, the VAR analysis does not show much evidence of a relationship between happiness and expectations at the national level, with the caveat that the bus12-happiness relationship merits further investigation.

Our time series have length of 66, and aggregate happiness does not vary much

[2]The Akaike Information Criterion and Schwartz Information Criterion are both maximized for five lags. However, we can't use lag 6, because this is the lag at which subjects are recontacted, and so our proxy of national aggregates would become biased.

over time (compared to the variance of happiness across individuals). Therefore, these time-series regressions have low power. By looking at the relationship between expectations and happiness at the individual level, we can make use of a huge amount of additional information. Also, we can dispense with the assumption that successive monthly averages are all perfect proxies for the national average. So in the next section, we turn to our individual-level analysis.

4.3 Individual-level analysis

Our panel data are daily. Therefore, from here on out, our variables are all indexed by individual i and by time t, where t represents a day.

Happiness and expectations are correlated at the individual level. Regression estimates from an OLS regression of expectations y_{it} on happiness x_{it} are shown in Table 7 for the five ICS variables. T-statistics range from 10.19 to 25.49. The point estimates are all around 0.1, meaning that on a given day, a person who is 1 standard deviation happier than the mean[3] is likely to be about 0.1 standard deviations more optimistic about the economy. Thus, people who are happier are more optimistic. This agrees with the findings of psychology studies like Wright & Bower (1992).

But we want to ask more specific questons about the relationship between affect and expectations. Our questions are:

1. How does the "national mood" affect individual expectations?
2. Do swings in an individual's happiness cause swings in her expectations?
3. Are people who are happier in general also more optimistic in general?

Because we have panel data, we can address these questions. At this point we return to the idea that there are multiple components of happiness. Psychology tells us that happiness is determined by (at least) two underlying processes - "trait" happiness that changes only over very long periods of time, and "state" happiness that varies from day to day or month to month. We call these the "persistent" and "transient" components of happiness. Also, we postulate that the transient part of happiness is really two parts: a "national mood" that is the same for all individuals in the entire country, and "transient personal happiness" that depends only on individual factors. We assume that "persistern personal happiness" doesn't

[3] "Standard deviation" and "mean," remember, refer to the standard deviation and mean across all people over the entire sample period, not across all people at that specific point in time.

change over six months, so this is just the individual fixed effect in our sample. Algebraically, we represent happiness x_{it} as the sum of these three components:

$$x_{it} = x_t^N + x_i^P + x_{it}^T \tag{2}$$

This is the typical three-component model found in many panel studies, with one component dependent only on time, one component dependent only on the individual, and one component dependent on both time and the individual.

We assume that each of these components affects expectations differently. Our basic model is:

$$y_{it} = \alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \varepsilon_{it} \tag{3}$$

Later, we will expand the model to include other factors.

4.3.1 Effect of national happiness

In the aggregate analysis, we examined the effect of national happiness on national expectations. In this section we look at the effect of national happiness on individual expectations. In other words, in this section we ask: "If a person wakes up on a certain day and finds that the nation as a whole is much happier than normal, is she likely to be much more optimistic about the economy than she normally is?"

The national happiness component x_t^N is assumed to be the same for all individuals. Therefore, we can estimate β_N by instrumenting for an individual's happiness with the average happiness of all other individuals on the same day (See Appendix A). This estimator is biased, because x_t^N is endogenous; better expectations about the future may make the nation happier. However, we assume that we know the sign of the true correlation - we assume that more optimism will always tend to make the nation happier rather than sadder, and that a better national mood will tend to make people more optimistic rather than less. With this assumption, we can know the *sign* of the bias. Specifically, we know that our estimate of the effect of national happiness is an upper bound on the true value (See Appendix A for specifics).

The (biased) estimates of β_N for various expectation variables are in Table 9. The estimate is not statistically significant for any of these variables except bus12 (p-value of 0.032). For bus12, the point estimate is 0.632, which is a substantial effect. As in the aggregate analysis, there appears to be a relationship between national happiness and bus12. However, the direction of causation is not identifiable.

It is also worth looking at the explanatory power of national happiness. Even if swings in the national mood can cause swings in expectations, these swings may be only a tiny fraction of the total. We can estimate an upper bound on the fraction of the variance of y_{it} that can be explained by x_t^N (see Appendix A). We call this value R_N^2. We estimate R_N^2 to be 0.004 for bus12, and lower for other expectation variables - a tiny amount, even though it is an upper bound. The reason for this is that the national mood simply does not swing by very much; see Table 8 for estimates of the variances the three happiness component.[4] The variance of x_t^N is two orders of magnitude lower than the variance of either of the other two components.

Individual-level analysis essentially confirms the conclusions of the aggregate analysis. Bus12 and happiness are related, but the direction of causality is unknown. National happiness is not detectably related to any other expectation variable. And the power of national happiness to explain variations in expectations is negligible. Therefore, we find very little evidence to support the "affective animal spirits" hypothesis at the national level, though the effect of bus12 is interesting.

4.3.2 Effect of transitory personal happiness

In this section we look at the effect of transitory happiness fluctuations on individual expectations. In other words, we ask: "If a person wakes up on a certain day and finds that she is much happier, relative to other people, than normal, is she likely to be much more optimistic about the economy than she normally is?"

To answer this question, we estimate β_T. To do this we regress the difference in an individual's expectations (between the first contact and the second) on her difference in happiness, after first subtracting out national happiness (see Appendix A). This estimator is also biased, for the same reason as in the last section; swings in happiness and optimism may cause each other. However, as before, we can assume that the effect is positive in both directions, and so we can sign the bias. Our estimates of β_T are upper bounds on the true effect of swings in personal happiness on swings in expectations.

Estimates of β_T for various expectation variables are in Table 10. A large fraction of these are significant at the 5% level. Most of the point estimates are on the order of 0.05; this is about an order of magnitude smaller than the correlation between expectations and happiness found at the beginnind of this section. Most of the fact that happier people are more optimistic is explained by the individual fixed effect.

As in the previous section, we estimate an upper bound on the fraction of the variance of y_{it} that can be explained by x_{it}^T. These values are never more than 0.042; we estimate that no more than 4% of swings in an individual's expectations can be explained by swings in her own happiness.

[4]These are in terms of number of unconditional standard deviations of total happiness.

4.3.3 Effect of Persistent personal happiness

If swings in happiness do not account for the correlation between happiness and expectations, then most of the relationship must be due to the individual fixed effect, or what psychologists call the "trait" of happiness. Here we confirm that intuition. To estimate β_P, we perform an instrumental variables regression of expectations on happiness, instrumenting for an individual's happiness with the same individual's happiness at the other contact date (See Appendix A). We assume that there is no individual fixed effect in expectations apart from the effect of persistent personal happiness; hence, we consider our estimates of β_P to be consistent.[5] Our estimates are in Table 10. We see that, as predicted, our estimates of β_P are about an order of magnitude larger than our estimates of β_T, and are very similar to the overall correlation between happiness and expectations.

4.3.4 Model with survey response error

Until now, we have worked with the happiness index x_{it}, instead of the individual answers to the four questions on our questionnaire. However, exploiting the variation between the answers to those four questions may help us get better estimates of β_P and β_T. We do that in this section.

Also, in this section we want to deal explicitly with the fact that our questions do not actually measure true happiness. It is possible that survey respondents differ more in *how they respond to questions* than in how they actually feel. So in this section we include "response errors" in our model of happiness. We consider response errors of four basic types:

- Errors that depend only on the individual (individual fixed effects)
- Errors that depend on individual and the time of the survey
- Errors that depend on the individual and the wording of the question, but are fixed in time
- Errors that depend on the individual, the wording of the question, and the time of the survey

We represent these four response errors as s_i, u_{it}, v_{iq}, and w_{itq}, respectively. For simplicity's sake we assume that all of these response errors show up in the

[5] This is motivated by the voluminous literature on hedonic adaptation.

happiness questions, though mathematically it doesn't matter if response errors in the expectation questions exist as well. So our new model of happiness is:

$$x_{itq} = x_t^N + x_i^P + x_{it}^T + s_i + u_{it} + v_{iq} + w_{itq} \tag{4}$$

This assumes that all four questions are noisy measures of the same thing (affect valence, happiness, etc.).

Our new model of expectations is:

$$y_{it} = \alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_s s_i + \beta_u u_{it} + \beta_v v_{iq} + \beta_w w_{itq} + \varepsilon_{it} \tag{5}$$

Derivations of the estimates for this model are in Appendix A. The estimate for β_N is unchanged. Two things about the estimates of β_P and β_T are different. First of all, they are no longer estimates of β_P and β_T! They are now estimates of $(1-\theta)\beta_P + \theta\beta_S$ and $(1-\xi)\beta_T + \xi\beta_T$, where θ and ξ are parameters (both between 0 and 1) representing the relative importance of the individual-specific response errors s_i and u_{it}:

$$\theta = \frac{Var(s_i)}{Var(s_i) + Var(x_i^P)} \tag{6}$$

$$\xi = \frac{Var(u_{it})}{Var(u_{it}) + Var(x_{it}^T)} \tag{7}$$

In other words, if you believe that most of the variance in survey responses is due to response error, then the estimates in this paper do not mean much; however, if you believe that true values vary about as much as response error, then the results in this paper stand.

The second change from the previous sections is that our estimates, and the associated R^2 values (again, upper bounds on the true values), are now both multiplied by correction factors that come from the variance across the four affect questions (see Appendix A). The correction factors are 1.07 for persistent personal happiness and 1.38 for transitory personal happiness. Results for the new estimates for β_P and β_T, and the associated R^2 values, can be seen in Table 12. Essentially, these results are unchanged from the previous sections.

