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Sentiments and Economic Activity:
Evidence from U.S. States

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ABSTRACT

Using data from the Michigan Survey, we find a strong relationship between expectations concerning national output growth and future state economic activity. This linkage suggests that sentiment influences aggregate demand. This relationship is robust to a battery of sensitivity tests. However, national sentiment is also positively related to past state economic activity. We therefore turn to instrumental variables, positing that agents in states with a higher share of congressmen from the political party of the sitting President will be more optimistic. This instrument is strong in the first stage, and confirms the relationship between sentiment and future state economic activity.

J.E.L. Classification Number: E20, E32

Keywords: Sentiments, U.S. states, panel estimation, political economy

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1. Introduction

There is some evidence of a contemporaneous correlation between measures of consumer sentiment and economic activity. The headline University of Michigan Index of Consumer Sentiment (ICS) has been shown to be closely correlated with growth in personal consumption expenditures over the postwar period [Carroll, et al (1994)]. The correlation observed in the data can be interpreted in different ways. It is possible that sentiments only reflect knowledge concerning current or future economic fundamentals. Much of the empirical literature has therefore concentrated on testing the restrictions that predict a causal link between sentiment changes and economic activity. Along these lines, there is evidence that sentiment measures unexplained by economic fundamentals are associated with spending shocks [e.g. Oh and Waldman (1990), Carroll, et al (1994), Starr (2012)]. However, the contribution of sentiment shocks "unrelated" to other measures of fundamentals has been found to be only temporary [e.g. Starr (2012)] and small [e.g. Ludvigson (2004)].[1]

Nonetheless, theory suggests that "self-fulfilling" changes in consumer sentiments, or sunspots, whereby positive shocks to expectations concerning, for example, future output or future output growth, can indeed bring them about as full rational expectations equilibria. Indeed these sentiment-driven equilibria can arise in models with distinct multiple equilibria in various models of growth or real business cycles with external effects, in models with collateral constraints, or in search models with aggregate demand externalities as well as in OLG models. Sentiments or sunspots can then randomize locally over a continuum of equilibria converging to

[1] Most of these studies concentrate on the implications of sentiment changes on consumption. Permanent income theories however suggest that agents should spread the impact of improved economic prospects on their consumption over the course of their lifetime. The observed response to sentiment shocks under those conditions over short horizons would be small. Observed responses over longer time horizons may also be difficult to identify as new shocks emerge and fundamentals respond to changes caused by sentiment shocks, leaving small changes in output left to be explained by the sentiment shocks themselves.

an indeterminate steady state, or across distinct multiple steady states, consistently with rational expectations[2][3] Alternatively, even if the fundamental based equilibrium is unique, information frictions and incomplete markets can give rise to distinct sentiment driven stochastic equilibria under rational expectations.[4]

Barsky and Sims (2012) distinguish between "animal spirits" shocks and news or information shocks using a VAR framework. They argue that animal spirits shocks unrelated to fundamentals are likely to have an immediate but transitory impact on economic activity. Positive shocks to animal spirits are likely to look like positive aggregate demand shocks in the short run, but eventually will peter out if they are not followed by real increases in productivity. Using this assumption as an identification strategy in their VARs, they find that unexplained innovations in measures of consumer confidence are followed by slowly building and "apparently permanent" implications for output and consumption. They interpret these results as suggesting that changes in sentiment reflect news about current and future economic fundamentals, rather than innovations in "animal spirits" that drive the economy across multiple equilibria or across multiple steady states based on self-fulfilling expectational shifts.

This interpretation is based on the assumption that sentiment shocks that do not reflect news about fundamentals have only temporary effects. It is therefore inconsistent with the

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[2] See for example Benhabib and Farmer (1999), Benhabib, Schmitt-Grohe and Uribe (2000, 2001), Benhabib and Wang (2013), Howitt and McAfee (1988), and Kaplan and Menzio (2013)].

[3] Self-fulfilling changes in consumer sentiment have also been identified in the literature in a number of alternative ways, as self-fulfilling prophecies [e.g. Azariadis (1981), Farmer (1999), herding [e.g. Blanchard (2016)], and animal spirits [e.g. Keynes (1936) and Akerlof and Shiller (2010)]. Here, unless indicated otherwise, we use changes in sentiments to describe changes in beliefs unrelated to fundamentals.

[4] See for example Shell (1977) and Cass and Shell (1983), Maskin and Tirole (1987), Aumann, Peck and Shell (1988), and more recently Angeletos and La'O (2013)], and Benhabib et al (2015).

[4] See for example Shell (1977) and Cass and Shell (1983), Maskin and Tirole (1987), Aumann, Peck and Shell (1988), and more recently Angeletos and La'O (2013)], and Benhabib et al (2015).

predictions of many economic models that generate multiple equilibria. In this paper we investigate whether sentiments, distinct from fundamentals, can give rise to self-fulfilling economic activity.

We concentrate on U.S. state economic activity as the focus of our analysis. We examine the responses of overall state economic activity to changes in sentiment about national economic conditions. Our identification strategy relies on the notion that changes in local sentiment about national economic prospects are likely to induce local changes in consumption and investment. As both consumption and investment are in play, a focus on overall activity seems useful. Moreover, the output response is useful as a guide to the implications of sentiment shocks for optimal stabilization policy.

The use of state data also allows us to condition for aggregate shocks, facilitating the identification of the direct impact of sentiment changes on economic activity at the state level.

We use Michigan Surveys (2016) questions concerning national economic conditions. Our base specification uses the question, "Looking ahead, 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 or depression, or what?" Our maintained hypothesis is that states are sufficiently small that attitudes about the local economy will not distort the response about national economic conditions. Given this assumption, our cross-sectional treatment should isolate the impact of differences in sentiment across states on future differences in state economic activity.

While sentiment data is available at the county level, it seems plausible that substantive leakage is likely to occur across county lines. This is of course a compromise, as leakages across state lines are also likely to take place, but they are much less likely to be prevalent than those across county lines. We test this hypothesis below and confirm the presence of a persistent positive relationship between sentiment and future economy activity at the state level. Sentiment at the state level about future national economic activity, as measured by the response to the question above, is shown to be positively and statistically significantly associated with State output growth over the following four quarters.

These results are shown to be robust to the inclusion or exclusion of state and time fixed effects, as well as a variety of sensitivity tests. These include weighting observations by either state size or the number of respondents, or changes in the sample population, dropping specific time periods, states with exceptionally high or low incomes, investment levels or populations, or dropping states identified as outliers based on residual values.[5] The results are also robust to the use of conventional, rather than heteroskedasticity-corrected standard errors, random instead of fixed effects, and regional instead of state dummies. We also examine the robustness to other sentiment questions. Here our results are more mixed, but they remain relatively robust for most alternative sentiment measures. Overall, our results are shown to be quite robust to all of these perturbations.

