Mood, Firm Behavior, and Aggregate Economic Outcomes*

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Abstract: This study examines whether mood affects the aggregate macroeconomy through its impact on firm-level decisions. Using sky-cloud-cover as a proxy for mood, we show that mood affects the economic expectations of small business managers. On relatively sunnier days, managers have more optimistic expectations and the component of their expectations related to mood influences hiring and investment decisions. Consequently, mood affects state-level job creation and new business starts, especially during periods of greater economic uncertainty. Collectively, these results suggest that mood-induced economic expectations influence firm-level managerial decisions and state-level economic fluctuations.

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1. Introduction

A growing literature in finance and economics demonstrates that mood influences individual-level economic decisions and stock market returns. Using weather as a proxy for mood, Saunders (1993) shows that cloud cover in New York City affects stock market returns through its impact on the mood of local traders. Hirshleifer and Shumway (2003) find similar evidence using international data. Further, Goetzmann and Zhu (2005) show that market makers are affected by the weather in New York City and Goetzmann, Kim, Kumar and Wang (2015) show that shifts in weather-induced mood affects perceptions of mispricing and investor trading.

A related strand of this literature examines the link between mood and economic activity using other mood proxies. In particular, Kamstra, Kramer and Levi (2000), and Kamstra, Kramer, and Levi (2003) use seasonal changes in biorhythm, Yuan, Zheng, and Zhu (2006) use astronomical events, Edmans, Garcia, and Norli (2007) use sporting events, and Garcia (2013) use media valence to capture mood.[1]

In this study, we extend this literature and examine whether mood influences aggregate macroeconomic fluctuations through its impact on managerial sentiment and corporate decisions. Our key conjecture is that the impact of mood on individual decisions can aggregate and could generate economic forces powerful enough to influence business cycles. This conjecture is inspired by Shiller's (2010) idea that "business recessions are caused by a curious mix of rational and irrational behavior," and "negative feedback cycles, in which pessimism inhibits economic activity, are hard to stop".

While Shiller's conjecture is intuitive, it is difficult to establish a direct link between mood and economic activity since people's mood is often unobservable. Further, the channels

[1]For additional evidence, see DeHaan, Madsen, and Piotroski (2015), Bushee and Friedman (2015), and Cortes, Duchin and Sosyura (2016).

through which mood might affect economic decisions are often difficult to identify. To address these potential difficulties, we use weather variables to proxy for managerial mood. Plus, we obtain a new and unique data set on the economic expectations and financial decisions of a large sample of small business managers. Using the locations of small business managers, we link the small business economic data with the weather data. This combined data set allows us to assess the direct impact of mood on economic expectations and financial decisions of managers. Subsequently, we are able to examine the impact of mood on aggregate business cycle fluctuations.

We focus on the economic behavior of managers at small businesses because these economic units account for a large fraction of economic output in the United States.[2] In addition, the effects of mood are likely to be stronger among managers of small businesses than corporate managers of large publicly traded companies since small business managers are likely to have greater autonomy in their financial decisions.

We propose three specific hypotheses that we test using micro-level data on small business managers and aggregate macroeconomic data about U.S. states. First, we hypothesize that mood would affect the macroeconomic expectations of small business managers. Second, we posit that the component of managerial expectations related to mood would affect key managerial decisions. Third, we conjecture that the effects of mood are likely to be systematic and would induce managers to act in a coordinated manner. Consequently, mood would affect aggregate economic outcomes. In particular, shifts in managerial mood can amplify expansions and prolong economic recessions.

[2] Kobe (2012) document that 45% of private, non-farm, U.S. gross domestic product in 2010 is accounted for by small businesses, defined as enterprises with less than 500 employees. Headd (2014) estimates that small businesses are responsible for 63% of net new jobs created between 1993 and 2013.

Our first hypothesis that links mood and expectations is motivated by evidence from social psychology. In particular, Schwarz and Clore (1981) provide experimental evidence that individuals misattribute mood for information in their decisions. Johnson and Tversky (1983) show that mood influences the way individuals form expectations about future events. Likewise, Wright and Bower (1992) provide experimental evidence that good mood increases the subjective probabilities of positive events and decreases those of negative events. Wegener, Petty, and Klein (1994) document similar effects, but also find that negative information has a minimal impact on the expectations of subjects primed with positive mood.

