Abstract

Using newly licensed individual-level data from Gallup Inc., this paper examines the underlying determinants of sentiments, or shifts in expectations about economic activity without shifts in preferences, and their role in accounting for the sluggish recovery since the Great Recession. First, measures of well-being are highly pro-cyclical and these movements are primarily driven by a combination of unemployment and earnings risk. Second, well-being accounts for up to 41% of the variation in economic sentiments, whereas actual economic activity accounts for only 14%. Third, after estimating a micro-elasticity between sentiments and non-durables consumption, the decline in sentiments during the Great Recession accounts for up to 16.4% of the decline in consumption and between 2.2-8.6% of the decline in employment. These results are consistent with a new class of macroeconomic theories that embed coordination failures and informational frictions into neoclassical models.

Keywords: Business cycles, coordination failure, life satisfaction, sentiments.

JEL: E20, E21, E32

1. Introduction

The years following the 2007-2009 Great Recession mark the slowest economic recovery in the United States’ post-WWII history (Taylor, 2014). While there are many factors that explain the sluggish recovery, recent contributions have emphasized the role of depressed aggregate demand facilitated by financial frictions (Mian and Sufi, 2009, 2011, 2014; Christiano et al., 2015) and heightened policy uncertainty (Jurado et al., 2015; Shoag and Veuger, forthcoming; Baker et al., 2016; Leduc and Liu, 2016).
Incomplete information has been frequently employed as a mechanism for generating declines in aggregate demand and business cycle fluctuations; see, for example, Morris and Shin (1998) Morris and Shin (2002), Angeletos and La’O (2013), Bergemann and Morris (2013), and Benhabib et al. (2015). Central to this literature is the role of sentiments, or shifts in expectations about economic activity without shifts in preferences, in explaining aggregate fluctuations (Angeletos and La’O, 2013; Benhabib et al., 2015). Dispersion in beliefs can generate: (i) inertia in the response to aggregate shocks (Angeletos and La’O, 2010), (ii) price rigidity (Angeletos and La’O, 2009), and (iii) welfare consequences (Angeletos et al., 2016). Theoretical models of self-fulfilling business cycles have, more generally, linked beliefs about low wealth with lower consumption (Farmer, 2012), volatility in asset prices and international credit (Bacchetta et al., 2012; Perri and Quadrini, 2016; Azariadis et al., 2016), consumption and housing prices (Kaplan et al., 2016), and even the transmission of the Great Recession across countries (Bacchetta et al., 2012; Bacchetta and van Wincoop, 2016).

What is conspicuously absent from these stories is microeconomic evidence behind the formation of beliefs and their real economic effects. My theoretical starting point is based on the on the following sequencing for an individual: an exogenous macroeconomic shock generates dispersion in well-being, subsequently generating dispersion in sentiments, and finally influencing real economic outcomes

\[ \text{Shock} \rightarrow \text{Happiness} \rightarrow \text{Sentiments} \rightarrow \text{Real Outcomes} \]  

The conceptual model in “Equation 1” is based on years of experimental and empirical research from psychology that external events shape an individual’s judgment and perceptions (Schwarz and Clore, 2007). Measuring sentiments on a comprehensive scale, however, has been challenging, limiting the amount of empirical work on the underlying mechanisms in models of self-fulfilling business cycles. Using newly licensed micro-data from Gallup Inc. between 2008 and 2016, this paper provides new evidence on the microeconomic determinants of sentiments and the elasticity between consumption and sentiments.

There are two useful facts that motivate the focus on micro-level sentiments as an object for macroeconomic analysis. The first fact is that the distribution of both perceptions about the current and future state of the economy not only declined in magnitude during the 2007-2009 recession, but also grew in skewness (see Figure 1). In particular, the standard deviations of sentiments about the current and future state of the economy in 2008-2009 are 111% and 318% as large as their 2014-2015 counterparts, suggesting that dispersion in beliefs grows during economic downturns. The second fact is that higher sentiments are closely linked with higher consumption (see Figure 2). In particular, the correlation

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1See Angeletos and Lian (2016) for a survey. Strategic complementarity among the actions of agents in an economy can give rise to coordination failures (Morris and Shin, 2002; Angeletos and Pavan, 2007), including bank runs (Diamond and Dybvig, 1983), and currency speculations (Obstfeld, 1996).
between the daily perception of the state of the economy and daily real consumption expenditures on non-durable goods is 0.42 and a standard deviation rise in sentiments is associated with an additional $50 in daily consumption spending.

![Distribution of Sentiments about the State of Economy](image)

**Figure 1:** Distribution of Sentiments about the State of Economy

*Notes.* Sources: Gallup. The figure begins by computing the $z$-score of the current and future state of the economy across years. The current state of the economy is an index with four values (poor, fair, good, excellent) and the future state of the economy is an index with three values (getting worse, staying the same, getting better). The variables are made continuous by averaging across all individuals within the same metro area. The sample is restricted to metro areas with over 250 observations, and collapsing to a metro-level by year with the survey sample weights. The figure subsequently plots the distribution of these values across metro areas.

After introducing the Gallup micro-data, documenting self-reported well-being and sentiments across space and time, and validating my measure of sentiments, the first part of the paper examines the cyclicity of life satisfaction and its determinants.\(^2\),\(^3\) Using changes in logged metropolitan employment and housing prices as proxies for local productivity shocks, I find that life satisfaction is highly procyclical, consistent with past evidence that used national changes in real GDP; see, for example, di Tella et al. (2001), di Tella et al. (2003), and Wolfers (2003).\(^4\) Even after controlling for individual income,

\(^2\)The constructed measures of sentiments exhibit a striking resemblance with the measure of economic policy uncertainty developed in Baker et al. (2016). The correlation between mean (standard deviation) sentiments and their economic policy uncertainty index is 0.67 (0.43). I also validate my measure using a Google trends count index for the words “economic uncertainty”, which produces similar correlations. Despite these similarities, there are two core advantages of the new measure: first, its micro-level variation (making it more plausibly exogenous) and second, its broader representation of perceptions of economic activity (rather than uncertainty).

\(^3\)Other perceptions, such as work-place practices and city satisfaction, are statistically associated with sentiments in the cross-section, but cannot explain the business cycle features.

\(^4\)Related to the business cycle phenomenon, Oswald and Wu (2011) examine the cross-sectional dispersion of job satis-
Figure 2: Sentiments and Real Consumption Expenditures

Notes. Sources: Gallup. The figure plots the daily z-score of the current state of the economy with daily real consumption expenditures on non-durable goods averaged across 1,000 individuals at a daily frequency. Nominal consumption is deflated using the 2009 real personal consumption expenditure index.

demographic covariates and location and time fixed effects, a 1% rise in employment growth and housing prices is associated with a 1.85 and 0.26 rise in the standard deviation of life satisfaction. These results are consistent with evidence from Benhabib and Spiegel (2016) on the microeconomic association between expectations and real economic activity.

Little, however is known about the cyclical determinants of happiness. For example, while a number of emerging macroeconomic models focus on unemployment risk and its effects on consumption (Carroll, 1992; Carroll and Dunn, 1997; Crossley and Low, 2014), aggregate demand and wealth (Ravin and Sterk, 2014; Challe et al., forthcoming; Beaudry et al., forthcoming; Heathcote and Perri, 2016), and the amplification of fluctuations (Den Haan et al., 2015), there is no microeconomic evidence over the link between unemployment risk and sentiments. Using quarterly county-by-skill bracket turnover rates from the Longitudinal Employer-Household Dynamics (LEHD), I find some evidence that unemployment risk...
affects well-being. However, the effects on consumption are concentrated among lower skilled workers, which is consistent with the fact that unemployment rates are very low among those with at least a college degree. However, I find that labor income risk is a much more common worry, even among higher earners. Using data on individuals’ stated concerns, I find that a 1% rise in the state unemployment rate is associated with between a 0.05 and 0.20 standard deviation increase in worry about having enough money. These results suggest that, while unemployment risk is primarily relevant for lower income workers, earnings risk (or at least its perception) is a more salient concern even for higher income workers.