Another potential problem with our specification is that household expectations about future national economic activity may be positively related to local experiences, raising the prospect of reverse causality in our empirics. We test for this possibility by examining the impact of past state growth on current sentiment. We do find evidence of such a relationship in the data, as our coefficient of interest enters at statistically significant levels without the inclusion of fixed effects, but the results are weaker when fixed effects are included. Still, our results overall confirm that expectations of future national activity might be colored by local

[5] For the sub-sample where we drop the first two years, our coefficient estimate remains positive, but loses its statistical significance, as shown in Table 3.

experience. We respond to this reverse causality challenge using instrumental variables estimation. Instrumental variables estimation will also serve to address the also-likely issue that answers to the Michigan Survey are noisy measures of consumer sentiment.

We turn to political data as an instrument for local sentiment levels that vary systematically across states. There is a large literature that demonstrates a positive relationship between partisanship and economic assessments. A survey respondent that self-identifies as a member of one of the major political party is more optimistic about the national economic picture when the sitting President is from that same party. In an early paper, Gerber and Huber (2009) demonstrate that consumption changes following a political election are correlated with whether or not the election was won by the preferred political party of the respondent. They interpret this correlation as working through the sentiment channel.

Political partisanship has also been used as an instrument for identifying a connection between sentiment and consumption. Mian, et al (2015) demonstrate that presidential elections are associated with changes in sentiment about the effectiveness of government policy in line with political partisanship. However, they find no statistically significant relationship between changes in the presidential party at the county level in the United States and changes in actual consumption.[6] In contrast, Gillitzer and Prasad (2015) show in Australian survey data that higher sentiment is associated with having a member from your political party in office at the federal level. Changes in sentiment associated with elections are shown to be associated with increased future vehicle purchase rates.

[6] Mian, et al (2015) examine the cases of the 2000 and 2008 elections. While in neither case do they find evidence of significant changes in consumption at the county level, they do find a significant correlation between the 2008 election outcome and planned consumption measures consistent with the predictions of a partisanship model of politically-driven sentiment changes.

One distinction that favors the Australian study is that Australian survey data has a direct question about political affiliation. U.S. consumer data, such as that used by Mian, et al (2015) - and also used in this study – require proxies for political partisanship. The Mian, et al study uses county-level data on voting in presidential elections. Below, we use the share of state congressional representatives from the same political party as the sitting president. The latter proxy has the advantage of changing every two years, yielding more variability in our sample and allowing us to use our full panel sample. This is desirable because our use of state-level data to mitigate consumption leakages across counties results in a smaller cross-section than the Mian, et al (2015) county-level study. We demonstrate below that our proxy is a strong instrument in the first stage of our IV specification, and that the instrumented measure of consumer sentiment is a significant predictor of persistent differences in state economic growth.

Finally, we consider longer-horizon sentiment impacts. We repeat our base OLS and IV specifications to investigate the impact of sentiment on state activity over 2 and 3 year horizons. These ranges obviously speak to persistent output effects of changes in sentiments. Our results for these longer horizons are even stronger than those we find for our one-year base specification. This might be attributable to the reduced noise in longer series, but appears to suggest persistent effects of sentiment changes on future economic activity.

The remainder of this paper is organized into 7 sections. The following section introduces our data summary statistics. Section 3 discusses our base specification results. Section 4 subjects these results to a battery of robustness tests. Section 5 discusses our IV specification and results. Section 6 reports our results for longer horizons. Section 7 concludes.

2. Data

Quarterly sentiment data is obtained from 2004 through 2013 from the University of Michigan Surveys of Consumers (2016). Our base gauge of consumer sentiment is the answer to question BUS5 in the survey, “Looking ahead, 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 or depression, or what?” Respondents’ answers are scored 1 through 5, with 1 representing the answer “Good times,” 2 representing “Good with qualifications,” 3 representing “Pro-Con,” 4 representing “Bad with Qualifications,” and 5 representing “Bad Times.” The distribution of responses for the entire sample is shown in Figure 1. It can be seen that extreme responses of 1 or 5 are most common.

Figure 2 displays the relationship between national sentiment and national economic activity. As in much of the literature, sentiment appears to track current economic activity closely. For example, it is clear that sentiment declines sharply in tandem with the onset of the Great Recession. Still, sentiment does not track activity perfectly. Sentiment reaches its lowest level in 2011, reflecting volatility in financial markets associated with the euro area debt crisis. Needless to say, while there is a decline in output at this time, it does not match that experienced during the Great Recession. During that period, sentiment appears to have held up on average while the US economy fell into recession, and then continued to fall after the recession had ended. Still, the great recession periods is notable, as sentiment appears to track activity much more closely both before and after the event.

It is also difficult to draw any causal inferences from this national picture. Changes in sentiment may be following national economic conditions, rather than leading them. For that reason, we turn to state activity data for identification. Figure 3 displays the distribution of average business sentiment over our sample by state. For our sample period, respondents in the state of Virginia are most optimistic about future national economic activity on average, while those from New Mexico proved the most pessimistic on average. Reassuringly, there appears to be no apparent cross-sectional pattern to state responses, either by income, geography, or for the purposes of our IV specification below, political partisanship. In the latter case, note that our sample period spans years with sitting Presidents from both political parties.

As our base measure of lagged sentiment, *GOOD*, we consider the share of a state i at time t-4 whose respondents' answers were scored 1 or 2.

We include other variables obtained from the Michigan Surveys to condition on the characteristics of individual respondents. As our observation is at the state level, these are measured as state respondent averages, also at time t-4. Our conditioning variables include income levels by state, *INCOME*, which is calculated as the average of reported levels of respondent incomes within a state, *EDUC*, which is the average of the highest year of education reported by respondents within a state, and *INVEST*, which is the share of state respondents who said that they hold investments. Growth at the state level from period t-4 to t, *GGDP*, is obtained from Haver analytics, as is our measure of the national output gap, *YGAP*.

Summary statistics are shown in Table 1. It can be seen that there is a lot of variability in the data in both growth and sentiment measures, unsurprising since our sample includes the Great Recession period as well as the boom that preceded it. The final three columns show average growth rates in our pooled sample for states exhibiting high (more than one standard deviation above the mean) sentiment levels, *HGGDP*, neutral (within one standard deviation of the mean) sentiment levels, *MGGDP*, and low (more than one standard deviation below the mean), *LGGDP*, sentiment levels. As expected, it can be seen that subsequent growth on average is higher following reports of high sentiment levels, and lower for states where low levels of sentiment on average are reported. However, t-tests for differences in these populations are not statistically significant.