4.3.5 Other Emotions

Our survey only contains questions about two kinds of emotion: happiness and ρsadness. But if we are really going to test the "affective animal spirits" hypothesis, shouldn't we look at other emotions too? What about fear, or excitement, or anger?

Our answer to this question is that different emotional states are probably correlated with each other. A person who answers that she is "happy" is probably more likely to report that she is "excited," and a person who answers that she is "sad" is probably more likely to answer that she is "worried" or "afraid." If different emotions are very correlated, our results hold true for all emotions; only an affect measure that was nearly orthogonal to happiness would still be a candidate for affective animal spirits. Our result is thus much broader than the limited scope of our survey questions might suggest.

To demonstrate this, we do a simple numerical experiment. Suppose that self-reported happiness is equal to true happiness , and that there exists another emotion – call it "Emotion Z" – that is imperfectly correlated with happiness. For simplicity, assume that Emotion Z has only a transitory component, z_{it}. Then we can write:

$$x_{it} = \rho z_{it} + \varsigma_{it} \tag{8}$$

Now assume that affective animal spirits are in fact caused by Emotion Z:

$$y_{it} = \alpha + \beta_z z_{it} + \varepsilon_{it} \tag{9}$$

We can show that R_z^2, the percentage of the variance of expectations explained by swings in Emotion Z, is bounded above by $\frac{1}{\rho} R_T^2$. In order for swings in Emotion Z to explain an economically significant amount of the swings in expectations, ρ must be very very small. For example, if ρ is equal to 0.2, then swings in Emotion Z explain no more than 20% of swings in expectations.

4.3.6 Subgroup Happiness

One final interesting possibility is that different demographic subgroups have common emotions. Suppose that there is a national election in the U.S., which the Democrats win. The happiness of Democrats surges; that of Republicans plummets by an equal amount. Since the nation is evenly divided between Republicans and Democrats (suppose the happiness of Independents is unchanged), the election will register no change in "national happiness" as we have defined it up until now. But if Democrats and Republicans have different roles in the economy – for example, if Republicans are more likely to be investors – it is possible to imagine that the emotional reaction to the election could have an effect on the economy. This effect could not be large, since it is bounded by the effect of transitory personal happiness. But it is an interesting possibility to investigate. Fortunately, our data includes many demographic characteristics that can be used to test this hypothesis.

We add two more components to the model of happiness – 1) a "persistent group happiness" component that represents the long-term happiness of a particular group (e.g., if Democrats are on average happier than Republicans), and 2) a "transitory group happiness" component that represents differential changes in these groups that arise in response to national events. Define γ_i as a dummy that indicates membership in some group (-1 or 1). So the model of happiness is now:

$$x_{itq} = x_t^N + x_i^P + x_{it}^T + \gamma_i x_t^G + \gamma_i \phi_G \tag{10}$$

Here, x_t^G is transitory group happiness, and ϕ_G is persistent group happiness. The model of expectations becomes:

$$y_{it} = \alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_G \gamma_i x_t^G \varepsilon_{it} \tag{11}$$

We are interested in the size of ϕ_G and the variance of x_t^G. In Appendix A we show how we estimate these from demographic data; the results are in Table 13. We see that the variance of group happiness is small - at least one order of magnitude smaller than the variance of the "personal happiness" components. For a couple of demographic groups - homeowners, and age over 44 - the variance of group happiness is an order of magnitude *larger* than the variance of national happiness; this means that the mood of certain groups may be a more interesting object of study than the mood of the nation as a whole. It also hints that the most important demographic distinction, in terms of happiness, may be related to wealth level.

5 Discussion

Our results are bad news for the "affective animal spirits" hypothesis of business cycles. The upper bounds on the explanatory power of national and transitory personal happiness mean that emotion is not a major cause of "animal spirits"; even swings in the happiness of a key individual or small group of individuals are unlikely to move those individuals' expectations by much. And the effect on real economic variables - at least, if it acts through expectations - must be even smaller. For example, let's take the most optimistic estimate of the effect of swings in consumer confidence on GNP - 26%, the highest value reported by Matsusaka and Sbordone (1995). Using our estimates for R_T^2, we can conclude that no more than 1% of swings in GNP can possibly be explained by swings in happiness. Suppose that it is actually fear that drives business cycles, and set the covariance between fear and happiness equal to only -0.2. Then less than 5% of the swings in GNP are due to fear. Remember, also, that these are upper bounds on upper bounds; the true value is bound to be much lower.

However, our results may be interesting for the field of finance. In finance, a profitable trading opportunity does not have to have a large R-squared; it just has to exist. Some papers have found that consumer confidence predicts stock returns, but consumer confidence surveys are very infrequent. Happiness surveys, however, are easy to do. Our results show a correlation between happiness (national or personal) and one measure of expectations (bus12). If this component of consumer confidence predicts stock returns, then traders may gain useful information from measuring national happiness, or from paying attention to public data on happiness as it emerges.

The hypothesis of "affective animal spirits" is often put forth as an alternative to Rational Expectations. Barsky and Sims (2008) showed, in the context of a specific macroeconomic model, that autonomous movements in consumer confidence don't cause swings in real economic variables. The results in this paper yield a similar result. Does this mean that our results support Rational Expectations? Actually, no. Rational Expectations requires expectations to be unbiased estimates of the predictions of the best model of the economy. But if expectations depend on psychological traits, this cannot be the case. Suppose that half of the population is naturally optimistic all the time, and half is naturally pessimistic, regardless of economic conditions. A composition shock - say, if the pessimistic people all decided to take the day off - would cause a bias to appear in the expectations of the representative agent.

In Section 4.3.3, we found that persistent personal happiness has a statistically significant effect on most survey measures of economic expectations. Persistent personal happiness is a psychological trait. This means that if A) survey responses are a good measure of expectations, and if B) survey responses are a good measure of true happiness, then this finding represents a violation of Rational Expectations. Because the economy does not usually suffer large composition shocks, the anomaly is unlikely to make a big difference in economic outcomes. But it may signal the existence of a wider class of ways in which individual psychological traits cause departures from rationality.

Our results are of minor importance for the cognitive economics literature. Studies have shown that recessions make people less happy. Our negative results for national and transitory personal happiness show that this effect probably does not work through expectations. In other words, recessions are not making people unhappy because they are making them pessimistic. This means that recessions' adverse effect on happiness probably cannot be allayed by taking steps to raise expectations about the economy's long-term performance.

6 Conclusion

In this paper, we investigated the relationship between affect and economic expectations, as measured by surveys. We found mostly no correlation between average national happiness and either average expectations or individual expectations, with one possible exception (the variable bus12), which deserves further study. In fact, we found only small and short-lived movements in average national happiness, meaning that the "national mood" is unlikely to drive much of anything. At the individual level, we found that the causal effect of happiness swings on expectation swings, at the 6-month frequency, is much smaller than the cross-sectional correlation; generally happy people are generally more optimistic, but this is a long-term fixed effect. We also found that fluctuations in happiness explain only a tiny percent of the observed fluctuations in expectations. This result is robust to question-specific response errors. It is also reasonably robust to misspecification of the relevant affective state; our results imply that fear, excitement, and other emotions are also unlikely to be significant causes of business cycles. However, we did find that individual fixed effects in happiness are associated with more optimistic expectations

The negative results in this paper deal a blow to the popular notion of "animal spirits" as being an emotional phenomenon. Even if business cycles can be caused by changes in the public's expectations, those expectation changes are almost certainly not caused by changes in the national mood, or in the mood of any special subset of the population. Although one might search for other emotions to explain expectation movements, such emotions would have to be unrelated to happiness; thus, we believe that it will be much more useful for advocates of "animal spirits" theories of the business cycle to look at expectation-formation processes rather than emotional factors. On the other hand, our results raise the possibility that survey measures of affect might be an important piece of data for financial traders. Also, the importance of slowly-changing psychological traits on expectations is worrisome for the Rational Expectations Hypothesis.

Future research in this area should focus on using a more diverse set of measures of both affect and expectations. Alternate measures of expectations might include betting on futures markets. Alternate measures of emotion might include questions on a wider range of emotions, or even neurological studies using fMRI to track emotional states.

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Appendix A: Models and Derivations

Definitions

Define:

$$R^2{}_N = \beta_N Var(x_t^N)$$
$$R^2{}_T = \beta_T Var(x_{it}^T)$$
$$R^2{}_P = \beta_P Var(x_i^P)$$

Define the "daily other-mean" of happiness, x_{-it}, as the mean of the happiness of everyone interviewed on the same day as individual i, *except* for individual i:

$$x_{-it} = \frac{\sum_{j \neq i} x_{jt}}{m_t - 1}$$

Where m_t is the number of individuals interviewed on day t.

Basic Model

Effect of x_t^N

We regress y_{it} on x_{it}, using x_{-it} as an instrument for x_{it}. The 2SLS estimator is therefore:

$$\beta^{2SLS} = \frac{Cov(y_{it}, x_{-it})}{Cov(x_{it}, x_{-it})}$$

Expanding the numerator and denominator, we get:

$$Cov(y_{it}, x_{-it}) = Cov(\alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \varepsilon_{it}, x_t^N + x_{-i}^P + x_{-it}^T)$$

$$Cov(x_{it}, x_{-it}) = Cov(x_t^N + x_i^P + x_{it}^T, x_t^N + x_{-i}^P + x_{-it}^T)$$

To simplify these expressions, we use the assumptions:

$$Cov(\varepsilon_{it}, x_j{}^P) = Cov(\varepsilon_{it}, x_{jt}{}^T) = 0$$

$$Cov(x_{it}^N, x_i^P) = Cov(x_{it}^T, x_i^P) = Cov(x_{it}^N, x_i^T) = 0$$

$$Cov(x_i^P, x_j^P) = Cov(x_{it}^T, x_{jt}^T) = 0 \text{ where } j \neq i$$

This leaves us with simplified expressions for numerator and denominator:

$$Cov(y_{it}, x_{-it}) = \beta_N Var(x_t^N) + Cov(\varepsilon_{it}, x_t^N)$$

$$Cov(x_{it}, x_{-it}) = Var(x_t^N)$$

Dividing these expressions and simplifying, we get:

$$\beta_N = \frac{Cov(y_{it}, x_{-it})}{Cov(x_{it}, x_{-it})} - \frac{Cov(\varepsilon_{it}, x_t^N)}{Var(x_t^N)}$$

Which is our desired result.