The second part of the paper focuses on explaining the cross-sectional determinants of sentiments by focusing on the contributions of self-reported well-being (i.e., indices of life satisfaction, work-place practices, and city satisfaction) and actual economic conditions (i.e., changes in logged metro employment and housing prices). Even after controlling for individual covariates and location / time fixed effects, these regressions may still produce spurious correlations. To isolate exogenous variation in individuals’ self-reported happiness, I use daily metro-level changes in maximum temperature interacted with age bins since hotter days tend to aggravate individuals, affecting their self-reported happiness (Baylis, 2015). My estimates suggest that life satisfaction accounts for at least 13%, and as much as 41%, of the variation in sentiments about current economic activity, whereas actual economic activity accounts for between 7-14%. The fact that variation in life satisfaction explains more of the variation in sentiments than actual economic activity is consistent with models of self-fulfilling fluctuations.

The third part of the paper estimates a micro-elasticity between sentiments and real economic behavior. The available macroeconomic evidence tends to rely on aggregate data and vector auto-regressions. These studies, however, have not yet produced a consensus since different methodologies generate different results (e.g., Barsky and Sims (2012) versus Beaudry and Portier (2006) and Beaudry et al. (2011)). Using measures of individual expenditures on non-durables and firm hiring/firing from Gallup, I estimate a micro-elasticity between sentiments and real economic activity. Unlike Mian et al. (2015) who find a null association between geographic-level consumption and sentiments, I find that a standard deviation rise in sentiments is associated with 0.008% rise in daily consumption (2.92% annual) and a 0.14 standard deviation in firm hiring. Instrumenting for sentiments using state-level changes in political control produces qualitatively similar results. These estimates are consistent with descriptive evidence from Pistaferri

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5For example, those with doctoral degrees have an unemployment rate of 1.7%, those with professional degrees have a rate of 1.5%, those with masters degrees have a rate of 2.4%, and those with bachelors degrees have a rate of 2.8%. These rates are in contrast to those with some college, but no degree, who have an unemployment rate of 5%, those with just a high school diploma who have a rate of 5.4%, and those with less than a high school diploma who have a rate of 8%. These rates are all for 2015; see https://www.bls.gov/emp/ep_chart_001.htm.

6These results are rooted in a broader literature about disagreement and ambiguity about economic activity; see, for example, Andrade et al. (2016) for evidence on disagreement among professional forecasters, Epstein and Schneider (2008) for a model of ambiguity and asset pricing, and Ilut and Schneider (2014) for a model of ambiguity and the business cycle. While the Gallup data is a random sample, rather than a set of professional forecasters, it still highlights the heterogeneity in attitudes, even after controlling for common signals (e.g., within-metro economic fluctuations and individual income).
(2016) that the continued sluggish growth in consumption is best explained by low consumer confidence and high uncertainty. I also find that sentiment shocks in metropolitan areas experiencing rising housing prices are associated with a marginal decline in hiring, consistent with models where uncertainty generates an option value for firms or households to delay investing (e.g., see Bloom (2009)). These results are also consistent with empirical evidence on the amplification of uncertainty on employment outcomes at the state-level (e.g., see Shoag and Veuger (forthcoming)).

2. Data and Measurement

2.1. Sources

*Gallup Daily Polling Repeated Cross-section.*—The primary source consists of newly licensed data with Gallup Inc. Gallup is the United States’ premier polling service and conducts daily surveys of 1,000 U.S. adults on various political, economic, and well-being topics. Specifically, 200 Gallup interviewers conduct computer-assisted telephone interviewers with randomly sampled respondents (age 18 or over) from all 50 states and the District of Columbia. Detailed location data, such as the zip-code and metro area, is also available with corresponding sample weights. The Appendix documents several descriptive statistics about the data and compares it with prior datasets containing measures of well-being (di Tella et al., 2001, 2003).

Gallup’s polling relies on live, not automated, interviews with dual-frame sampling (including random-digit-dial [RDD]) landline and wireless phone sampling. Half of the respondents receive the “well-being track” version (with a 9% survey response) of the survey questions, whereas the other half receives the “politics and economy track” (with a 12% survey response). The two surveys contain different topical questions, but both contain the same identifying demographic information. Gallup also conducts the survey in Spanish to record replies from those Spanish speakers who do not also speak English. The sampling methodology also uses a three-call design to reach respondents who do not pick up on the original attempt. The survey has changed in some dimensions since 2008 with the inclusion of detailed well-being related indices since 2014, but the main outcomes of the analysis are available throughout.

While the survey does not cover every county in the United States, it does reach 1473 counties (over a third of all counties) with at least 300 respondents. Figure 3 plots the weighted average of life satisfaction indices pooled between 2008 and 2015 across all states. Geographies (e.g., states or counties) with higher populations and wages also tend to have higher levels of life satisfaction with coefficients of 0.038 and 0.158 ($p$-values = 0.00 and 0.007), respectively, from a regression of life satisfaction on logged population and wages. The survey prompt for life satisfaction, together with other relevant survey questions employed in this paper, are summarized in Table 1. A particularly unique feature of the data is its measurement of
consumption on non-durable goods. While a limitation is that it only asks the respondent about their spending the day before, the Data Appendix compares the Gallup measure with the Bureau of Economic Analysis state-level personal consumption panel between 2008 and 2014.

Figure 3: Geospatial Dispersion in Life Satisfaction Index

Notes. - Sources: Gallup. The figure plots the geospatial variation in life satisfaction, which is rated on a one to ten scale, in response to the following prompt: “Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?” Nationally representative sample weights are used.

There are a number of limitations to subjective survey questions. The first is the “halo effect”. Recipients answer different questions with the same mental state of mind, which produces a mood that can spill over from the answer in one question to another. The second is the potential wedge between

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7Since the measure is specifically about the individual’s spending on the prior day, there is a potential selection problem: individuals who did not go shopping the day before will have zero consumption expenditures. Fortunately, the day of the week that the interview takes place appears to explain some of the censoring, meaning that these censored observations are not crucial for identification. For example, 13.5% of the consumption observations are missing for individuals interviewed on Sunday, 18.3% for Monday, 15.2% for Tuesday, 14.1% for Wednesday, 13.5% for Thursday, 14.2% for Friday, and 13.1% for Sunday. While one approach would be to use these fixed effects with a Heckman (1979) selection correction, they do not do a very good job. Censored values are, therefore, omitted, but day of the week fixed effects are included as controls to remove potential bias.

8Oswald (2008) examines the validity of subjective measures by leveraging information on individuals’ self-reported measures of relative height to other individuals of the same gender (e.g., “how tall do you feel you are relative to your gender?”). Using the auxiliary height information, together with actual height, Oswald (2008) is able to measure the reporting
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<thead>
<tr>
<th>Variable</th>
<th>Survey Question</th>
<th>Rating</th>
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<tbody>
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<td>Life Satisfaction</td>
<td>Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?</td>
<td>1-10 scale</td>
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<td>Perception of Current Economic Activity</td>
<td>How would you rate economic conditions in this country today: as excellent, good, only fair, or poor?</td>
<td>1-4 scale</td>
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<tr>
<td>Perception of Future Economic Activity</td>
<td>Right now, do you think that economic conditions in this country, as a whole, are getting better or getting worse?</td>
<td>1-3 scale</td>
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<tr>
<td>Hiring</td>
<td>Now thinking more generally about the company or business you work for, including all of its employees. Based on what you know or have seen, would you say that, in general, your company or employer is (a) hiring new people and expanding the size of its workforce, (b) not changing the size of its workforce, or (c) letting people go and reducing the size of its workforce.</td>
<td>1-3 scale</td>
</tr>
<tr>
<td>Non-durables consumption expenditures</td>
<td>Next, we’d like you to think about your spending yesterday, not counting the purchase of a home, motor vehicle, or your normal household bills. How much money did you spend or charge yesterday on all other types of purchases you may have made.</td>
<td>Continuous</td>
</tr>
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</table>

Table 1: Main Gallup Survey Questions

Notes: Sources: Gallup. The table reports the survey questions and associated rating index used by Gallup when speaking with respondents.

stated and revealed preferences. Recent evidence from Benjamin et al. (2012), for example, finds many individuals are not well-informed about their options and/or may respond very different to different sets of question cues. The third is that the ordering of questions in surveys—that is, whether questions about politics and the economy are asked first, for example—exerts a great deal of influence over the elicited life satisfaction indices (Deaton, 2011). In spite of these limitations, self-reported measures of well-being still contain important information. Gallup prides itself on professional and rigorous polling methodology, which helps obviate concerns about the underlying tone and sampling frame of the survey.