3. Base specification

Our base specification is a conventional least-squares panel estimator:

$$\Delta y_{it} = \alpha + \beta GOOD_{it-4} + \gamma X_{it-4} + \{\delta_i\} + \{\varepsilon_t\} + \eta_{it} \tag{1}$$

where Δy_{it} represents income growth in state i from period $t-4$ to the present, $GOOD_{it-4}$ represents the share of respondents with positive sentiment responses in state i in period $t-4$, X_{it-4} is a vector of controls linked to state growth via a set of nuisance parameters γ , $\{\delta_i\}$ and $\{\varepsilon_t\}$ are respectively country and time-specific fixed effects, and η_{it} is a is a residual, assumed to be well behaved. Our coefficient of interest is β , the partial-correlation between sentiment and subsequent state income growth. We use three covariates in X_{it-4} to control for other determinants of state growth available from the respondent survey, including, *INCOME*, *EDUC*, and *INVEST*, all described above.

We consider two alternative methods for conditioning for prevailing economic conditions. First, we include the start-of-period output gap, $YGAP_{t-4}$. Alternatively, we include yearly time dummies, $\{\varepsilon_t\}$. Quarterly time dummies are included below in our robustness checks.

It is also quite possible that our data may exhibit heteroscedasticity and correlations within and across state groups. We therefore use heteroscedasticity-corrected standard errors throughout, and also allow for cross-sectional or state-specific dependence. For cross-sectional dependence, which is likely across states in our panel, we use Driscoll-Kraay (1998) estimators. Hoechle (2007) demonstrates that Driscoll-Kraay standard errors are well-calibrated when cross-sectional dependence is present. For state-specific dependence, we include state dummies and cluster by state.

For those specifications that include a comprehensive set of both time and country specific fixed effects, our specification can be interpreted as a difference-in-differences estimator of the impact of changes in the share of agents within a state holding positive sentiment about future national economic prospects or not.

Our results for OLS estimation under our base specifications with robust standard errors are shown in Table 2. We consider six variations: Models 1 through 3 include the lagged output gap, while models 4 through 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. We include state fixed effects throughout.

Our point estimate for the coefficient of interest, changes in the sentiment share, with the output gap included is equal to 0.026, implying that a one standard deviation increase in our sentiment measure would be associated with a predicted increase in annualized state GDP growth of approximately 49 basis points. This seems to be a non-trivial effect, but one that is not too large to be plausible. Our point estimate with time dummies instead of the output gap is qualitatively similar, albeit modestly smaller at 0.018. Using either heteroscedasticity-robust or Driscoll-Kraay standard errors, our coefficient estimates are all statistically significant at a 1%

confidence level, while with standard errors clustered by states our results are statistically significant at a 10% confidence level.[7]

The performances of the conditioning variables are mixed. Only the *INVEST* variable enters consistently with statistical significance; it enters positively.

Overall, the data support a non-trivial sentiment channel for differences in economic growth across US states.

4. Sensitivity analysis

In this section, we demonstrate that our base results, that state sentiments about national economic prospects have a direct impact on future state output, are quite robust. We first demonstrate that our base specifications results are largely robust to a wide variety of sample perturbations (Table 3).

For each sample perturbation, we report the point estimate and standard error for the coefficient of interest, *GOOD*, for the six Models in our base specification in Table 2. First, we drop various time periods, including the first 8 quarters of our sample, the financial crisis period, which we interpret as spanning from 2007Q4 to 2009Q2, and the final 8 quarters of our sample. It can be seen that all sub-samples with *YGAP* included (Models 1-3) enter positively with qualitatively similar coefficient estimates and are statistically significant at standard confidence levels. The same is true for the models with time dummies estimated with robust standard errors or Driscoll-Kraay estimators (Models 4 and 5).

[7] In general, our results with clustered fixed effects are weaker than those we obtain with Driscoll-Kraay estimators. Indeed, because our time series is limited in length due to the availability of sentiment data, our estimates with clustered standard errors may be inconsistent [e.g. Cameron and Trivedi (2005)].

Our results are more sensitive with time dummies and clustering by state (Model 6). These continue to enter positively with qualitatively similar point estimates, but often miss statistical significance. However, it should be stressed that this sample truncation leaves our clusters even smaller than they are under our full sample, leaving the consistency of these estimates in question. Moreover, our results are usually robust to clustering by state in Model 3, which conditions for current economic conditions via the prevailing income gap.

We next drop observations from "high" (more than one standard deviation above the mean) and "low" (more than one standard deviation below the mean) average state income levels. We do the same for high and low reported share of households with investments, and states with large and small GDPs. Finally, we drop outlier observations, measured as those with residuals more than two standard deviations above or below zero in our base specification.

It can be seen that our base specification results are robust to all of these sample perturbations. Our coefficient of interest tends to enter positively at statistically significant levels throughout, usually with point estimates comparable to those obtained in our full sample. The one exception is again our Model 6 estimates for estimation with time dummies and clustering by state. These are often not significant at a 10% confidence level, but even in these cases are usually close to significance.

Table 4 considers the robustness of our results to changes in estimation methodology. First, one might think that averages of sentiment responses from larger states might be more informative, as these are taken from a larger sample of individual responses. We respond with two types of weighted least squares estimators, weighting by state GDP and the number of Michigan Surveys respondents in the state for that time period. The results for the six specifications with these weighting schemes for the sample are in the first two rows of Table 4.

Weighting in either manner raises our point estimates to around 0.043, which would increase the predicted response to a one-standard deviation increase in sentiment to around 82 basis points. All of our specifications using weighted least squares are statistically significant, with 11 of the 12 specifications significant at at least a 5% confidence level. The lone exception is Model 2, which uses Driscoll-Kraay estimators with the income gap included. That specification is statistically significant at a 10% confidence level.

We also consider conventional, rather than robust standard errors, random, rather than fixed effects, quarterly, instead of annual, time dummies, and regional dummies instead of state fixed effects. All specifications continue to enter positively at standard confidence levels. The sole exception is the specification with quarterly time dummies, which enters at a 5% confidence level using the Driscoll-Kraay standard errors, but is insignificant using either robust or clustered standard errors. Except for this case, our base specification results are robust to these perturbations of our estimation method.

Finally, Table 5 considers several alternative sentiment measures to the Michigan Surveys. First, we consider negative responses to the question about future national economic conditions, i.e. those that answered response "5" to the question above. We term this variable *"BAD5"*. Second, we consider the share of respondents in state *i* at time *t* that answered the question above that national economic conditions over the next five years would be "good," without qualifications, i.e. with responses that were coded "1" to the question above. We term this variable *"GOOD1."* We also consider responses to question BAGO (109) which asks whether business conditions are better or worse than the previous year, which we term *"BETTER"*. Finally, we use the sentiment measure studied by Mian, et al (2015) on the quality of government performance, which we term *"GOVT."* We measure this variable as the share of respondents who answered "1," indicating that they thought that the government was doing a "good job" in its economic policy.