Effect of x_{it}^T

Define:

$$x_{it} = x_{it} - x_{-it}$$

We regress Δy_{it} on Δx_{it}. The estimator for this first-difference regression is:

$$\beta_T^{FDIV} = \frac{Cov(\Delta y_{it}, \Delta x_{it})}{Cov(\Delta x_{it}, \Delta x_{it})}$$

Expanding the numerator and denominator, we get:

$$Cov(y_{it_2} - y_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = Cov(\beta_N [x_{t_2}^N - x_{t_1}^N] + \beta_T [x_{it_2}^T - x_{it_1}^T] + [\varepsilon_{it_2} - \varepsilon_{it_1}], [x_{it_2}^T - x_{it_1}^T] - [x_{-it_2}^T - x_{-it_1}^T])$$

$$Cov(x_{it_2} - x_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = Cov([x_{t_2}^N - x_{t_1}^N] + [x_{it_2}^T - x_{it_1}^T], [x_{it_2}^T - x_{it_1}^T] - [x_{-it_2}^T - x_{-it_1}^T])$$

To simplify these expressions, we use the following additional assumptions:

$$Cov(\varepsilon_{it_1}, x_{it_2}^T) = Cov(\varepsilon_{it_2}, x_{it_1}^T) = 0$$
$$Cov(\varepsilon_{it_2}, x_{jt_2}^T) = Cov(\varepsilon_{it_1}, x_{jt_2}^T) = Cov(\varepsilon_{it_2}, x_{jt_1}^T) = Cov(\varepsilon_{it_1}, x_{jt_1}^T) = 0$$

This leaves us with simplified expressions for the numerator and denominator:

$$Cov(y_{it_2} - y_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = 2\left[\beta_T Var(x_{it}^T) + Cov(\varepsilon_{it}, x_{it}^T)\right]$$

$$Cov(x_{it_2} - x_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = 2Var(x_{it}^T)$$

Dividing these expressions, we get:

$$\beta_T = \frac{Cov(\Delta y_{it}, \Delta x_{it})}{Cov(\Delta x_{it}, \Delta x_{it})} - \frac{Cov(\varepsilon_{it}, \Delta x_{it})}{Cov(\Delta x_{it}, \Delta x_{it})}$$

Which is the desired result.

Effect of x_i^P

We regress y_{it_2} on x_{it_2}, using as an instrument for. The 2SLS estimator is therefore:

$$\beta_P^{2SLS} = \frac{Cov(y_{it_2}, x_{it_1})}{Cov(x_{it_1}, x_{it_2})}$$

Expanding the numerator and denominator, we get:

$$Cov(y_{it_2}, x_{it_1} - x_{-it_1}) = Cov(\alpha + \beta_N x_{t_2}^N + \beta_P x_i^P + \beta_T x_{it_2}^T + \varepsilon_{it_2}, x_i^P - x_{-it_1}^P + x_{it_1}^T - x_{-it_1}^T)$$

$$Cov(x_{it_2}, x_{it_1} - x_{-it_1}) = Cov(x_{t_2}^N + x_i^P + x_{it_2}^T, x_i^P - x_{-it_1}^P + x_{it_1}^T - x_{it_1}^T)$$

To simplify these expressions, we use assumptions already listed above. This leaves us with simplified expressions for numerator and denominator:

$$Cov(y_{it_2}, x_{it_1} - x_{-it_1}) = \beta_P Var(x_i^P)$$

$$Cov(x_{it_2}, x_{it_1} - x_{-it_1}) = Var(x_i^P)$$

Dividing these expressions, we get:

$$\beta_P = \frac{Cov(y_{it_2}, x_{it_1})}{Cov(x_{it_1}, x_{it_2})}$$

This estimator is unbiased.

Variances of Happiness Components

Our model of observed happiness, given in Equation 2, is:

$$x_{it} = x_t^N + x_i^P + x_{it}^T$$

x_{it}, the left-hand variable, is self-reported happiness, which is what we observe with our survey data; i indicates the individual interviewed, and t indicates the date of the interview. The three variables on the right-hand side are the happiness "components," representing the underlying emotional processes that determine self-reported happiness. x_t^N is "national happiness," which represents the overall national mood at a given point in time. x_i^P is "persistent personal happiness," an individual's fixed baseline level of happiness. x_{it}^T is "transitory personal happiness," that portion of an individual's mood that arises in response to events in that individual's personal life.

All three of the happiness components are assumed to have mean zero, and all are assumed to be uncorrelated with each other. And are assumed to be "transitory", or uncorrelated across a 6-month time interval: $Cov(x_{it_2}^T, x_{it_1}^T) = Cov(x_{t_2}^N, x_{t_1}^N) = 0$.
The variances of the happiness components can be computed directly:

$$Var(x_t^N) = Cov(x_{it}, x_{-it})$$

$$Var(x_i^P) = Cov(x_{it_2}, x_{it_1} - x_{-it_1})$$

$$Var(x_{it}^T) = \frac{1}{2} Cov(\Delta x_{it}, \Delta x_{it} - \Delta x_{-it})$$

Where we have additionally defined:

$$\bar{x}_t \equiv \frac{\sum_j x_{jt}}{m_t}$$

Proofs are included in the subsection below on estimation of the beta coefficients.

Note that x_{it_2} represents individual i's (self-reported) happiness on the date of her second interview, and Δx_{it} represents an individual's change in happiness between her first and second interview, etc.

The estimated variances of the three happiness components are listed in Table 8.

Full Model

Our "full" model of happiness, given in Equation 4, is:

$$x_{itq} = x_t^N + x_i^P + x_{it}^T + s_i + u_{it} + v_{iq} + w_{itq}$$

x_t^N, x_i^P, x_{it}^T, s_i, u_{it}, v_{iq}, and w_{itq} are taken to be iid mean-zero random variables that are orthogonal to one another.

In our data set, self-reported happiness is just the average of these four components. We write:

$$x_{it} = x_t^N + x_i^P + x_{it}^T + s_i + u_{it} + v_i + w_{it}$$

Where:

$$x_{it} \equiv (x_{it1} + x_{it2} + x_{it3} + x_{it4})/4$$
$$v_i \equiv (v_{i1} + v_{i2} + v_{i3} + v_{i4})/4$$
$$w_{it} \equiv (w_{it1} + w_{it2} + w_{it3} + w_{it4})/4$$

Our expressions for the variances of the happiness components now represent the sum of the variances of the happiness components and (where applicable) of the response errors that are not observably different from the happiness components:

$$Cov(x_{it}, x_{-it}) = Var(x_t^N)$$

$$Cov(x_{it_2}, x_{it_1} - x_{-it_1}) = Var(x_i^P) + Var(s_i)$$

$$\frac{1}{2} Cov(\Delta x_{it}, \Delta x_{it} - \Delta x_{-it}) = Var(x_{it}^T) + Var(u_{it})$$

Expectations with response errors

We may safely assume that expectation questions produce similar "response errors". Allowing that expectation-question response errors may be correlated with happiness-question response errors, our model of expectations becomes:

$$y_{it} = \alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_s s_i + \beta_u u_{it} + \varepsilon_{it}$$

This model includes the effect of a respondent's mood on their expectations (β_P for the long-term components of mood, β_T for the transitory components); the relationship between a respondent's tendency to answer happiness-related questions in a particular way and his/her tendency to answer expectation-related questions in a particular way (β_s and β_u); and the potential for the social construction of expectations (β_N)[1]. Again, we assume that the error term, ε_{it} , is mean-zero and is uncorrelated with x_i^P , s_i , and u_{it} .

Our purpose is, again, to identify the coefficients β_N , β_P , and β_T . For the latter two, this will no longer be possible; we will only be able to identify expressions that contain the effects of the response styles, β_s and β_u . Obtaining economically significant results must depend on our belief that the variances of s_i and u_{it} are small.