Metro Panel of Employment, Wages, and Housing.-Since the Gallup data contains significant geographic detail across both space and time, I subsequently match the micro-data with the Quarterly Census of Employment and Wages (QCEW) at the metro-level and Zillow data at both the metro-level and zip-code level between 2008 and 2015. The QCEW contains measures of a number of labor market characteristics, but I primarily draw on weekly wages and employment to construct proxies for local de-

function for subjective measures of well-being, finding that the subjective and objective measures have an approximately 0.80 correlation; see Oswald and Wu (2010) provide additional evidence in another setting. In this sense, while a concern may remain about subjective measures, it appears that they are capturing the underlying fundamentals.
mand shocks by putting them in logs and first-differencing them. Zillow’s data also contains a wide array of housing information, most notably the median home value per square foot, which is a useful sufficient statistic for housing prices since it incorporates both quantity of housing and the underlying value. I also draw partially on the Longitudinal Employer-Household Dynamics (LEHD) county-by-group-level data to examine the impact of unemployment risk on happiness and sentiments.

2.2. Measuring Economic Sentiments

Economic sentiments are measured using perceptions about the state of the economy. The Gallup micro-data surveys individuals about both the current and future state. Individuals are asked to rank their perceptions of the current state of the economy based on one of four values, whereas they are asked to rank their perceptions of the future state of the economy based on one of three values (see Table 1 for the wording). While the conditional mean characterizes an important dimension of economic sentiments, the standard deviation can also be used to help characterize higher-order sentiments and uncertainty (Angeletos and La’O, 2009; Angeletos et al., 2014).

How do such measures of sentiments and uncertainty compare with existing measures? Figure 4 compares the standard deviation of the measure produced from the Gallup micro-data with a more standard measure of economic policy uncertainty from Baker et al. (2016). Whereas greater values of my index imply a more certain state of the economy, greater values of the Baker et al. (2016) index imply a more uncertain state of the economy. It is, therefore, remarkable that there is a -0.67 correlation between the two, suggesting that they are capturing similar dimensions of uncertainty in the U.S. economy. I further compare my measure with a monthly frequency of the search terms “economic uncertainty” generated from Google Trends, producing a -0.41 correlation, as well as with the daily volatility index, producing a correlation of -0.42. The correlations are also similar when comparing with the mean, rather than standard deviation, of economics sentiments. Despite these similarities, it is again useful to underscore that the advantages of the Gallup measure involve its micro-level heterogeneity and better representation of economic sentiments (rather than underlying uncertainty).

2.3. Cross-Sectional Dispersion during Booms/Busts

While there is some literature characterizing the cross-sectional dispersion of life satisfaction indices (e.g., see Oswald and Wu (2011) and Glaeser et al. (2016)), there is little evidence on not only the dispersion of other indices, but also the dispersion during a boom versus a recession. Using information on the underlying state of the economy, perceptions of work place practices, and perception of city amenities, I collapse across all individuals within the same metropolitan area using the national sample weights and

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9The correlation between economic policy uncertainty from Baker et al. (2016) and the Google Trends index is 0.36.
plot the distribution of each variable across all metro areas. The state of the economy and future city prospect measures are in the form of an index (poor, only fair, good, excellent for state of the economy and getting worse, the same, and getting better for future city prospects), whereas the work-place practices and city satisfaction measures are binary indicators.

These distributions are each plotted in Figure 5. Beginning with the state of the economy, there is a stark dispersion both in current and future attitudes during and after the Great Recession. While the distribution of sentiments is substantially shifted towards the right between 2014-2015, relative to 2008-2009, for the current state of the economy, it is interesting to note that the attitudes about the future state of the economy are bi-modal in 2008-2009. A similar mass of individuals who thought the economy was weakening even further and those who thought it would remain stagnant at best.

Turning towards the measures of work-place practices and city satisfaction, there is not a statistically significant difference in any of them pre and post recession. It is possible that these attitudes tend to be relatively sticky, or at least tied closely with the underlying job or location, rather than the business cycle. In contrast, as Figure 1 in the Introduction documented, the distribution of life satisfaction differs remarkably pre and post recession.

Figures 6 and 7 plot average life satisfaction, perceptions of the state of the economy, perceptions of trust at work, and city satisfaction over the distribution of age and educational attainment brackets, respectively, during 2008-2009 and 2014-2015. While there is not a statistically significant difference between 2008-2009 and 2014-2015 for perceptions of trust at work and city satisfaction, there is a stark difference for life satisfaction and economic sentiments, consistent with the earlier non-parametric results. The plots also reveal a significant amount of variation across age and education brackets. For example,
Figure 5: Dispersion in Sentiments Across Metro Areas, 2008-2009 and 2014-2015

Notes. – Sources: Gallup. The figure plots (i) the dispersion of standardized $z$-scores for the state of the economy, current and future in the first column, (ii) the dispersion of the fraction of people reporting (in a metro area) that they perceive trust at work and are able to leverage their strengths at work in the second column, and (iii) the dispersion of the fraction of people reporting that they are satisfied with their city and the standardized $z$-score for perceptions of future city prospects (getting worse, staying the same, getting better). in the third column. The index for the state of the economy ranges between 1 and 4: poor, only fair, good, and excellent. The workplace practices measures are indicators, so their collapsed measures represent percent shares. City satisfaction is also an indicator, but future city prospects is an index (getting worse, the same, getting better). Each plot collapses across individuals within a metro area and secondly plots the kernel density across all metro areas.

whereas life satisfaction tends to reach a low between ages 50-55 and a peak between ages 30-35 during the 2008-2009 recession, average life satisfaction tends to be fairly constant across the age distribution during 2014-2015.

3. Well-being Over the Business Cycle

3.1. The Cyclicality of Happiness

Before examining whether self-reported well-being is an important determinant of economic sentiments, a necessary condition is that it is sufficiently cyclical. This sub-section examines the cyclicality of well-being by quantifying how it responds to fluctuations in local economic activity (e.g., metropolitan changes in
logged employment and housing prices). Specifically, I run the following regression

$$LifeSat_{imt} = \beta X_{it} + \gamma \Delta y_{mt} + \phi_m + \lambda_t + \epsilon_{imt}$$ (2)

where $LifeSat$ denotes the individual’s reported life satisfaction, $X$ denotes a vector of individual covariates, $y$ denotes either logged metro employment or housing values per square foot, and $\phi$ and $\lambda$ are metro and time (year and quarter) fixed effects. Controls include a quadratic in age and educational attainment, logged income, marital status, height, gender, race, and day of the week interview fixed effects (sampling variability). Although Equation 2 differs in the source of identifying variation, it builds on a series of regressions in early work that use national changes in GDP to measure business cycle fluctuations; see, for example, di Tella et al. (2001), di Tella et al. (2003), and Wolfers (2003).

There are two potential identification problems associated with Equation 2. The first potential identification problem is unobserved heterogeneity in life satisfaction could be correlated with local economic activity. For example, if more optimistic workers locate in one type of metro area over another because of

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10I also examined the cyclicality of other attitudes, such as perceptions of work-place practices and city satisfaction. However, the estimated coefficients on employment and housing shocks were statistically insignificant, indicating that these attitudes are relatively acyclical and only useful for explaining the cross-section of happiness.
an amenity that is correlated with employment growth, then variation in life satisfaction will spuriously be attributed to $\gamma$. In addition to the richness of the standard controls, Equation 2 contains metropolitan and time fixed effects to remove bias emerging with non-random sorting. Violations to the identifying assumption would require that individuals sort based on changes in the growth rate of employment, which is unlikely in the presence of moving costs, location-specific human capital, and search costs.