Our results for these alternative sentiment measures continue to enter with their expected signs, but their performances in terms of statistical significance is uneven. Our results for negative sentiment responses, *"BAD5,"* universally enter positively at statistically significant levels. Our point estimates for this variable indicate a comparable response to what we saw ofr our positive sentiment variable. Given the standard error for this variable in our sample of 0.19, our point estimate of, for example, our base specification with the income gap included and robust standard errors (Model 1) implies that a one standard deviation increase in the share of negative sentiment is associated with a 47 basis point decrease in state output growth.

Our coefficient estimates for the *GOOD1* variable are of similar magnitude to our base specification above, and are significant for the specifications that include the income gap with either robust standard errors or the Driscoll-Kraay estimator (Models 1 and 2). However, they are uniformly insignificant for the specifications that include state fixed effects (Models 4 through 6), as well Model 3 with the income gap included and clustered standard errors. Our results do not seem very sensitive to the horizon of the survey question, as the impact of those with higher expectations concerning business conditions a year from now, *BETTER*, consistently enters with its expected positive sign and is statistically significant for all of the specifications that include the income gap (Models 1 through 3). However in Models 4 through 6, which include state fixed effects, the alternative sentiment variable enters insignificantly.

We obtain similar results for the specifications where sentiment is measured in terms of attitudes about the government's performance, *GOVT*. These enter significantly for the specifications including the income gap (Models 1 through 3), but insignificantly when state fixed effects are included (Models 4 through 6). Our point estimates are also very similar to those obtained for other alternative sentiment measures.

All of the alternative measures considered enter with their expected signs in all of our specifications. Not all of these are statistically significant for our sentiment variable of interest, but then, neither were the specifications with our base sentiment measure in Table 2. Overall, then, while we acknowledge some sensitivity to the sentiment measure used, our results continue to indicate a positive (negative) impact on state output with higher (lower) measures of sentiment about future economic activity used.[8]

5. IV estimation

One potential problem with our OLS specification is that opinions about future national economic performances may be based on individual experiences, and hence tied to the fortunes of the local economy. [9] This would render our least-squares identification strategy invalid. To test if this is the case, we examine the relationship between current state economic growth and current sentiment levels. Our reverse specification satisfies

$$GOOD_{it} = \alpha + \beta \Delta y_{it} + \gamma X_{it-4} + \{\delta_i\} + \{\varepsilon_t\} + \eta_{it} \tag{1.1}$$

where variable definitions are the same as in our base specification.

[8] Using our IV estimation methodology discussed in Section 5, we re-estimated our specifications for these alternative sentiment measures. Our results for these instrumented specifications were quite similar, and are shown in Appendix Table 1.

[9] We do find positive, albeit modest, correlations in the survey between responses to our national outlook question and individual household experiences and expectations. The estimated correlation coefficient between positive responses to the national economic outlook and positive responses to the question about whether a household's financial condition is better or worse off than it was a year ago (question PAGO in the survey) is 0.32, while the estimated correlation coefficient between expected future national economic conditions and expected household financial conditions five years in the future (question PEXP5 in the survey) is 0.23.

Our results are shown in Table 6. The data do appear to indicate that sentiment is associated with local activity. All of the specifications enter with statistically significant coefficient estimates for the GGDP variable of interest except for the estimation with robust standard errors with state fixed effects included (Model 4). In particular, our base specification with the income gap and robust standard errors indicates a positive relationship between lagged local growth and sentiment at a 5% confidence level. Overall, there does seem to be a risk of reverse causality.

We address this potential issue through instrumental variables (IV). We follow the literature in turning to political data as an instrument for differences in sentiment levels that vary systematically across regions. Our posited relationship is that survey respondents will be more optimistic about national economic prospects if the sitting president is from his or her political party. The relationship between political partisanship and economic sentiment has been shown in the literature [e.g. Mian, et al (2015) and Gillitzer and Prasad (2015)], and sentiment has been shown to correspond to economic activity, as in Gerber and Huber (2009), who identify a positive relationship between partisanship and economic activity, as consumption changes following a political election are correlated with whether or not the election was won by the preferred political party of the respondent.

Mian, et al (2015) also demonstrate that presidential elections are associated with changes in sentiment about the effectiveness of government policy in line with political partisanship. However, they find no statistically significant relationship between changes in the presidential party at the county level in the United States and changes in actual consumption. In contrast, Gillitzer and Prasad (2015) show in Australian survey data that higher sentiment is associated with having a member from your political party in office at the federal level. Changes in sentiment associated with elections are shown to be associated with increased future vehicle purchase rates.

One distinction that favors the Australian study is that Australian survey data has a direct question about political affiliation. U.S. consumer data, such as that used by Mian, et al (2015) have to use proxies for political partisanship. Their study uses county-level data on voting in presidential elections. Our study using U.S. data faces the same challenge. To proxy for political partisanship at the state level, we use the share of state congressional representatives from the same political party as the sitting president, which we term *CONGPRES.* Our proxy has the advantage of changing every two years, with each congressional election, and therefore yields more variability in our sample.

One potential concern with our instrument is the possibility that the political situation may directly affect underlying economic fundamentals. In particular, it is possible that states with a higher number of congressional representatives from the same political party as the sitting president will be favored in political outcomes in a manner that directly supports local economic conditions. For example, decision about military base closures may be made in geographically partisan manners.

Mian, et al (2015) provide two pieces of evidence against this possibility. First, they look at income growth in U.S. counties before and after Presidential elections. They find no evidence that Presidential elections are systematically related to changes in county growth in manner associated with local political leanings. Second, they also find no relationship between election outcomes and changes in government transfers to localities. Given this evidence, we proceed under the assumption that the sentiment channel is the only channel through which the political characteristics of a state influence its economic activity, rendering our IV specification valid.

We first examine the first stage of our IV specification to demonstrate that we have a strong instrument. We include our conditioning variables as well. Our panel results are shown in Table 7. Our variable of interest, *CONGPRES*, consistently enters significantly with its expected positive sign, indicating significant correlation with our sentiment variable.

The second stage results are shown in Table 8. It can be seen that our variable of interest, *GGDP*, continues to enter significantly positively. The instrumented coefficient point estimate in our IV specification is much larger. With the income gap included, it comes in at 0.169 and with state fixed effects included it comes in at 0.104.

These point estimates are probably too high, in the sense that under our sample, a one standard deviation increase in sentiment would be associated with a 3.2 percentage point increase in state output growth in Models 1 through 3, and a 2.0 percentage point increase in Models 4 through 6. However, the 95% confidence intervals for these coefficients allow a one standard deviation increase in sentiment to be associated with an increase in state output of as low as 90 basis points, a much more plausible figure, for our base specification with robust standard errors and the income gap included (Model 1), and as low as 98 basis points with robust standard errors and state fixed effects included (Model 4).[10]

6. Impact on activity over longer horizons

Finally, we consider the impact of sentiment over longer horizons. We redo our base specifications with a two-year lag for sentiment. Our dependent variable is now $\overline{GGDP}_{it,t+8}$, average annual state growth from period *t* through period *t+8*.