Effect of x_t^N with response errors

We now define the "daily other mean" of happiness, x_{-it} , as:

$$x_{-it} = x_t^N + x_{-it}^P + x_{-it}^T + s_{-it} + u_{-it} + v_{-it} + w_{-it}$$

Using the same regression as in the basic model, our estimator is:

$$\beta^{MOM} = \frac{Cov(y_{it}, x_{-it})}{Cov(x_{it}, x_{-it})}$$

We can rewrite the numerator and denominator:

$$Cov(y_{it}, x_{-it}) = Cov(\alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_s s_i + \beta_u u_{it} + \varepsilon_{it}, x_t^N + x_{-i}^P + x_{-it}^T + s_{-i} + u_{-it} + v_{-i} + w_{-it})$$

$$Cov(x_{it}, x_{-it}) = Cov(x_t^N + x_i^P + x_{it}^T + s_i + u_{it} + v_i + w_{it}, x_t^N + x_{-i}^P + x_{-it}^T + s_{-i} + u_{-it} + v_{-i} + w_{-it})$$

We can simplify these expressions using the orthogonality assumptions:

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[1] The question-specific response style terms from the measurement model - v_{iq} and w_{itq} - do not enter the structural model, since a respondent's answer to an expectation-related question is presumably not related to the particular set of happiness-related questions that were asked on his/her survey – especially because the latter are asked after the former.

$$Cov(\varepsilon_{it}, x_j{}^P) = Cov(\varepsilon_{it}, x_{jt}{}^T) = Cov(\varepsilon_{it}, s_j) = Cov(\varepsilon_{it}, u_{jt}) = Cov(\varepsilon_{it}, v_j) = Cov(\varepsilon_{it}, w_{jt}) = 0$$
$$Cov(x_t^N, s_j) = Cov(x_t^N, u_{jt}) = Cov(x_t^N, v_j) = Cov(x_t^N, w_{jt}) = 0$$
$$Cov(x_i^P, s_j) = Cov(x_i^P, u_{jt}) = Cov(x_i^P, v_j) = Cov(x_i^P, w_{jt}) = 0$$
$$Cov(x_{it}^T, s_j) = Cov(x_{it}^T, u_{jt}) = Cov(x_{it}^T, v_j) = Cov(x_{it}^T, w_{jt}) = 0$$
$$Cov(s_i, u_{it}) = Cov(s_i, v_i) = Cov(s_i, w_{it}) = Cov(u_{it}, v_j) = Cov(u_{it}, w_{jt}) = Cov(v_i, w_{jt}) = 0$$
$$Cov(s_i, s_j) = Cov(v_i, v_j) = Cov(w_{it}, w_{jt}) = 0$$

These let us cancel most of the terms in the numerator and denominator, leaving us with:

$$Cov(y_{it}, x_{-it}) = \beta_N Var(x_t^N) + Cov(\varepsilon_{it}, x_t^N)$$

$$Cov(x_{it}, x_{-it}) = Var(x_t^N)$$

Dividing then yields:

$$\beta_N = \frac{Cov(y_{it}, x_{-it})}{Cov(x_{it}, x_{-it})} - \frac{Cov(\varepsilon_{it}, x_t^N)}{Var(x_t^N)}$$

Thus, the presence of response errors does not change our result for the effect of x_t^N.

Effect of x_{it}^T with response errors

This time, our estimator is:

$$\beta_T^{MOM} = \frac{Cov(\Delta y_{it}, \Delta x_{it})}{Cov(\Delta x_{itr}, \Delta x_{itq})}$$

Expanding the numerator and denominator, we have:

$$Cov(y_{it_2} - y_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = Cov(\beta_N[x_{t_2}^N - x_{t_1}^N] + \beta_T[x_{it_2}^T - x_{it_2}^T] + \beta_u[u_{it_2} - u_{it_1}] + [\varepsilon_{it_2} - \varepsilon_{it_1}],$$
$$[x_{it_2}^T - x_{it_1}^T] + [u_{it_2} - u_{it_1}] + [w_{it_2} - w_{it_1}] - [x_{-it_2}^T - x_{-it_1}^T] - [u_{-it_2} - u_{-it_1}] - [w_{-it_2} - w_{-it_1}])$$
$$Cov(x_{it_2q} - x_{it_1q}, [x_{it_2r} - x_{it_1r}] - [x_{-it_2r} - x_{-it_1r}]) = Cov([x_{t_2}^N - x_{t_1}^N] + [x_{it_2}^T - x_{i1}^T] + [u_{it_2} - u_{it_1}] + [w_{it_2q} - w_{it_1q}],$$
$$[x_{it_2}^T - x_{it_1}^T] + [u_{it_2} - u_{it_1}] + [w_{it_2r} - w_{it_1r}] - [x_{-it_2}^T - x_{-it_1}^T] - [u_{-it_2} - u_{-it_1}] - [w_{-it_2r} - w_{-it_1r}])$$

We can simplify these with the aforementioned assumptions, plus the following:

$$Cov(\varepsilon_{i1}, x_{i2}^T) = Cov(\varepsilon_{i2}, x_{j2}^T) = 0$$
$$Cov(\varepsilon_{i1}, u_{i2}) = Cov(\varepsilon_{i1}, w_{i2}) = 0$$

Simplified, the numerator and denominator become:

$$Cov(y_{it_2} - y_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = 2\left[\beta_T Var(x_{it}^T) + \beta_u Var(u_{it}) + Cov(\varepsilon_{it}, x_{it}^T)\right]$$
$$Cov(x_{it_2} - x_{it_1}, [x_{it_2} - x_{it_1}] - [x_{-it_2} - x_{-it_1}]) = 2\left[Var(x_{it}^T) + Var(u_{it})\right]$$

We take the ratio of the two, to get:

$$(1-\xi)\beta_T + \xi\beta_u = \frac{Cov(y_{i2} - y_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}{Cov(x_{i2q} - x_{i1q}, [x_{i2r} - x_{i1r}] - [x_{-i2r} - x_{-i1r}])} + \frac{Cov(\varepsilon_{it}, x_{it}^T)}{Var(x_{it}^T) + Var(u_{it})}$$

Where:

$$\xi \equiv \frac{Var(u_{it})}{[Var(x_{it}^T) + Var(u_{it})]}$$

As before, if the variance of u_{it} is small relative to the variance of x_{it}^T, then $(1-\xi)\beta_T + \xi\beta_u$ is close to β_T.

We can decompose the moment ratio for $(1-\xi)\beta_T + \xi\beta_u$ into the product of a moment ratio and a "correction factor":

$$\begin{aligned}(1-\xi)\beta_T + \xi\beta_u &= \frac{Cov(y_{i2} - y_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}{Cov(x_{i2q} - x_{i1q}, [x_{i2r} - x_{i1r}] - [x_{-i2r} - x_{-i1r}])} + \frac{Cov(\varepsilon_{it}, x_{it}^T)}{Var(x_{it}^T) + Var(u_{it})} \\ &= \left[\frac{Cov(x_{i2} - x_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}{Cov(x_{i2q} - x_{i1q}, [x_{i2r} - x_{i1r}] - [x_{-i2r} - x_{-i1r}])}\right] \bullet \left[\frac{Cov(y_{i2} - y_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}{Cov(x_{i2} - x_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}\right] \\ &+ \frac{Cov(\varepsilon_{it}, x_{it}^T)}{Var(x_{it}^T) + Var(u_{it})}\end{aligned}$$

The "correction factor" $\left[\frac{Cov(x_{i2} - x_{i1}, [x_{i2} - x_{i1}] - [x_{-i2} - x_{-i1}])}{Cov(x_{i2q} - x_{i1q}, [x_{i2r} - x_{i1r}] - [x_{-i2r} - x_{-i1r}])}\right]$ must only be estimated once for all expectation variables. The denominator can be found by averaging the off-diagonal elements of a cross-question covariance matrix of $Cov(x_{i2q} - x_{i1q}, [x_{i2r} - x_{i1r}] - [x_{-i2r} - x_{-i1r}])$ for all pairs of q and r (shown in Table 11).

Our estimate for the "correction factor" for β_T in this simple model is 1.38, and our estimates for $(1-\xi)\beta_T + \xi\beta_u$ can be found in Table 12. A quick inspection of this table reveals that most estimates of $(1-\xi)\beta_T + \xi\beta_u$ are neither large nor significant, a fact which will be important in showing that transitory movements in happiness have relatively little effect on economic expectations.

Effect of x_i^P with response errors

Our estimator is now:

$$\beta_P^{MOM} = \frac{Cov(y_{it_2}, x_{it_1})}{Cov(x_{it_2q}, x_{it_1r})}$$

Expanding the numerator and denominator, we have:

$$\begin{aligned}
Cov(y_{it_2}, x_{it_1} - x_{-it_1}) = Cov(&\alpha + \beta_N x_{t_2}^N + \beta_P x_i^P + \beta_T x_{it_2}^T + \beta_s s_i + \beta_u u_{it_2} + \varepsilon_{it_2}, \\
&x_i^P - x_{-it_1}^P + x_{it_1}^T - x_{-it_1}^T + (s_i + u_{it_1} + v_i + w_{it_1}) - (s_{-it_1} + u_{-it_1} + v_{-it_1} + w_{-i1})) \\
Cov(x_{it_2q}, x_{it_1r} - x_{-it_1r}) = Cov(&x_{t_2}^N + x_i^P + x_{it_2}^T + (s_i + u_{it_2} + v_{iq} + w_{it_2q}), \\
&x_i^P - x_{-it_1}^P + x_{it_1}^T - x_{it_1}^T + (s_i + u_{it_1} + v_{ir} + w_{it_1r}) - (s_{-i} + u_{-it_1} + v_{-ir} + w_{-it_1r}))
\end{aligned}$$

With the orthogonality assumptions already listed above, these simplify to:

$$Cov(y_{i2}, x_{i1} - x_{-i1}) = \beta_P Var(x_i^P) + \beta_s Var(s_i)$$

$$Cov(x_{i2q}, x_{i1r} - x_{-i1r}) = Var(x_i^P) + Var(s_i)$$

Dividing, we get:

$$(1-\theta)\beta_P + \theta\beta_s = \frac{Cov(y_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2q}, x_{i1r} - x_{-i1r})}$$

Where:

$$\theta \equiv \frac{Var(s_i)}{[Var(x_i^P) + Var(s_i)]}$$

As previously stated, if the variance of s_i is small relative to the variance of x_i^P - if the response error matters less than the true emotional process driving the response - then $(1-\theta)\beta_P + \theta\beta_s$ is close to β_P.

Conceptually, this moment ratio "cleans out" the effects of the transient components of happiness by instrumenting for today's happiness with happiness at a different date[2].