The second potential identification problem is that employment or housing shocks confound demand versus supply side effects. For example, if a new and more productive business moves to a metro area changes, then $\gamma$ might reflect variation in the underlying local technology, which might affect the quality of job opportunities for individuals. To address this potential concern, and exploit only demand side variation in local employment shocks, I use a standard Bartik-like instrument (Blanchard and Katz, 1992; Autor and Duggan, 2003; Notowidigdo, 2013; Diamond, 2016). However, constructing a Bartik-like measure for changes in housing values is less straightforward. Following the approach in Makridis et al. (2016), using Census micro-data, I compute the fraction of households in metro $m$ living in a house with $k$ bedrooms ($k = \{1, 2, 3, 4, 5+\}$) within a particular period $t$. Using these shares, the instrument is simply the sum over the product of these shares and the national change in housing values corresponding homes.

Table 2 documents these results by pooling all individuals together and by allowing for separate coef-
ficients by occupation (normalized to professional workers and managers). Income enters the regression almost identically throughout every specification: a 1% rise in income is associated with a 0.40 standard deviation rise in life satisfaction.\footnote{There are 13 bins for income that are made continuous by averaging across the lower and upper bounds of the bins. It is plausible that these coefficients on income would be more sensitive if the variable was truly continuous.} When pooling all individuals together (columns 1 and 5), a 1% rise in employment and housing price growth is associated with a 0.43 and 0.67 standard deviation rise in life satisfaction, respectively. Why is the gradient on housing greater than employment? One possibility is that housing wealth shocks are capitalized into current consumption. Housing values and consumption are intimately tied (Mian and Sufi, 2011).

When separate coefficients are allowed for by interacting occupation fixed effects with the productivity shock (columns 2 and 6), normalizing the base case to professional workers and managers, the results suggest that business owners respond the most elastically to cyclical shocks. For example, a 1% rise in employment and housing price growth is associated with a 2.90 (= 2.07 + 0.83) and 1.53 (= 1.15 + 0.38) standard deviation rise in life satisfaction. In contrast, transport and repair workers respond less elastically with an average effect of 0.21 (= 2.07 − 1.26) and 0.32 (= 1.15 − 0.83) to employment and housing price growth, respectively. Interestingly, life satisfaction among sales workers is also much more acyclical than their counterparts. Although wages among sales workers are very elastic, since they depend so heavily on product demand, these results suggest a wedge between well-being and income. For example, it is possible that, because sales workers allocate much more time at work during a boom, their reported well-being is lower.

Turning towards the fixed effects specifications (columns 3-4 and 5-6), a 1% rise in employment and housing price growth is associated with a 1.51 and 0.33 standard deviation rise in life satisfaction. Interestingly, the significance on housing prices declines remarkably, suggesting that labor market outcomes are a bigger determinant of well-being. One possibility is that more of the variation in housing values is driven by non-random sorting among individuals with systematically different tastes, which is consistent with any standard Tiebout sorting model (Rhode and Strumpf, 2003). The estimates are also qualitatively robust to using the Bartik-like instrument for employment and housing price growth, although the coefficients decline in precision.

3.2. Identifying the Driving Forces

What explains the significant pro-cyclicality of happiness, even after controlling for income and employment status? Prior literature (e.g., di Tella et al. (2001) and di Tella et al. (2003)) interprets the negative relationship between happiness and real GDP growth as evidence of fear about unemployment. However, there is not yet any direct evidence. Understanding the implications of unemployment and labor income
Table 2: The Cyclicality of Self-reported Life Satisfaction

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<td>productivity shock</td>
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<tr>
<td>Year/Qtr FE</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
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</tbody>
</table>

Notes. -- Sources: Gallup, Quarterly Census of Employment and Wages, Zillow. The table reports the coefficients associated with regressions of an individual z-score of life satisfaction on the change in logged metro employment and median housing value per square foot (separately), conditional on controls. The change in logged metro employment is instrumented using a Bartik-like measure constructed by taking the employment share of industry $k$ in metro $m$ in period $t$ and multiplying it by the national change in logged hourly wages for industry $k$ in period $t$. The change in logged metro housing values per square foot is instrumented using another Bartik-like measure constructed by taking the share of individuals in each metro area living in a home with $k$ bedrooms ($k = 1, 2, 3, 4, 5+$) in metro $m$ in period $t$ and multiplying by the national change in logged median home values per square foot for home type $k$ in period $t$. Controls include: day of the week fixed effects, an indicator for whether the individual is employed, a quadratic in age, number of children, weight and a body mass index, male, education fixed effects, race (black/white). Standard errors are clustered at the metro-level.
risk is vastly important for quantifying the effects of aggregate fluctuations on consumption (Carroll, 1992; Carroll and Dunn, 1997; Crossley and Low, 2014), aggregate demand and wealth (Heathcote and Perri, 2016; Challe et al., forthcoming; Ravin and Sterk, 2014), and amplification for large swings in unemployment (Den Haan et al., 2015).

The first empirical exercise exploits group-by-location variation in employee turnover rates from the Longitudinal Employer-Household Dynamics (LEHD). In particular, using turnover at the county-by-gender-education quarterly-year level between 2008 and 2016, I run regressions of the form

\[ S_{igct} = \beta X_{igct} + \gamma \text{Turnover}_{gct} + \eta_g + \phi_c + \lambda_t + \epsilon_{igct} \]  

(3)

where \( i \) denotes the individual, \( g \) denotes the group, \( c \) denotes the county, and \( t \) denotes the year-quarter, \( S \) denotes either standardized life satisfaction or perceptions of the current state of the economy, and \( \eta, \phi, \) and \( \lambda \) are fixed effects on group, county, and time.\(^\text{12}\) Similar results emerge if county-by-gender-by-age turnover rates are used as an alternative proxy for skill.

Equation 3 is estimated separately by income bracket, partitioning the labor market into those who earn between $500-1,999, $2,000-2,999, $3,000-3,999, $4,000-4,999, $5,000-7,499, $7500-9,999, and $10,000+ in labor income per month. Since the sample is restricted to full-time workers, turnover behaves as a proxy for unemployment risk within individual’s skill bracket. County, group, and time fixed effects remove unobserved heterogeneity so that the statistical experiment is to exploit cross-sectional variation in life satisfaction within the same geography and skill bracket at different points in time. Standard errors are clustered conservatively at the county-level to allow for arbitrary degrees of correlation in unobserved characteristics within-county since the demand and supply for different brackets of skilled workers are likely correlated with unobserved heterogeneity in life satisfaction.

Estimating Equation 3 by pooling all workers together produces a noisy estimate of \( \hat{\gamma} = -0.32 \). However, different types of workers face different types of risk over the business cycle; see, for example, Jaimovich et al. (2013) for evidence by age bracket. To allow for greater heterogeneity, Figure 8 plots the estimated \( \gamma \)'s separately by income bracket. Starting with the bottom quantile among those earning less than $2,000 per month, a percentage point rise in the turnover rate is associated with a large 1.43 standard deviation decline in life satisfaction (\( p \)-value = 0.09). However, as individuals become increasingly more wealthy, the conditional correlation fades. For example, the second quantile has a point estimate of -0.90 (\( p \)-value = 0.236), the second quantile has an estimate of -0.455 (\( p \)-value = 0.445), and so on.

Does the fact that sentiments are not statistically associated with declines in life satisfaction after the first two quantiles imply that unemployment risk is not important beyond the bottom tail of the earnings

\(^{12}\)Age brackets include: 14-18, 19-21, 22-24, 25-34, 35-44, 45-54, 55-64, and 65-99. Educational brackets include: less than high school, high school, some college or associates, bachelors or advanced degree.
Figure 8: Unemployment Risk, by Income Bracket

Notes. Sources: Gallup, Longitudinal Employer-Household Dynamics. The figure plots the coefficients associated with regressions of an individual z-score of life satisfaction on the quarterly turnover rates measured at a county-by-education-by-gender level (four education brackets: less than high school, high school, some college, and college or more), conditional on controls. Controls include: day of the week fixed effects, weight and a body mass index, education and age bracket fixed effects, race (black/white). Standard errors are clustered at a county-by-educational bracket level. Observations are weighted by the Gallup combined national sample weights.

distribution? Not necessarily. The second empirical exercise exploits a set of questions available in the micro-data from 2013 onward about two sets worries among individuals. Recipients answer the following questions on a scale of one to five: (i) “you have worried about money”; (ii) “you have enough money to do everything you want to do”.