[10] Hausman test results are inconclusive about the need for instrumenting. We obtain a p-value of 1.00 for Model 1, which includes state, but not time, fixed effects, but a p-value of 0.00 for Model 4, which includes both. However, it is reassuring that our exact method of estimation matters little. We find a strong relationship between levels of sentiment and future state economic performances under either OLS or our IV estimation.

Our results for the variable of interest, *GOOD*, over a two-year horizon are shown in Table 9. Our base specifications estimated using OLS are shown in the first row. Our specification with robust standard errors (Models 1 and 4) enters positively with statistical significance at a 5% confidence level with either the income gap included or state fixed effects. With Driscoll-Kraay standard errors, our results are similar, with 10% significance with the income gap included and 5% significance with state fixed effects included. However, we obtain insignificant coefficient estimates with clustered standard errors. As above, we have some reservations about our standard error estimates for these clustered specifications because our panel is small in the time dimension. Indeed, it is even smaller in the time dimension than our base specification because of our longer lags at a two-year horizon.

The point estimates for average annual growth are smaller over a two year horizon, as would be expected. Our point estimates suggest that under our sample a one standard deviation increase in sentiment is associated with only a 19 basis point increase in average state growth over the next two years for the specifications with the income gap included (Models 1 through 3), and even smaller effects . However, a 95% confidence interval would include values similar to our point estimates for the one year horizon.

Our IV estimates over the 2-year horizon are in the second row. We obtain significant results with either robust standard errors or Driscoll-Kraay estimators in our specifications including income gaps, but our results become less insignificant with fixed effects included. Only the Driscoll-Kraay IV estimator enters significantly, and then only at a 10% confidence level.

As was the case for the one year horizon, our point estimates for the IV regressions are much larger. However, they not as large as those over a one year horizon. For example, over a two year horizon, our point estimate for our base IV specification with robust standard errors and the income gap included implies that a one standard deviation increase in sentiment would be associated with 1.6 percentage point increase in average state GDP growth over the following two years. These are probably implausibly large, but similar to our findings above, a 95% confidence interval for our results for that specification would include responses as low as 60 basis points.[11]

Over a 3 year horizon, our OLS results appear even stronger. Our variable of interest enters with its expected positive sign and is statistically significant for all estimation methods. Indeed, in terms of our point estimates, the impact of sentiment on average annual growth is even modestly larger over a three year horizon than it was over a two-year horizon, although it still implies a rather small response. For example, over a three year horizon, our point estimate for our base OLS specification with robust standard errors and the income gap included implies that a one standard deviation increase in sentiment would be associated with about a 21 basis point increase in average state GDP growth.

Our IV results again obtain larger point estimates, but over a 3 year horizon are statistically insignificant for all specifications. Hausman test results for the need for instrumenting are similarly inconclusive to those we obtained for a 1-year horizon, with a p-value of 1.00 for Model 1, and one of 0.00 for model 4.

Overall, our results confirm that the relationship between sentiment and future economic activity at the state level is persistent. These results are robust to a variety of estimation methods, as well as our instrumenting methodology over the two year horizon. Our point estimates under least squares indicate that the sensitivity is weaker over the 2 and 3 year

[11] Hausman test results are again mixed, with Model 1 obtaining a p-value of 1.00, while we fail to obtain a solution for Model 4.

horizons, but the continued strength over the three year horizon indicates that the impact is quite persistent.

7. Conclusion

We revisit the relationship between consumer sentiment and economic activity. Our identification strategy is based on using the cross-sectional information in state data. We examine individual responses to survey questions about long-term prospects for the national economy. If sentiment drives activity, states in which agents hold more optimistic outlooks about national economic prospects should undertake higher levels of economic activity: Sentiments about economic prospects can thereby affect output at the state level.

In a standard panel specification, we examine the relationship between household survey responses and future economic growth at the state level. Our results demonstrate a statistically and economically significant relationship between sentiment levels and state GDP growth. Our point estimate under our base specification indicates that a one standard deviation increase in sentiment is associated with additional 49 basis points of growth in the following year. This result is robust to a wide variety of robustness tests, including sample perturbations, changes in estimation methods, and the use of alternative sentiment measures.

A potential problem with our strategy is that it is possible that agents' responses to questions about future national economic conditions may reflect local conditions. Our reverse regression results suggest that reverse causality along these lines may indeed be an issue, although formal Hausman tests do not indicate endogeneity at statistically significant levels. To address this potential problem, we turn to IV estimation, based on a predicted relationship between political partisanship and economic sentiment concerning national economic prospects.

Our results demonstrate a strong first stage relationship between our instrument and our sentiment measure. Our instrumented sentiment measure then confirms our least squares results, again for a variety of specifications.

Finally, we consider the impact of sentiment over two and three year horizons. Our results over these longer horizons are quite robust, usually entering at statistically significant levels, although our point estimates of the impact of sentiment levels on average annual growth are modestly smaller than those that we obtained over a one year horizon. Moreover, we obtain modestly larger point estimates over our 3 year horizon than we obtain over a two-year horizon, supporting our inference that the relationship between sentiment and economic activity is persistent. However, sentiment levels enter insignificantly in our instrumented specifications over a three year time horizon.

Our overall results therefore support the notion of a persistent positive empirical relationship between sentiment and future economic activity that appears to reflect changes in aggregate demand, rather than information about future technology shocks.

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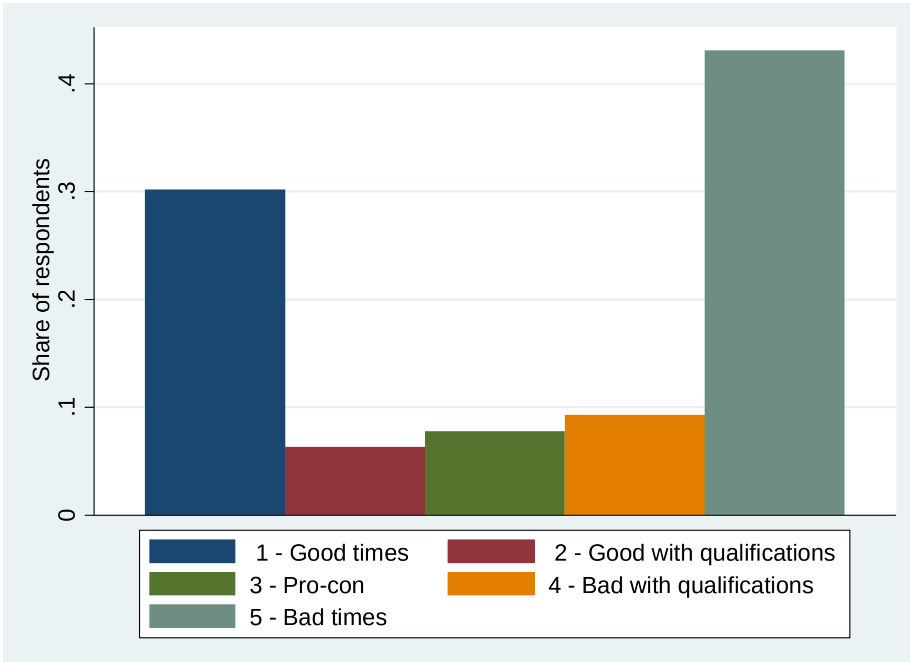
Figure 1