As before, we can decompose the moment ratio for $(1-\theta)\beta_P + \theta\beta_s$ into the product of a moment ratio and a "correction factor":

$$(1-\theta)\beta_P + \theta\beta_s = \frac{Cov(y_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2q}, x_{i1r} - x_{-i1r})} = \frac{Cov(x_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2q}, x_{i1r} - x_{-i1r})} \frac{Cov(y_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2}, x_{i1} - x_{-i1})}$$

In order to test that $(1-\theta)\beta_P + \theta\beta_s$ is significantly nonzero, we must only test the significance of the second term in this product, $\frac{Cov(y_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2}, x_{i1} - x_{-i1})}$ [3]. Similarly, the "correction factor" $\frac{Cov(x_{i2}, x_{i1} - x_{-i1})}{Cov(x_{i2q}, x_{i1r} - x_{-i1r})}$ must only be estimated once, which will be useful when comparing β_P and β_T.

Our estimate for the "correction factor" for β_P in this simple model is 1.07, and our estimates for $(1-\theta)\beta_P + \theta\beta_s$ can be found in Table 12. A glance at this table shows that most estimates of $(1-\theta)\beta_P + \theta\beta_s$ are significant (with the exception of estimates for price-related expectation variables), and the point estimates are generally in the 0.1-0.3 range.

Proof that estimated R^2 is an upper bound on the true value

As shown above:

$$\frac{1}{2} Cov(\Delta x_{it}, \Delta x_{it} - \Delta x_{-it}) = Var(x_{it}^T) + Var(u_{it})$$

Our R^2 measure is given by:

$$R^2{}_T = CF_T * \beta_T^{FDIV} * \frac{1}{2} Cov(\Delta x_{it}, \Delta x_{it} - \Delta x_{-it}) = CF_T * \beta_T^{FDIV} \left(Var(x_{it}^T) + Var(u_{it}) \right)$$

Rearranging the expression for β_T^{FDIV} defined above, we have:

---

[2] As a robustness check, we also estimated $\frac{Cov(y_{i1}, x_{i2} - x_{-i2})}{Cov(x_{i1q}, x_{i2r} - x_{-i2r})}$ for each dependent variable; in theory, this should yield the same result.

[3] Confidence intervals for $(1-\theta)\beta_P + \theta\beta_s$, though, must be estimated either using the original moment ratio, or by the delta method.

$$\beta_T^{FDIV} = \frac{1}{CF_T}\left[\frac{Var(x_{it}^T)}{[Var(x_{it}^T)+Var(u_{it})]}\beta_T + \frac{Var(u_{it})}{[Var(x_{it}^T)+Var(u_{it})]}\beta_u\right] + bias$$

Where the bias term is known to be positive.

Plugging this into the previous equation gives us:

$$R^2{}_T = \beta_T Var(x_{it}^T) + \beta_u Var(u_{it}) + bias$$

Since the second and third terms are known to be positive, and using our point estimate for the correction factor, we know that:

$$R^2{}_T \geq \beta_T Var(x_{it}^T)$$

Group Effects Model

With group effects, our happiness measurement model becomes:

$$x_{itq} = x_t^N + x_i^P + x_{it}^T + \gamma_i x_t^G + \gamma_i \phi_G + s_i + u_{it} + v_{iq} + w_{itq}$$

Here, γ_i is a mean-zero discrete group affiliation variable. The variable might represent political affiliation, gender, stockholders vs. nonstockholders, black vs. nonblack, age>60 vs. age<60, etc. For the purposes of exposition, let us assume that the group in question is political preference; γ_i will take integer values ranging from -2 ("strong Democrat") to 2 ("strong Republican")[4]. x_t^G indicates the size of the group happiness effect; a large value of x_t^G indicates that Republicans are relatively happy and Democrats relatively unhappy at time t, etc.

We assume that γ_i and x_t^G are both uncorrelated with all other terms in the happiness measurement model.

Our model of expectations becomes:

$$y_{it} = \alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_G \gamma_i x_t^G + \beta_\phi \gamma_i \phi_G + \beta_s s_i + \beta_u u_{it} + \varepsilon_{it}$$

[4] The political preference variable represents an individual's distance from the center (mean) of the Democrat-Republican political spectrum; hence, γ_i is taken to be mean zero. A second assumption is that this variable does not change over any 6-month period; though the center may move around in half a year's time, people's distance from the center is assumed to take longer to shift.

The constant ϕ_G is the permanent group differential in happiness; if Republicans are generally happier than Democrats, ϕ_G will be positive.

Using this model, our method-of-moment estimators from the previous section contain some additional terms:

$$\beta_N^{MOM} \frac{Cov(y_{it}, x_{it})}{Cov(x_{it}, x_{-it})} = \beta_N + \frac{Cov(\varepsilon_{it}, x_t^N)}{Var(x_t^N)}$$

$$\beta_T^{MOM} \frac{Cov(\Delta y_{it}, \Delta x_{it})}{Cov(\Delta x_{itq}, \Delta x_{itr})} = \beta_T \left(\frac{Var(x_{it}^T)}{\xi_T}\right) + \beta_u \left(\frac{Var(u_{it})}{\xi_T}\right) + \beta_G \left(\frac{Var(x_t^G)}{\xi_T}\right) + \frac{Cov(\varepsilon_{it}, x_{it}^T)}{Var(x_{it}^T) + Var(u_{it}) + Var(x_t^G)}$$
$$\xi_T \equiv Var(x_{it}^T) + Var(u_{it}) + Var(x_t^G)$$

$$\beta_P^{MOM} \frac{Cov(y_{it_2}, x_{it_1})}{Cov(x_{it_2 q}, x_{it_1 r})} = \beta_p \left(\frac{Var(x_i^P)}{\xi_P}\right) + \beta_s \left(\frac{Var(s_i)}{\xi_P}\right) + \beta_\phi \left(\frac{\phi_G{}^2}{\xi_P}\right),$$

$$\xi_P \equiv Var(x_i^P) + Var(s_i) + \phi_G{}^2$$

Proofs of these relationships follow.

Effect of x_t^N with group effects

Expanding the numerator and denominator of the moment ratio, we have:

$$Cov(y_{it}, x_{-it}) = Cov(\alpha + \beta_N x_t^N + \beta_P x_i^P + \beta_T x_{it}^T + \beta_G \gamma_i x_t^G + \beta_\phi \gamma_i \phi_G + \beta_s s_i + \beta_u u_{it} + \varepsilon_{it},$$
$$x_t^N + x_{-i}^P + x_{-it}^T + \gamma_{-i} x_t^G + \gamma_{-i}\phi_G + s_{-i} + u_{-it} + v_{-i} + w_{-it})$$

$$Cov(y_{it}, x_{-it}) = Cov(x_t^N + x_i^P + x_{it}^T + \gamma_i x_t^G + \gamma_i \phi_G + s_i + u_{it} + v_i + w_{it},$$
$$x_t^N + x_{-i}^P + x_{-it}^T + \gamma_{-i} x_t^G + \gamma_{-i}\phi_G + s_{-i} + u_{-it} + v_{-i} + w_{-it})$$

In addition to the conditions listed in the previous section, we use the orthogonality conditions:

$$Cov(\gamma_i x_t^G, x_t^N) = Cov(\gamma_i x_t^G, x_j^P) = Cov(\gamma_i x_t^G, x_{jt}^T) = 0$$
$$Cov(\gamma_i x_t^G, s_j) = Cov(\gamma_i x_t^G, u_{jt}) = Cov(\gamma_i x_t^G, v_j) = Cov(\gamma_i x_t^G, w_{jt}) = 0$$
$$Cov(\gamma_i, x_t^N) = Cov(\gamma_i, x_j^P) = Cov(\gamma_i, x_{jt}^T) = 0$$
$$Cov(\gamma_i, s_j) = Cov(\gamma_i, u_{jt}) = Cov(\gamma_i, v_j) = Cov(\gamma_i, w_{jt}) = 0$$

Also, using the law of total expectations, the independence of x_t^G and γ_i, and the assumption of iid γ_i, we can write:

$$Cov(\gamma_i x_t^G, \gamma_j x_t^G) = E\left(x_t^G\right)^2 E\left[\gamma_i \gamma_j \mid x_t^G\right] = E\left(x_t^G\right)^2 E\left[\gamma_i \gamma_j\right] = 0$$

$$Cov(\gamma_i x_t^G, \gamma_j \phi_G) = E\left(x_t^G \phi_G\right) E\left[\gamma_i \gamma_j \mid x_t^G\right] = E\left(x_t^G \phi_G\right) E\left[\gamma_i \gamma_j\right] = 0$$

This leaves us with:

$$Cov(y_{it}, x_{-it}) = \beta_N Var(x_t^N) + Cov(\varepsilon_{it}, x_t^N)$$

$$Cov(x_{it}, x_{-it}) = Var(x_t^N)$$

as before. Dividing yields the result listed above. The presence of group effects does not change our estimation for the effect of national happiness.