Using state-level monthly variation in the unemployment rate, I now examine how earnings risk affects these two aforementioned types of worries. Figure 9 plots the coefficients associated with regressions of the first (i) worry index on the one-year change in the state unemployment rate, conditional on controls and both state and year/quarter fixed effects. Unlike the estimates in Figure 10, which were concentrated in the lower tail of the distribution, the estimates in Figure 9 are concentrated throughout the income distribution. For example, the average treatment effect when pooling all workers together is 0.115 (p-value = 0.015).

Motivated by these two sets of empirical results, a related question is whether changes in sentiment are associated with changes in wealth. While the Gallup micro-data does not contain information on wealth, it does contain a measure of monthly income and expenditures on non-durable consumption. To
proxy for wealth effects of unemployment risk on currently employed workers, I now regress logged daily non-durables consumption on the current and future perception of the state of the economy separately by income bracket (see Figure 10). Controls include the usual individual covariates and logged metropolitan employment and wages. Standard errors are clustered at the metro-level.

For both measures of economic sentiments, the estimated coefficient in Figure 10 is largest in magnitude in the lower-to-middle tier of the income distribution. For example, among those earning between $1,000-1,999 per month, a standard deviation rise in perceptions of the future (current) state of the economy is associated with a 0.10% (0.08%) rise in monthly consumption expenditures. In contrast, the coefficient is close to zero for those earning over $4,000 per month. These results provide microeconomic evidence behind the mechanism in models about the self-fulfilling effects of expectations (e.g., Heathcote and Perri (2016)) and partial insurance against cyclical risk (e.g., Blundell et al. (2008), Low et al. (2010), and Heathcote et al. (2014)).

4. Explaining Dispersion in Economic Sentiments
4.1. Conceptual Argument

Given that reported well-being is sufficiently cyclical and responsive to both unemployment and labor income risk, this section now examines the underlying determinants of economic sentiments. The starting point of the following exercise is that there are two broad factors. The first is actual economic activity. For example, a local labor or housing market boom might raise expectations about future economic activity and perceptions of current activity. The second is well-being, which affects the perception of economic activity. Motivated by a wide array of results from the psychology literature, well-being shapes the perception of otherwise objective external events (Schwarz and Clore, 1983, 2007).

The connection between hedonic utility and choice is not in itself new; see, for example, Markowitz (1952), Stigler and Becker (1977), and Constantinides (1990). However, the insight that well-being responds to aggregate fluctuations due to, for example, unemployment and labor income risk, and drives the variation in sentiments at a microeconomic level sheds light on the underlying mechanisms at play in models with self-fulfilling business cycles.
4.2. Identification

To understand the factors that explain dispersion in economic sentiments, I pool individuals $i$ located in metropolitan area $j$ in year/quarter $t$ through regressions of the form

$$S_{ijt} = \alpha A_{ijt} + \beta X_{ijt} + \omega w_{ijt} + \gamma \Delta e_{jt} + \delta LifeSat_{ijt} + \phi + \lambda_t + \epsilon_{ijt} \quad (4)$$

where $S$ denotes a measure of sentiments about the state of the economy (current or future), $A$ denotes a vector of individual-level attitudes that help control for unobserved person-specific heterogeneity, $X$ denotes a vector of individual covariates, $w$ denotes the individual’s logged monthly income, $\Delta e$ denotes the change in logged metro employment, $LifeSat$ denotes the individual’s reported life satisfaction, and $\phi$ and $\lambda$ are location and year/quarter fixed effects.

There are two main identification problems associated with estimating Equation 4. The first problem is unobserved heterogeneity in self-reported measures of well-being or city amenities may be correlated with unobserved heterogeneity in perceptions of either their hedonic state or external environment. For example, more productive workers might also be more optimistic about both life and the economy, which will produce upwards bias. The second problem is reverse causality in unobserved shocks to sentiments affecting an individual’s underlying temperament. For example, if an individual receives a new piece of news about the economy, it may cause them to worry, which reduces their contemporaneous life satisfaction and produces downwards bias.

While the inclusion of location-specific fixed effects helps control for heterogeneity arising from non-random sorting across metro areas, there is still significant within-metro sorting. I address this concern in two ways. The first solution involves controlling directly for individual covariates and other attitudinal measures, such as the individuals’ perception of the city and their work-place practices. These controls and attitudinal measures include: fixed effects on educational attainment (e.g., high school, some college, college, graduate), age, body mass index, gender, race, perceptions of trust, collaboration, and managerial quality in the workplace, and perceptions of city amenities.

The second solution involves implementing an instrumental variables estimator that exploits fluctuations in daily metro temperatures. The intuition behind the first-stage correlation between temperature and life satisfaction arises from the impact of excessive heat on an individual’s hedonic state. Using millions of observations from Twitter, Baylis (2015) shows that individuals become significantly more irritable on hot days, relative to temperate or cold days. In this sense, exogenous shocks in the temperature provide variation in an individual’s mood and perception of events, affecting their self-reported happiness. To generate individual-level variation, I interact maximum daily temperature with age bin.

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13See Levinson (2012) for additional evidence using a separate survey.
fixed effects since temperature should affect older versus younger individuals differently. The first-stage
test for significance is documented in Table 3, illustrating that each of estimated coefficients on the in-
struments are significant. The identifying assumption is that temperature does not affect sentiments
about the state of the economy other than through its effects on an individual’s hedonic state.

<table>
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<th>Main Effect</th>
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<th>25-29</th>
<th>30-34</th>
<th>35-39</th>
<th>40-44</th>
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<th>50-54</th>
<th>55-59</th>
<th>60-65</th>
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<td>0.068</td>
<td>0.052</td>
<td>0.087</td>
<td>0.092</td>
<td>0.076</td>
<td>0.086</td>
<td>0.067</td>
<td>0.047</td>
</tr>
<tr>
<td>S.E.</td>
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<td>0.032**</td>
<td>0.035**</td>
<td>0.038</td>
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<td>0.034***</td>
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<td>0.033</td>
</tr>
</tbody>
</table>

Table 3: Test of First-Stage Significance

Notes. -Sources: Gallup and NOAA. The table reports the coefficients associated with a regression of standardized life satisfaction on
logged maximum daily temperature at a county-level interacted with age bins (normalized to ages 15-19). Controls include: city
satisfaction, employment, day of the week for the interview fixed effects, height, gender, education fixed effects (no high school,
technical degree, some college, college, post-graduate—normalized to college), race (white, black), and the direct effects of the age bin
fixed effects. Standard errors are clustered at the county-level and observations are weighted by the sample weights.

4.3. Results

Table 4 documents the results associated with Equation 4. There are two important observations to
take away. The first observation is that attitudes and perceptions of the work-place and city are both
statistically and economically significant in their relation with sentiments about current and future eco-
nomic activity. City satisfaction tends to matter most—those who are satisfied with their city have a
0.18 greater standard deviation in sentiments about the current and future economic outlook. Life satis-
faction has a comparable association: moving an individual at the 25th percentile of the life satisfaction
distribution (z-score of -1.07) to the 75th percentile of the distribution (z-score of 0.96) is associated with
approximately a 0.142 (= 0.07 × (0.96 + 1.07)) and 0.0812 (= 0.04 × (0.96 + 1.07)) standard deviation
rise in sentiments about the current and future state of the economy, respectively. Work-place practices
also matter with perceptions of trust at work exerting the greatest influence: perceptions of trust at work
are associated with a 0.09 rise in the standard deviation of sentiments. However, only life satisfaction is
sufficiently cyclical, so the focus turns towards it.