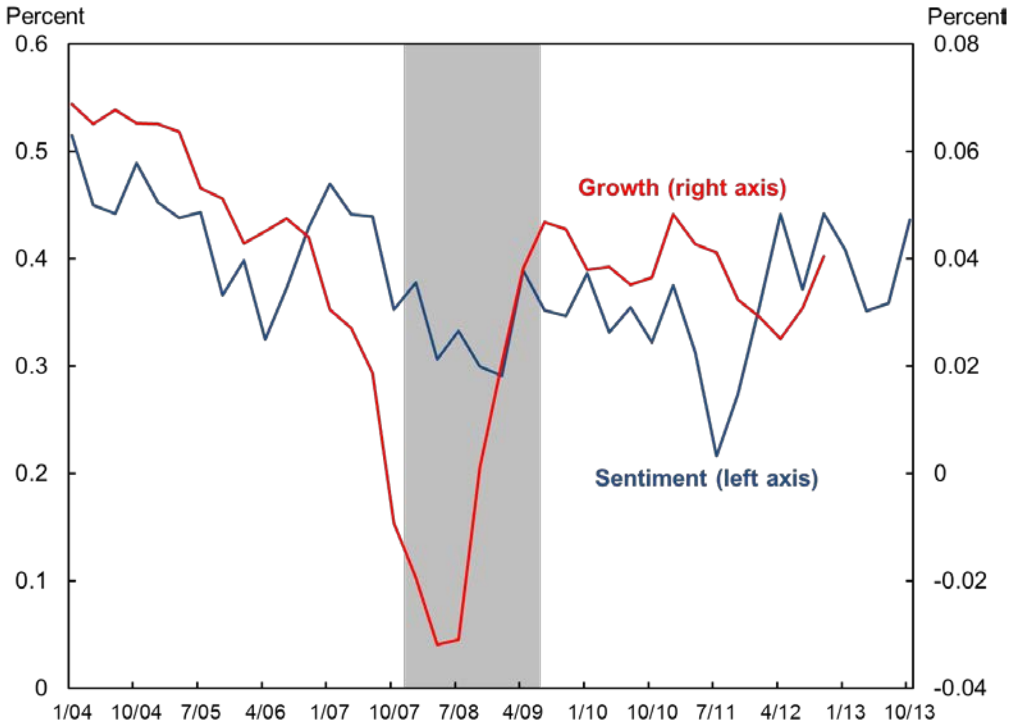
Distribution of responses to base sentiment question



Source: Michigan Survey of Consumers, 2004-2013. Histogram of percentages of each answer to survey question BUS5. See text for question.

Figure 2

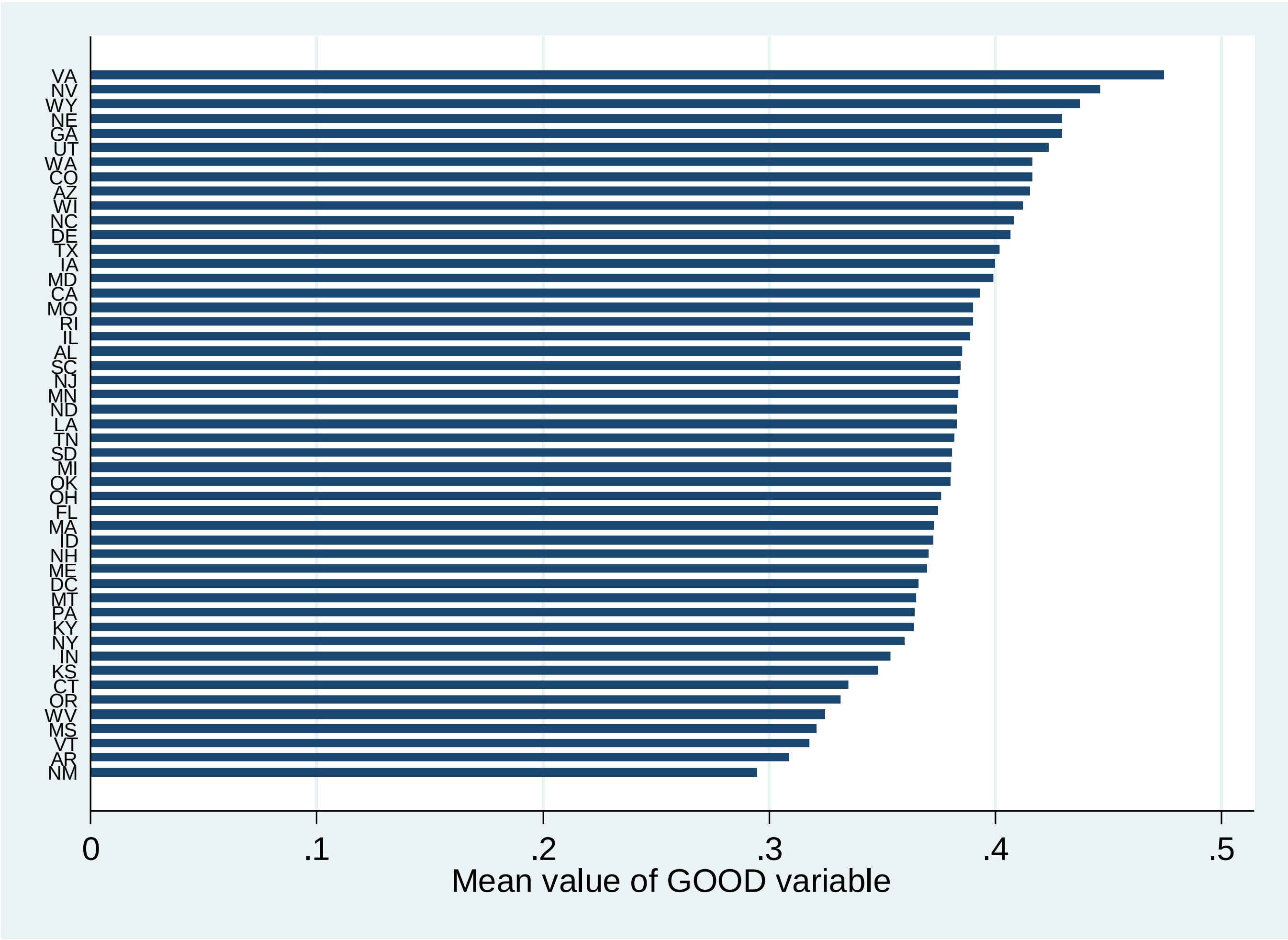
Average sentiment and national output growth
(2004-2013)



Note: Source: Michigan Survey of Consumers, 2004-2013. Sentiment measured by average share of "GOOD" responses (1 or 2) to question BUS5. See text for question. Output growth from current quarter to four quarters in future.