Effect of x_{it}^T with group effects

Expanding the numerator and denominator of the moment ratio in the estimator, we have:

$$\begin{aligned} &Cov(y_{it_2} - y_{it_1}, x_{it_2} - x_{-it_2} - x_{it_1} + x_{-it_1}) = Cov(\beta_N x_{t_2}^N + \beta_T x_{it_2}^T + \beta_G \gamma_i x_{t_2}^G + \beta_u u_{it_2} + \varepsilon_{it_2} \\ &-\beta_N x_{t_1}^N - \beta_T x_{it_1}^T - \beta_G \gamma_i x_{t_1}^G - \beta_u u_{it_1} - \varepsilon_{it_1}, x_{it_2}^T + \gamma_i x_{t_2}^G + u_{it_2} + w_{it_2} - x_{-it_2}^T - \gamma_{-i} x_{t_2}^G - u_{-it_2} - w_{-it_2} \\ &-x_{it_1}^T - \gamma_i x_{t_1}^G - u_{it_1} - w_{it_1} + x_{-it_1}^T + \gamma_{-i} x_{t_1}^G + u_{-it_1} + w_{-it_1}) \end{aligned}$$

$$\begin{aligned} &Cov(x_{it_2q} - x_{it_1q}, x_{it_2r} - x_{-it_2r} - x_{it_1r} + x_{-it_1r}) = Cov(x_{it_2}^T + \gamma_i x_{t_2}^G + u_{it_2} + w_{it_2r} - x_{it_1}^T - \gamma_i x_{t_1}^G - u_{it_1} - w_{it_1r}, \\ &x_{it_2}^T + \gamma_i x_{t_2}^G + u_{it_2} + w_{it_2r} - x_{-it_2}^T - \gamma_{-i} x_{t_2}^G - u_{-it_2} - w_{-it_2r} - x_{it_1}^T - \gamma_i x_{t_1}^G - u_{it_1} - w_{it_1r} + x_{-it_1}^T + \gamma_{-i} x_{t_1}^G + u_{-it_1} + w_{-it_1r}) \end{aligned}$$

We need the additional orthogonality conditions:

$$\begin{aligned} &Cov(\gamma_i x_t^G, x_i^P) = Cov(\gamma_i x_t^G, x_{it}^T) = 0 \\ &Cov(\gamma_i x_t^G, s_i) = Cov(\gamma_i x_t^G, u_{it}) = Cov(\gamma_i x_t^G, v_i) = Cov(\gamma_i x_t^G, w_{it}) = 0 \\ &Cov(\gamma_i, x_i^P) = Cov(\gamma_i, x_{it}^T) = 0 \\ &Cov(\gamma_i, s_i) = Cov(\gamma_i, u_{it}) = Cov(\gamma_i, v_i) = Cov(\gamma_i, w_{it}) = 0 \end{aligned}$$

and the following application of the Law of Total Expectations:

$$Cov(\gamma_i x_t^G, \gamma_i x_t^G) = E\left(x_t^G\right)^2 E\left[\gamma_i^2 \mid x_t^G\right] = E\left(x_t^G\right)^2 E\left[\gamma_i^2\right] = Var(x_t^G)$$

The numerator and denominator then become:

$$Cov(y_{it_2} - y_{it_1}, x_{it_2} - x_{-it_2} - x_{it_1} + x_{-it_1}) = \beta_T Var(x_{it}^T) + \beta_u Var(u_{it}) + \beta_G Var(x_t^G) + Cov(\varepsilon_{it}, x_{it}^T)$$

$$Cov(x_{it_2q} - x_{it_1q}, x_{it_2r} - x_{-it_2r} - x_{it_1r} + x_{-it_1r}) = Var(x_{it}^T) + Var(u_{it}) + Var(x_t^G)$$

Dividing gives us the result listed above.

Effect of x_i^P with group effects

Expanding the numerator and denominator of the moment ratio in the estimator, we have:

$$\begin{aligned} Cov(y_{it_2}, x_{it_1} - x_{-it_1}) = Cov(&\alpha + \beta_N x_{t_2}^N + \beta_P x_i^P + \beta_T x_{it_2}^T + \beta_G \gamma_i x_{t_2}^G + \beta_\phi \gamma_i \phi_G + \beta_s s_i + \beta_u u_{it_2} + \varepsilon_{it_2}, \\ &x_i^P - x_{-i}^P + x_{it_1}^T - x_{-it_1}^T + \gamma_i x_{t_1}^G - \gamma_{-i} x_{t_1}^G + \gamma_i \phi_G - \gamma_{-i}\phi_G + (s_i + u_{it_1} + v_i + w_{it_1}) \\ &-(s_{-it_1} + u_{-it_1} + v_{-it_1} + w_{-it_1})) \end{aligned}$$

$$\begin{aligned} Cov(x_{it_2q}, x_{it_1r} - x_{-it_1r}) = Cov(&x_t^N + x_i^P + x_{it_2}^T + \gamma_i x_{t_2}^G + \gamma_i \phi_G + s_i + u_{it_2} + v_{iq} + w_{it_2q}, \\ &x_i^P - x_{-i}^P + x_{it_1}^T - x_{-it_1}^T + \gamma_i x_{t_1}^G - \gamma_{-i} x_{t_1}^G + \gamma_i \phi_G - \gamma_{-i}\phi_G + (s_i + u_{it_1} + v_{ir} + w_{it_1r}) \\ &-(s_{-it_1} + u_{-it_1} + v_{-it_1r} + w_{-it_1r})) \end{aligned}$$

We use the following application of the Law of Total Expectations:

$$Cov(\gamma_i x_t^G, \gamma_j \phi_G) = E\left(x_t^G \phi_G\right) E\left[\gamma_i \gamma_j \mid x_t^G\right] = E\left(x_t^G \phi_G\right) E\left[\gamma_i \gamma_j\right] = 0$$

$$Cov(\gamma_i x_{t_2}^G, \gamma_j x_{t_1}^G) = E\left(x_{t_2}^G x_{t_1}^G\right) E\left[\gamma_i \gamma_j \mid x_{t_2}^G, x_{t_1}^G\right] = E\left(x_{t_2}^G x_{t_1}^G\right) E\left[\gamma_i \gamma_j\right] = 0$$

This leaves us with:

$$Cov(y_{it_2}, x_{it_1} - x_{-it_1}) = \beta_P Var(x_i^P) + \beta_s Var(s_i) + \beta_\phi \phi_G^2$$
$$Cov(x_{it_2q}, x_{it_1r} - x_{-it_1r}) = Var(x_i^P) + Var(s_i) + \phi_G^2$$

The ratio of these two then yields the result given above.

Correction factor forms

Rewriting the estimators for in "correction factor form as above yields:

$$\beta_T\left(\frac{\mathrm{var}(x_{it}^T)}{\xi_T}\right)+\beta_u\left(\frac{\mathrm{var}(u_{it})}{\xi_T}\right)+\beta_G\left(\frac{\mathrm{var}(x_t^G)}{\xi_T}\right)+\frac{Cov(\varepsilon_{it},x_{it}^T)}{Var(x_{it}^T)+Var(u_{it})+Var(x_t^G)}=$$

$$\left[\frac{Cov(x_{i2}-x_{i1},[x_{i2}-x_{i1}]-[x_{-i2}-x_{-i1}])}{Cov(x_{i2q}-x_{i1q},[x_{i2r}-x_{i1r}]-[x_{-i2r}-x_{-i1r}])}\right]\bullet\left[\frac{Cov(y_{i2}-y_{i1},[x_{i2}-x_{i1}]-[x_{-i2}-x_{-i1}])}{Cov(x_{i2}-x_{i1},[x_{i2}-x_{i1}]-[x_{-i2}-x_{-i1}])}\right]$$

$$\beta_p\left(\frac{\mathrm{var}(x_i^P)}{\xi_P}\right)+\beta_s\left(\frac{\mathrm{var}(s_i)}{\xi_P}\right)+\beta_\phi\left(\frac{{\phi_G}^2}{\xi_P}\right)=\frac{Cov(x_{i2},x_{i1}-x_{-i1})}{Cov(x_{i2q},x_{i1r}-x_{-i1r})}\frac{Cov(y_{i2},x_{i1}-x_{-i1})}{Cov(x_{i2},x_{i1}-x_{-i1})}$$

These can be computed as in the previous section.

First-stage estimation of ϕ_G and $Var(x_t^G)$

Note that while the expression for β_N is the same as in the simple model, the expressions for β_P and β_T contain additional terms. These terms can be consistently estimated from our data on self-reported happiness and political preference. To do this, we create a measurement model relating self-reported political preference, f_{it}, to the unobserved true political preference γ_i:

$$f_{it}=A\gamma_i+\mu_t+\upsilon_{it}$$

Where A is a constant, μ_t is the time-varying political "center", and υ_{it} is a classical measurement error. Correspondingly, define f_{it} and π_{it} as:

$$f_{it}\equiv f_{it}-\frac{1}{n_t-1}\sum_{j\neq i}f_{jt}=A\left(\gamma_i-\frac{1}{n_t-1}\sum_{j\neq i}\gamma_j\right)+\upsilon_{it}-\frac{1}{n_t-1}\sum_{j\neq i}\upsilon_{jt}$$

$$\pi_{it}\equiv f_{it}x_{it}$$

We can then write method-of-moment expressions for $\mathrm{var}(x_t^G)$ and ${\phi_G}^2$ in terms of this observable:

$$\phi_G=\frac{Var(f_{it})}{\sqrt{Cov(f_{it_1},f_{it_2})}}*\frac{Cov(x_{it},f_{it})}{Var(f_{it})}$$

$$Var(x_t^G)=\frac{Cov(\pi_{it},\pi_{-it})-Cov(f_{it},f_{-it})Cov(x_{it},x_{-it})}{Cov(f_{i1},f_{i2})}-\left(\frac{Cov(f_{it},x_{it})}{Var(f_{it})}*\frac{Var(f_{it})}{\sqrt{Cov(f_{i2},f_{i1})}}\right)^2$$

Proof: ϕ_G

Observe that:

$$E\,f_{it}x_{it} = E\left[\left(A\left(\gamma_i - \frac{1}{n_t-1}\sum_{j\neq i}\gamma_j\right) + \upsilon_{it} - \frac{1}{n_t-1}\sum_{j\neq i}\upsilon_{jt}\right)\left(x_t^N + x_i^P + x_{it}^T + \gamma_i x_t^G + \gamma_i\phi_G + s_i + u_{it} + v_i + w_{it}\right)\right]$$