The second observation is the relative contribution of well-being versus actual economic activity as
determinants of economic sentiments. The OLS results suggest that a standard deviation rise in the
growth rate of employment is associated with a statistically significant 0.63 standard deviation increase
in perceptions of the current economy, but statistically insignificant decline in the future state. One
possibility is that the endogeneity problem is more serious over expectations about future states, relative
to perceptions of the present, since individual types interpret already noisy signals in very different ways.
That is, given that the dispersion of perceptions about future economic activity became bimodal during
the Great Recession, the presence of individual heterogeneity could make local employment shocks noisy
When instrumenting for life satisfaction, the coefficient rises from 0.07 to 0.21 when the outcome variable is perceptions of the current state of the economy, but the coefficient stays almost the same when the outcome variable is expectations of the future state of the economy. The fact that it rises in magnitude suggests that the simple least squares estimates is downwards biased. There are several pieces of evidence that point towards this possibility. For example, while some may suspect that happier individuals also vary in their unobserved productivity, which may be positively correlated with optimism about the economy, the fact that income (a correlate of productivity) enters the regressions only weakly suggests that it may not be a primary threat. An additional strategy is to use educational attainment as a proxy for productivity and examine the correlation between economic sentiments and real economic activity separately for each education bracket. Indeed, those with post-graduate education have a correlation of 6% between perceptions of the current state of the economy ($z$-score) and the growth rate of metropolitan employment, whereas those with a high school degree have a correlation of 3.6%, suggesting that more educated workers have a more realistic perception of the economy, which between the 2008 and 2016 years is relatively low.

These pieces of evidence suggest that unobserved heterogeneity is not likely to create upwards bias, but they do not provide evidence of downwards bias. Reverse causality is likely to be a serious threat for least squares estimates of Equation 4, which will tend to produce downwards bias. In particular, if an individual receives an exogenous boost in their perceptions of economic activity, it is likely to also raise their life satisfaction since earnings risk is an important correlate of life satisfaction. To test this hypothesis, the Appendix examines a series of regressions of life satisfaction and economic sentiments on measures of economic worry—namely, concerns about having enough money to pay the bills and to do the things they want to do. Across every margin, increases in worry are associated with declines in sentiment and life satisfaction, suggesting that unobserved shocks to sentiments are likely to drive changes in life satisfaction in the pure cross-section. The instrumental variables estimate, however, exploits plausibly exogenous variation in temperatures, which affects an individual’s mood, but not their underlying perception of economic activity.

How are these coefficients interpreted in light of changes in sentiments between the start of the Great Recession in 2008 and the “recovery” in 2015? As Figure 5 illustrates, there is very little movement in work-place practices and city satisfaction. For example, the fraction of people reporting that there is trust at work was about 78% in 2008, but 81% in 2015, and the fraction reporting that they are satisfied with their city was about 87% between both years. Given that standardized life satisfaction moved from -0.284 to 0.142 between 2008 and 2015, whereas standardize state of the economy moved from -0.0059 to 0.224 (a difference of 0.2181), then the change in life satisfaction accounts for about 13% ($= 0.07 \times$
$(0.142 - (-0.284))/0.2181$) to 41% $(= 0.21 \times (0.284 + 0.142)/0.2181)$ of the overall variation in sentiments, whereas actual economic activity accounts for between 7% $(= 0.63 \times (0.015 - (-0.01))/0.2181)$ and 14.1% $(= 1.21 \times (0.015 - (-0.01))/0.2181)$ of the variation in sentiments. Turning towards expectations over the future state, life satisfaction accounts for between 39% $(= 0.07 \times (0.142 - (-0.284))/0.0752)$ and 62% $(= 0.11 \times (0.284 + 0.142)/0.0752)$ of the variation, whereas actual economic activity accounts for between 0% $(\approx -0.06 \times (0.015 - (-0.01))/0.0752)$ and 15% $(= 0.47 \times (0.015 - (-0.01))/0.0752)$.

Table 4: Explaining the Dispersion in Economic Sentiments

<table>
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<th>Dep. var. =</th>
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<th>future state of economy</th>
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<td>.07***</td>
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<td>.07***</td>
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<td>.06***</td>
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Notes. Sources: Gallup, Quarterly Census of Employment and Wages. The table reports the coefficients associated with regressions of the standardized perception of state of the economy and future of the economy on standardized life satisfaction, indicators for the work environment (whether the individual has good partnerships at work, trust at work, using strengths at work), an indicator for city satisfaction, and controls. The instrumental variable columns use the logged maximum daily temperature at a metro-level, together with its interactions with age bins (10 groups, each spaced with 5 years apart). Controls include: the age bins, logged income, employment status, day of the week interview fixed effects, personal weight, male, marital status, education fixed effects (no high school, high school, some college, college, or post-graduate), race (white and black). Standard errors are clustered at the metro-level and national sample weights are used.

5. Quantifying the Real Effects of Sentiments

5.1. The Micro-Elasticity of Sentiments and Consumption

Having documented the relative pro-cyclical nature of life satisfaction and the role it plays in driving perceptions of economic activity (i.e., sentiments), this section now focuses on estimating the real effects
of these sentiment shocks. The primary focus is on consumption expenditures given the large decline experienced during the Great Recession; see, for example, evidence from Mian et al. (2013) and Pistaferri (2016). However, I also provide motivating conditional correlations between sentiments and both employment and financial returns as supplemental evidence on their real effects.

5.1.1. Identification

The emerging literature on the role of sentiments emphasizes the effects of informational frictions (e.g., expectations and disagreement) on short-run demand. While a fundamental theme in these models is that self-fulfilling fluctuations occur endogenously based on the formulation of beliefs, these models need microeconomic evidence to discipline their theoretical predictions. One way to do so is by estimating a micro-elasticity between sentiments and real economic outcomes realized at an individual level through regressions of the form

\[ y_{ijt} = \beta X_{ijt} + \sigma S_{ijt} + \phi_j + \lambda_t + \epsilon_{ijt} \]  

where \( y \) denotes the outcome variable, \( w \) denotes logged monthly income, \( X \) denotes a vector of demographic controls, \( S \) denotes a revised measure of sentiments that is the standardized sum of perceptions of both current and future economic activity (which produces increased variation), and \( \phi \) and \( \lambda \) denote fixed effects on location and time, respectively. The sample is restricted to the set of employed individuals and those with non-zero consumption expenditures. Equation 5 is estimated through two exercises. The first uses a measure of the individual’s expenditures on non-durables consumption the day before the interview. The second uses a measure for whether the individual’s firm is hiring. Individuals are asked about hiring at their company: whether hiring is taking place, whether it is at a stand-still, or whether there are lay-offs.\(^\text{14}\)

Unfortunately, estimating \( \sigma \) in Equation 5 is challenged by the presence of individual unobserved heterogeneity and reverse causality. Unobserved heterogeneity may produce upwards biased estimates if more optimistic workers are also wealthier and consume more goods. However, the direction of the bias is inherently hard to sign given that an individual’s perception of current and future economic activity depends in part on their occupation, industry, and location. In this sense, even if more productive workers tend to have a more reliable view of the economy, their view is influenced by their non-random sorting into jobs, which are heterogeneously impacted by the Great Recession (Jaimovich and Siu, 2014). Reverse causality will tend to produce downwards bias since changes in purchasing and/or hiring patterns can reinforce views about the economy. For example, if an individual’s firm begins hiring again, even if the

\(^{14}\)In the absence of firm-level data, these individual responses provide a suitable proxy. The variable is highly predictive of employment at a metro-level.
economy is performing poorly, the individual receives a signal that it is improving.