Figure 3

Average business sentiment by state, 2004-2013



Note: Source: Michigan Survey of Consumers. Mean value of *GOOD* variable (average share of respondences of 1 or 2 for question BUS5) over entire sample, 2004-2013, by state.

Table 1

Summary Statistics

	GOOD	GGDP	INCOME	EDUC	INVEST	HGGDP	MGGDP	LGGDP
mean	0.382	0.032	79809.550	14.723	0.678	0.035	0.032	0.030
sd	0.190	0.039	30916.220	2.229	0.178	0.052	0.036	0.032
min	0	-0.178	4416	8	0	-0.178	-0.119	-0.058
max	1	0.257	330201.600	47.494	1	0.238	0.257	0.115
N	1953	1562	1953	1953	1953	252	1086	224

Note: See text for variable definitions. Test for *HGGDP* > *MGGDP* has p-value 0.16; test for *HGGDP* > *LGGDP* has p-value 0.11, while test for *MGGDP* > *LGGDP* has p-value 0.21.

Table 2

Base Specification

Dep. Variable: GGDP						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GOOD	0.026***	0.026***	0.026*	0.018***	0.018***	0.018*
	(3.965)	(2.985)	(1.979)	(3.277)	(3.721)	(1.684)
YGAP	-0.000	-0.000	-0.000			
	(-0.549)	(-0.089)	(-0.299)			
INCOME	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(-1.385)	(-1.232)	(-1.192)	(0.057)	(0.054)	(0.057)
EDUC	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.583)	(-1.268)	(-1.105)	(-1.195)	(-1.275)	(-0.871)
INVEST	0.014*	0.014***	0.014**	0.008	0.008*	0.008*
	(1.827)	(4.290)	(2.084)	(1.179)	(1.956)	(1.770)

Note: OLS estimation. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$.

Table 3

Sample Sensitivity Analysis

Tests	(1)	(2)	(3)	(4)	(5)	(6)
	Base, YGAP	**DK se**	**YGAP, cluster**	**Base, dum**	**DK se, yr dum**	**Base, cluster**
Base	0.026***	0.026***	0.026**	0.018***	0.018***	0.018*
	(3.965)	(2.985)	(1.979)	(3.277)	(3.721)	(1.684)
Drop early	0.020***	0.020**	0.020*	0.011	0.011	0.011
	(2.698)	(1.993)	(1.655)	(1.554)	(1.518)	(1.076)
Drop fin crisis	0.024***	0.024***	0.024*	0.018***	0.018***	0.018
	(3.498)	(2.650)	(1.797)	(3.034)	(2.721)	(1.621)
Drop late	0.033***	0.033**	0.033**	0.019***	0.019***	0.019*
	(3.789)	(2.485)	(2.541)	(2.703)	(3.665)	(1.877)
Drop high inc	0.028***	0.028***	0.028**	0.018***	0.018***	0.018
	(4.049)	(3.059)	(2.005)	(3.088)	(3.479)	(1.575)
Drop low inc	0.028***	0.028***	0.028*	0.022***	0.022***	0.022*
	(3.691)	(2.922)	(1.828)	(3.443)	(4.000)	(1.794)
Drop high inv	0.022***	0.022**	0.022	0.015**	0.015***	0.015
	(3.117)	(2.404)	(1.538)	(2.460)	(2.787)	(1.255)
Drop low inv	0.024***	0.024***	0.024*	0.018***	0.018***	0.018
	(3.452)	(3.032)	(1.668)	(2.980)	(3.585)	(1.503)
Drop large GDP	0.025***	0.025***	0.025*	0.017***	0.017***	0.017
	(3.716)	(3.071)	(1.861)	(3.072)	(3.408)	(1.582)
Drop small GDP	0.021***	0.021**	0.021***	0.014***	0.014***	0.014**
	(3.880)	(2.138)	(2.844)	(3.219)	(3.459)	(2.543)
Drop outliers	0.023***	0.023***	0.023***	0.018***	0.017***	0.018**
	(3.977)	(2.861)	(3.300)	(3.464)	(3.409)	(2.130)

Note: Coefficient estimates for GOOD variable in Models 1 through 6 in base specification (Table 2), with noted changes. See text for details. OLS estimation. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$.

Table 4

Estimator Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
StateGDP weighted	0.043***	0.043*	0.043**	0.028***	0.028***	0.028***
	(4.662)	(1.980)	(2.606)	(4.753)	(4.862)	(3.023)
Number of responses weighted	0.043***	0.043**	0.043***	0.029***	0.029***	0.029***
	(5.489)	(2.349)	(3.270)	(5.311)	(5.462)	(3.257)
OLS (not robust SE)	0.026***		0.026*	0.018***		0.018*
	(5.174)		(1.979)	(4.379)		(1.684)
Random Effects	0.026**		0.026**	0.018*		0.018*
	(1.979)		(1.979)	(1.684)		(1.684)
Quarterly dummies				0.013	0.013**	0.013
				(1.196)	(2.474)	(1.196)
Regional dummies	0.026**	0.026**	0.026**	0.018*	0.018**	0.018*
	(2.009)	(2.456)	(2.009)	(1.712)	(2.522)	(1.712)

Note: Coefficient estimates for GOOD variable in Models 1 through 6 in base specification (Table 2), with noted changes. See text for details. OLS estimation. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$.

Table 5

Alternative Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Good1	0.016**	0.016*	0.016	0.009	0.009	0.009
	(2.222)	(1.690)	(1.430)	(1.517)	(1.593)	(1.139)
BAD5	-0.024***	-0.024***	-0.024**	-0.021***	-0.021***	-0.021**
	(-3.696)	(-4.018)	(-2.291)	(-3.878)	(-5.939)	(-2.560)
Better1	0.039***	0.039*	0.039***	0.005	0.005	0.005
	(8.051)	(1.744)	(4.584)	(0.855)	(0.771)	(0.563)
GOVT	0.040***	0.040**	0.040***	0.008	0.008	0.008
	(4.851)	(2.502)	(4.405)	(1.019)	(1.103)	(1.313)

Note: Coefficients for alternative sentiment measures in Models 1 through 6 in base specification (Table 2). See text for details. OLS estimation. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * p < 0.10, **p < 0.5, ***p < 0.01.