Using the orthogonality conditions on γ_i and υ_{it}, this reduces to:

$$E\,f_{it}x_{it} = AE\left[\left(\gamma_i - \frac{1}{n_t-1}\sum_{j\neq i}\gamma_j\right)\left(\gamma_i x_t^G + \gamma_i\phi_G\right)\right]$$

Now apply the law of total expectations:

$$E[\gamma_i^2 x_t^G] = E\gamma_i^2 E[x_t^G \mid \gamma_i] = E\gamma_i^2 E[x_t^G] = 0$$

And use the fact that:

$$E[\gamma_i\gamma_j] = 0$$

To get:

$$E\,f_{it}x_{it} = A\phi_G$$

Now observe that:

$$E\,f_{it_2}f_{it_1} = E\left[\left(A\left(\gamma_i - \frac{1}{n_2-1}\sum_{j\neq i}\gamma_j\right) + \upsilon_{it} - \frac{1}{n_2-1}\sum_{j\neq i}\upsilon_{j1}\right)\left(A\left(\gamma_i - \frac{1}{n_1-1}\sum_{k\neq i}\gamma_k\right) + \upsilon_{i1} - \frac{1}{n_1-1}\sum_{k\neq i}\upsilon_{kt}\right)\right]$$

Also observe that $E\left[\sum_{j\neq i}\gamma_j\sum_{k\neq i}\gamma_k\right] = 0$ iff no two individuals are interviewed on the same day. For this estimation, we restrict our dataset such that no such same-day pairs of interviews exist (this results in the throwing away of about 5% of our observations), and hence can safely set this expectation to 0. Thus, our total expression reduces to:

$$E\,f_{it_2}f_{it_1} = A^2$$

Combining this with the result in (), we get:

$$\phi_G = \frac{Cov(f_{it}, x_{it})}{\sqrt{Cov(f_{it_2}, f_{it_1})}} = \frac{Cov(f_{it}, x_{it})}{Var(f_{it})} * \frac{Var(f_{it})}{\sqrt{Cov(f_{it_2}, f_{it_1})}}$$

This is our desired result.

Proof: $Var(x_t^G)$

Observe that:

$$E\left[f_{it} x_{it} f_{jt} x_{jt} \right] = E\left[\begin{array}{l} \left(A^2 \gamma_i \gamma_j + \mu_t^{\ 2} + \upsilon_{it}\upsilon_{jt} + A\mu_t(\gamma_i + \gamma_j) + A(\gamma_i \upsilon_{jt} + \gamma_j \upsilon_{it}) + \mu_t(\upsilon_{it} + \upsilon_{jt}) \right) \\ * \left(x_{it} x_{jt} + \gamma_i \gamma_j (x_t^{G2} + \phi_G^{\ 2}) + \gamma_i x_{jt} + \gamma_j x_{it} \right) \end{array} \right]$$

$$x_{it} \equiv x_t^N + x_i^P + x_{it}^T + s_i + u_{it}$$

We use the following conditions to eliminate terms from the expectation:

$$E\left[\gamma_i \gamma_j x_{it} x_{jt} \right] = E\left[\gamma_i^{\ 2} \gamma_j x_{jt} \right] = 0$$

$$E\left[\mu_t^{\ 2} \gamma_i \gamma_j (x_t^{G2} + \phi_G^{\ 2}) \right] = E\left[\mu_t^{\ 2} \gamma_i x_{jt} \right] = 0$$

$$E\left[\mu_t \gamma_i x_{it} x_{jt} \right] = E\left[\mu_t \gamma_i^{\ 2} \gamma_j (x_t^{G2} + \phi_G^{\ 2}) \right] = E\left[\mu_t \gamma_i^{\ 2} x_{jt} \right] = 0$$

$$E\left[\upsilon_{jt} \gamma_i x_{it} x_{jt} \right] = E\left[\upsilon_{jt} \gamma_i^{\ 2} \gamma_j (x_t^{G2} + \phi_G^{\ 2}) \right] = E\left[\upsilon_{jt} \gamma_i^{\ 2} x_{jt} \right] = 0$$

$$E\left[\mu_t \upsilon_{it} x_{it} x_{jt} \right] = E\left[\mu_t \upsilon_{it} \gamma_i \gamma_j (x_t^{G2} + \phi_G^{\ 2}) \right] = E\left[\mu_t \upsilon_{it} \gamma_i x_{jt} \right] = 0$$

These conditions are obtained using our orthogonality conditions, as well as the fact that:

$$E\left[\gamma_i \right] = E\left[\gamma_i \gamma_j \right] = E\left[\gamma_i^{\ 2} \gamma_j \right] = 0$$

$$E \gamma_i^{\ 2} \gamma_j^{\ 2} = 1$$

$$E\left[x_{it} \right] = 0$$

This gives us:

$$E\left[\pi_{it} \pi_{-it} \right] = E\left[A^2 \gamma_i^{\ 2} \gamma_j^{\ 2} (x_t^{G2} + \phi_G^{\ 2}) + \mu_t^{\ 2} x_t^{N2} \right] = A^2 \left(Var(x_t^G) + \phi_G^{\ 2} \right) + Var(\mu_t) Var(x_t^N)$$

We now use:

$$E\left[f_{it}f_{jt}\right]=E\left[\left(A^2\gamma_i\gamma_j+\mu_t^{\ 2}+\upsilon_{it}\upsilon_{jt}+A\mu_t(\gamma_i+\gamma_j)+A(\gamma_i\upsilon_{jt}+\gamma_j\upsilon_{it})+\mu_t(\upsilon_{it}+\upsilon_{jt})\right)\right]=Var(\mu_t)$$

And:

$$E\left[x_{it}x_{jt}\right]=E\left[x_{it}x_{jt}+\gamma_i\gamma_j(x_t^{G2}+\phi_G^{\ 2})+\gamma_i x_{jt}+\gamma_j x_{it}\right]=Var(x_t^N)$$

Rearranging our expression and substituting in for $\phi_G^{\ 2}$, we get:

$$Var(x_t^G)=\frac{Cov(\pi_{it},\pi_{-it})-Cov(f_{it},f_{-it})Cov(x_{it},x_{-it})}{Cov(f_{it_1},f_{it_2})}-\left(\frac{Cov(f_{it},x_{it})}{Var(f_{it})}*\frac{Var(f_{it})}{\sqrt{Cov(f_{it_2},f_{it_1})}}\right)^2$$

This is the result we wanted.

With this machinery, we can obtain point estimates for the "correction terms" that must be added to the estimators for the coefficients in the simple model to account for the presence of any single group-specific effect. Note that this model cannot easily be extended to account for the simultaneous existence of multiple group effects, since membership in various groups will generally be correlated. However, our aim is to show that the "correction terms" in the estimators for the effect of happiness on expectations are small for any given group; thus, the fact that we cannot include all groups at once will not alter our basic result.

Estimates for these quantities for various groups can be found in Table 13. The correction terms are small compared to the variances of the happiness components.

"Emotion Z"

We hypothesized that another emotion, and not happiness, drives affective animal spirits. We postulated that this emotion, called "Emotion Z," is imperfectly correlated with happiness:

$$x_{it}^T=\rho z_{it}+\varsigma_{it}$$

$$y_{it}=\alpha+\beta_Z z_{it}+\varepsilon_{it}$$

The parameter ρ is assumed to be between 0 and 1.
Differencing, we have:

$$\Delta x_{it}=\rho\Delta z_{it}+\Delta\varsigma_{it}$$

$$\Delta y_{it}=\beta_Z\Delta z_{it}+\Delta\varepsilon_{it}$$

Our first-difference estimator is still:

$$\beta_{FD} = \frac{Cov(\Delta y_{it}, \Delta x_{it})}{Var(\Delta x_{it})}$$

Evaluating the top and bottom of this expression, and dividing, gives us:

$$Cov(\Delta y_{it}, \Delta x_{it}) = 2\beta_Z \rho Var(z_{it}) + 2\left(\rho Cov(\varepsilon_{it}, z_{it}) + Cov(\varepsilon_{it}, \varsigma_{it})\right)$$

$$Var(\Delta x_{it}) = 2\left(\rho^2 Var(z_{it}) + Var(\varsigma_{it})\right)$$

$$\beta_T^{FD} = \beta_Z \frac{\rho Var(z_{it})}{\rho^2 Var(z_{it}) + Var(\varsigma_{it})} + \frac{\rho Cov(\varepsilon_{it}, z_{it}) + Cov(\varepsilon_{it}, \varsigma_{it})}{\rho^2 Var(z_{it}) + Var(\varsigma_{it})}$$

Now we use:

$$R^2{}_T = \beta_T^{FD} * \frac{1}{2} Var(\Delta x_{it})$$

Substituting, we have:

$$R^2{}_T = \beta_Z \rho Var\left(z_{it}\right) + \rho Cov\left(\varepsilon_{it}, z_{it}\right) + Cov\left(\varepsilon_{it}, \varsigma_{it}\right)$$

This is the result we wanted.