To address these two potential sources of endogeneity, I instrument for sentiments using state-level changes in political control (legislature and governor) using data from the National Conference of State Legislatures (NCSL), interacted with individual indicators for party affiliation.\(^{15}\) These NCSL variables are measured as indicators based on whether the state is Republican in period \(t\), but not in \(t-1\), and similarly for Democrat. Interacting them with individual covariates for party affiliation—conditioning on the direct effects of party affiliation—exploits the variation in expectations about economic activity given a victory for their own party. The estimated first-stage regression (displaying only the interactions) is

\[
S_{ijt} = \beta X_{ijt} + 0.26 (1[SwitchToRepub_{jt}] \times 1[Repub]) - 0.099 (1[SwitchToDem_{jt}] \times 1[Dem]) + \phi_j + \lambda_t + \epsilon_{ijt}
\]

where the coefficient on a switch to Republican control suggests a 0.26 standard deviation rise in sentiments (significant at the 5% level), whereas a switch to Democratic control suggests a statistically insignificant 0.099 standard deviation decline in sentiments. The intuition is that abrupt change in governance (e.g., “Republicans taking over the house”) behave as political news shocks, as in Mian et al. (2015). For example, if a state was primarily run by Democrats, but is taken over by Republicans, expectations for more business-friendly and lower taxation policies may rise, thereby triggering a wave of optimism that manifests itself in increased hiring and spending. A particularly current example of this optimism is evident on the national scale with the election of Donald Trump; markets have clamored in expectation of lower regulation.\(^{16}\) The exclusion restriction requires that changes in state legislative control affect daily consumption expenditures only through their effects on sentiments. Of course, policy has direct and tangible effects on real consumption activity, but policies take time to pass in the legislature and are, therefore, reasonable to take as exogenous to the individual over the sample period considered.

There are several notes of caution about the instrumental variables strategy. The first concern is that political switches are not common. Approximately 10% of the sample experiences a switch between 2009 and 2016. That means the variation only identifies, at best, a local average treatment effect (LATE) based on the states that do change over the sample. The second concern is that the instrument operates at a broad state-level, rather than at a more local or, ideally, individual level. That produces an intent to treat estimate, pooling responses across individuals within a state. The degree of variation is further constrained by the fact that the instruments are binary. For these reasons, the instrument merely serves as a heuristic to illustrate that the OLS results are not fundamentally (i.e., qualitatively) flawed, rather


than as the baseline estimates of interest.

5.1.2. Results

Table 5 documents these results. From the standard OLS estimates, a one standard deviation increase in sentiments is associated with a 0.008 percent rise in daily spending on non-durable consumption goods and a 0.096 standard deviation rise in hiring. These estimates climb significantly under the instrumental variables specification. For example, a standard deviation rise in sentiments is now associated with a 0.11% rise in consumption and a 0.249 standard deviation rise in hiring, although the former just barely misses the 10% significance level. The direction, however, is consistent with the aforementioned discussion of likely bias, namely the presence of reverse causality.

The estimates may initially appear small in magnitude. However, begin by converting daily consumption of 0.008 into its annual equivalent of 2.92 (= 0.008 × 365). Given that consumption spending was $10,410 per capita in 2009 and $12,146 in 2015—a 16% growth rate between 2009 and 2015—and the standardized $z$-score of the state of the economy was -0.56 in 2008 and 0.34 in 2015—a difference of 0.90 between 2008 and 2015—then the estimate implies that the fluctuations in sentiments can account for 16.4% (= 2.92 × (0.56 + 0.34)/0.16) of the overall “recovery” in consumption between 2009 and 2015.\textsuperscript{17}

In light of the fact that the identifying variation involves the massive fluctuations in uncertainty over the Great Recession, I also examine whether sentiments amplify the effects of housing market shocks by interacting an indicator for positive metro-level housing price growth with perceptions of the current state of the economy. It is possible, for example, that the interaction between housing shocks and uncertainty amplified the decline in consumption documented by Mian and Sufi (2011) and the decline in employment documented by Mian and Sufi (2014). However, housing price growth is not statistically associated with logged consumption, although the estimates are in the expected direction—that is, growth in home prices matters more when people view the economy favorably.

It is also positively associated with hiring, but, surprisingly, its interaction with sentiments is negative. In other words, improvements in the perception of economic activity during housing price booms are negatively associated with hiring. One reason is because of the uncertainty associated with the housing sector during the Great Recession; see, for example, Bloom (2009) for a model where uncertainty generates an option value to delay hiring until the realization of uncertainty.

\textsuperscript{17}The statistics on real per capita consumption come from the St. Louis Federal Reserve real personal consumption expenditures per capita (Goods) series.
Table 5: The Micro-elasticity of Sentiments and Real Economic Behavior

<table>
<thead>
<tr>
<th></th>
<th>logged consumption</th>
<th></th>
<th>hiring, z-score</th>
<th></th>
</tr>
</thead>
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<tr>
<td></td>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>current state of economy, z-score</td>
<td>0.008***</td>
<td>0.102</td>
<td>0.005*</td>
<td>0.096***</td>
</tr>
<tr>
<td></td>
<td>[0.002]</td>
<td>[0.068]</td>
<td>[0.003]</td>
<td>[0.001]</td>
</tr>
<tr>
<td>future state of economy, z-score</td>
<td>0.002</td>
<td>0.021*</td>
<td></td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>[0.019]</td>
<td>[0.012]</td>
<td></td>
<td>[0.005]</td>
</tr>
<tr>
<td>1[housing price growth]</td>
<td>.05</td>
<td>.05</td>
<td>.05</td>
<td>.06</td>
</tr>
<tr>
<td>×, current state of economy</td>
<td>.05</td>
<td>.05</td>
<td>.05</td>
<td>.06</td>
</tr>
<tr>
<td></td>
<td>[0.005]</td>
<td>[0.003]</td>
<td></td>
<td>[0.005]</td>
</tr>
<tr>
<td>R-squared</td>
<td>257684</td>
<td>175770</td>
<td>212719</td>
<td>332253</td>
</tr>
<tr>
<td>Sample Size</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>State FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes. - Sources: Gallup, Quarterly Census of Employment and Wages. The table reports the coefficients associated with regressions of logged consumption (spending on non-durables yesterday) and a z-score of hiring at the firm-level (the firm the individual works at) on on a z-score of perceptions over the current and future state of the economy at the individual-level, as well as an indicator for positive metro-level housing price growth and its interaction with perceptions of the current state of the economy, conditional on controls. Controls include the standard individual-level measures: a quadratic in age, education fixed effects, race fixed effects, employment status, body mass index, and gender. Standard errors are clustered at the metro-level and observations are using the Gallup sample weights.

5.1.3. Discussion

Why do these results differ from those in Mian et al. (2015) who find a null relationship? Their identification strategy is based on the clever application of an event study approach that exploits the response of county-level auto purchases to changes in voting during the course of four Presidential elections (2000, 2004, 2008, and 2012). Rather than using geographic data, one important difference in this paper is the use of individual data. Aggregation bias is a well-known problem in economics; see, for example, Blundell and Stoker (2005). Since consumption is chosen optimally based on forward-looking thinking from individuals, a large macroeconomic shock (e.g., the Great Recession) can induce heterogeneous effects, i.e., causing some households to move to cheaper locations and others to simply cut back on spending in their current location. For example, when estimating the intertemporal elasticity of substitution, Attanasio and Weber (1993) find an elasticity of 0.35 in the aggregate data, but an elasticity of roughly 0.70 in the micro-data.

Blundell and Stoker (2005) also discuss (see p. 371) that omitting aggregation bias terms can invalidate instrumental variable strategies, but can be partially addressed by including demographic controls that help remove variation emerging from sorting (Attanasio and Browning, 1995). Since the share of individuals voting for a particular party at a county-level is a function on time-varying flows in and out of
the county, it is possible that reallocation attenuates the second-stage estimate. That is, since the change in political ideology is also correlated with other time-varying compositional changes, then the change in composition will also affect real consumption expenditures.\textsuperscript{18} Using individual-level data, together with core demographic controls, helps address aggregation bias.

An additional difference with Mian et al. (2015) is the data. Whereas they use auto purchases from R.L. Polk, I use self-reported measures of non-durables. Some types of consumption goods are more cyclical than others. For example, using quarterly consumption data from the BEA, I found that a regression of logged total consumption, durables, non-durables, and services on my measure of sentiments produces coefficients of 0.107, 0.32, 0.09, and 0.07, suggesting that durables have a more elastic response.\textsuperscript{19} While that could bias Mian et al. (2015) towards finding an effect of sentiments, rather than the null association that they find, their sample overlaps with several federal policies that could introduce confounding variation, such as the stimulus (Parker et al., 2013; Broda and Parker, 2014) and cash-for-clunkers (Green et al., 2016) federal programs. In particular, it is possible that these policies partially counteracted the decline in transitory consumption, attenuating the relationship between sentiments and consumption. In either case, the differences between our results underscores the importance of continued work to understand the microeconomic effects of sentiment shocks on real activity.