Table 6

Lagged Growth and Sentiment

Dep. Variable: GOOD						
	(1)	(2)	(3)	(4)	(5)	(6)
GGDP	0.380**	0.380***	0.380***	0.310	0.310*	0.310*
	(2.221)	(2.800)	(2.723)	(1.437)	(1.867)	(1.679)
YGAP	0.005**	0.005	0.005*			
	(2.502)	(1.081)	(1.964)			
INCOME	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.567)	(-0.570)	(-0.545)	(-0.396)	(-0.393)	(-0.362)
EDUC	0.002	0.002	0.002	0.002	0.002	0.002
	(0.742)	(0.859)	(1.002)	(0.562)	(0.630)	(0.711)
INVEST	-0.005	-0.005	-0.005	0.004	0.004	0.004
	(-0.119)	(-0.100)	(-0.095)	(0.094)	(0.080)	(0.076)

Note: OLS regressions of GOOD on four-quarter lags of GGDP in Models 1 through 6 in base specification (Table 2). See text for details. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$.

Table 7

1st Stage IV Estimator

Dep. Variable: GOOD						
	(1)	(2)	(3)	(4)	(5)	(6)
Congpres	0.090***	0.090***	0.090***	0.083***	0.083***	0.083***
	(4.341)	(5.048)	(4.319)	(3.936)	(4.642)	(3.926)
YGAP	0.015***	0.015***	0.015***			
	(8.041)	(3.519)	(6.015)			
INCOME	0.000	0.000	0.000	0.000	0.000	0.000
	(0.093)	(0.114)	(0.106)	(0.895)	(1.549)	(0.993)
EDUC	-0.002	-0.002	-0.002	-0.003	-0.003*	-0.003
	(-1.025)	(-1.440)	(-0.964)	(-1.239)	(-1.774)	(-1.177)
INVEST	0.097**	0.097***	0.097***	0.082*	0.082**	0.082**
	(2.261)	(2.806)	(2.720)	(1.921)	(2.429)	(2.425)

Note: First stage of IV estimation. OLS regressions of GOOD on CONGPRES instrument with covariates from Models 1 through 6 in base specification (Table 2) also included. See text for details. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$.

Table 8

IV Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
GOOD	0.169***	0.169***	0.169*	0.104**	0.104**	0.104
	(2.793)	(3.338)	(1.839)	(2.021)	(2.535)	(0.995)
YGAP	-0.002**	-0.002**	-0.002*			
	(-2.266)	(-2.458)	(-1.742)			
INCOME	-0.000*	-0.000**	-0.000*	-0.000	-0.000	-0.000
	(-1.664)	(-2.010)	(-1.788)	(-0.515)	(-0.628)	(-0.593)
EDUC	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.687)	(-0.622)	(-0.494)	(-0.638)	(-0.681)	(-0.483)
INVEST	0.004	0.004	0.004	0.002	0.002	0.002
	(0.347)	(0.472)	(0.420)	(0.241)	(0.325)	(0.267)

Note: IV estimation, with CONGPRES as instrument. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$. Hausman tests for conventional standard errors for models 1 and 4 yield chi-square statistics of 9.03 and 690.77 respectively, corresponding to p-values of 1.00 and 0.00.

Table 9

Longer Horizon Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
2 year OLS	0.010**	0.010*	0.010	0.008**	0.008**	0.008
	(2.319)	(1.734)	(1.181)	(1.969)	(1.985)	(0.968)
2 year IV	0.086**	0.086***	0.086	0.042	0.042*	0.042
	(2.517)	(2.776)	(1.455)	(1.467)	(1.722)	(0.614)
3 year OLS	0.011***	0.011**	0.011**	0.007**	0.007*	0.007*
	(3.074)	(2.000)	(2.282)	(2.307)	(1.862)	(1.746)
3 year IV	0.038	0.038	0.038	0.014	0.014	0.014
	(1.218)	(1.552)	(0.637)	(0.460)	(0.651)	(0.218)

Note: OLS estimation for state GDP growth over 2 and 3 years, as indicated. Coefficients sown for GOOD variable only. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$. Hausman tests for conventional standard errors for IV regressions for model 1 with a 2-year horizon yields chi-square statistic of 6.10 for a p-values of 1.00, but yielded no solution for model 4 with a 2-year horizon, while for Models 1 and 4 with 3-year horizons yielded chi-square statistics of 1.23 and 75.26 respectively, corresponding to p-values of 1.00 and 0.04.

APPENDIX

A.1 Variable definitions and sources

Better1= Sentiment – percent of people who answered 1 to the “bago” survey question (think business conditions are “better now” than they were one year ago)

Good1= Sentiment **–** Percent of people who answered 1 to the “bus5” survey question (think the country will be doing “Good” in the next 5 years)

Good12= Sentiment- Percent of people who answered 1 or 2 to the “bus5” survey question (think the country will be doing “Good” or “good with qualifications” in the next 5 years)

Congpres= Percent of Congress representatives in each state that share the same party as the sitting president

Educ= highest level of education attained

GGDP = GDP growth by state over the past 4 quarters

GHSENT= gdpgrowth in states that have 4-quarter lagged sentiment greater than 1 SD above the mean

GNSENT= gdpgrowth in states that have 4-quarter lagged sentiment within 1 SD of the mean

GLSENT= gdpgrowth in states that have 4-quarter lagged sentiment greater than 1 SD below the mean

GOVT= Sentiment – percent of people who answered 1 to the “govt” survey question (think the government is doing a “good job” on economic policy)

INVEST= Percent of people who said they invest, by state and quarter

i.region = regional dummies (4 total regions)

i.time = quarter dummies

i.state= state dummies (49 total states – no HI or AK)

LGOOD12 = bus5_1and2 lagged 4 quarters

NRESP= Number of individual respondents to the Michigan Survey in that state in that quarter

STATEGDP= GDP by state

Table A1 : Table 5 with IV Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
BAD5	-0.125***	-0.125***	-0.125*	-0.074**	-0.074***	-0.074
	(-3.094)	(-3.611)	(-1.857)	(-2.150)	(-2.715)	(-0.989)
Good1	0.238**	0.238***	0.238	0.145*	0.145**	0.145
	(2.290)	(2.825)	(1.628)	(1.761)	(2.248)	(0.921)
Better1	0.361	0.361*	0.361	0.149	0.149**	0.149
	(1.459)	(1.806)	(0.915)	(1.565)	(2.077)	(0.798)
GOVT	0.147***	0.147***	0.147	0.104**	0.104***	0.104
	(3.075)	(3.770)	(1.517)	(2.036)	(2.583)	(0.875)

Note: Coefficients for alternative sentiment measures in Models 1 through 6 in base specification (Table 2). See text for details. IV estimation with CONGPRES as instrument for GOOD. T-statistics in parentheses. All models have state dummies. Models 4, 5 and 6 include annual time dummies. Models 1 and 4 use robust standard errors, models 2 and 5 use the Driscoll-Kraay estimators, and models 4 and 6 allow for clustered standard errors by state. * $p < 0.10$, **$p < 0.5$, ***$p < 0.01$.