Table 1: Variable Definitions and Text of Survey Questions

	Expectation Questions	Mean (0-100)	Std. Dev.
pago	"Would you say that you (and your family living there) are better off or worse off financially than a year ago?"	49.1	43.0
pexp	"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?"	57.4	32.8
bus12	"Do you think that during the next 12 months we'll have good times financially, or bad times, or what?"	36.9	46.8
bus5	"Which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment and depression, or what?"	42.5	44.6
dur	"Generally speaking, do you think now is a good time or a bad time for people to buy major household items?"	70.0	45.1
v228	"Compared with 5 years ago, do you think the chances that you (and your husband/wife) will have a comfortable retirement have gone up, gone down, or remained about the same?"	42.9	36.2
hom	"Generally speaking, do you think now is a good time or a bad time to buy a house?"	66.4	47.0
car	"Do you think the next 12 months will be a good time or a bad time to buy a vehicle?"	62.6	47.9
homeval	"Do you think the present value of your home – I mean what it would bring you if you sold it today – has increased compared with a year ago, decreased, or stayed about the same?"	57.2	40.4
bago	"Would you say that at the present time business conditions are better or worse than they were a year ago?"	29.5	43.1
bexp	"A year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?"	46.9	34.4
govt	"As to the economic policy of the government – I mean steps taken to fight inflation or unemployment – would you say the government is doing a good job, only fair, or a poor job?"	38.5	34.7
unemp	"How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?"	68.2	32.5
ratex	"What do you think will happen to interest rates for borrowing money over the next 12 months – will they go up, stay the same, or go down?"	68.3	38.0
gaspx1	"Do you think that the price of gasoline will go up during the next 5 years, go down, or stay about the same?"	83.5	30.6
pas1px1	"Do you think that the price of gasoline will go up during the next 12 months, go down, or stay about the same?"	77.6	31.0
px1q1	"Do you think that during the next 12 months, prices will go up, or go down, or stay where they are now?"	87.0	25.7

px5q1	“Do you think prices will be higher, about the same, or lower 5 to 10 years from now?”	91.8	23.2
inexq1	“During the next 12 months, do you expect your (family) income to be higher or lower than during the past year?”	70.9	38.2

Happiness Questions			
h1	"Much of the time during the past week, you were happy. Would you say yes or no?"		
h2	Much of the time during the past week, you felt depressed. Would you say yes or no?		
h3	Much of the time during the past week, you enjoyed life. Would you say yes or no?		
h4	Much of the time during the past week, you felt sad. Would you say yes or no?		

Table 2: Descriptive Statistics of Expectation Variables

Variable	Mean (0-100)	Std. Dev.	Monthly Autocorrelation
pago	49.11055	42.9894	0.9239844
pexp	57.40129	32.82136	0.7336556
bus12	36.86633	46.8332	0.883168
bus5	42.46692	44.59298	0.7417708
dur	69.96931	45.09582	0.9414125
v228	42.89257	36.18702	0.9537151
hom	66.38178	47.01845	0.5820837
car	62.62003	47.85798	0.7537006
homeval	57.18434	40.38231	1.005878
bago	29.47323	43.08096	0.95177
bexp	46.94204	34.44437	0.6778381
govt	38.48794	34.65645	0.8838241
unemp	68.16484	32.4876	0.8819922
ratex	68.32524	37.98214	0.9451561
gaspx1	83.54851	30.58962	0.6798456
gas1px1	77.63453	31.00777	0.5259262
px1q1	87.00653	25.71077	0.9428394
px5q1	91.81461	23.22353	0.8203673
inexq1	70.85519	38.24415	0.8650071

Table 3: Happiness Question Covariances

	h1	h2	h3	h4
h1				
h2	0.5861			
h3	0.5633	0.4625		
h4	0.5269	0.6092	0.416	

Table 4: Correlation of Average National Happiness with Bus12(-i) and Bus12(+i)

i (months)	lag	lead
0	0.0879	0.0879
1	0.021	0.0465
2	-0.0219	-0.0397
3	0.0693	-0.0332
4	0.0226	-0.1847
5	0.0615	-0.1244
6	0.1487	-0.0944

Table 5: Autocorrelations of aggregate variables

Lag (months)	Autocorrelation of Happiness	Autocorrelation of Bus12
1	-0.073	0.852
2	0.138	0.747
3	0.075	0.701
4	-0.128	0.642
5	-0.072	0.563
6	0.161	0.513

Table 6: VAR of Bus12 and Happiness

		LHS Variable	
RHS Variable	Lag (months)	Bus12	Happiness
Bus12			
	1	0.912***	0.161**
	2	-0.114	-0.368***
	3	0.149	0.326***
	4	0.045	-0.177*
	5	-0.095	0.0784
Happiness			
	1	0.016	0.199
	2	-0.177	0.050
	3	-0.092	0.119
	4	-0.552**	-0.140
	5	0.279	0.044

Note: *** = significant at the 1% level; ** = significant at the 5% level; * = significant at the 10% level

Table 7: OLS of happiness on expectations

Variable	Effect of Expectations
pago	0.165
pexp	0.066
bus12	0.111
bus5	0.146
dur	0.081
v228	0.123
hom	0.086
car	0.084
homeval	0.038
bago	0.082
bexp	0.080
govt	0.110
unemp	0.067
ratex	0.029
gaspx1	0.007
gas1px1	0.019
px1q1	0.024
px5q1	0.044
inexq1	0.094

Note: Regressors not significant at the 5% level are listed in italics.

Table 7: Estimated Variances of Happiness Components

Component	Estimated Variance
National Happiness	0.005774
Transitory Personal Happiness	0.571992132
Persistent Personal Happiness	0.427421

Note: Total happiness is normalized to have a variance of 1.

Table 9: Effect of national happiness

Variable	Effect of National Happiness	P-Value	R^2_N
pago	*0.015*	0.956	0.000
pexp	*0.035*	0.904	0.000
bus12	0.632	0.037	0.004
bus5	*0.295*	0.273	0.002
dur	*0.403*	0.211	0.002
v228	*0.469*	0.114	0.003
hom	*-0.230*	0.472	-0.001
car	*-0.377*	0.243	-0.002
homeval	*0.467*	0.116	0.003
bago	*0.532*	0.094	0.003
bexp	*0.280*	0.343	0.002
govt	*-0.315*	0.316	-0.002
unemp	*0.577*	0.065	0.003
ratex	*-0.548*	0.089	-0.003
gaspx1	*0.558*	0.098	0.003
gas1px1	*0.410*	0.270	0.002
px1q1	1.120	0.012	0.006
px5q1	*0.456*	0.132	0.003
inexq1	0.684	0.038	0.004

Note: Statistically insignificant effects are given in *italics.*

Table 10: Effects of personal happiness

Variable	Transitory Effect	Persistent Effect	R^2_T
pago	0.051	0.355	0.029
pexp	0.028	0.115	0.016
bus12	0.053	0.202	0.030
bus5	0.025	0.348	0.014
dur	0.030	0.167	0.017
v228	0.048	0.210	0.028
hom	*0.003*	0.203	0.002
car	*0.011*	0.214	0.006
homeval	*0.004*	0.085	0.002
bago	0.034	0.181	0.020
bexp	0.024	0.187	0.014
govt	0.037	0.211	0.021
unemp	-0.045	-0.099	-0.026
ratex	*-0.006*	-0.060	-0.003
gaspx1	*-0.013*	*0.008*	-0.007
gas1px1	*-0.014*	*-0.024*	-0.008
px1q1	*-0.015*	-0.049	-0.009
px5q1	*0.003*	0.106	0.002
inexq1	0.051	0.153	0.029

Note: Statistically insignificant effects are given in *italics.*

Table 11a: Covariance Matrix for Transitory Personal Happiness Correction Factor

	$\Delta x_{ft,1}$	$\Delta x_{ft,2}$	$\Delta x_{ft,3}$	$\Delta x_{ft,4}$
$\Delta \hat{x}_{ft,1}$	2.25459	1.01869	0.713366	1.0043
$\Delta \hat{x}_{ft,2}$	1.02639	2.13355	0.535516	1.153
$\Delta \hat{x}_{ft,3}$	0.714007	0.529825	1.25213	0.513164
$\Delta \hat{x}_{ft,4}$	1.01096	1.1538	0.518597	2.73286

Correction Factor = Average of all off-diagonal elements = **1.38**

Table 11b: Covariance Matric For Persistent Personal Happiness Correction Factor

	$x_{f2,1}$	$x_{f2,2}$	$x_{f2,3}$	$x_{f2,4}$
$\hat{x}_{f1,1}$	0.557261	0.461986	0.347688	0.452042
$\hat{x}_{f1,2}$	0.458084	0.568069	0.300664	0.512136
$\hat{x}_{f1,3}$	0.347396	0.303477	0.304667	0.301612
$\hat{x}_{f1,4}$	0.448728	0.511628	0.298843	0.591986

Correction Factor = Average of all off-diagonal elements = **1.07**

Table 12: Effects of personal happiness (with response errors)

Variable	Transitory Effect	Persistent Effect	R^2_T
pago	0.070	0.380	0.040
pexp	0.039	0.123	0.022
bus12	0.073	0.216	0.042
bus5	0.034	0.373	0.019
dur	0.041	0.179	0.023
v228	0.067	0.224	0.038
hom	*0.004*	0.218	0.002
car	*0.015*	0.229	0.009
homeval	*0.005*	0.091	0.003
bago	0.047	0.194	0.027
bexp	0.033	0.201	0.019
govt	0.051	0.226	0.029
unemp	-0.062	-0.106	-0.036
ratex	*-0.008*	-0.064	-0.005
gaspx1	*-0.018*	*0.008*	-0.010
gas1px1	*-0.019*	*-0.026*	-0.011
px1q1	*-0.021*	-0.052	-0.012
px5q1	*0.004*	0.113	0.002
inexq1	0.070	0.164	0.040

Note: Statistically insignificant effects are given in *italics.*

Table 13: Group Effects

Group	Persistent group happiness	Variance of transitory group happiness
Political	0.020	0.000
Over 44	0.007	0.021
Income over $100k	0.118	0.000
Homeowner	0.114	0.044
Stockholder	0.159	0.000
College Degree	0.110	0.000
Race (White/Nonwhite)	0.057	0.070

Figure 1: Bus12 and happiness monthly averages