5.2. Sentiments and the Labor Market

I now regress quarterly logged metro employment on the standardized metro-level measure of dispersion in perceptions of the current state of economy. Using Census micro-data, I construct a semi-parametric vector of demographic controls, including: average household size, average year homes were built, fraction that are male, fraction in different age brackets (0-17, 18-34, 35-65, 65+), fraction of different races (white/black), fraction married, fraction in different education brackets (no high school, high school, some college, college, and graduate degree). I also control for metro and time fixed effects.

The estimated coefficients on the dispersion of perceptions of the current state of the economy without and with metro / time fixed effects are 0.138 and 0.038, respectively, both with \( p \)-values of 0.00. How large are these effects, especially in light of the consumption channel discussed above? Between 2008 and 2015, weighted employment grew by 0.436 log points, meaning that sentiments account for between 2.2\% \( (= 0.04 \times (0.029 + 0.214)/0.436) \) and 7.8\% \( (= 0.138 \times (0.029 + 0.214)/0.436) \) of the variation in metropolitan employment. By controlling for both demographics and time-invariant heterogeneity, my

\textsuperscript{18} Although Mian et al. (2015) importantly control for income and employment at a two-digit county level, as well as time-invariant (2000 Census) measures of demographics, the underlying composition of these workers is also changing. Composition effects have played a key role in explaining contrasting results in wage rigidity literature; see, for example, Solon et al. (1994).

\textsuperscript{19} I also have aggregated the sentiments measures to the state-by-quarter-by-year level and used micro-data from the Consumption Expenditure Survey (CES).
goal is not to estimate a “causal” elasticity parameter, but rather illustrate that the correlation between sentiments and labor market outcomes is robust to standard measures of “selection” and non-random sorting. Interestingly, however, the results are qualitatively robust to exploiting cross-sectional variation in land use regulation, measured through the index constructed by Gyourko et al. (2007).

5.2.1. Sentiments and Financial Returns

There is an existing literature on consumer sentiments and stock returns. For example, Lemmon and Portniaguina (2006) find that measures of consumer confidence from the University of Michigan’s consumer confidence survey forecasts the size premium (i.e., the tendency of stocks for firms with a smaller market capitalization to outperform the stocks for firms with a larger market capitalization). Kaplanski and Levy (2010) find that stock prices in the airline industry sharply “over-react” to plane crashes, consistent with behavioral models of salience. Baker and Wurgler (2006) find that sentiments affect stock prices for companies with which have ambiguous investor expectations.

Using monthly stock returns from the set of publicly traded companies, I now consider regressions of both logged firm stock prices on a z-score of monthly average life satisfaction with and without fixed effects on firm, month, and year, producing coefficients of 0.91 and 0.84 (p-values = 0.00). Not surprisingly, higher levels of reported life satisfaction are associated with higher realized stock prices. The more interesting empirical regularity is that a regression of the standard deviation of logged stock prices (across all publicly traded companies) on the standard deviation of life satisfaction with and without time fixed effects produces coefficients of 0.68 and 0.66 (p-values = 0.00). Remarkably, dispersion in life satisfaction explains nearly 20% of the volatility in stock prices over the 2008-2015 period. While the estimated coefficients do not have a causal interpretation, they are consistent with the theme that fluctuations in individuals’ hedonic state can potentially explain swings in sentiments and realized economic outcomes.

6. Conclusion

The period following the Great Recession has been the slowest U.S. recovery in the post-WWII era. While neoclassical business cycle models can account for the fluctuations in productivity by incorporating both intangible and tangible capital (McGrattan and Prescott, 2014), other production-side mechanism (e.g., changes in labor market dynamism as documented by Davis and Haltiwanger (2014)) appear to play less

\[^{20}\text{The intuition behind the first-stage correlation is that individuals living in areas with more versus less land use regulation have different underlying preferences about the set of desired amenities in a city. The exclusion restriction is that unobserved variation in employment (not due to composition shifts captured through the demographic controls) is uncorrelated with stringency in land use regulation. Comparing the means above and below the median regulatory stringency implies incredible overlap: a mean of 11.8154 logged employment in more stringent areas and 11.8167 logged employment in less stringent areas. The exclusion is less likely to hold if the outcome variable is wages. The mean logged wage is 6.622 in more stringent areas and 6.664 in less stringent areas.}\]
of a role in the recent Great Recession (Foster et al., 2016). Instead, an increasing body of evidence points towards the role of financial / informational frictions (Mian and Sufi, 2009, 2011, 2014; Christiano et al., 2015) and heightened uncertainty (Jurado et al., 2015; Shoag and Veuger, forthcoming; Baker et al., 2016; Leduc and Liu, 2016) as channels that have depressed economic growth and aggregate demand.

This paper is the first to the necessary microeconomic evidence for disciplining heterogeneous agent models specifically along the margins of unemployment and labor income risk, which are important mechanisms for generating precautionary saving and aggregate demand effects (Ravin and Sterk, 2014; Challe et al., forthcoming; Challe and Ragot, 2016) with those that allow for information frictions that give rise to coordination failures and self-fulfilling fluctuations (Angeletos and La’O, 2013, 2009; Angeletos and Werning, 2006; Heathcote and Perri, 2016). The core insight is that macroeconomic shocks affect well-being, which shapes the perception of current and future economic activity and, in turn, leads to measured changes in economic behavior (e.g., consumption and leisure) at the individual-level. Recessions are periods when dispersion over the state of the economy widens. By amplifying individual-level heterogeneity, risk averse preferences can give rise to an asymmetry over the business cycle whereby recessions produce greater swings in behavior than booms.

Using newly licensed micro-data from Gallup Inc. between 2008 and 2015, this paper documented three results. First, well-being is highly pro-cyclical and responds primarily to labor market (rather than housing market) shocks. The variation is primarily explained by a combination of unemployment and labor income risk, although unemployment risk only affects well-being and consumption behavior at the bottom of the income distribution. However, worry about having sufficient income to meet one’s prior expectation explains much of the variation even among otherwise wealthy individuals.

Second, well-being explains the bulk of the variation in economic sentiments. For example, while actual economic activity, measured through metropolitan changes in logged employment, explains only 7% of the variation in sentiments between 2008 and 2015, self-reported happiness explains 14% when a naive least squares estimator is used and 41% when an instrumental variables estimator is used. The latter results exploit quasi-experimental variation in daily maximum temperatures at a metro-level as an instrument for happiness. The fact that an individual’s underlying hedonic explains more of the variation in sentiments than actual economic activity suggests that there are important non-pecuniary factors.

Third, a standard deviation rise in sentiments is associated with a 0.008% rise in daily consumption (2.92% annual equivalent). Through a back-of-the-envelope calculation, I find that sentiments can account for 16.4% of the variation in individual consumption expenditures, which is large in light of evidence of the role of housing wealth from Mian and Sufi (2011). These estimates are identified off of variation in beliefs after controlling for local economic activity, individual income, and other individual covariates. The results are also qualitatively robust to instrumenting using state-level changes in political control,
which behave as news shocks. I also show that a standard deviation rise in sentiments is associated with a similar 0.04% rise in local employment. Quantitatively, sentiments account for approximately 2.2% of the variation in metropolitan employment, suggesting that the main mechanism through which sentiments affect economic activity may be through the consumption, rather than labor, channel.

The microeconomic evidence established in this paper points towards several fruitful areas of additional research. First, even after controlling for income and individual covariates, there is a great deal of residual variation in happiness. Is all of this residual variation explained by worry over the business cycle, or are there other potentially important cyclical determinants? In particular, might time varying risk aversion play a role (Guiso et al., 2015)? Second, what are the mechanisms through which sentiments affect real economic activity? While an obvious channel that was tested here is the decline in consumer spending, heterogeneity in beliefs about the economy may also affect stock market participation and the over-accumulation of capital as in Perri and Quadrini (2016) and Beaudry et al. (forthcoming). Integrating microeconomic data with these macroeconomic heterogeneous agent models will be an essential step forward in understanding these broader phenomena.

References