In other related studies, Clore, Schwarz and Conway (1994) and Forgas (1995) find that mood affects abstract judgments when the available information is limited. Mood-related biases are especially strong when individuals perceive that they have low expertise (Ottati and Isbell (1996), Sedikides (1995)), or low processing capacity (Greifeneder and Bless (2007), Siemer and Reisenzein (1998)). Finally, Williams and Voon (1999) find that managers primed with good mood are more likely to believe that they could influence risky outcomes, and thus, they are more willing to make risky decisions. Overall, motivated by these earlier findings, we posit that small business managers' expectations would be influenced by their mood.

To test this hypothesis, we use data from the Small Business Economic Trends (SBET) survey. Using the SBET data, we extract information about managerial expectations about future macroeconomic conditions. We focus on expectations related to macroeconomic conditions because evidence from social psychology suggests that mood-induced biases are likely to be stronger in complex decision making tasks. Specifically, mood should affect macroeconomic forecasts because it is a complex task for which managers at small businesses might have little expertise or relevant information. In contrast, mood should have less impact on firm-level forecasts, such as sales, which are more tangible.

We proxy for managerial mood using the average deseasonalized sky-cloud-cover at the location of the firm. We use sky-cloud-cover as a proxy for mood because evidence from social psychology suggests that sunshine affects individual behavior. In particular, sunshine affects tipping (Cunningham (1979); Rind (1996)), life satisfaction (Schwarz and Clore (1983)), and responsiveness to persuasion (Clore, Schwarz, and Conway (1994)). The association between sunlight and mood may even have a neuro-foundation as simulated sunlight has been shown to have therapeutic effects on depression (Rosenthal et al. (1984) and Kripke (1998)). Further, sunshine is a quasi-exogenous source of variation that can influence people's mood but it is unlikely to be related to actual economic outcomes.

Consistent with our first hypothesis, we find that, in relatively sunnier months, managers have more favorable expectations about future macroeconomic conditions than in cloudier months. This effect is robust to the inclusion of seasonal, regional and other firm-specific factors that can affect managerial forecasts (e.g., current sales, expected sales, financing difficulties, and labor availability). Moreover, we find that the effects of weather-induced mood are short-lived.

Evidence from additional tests indicate that the mood effect is not driven by managers' response to shifts in consumer mood. In our main tests, when we account for consumer mood using various control variables related to sales, we find that the impact of weather-induced mood remains significant. To further account for the effect of consumer mood, we estimate a system of two equations. The dependent variable in the first equation is the managerial expectations about the economy and in the second equation, we use the change in firm sales as the dependent variable. In this estimation, we allow the shocks to expectations and changes in sales to be correlated. Such correlations can arise because consumer mood can affect managerial expectations and sales. We estimate the system of equations with a seemingly unrelated regression approach and find that in the presence of our rich set of control variables, the weather mood proxy is related to managerial expectation but it is not related to changes in sales.

In a related placebo test, we also examine whether managerial forecasts about firm sales are affected by mood. Forming expectations about firm-specific factors is relatively less complex because firm sales are more tangible and may depend on past decisions of the manager. Therefore, we expect to find *weaker* or *no mood related biases* in this instance. Consistent with our expectations, we find that the sky-cloud-cover mood proxy is not related to sales forecasts. This finding suggests that our mood proxy is exogenous and unlikely to be related to the current economic conditions faced by the firm. It is also unlikely to capture managerial response to changes in consumer mood, which could affect their sales forecast.

To provide further evidence that sky-cloud-cover is related to mood, we examine whether forecast accuracy of managers is related to the weather variable. This test is based on the prior evidence that mood biases lead to inaccurate forecasts (Johnson and Tversky (1983)) and such biases are more severe for good rather than bad moods (Schwartz (1991)). For this analysis, we construct a pseudo-panel of all managers in a given state because our firm-level data set is a repeated cross-section sampling different managers every month. Following Gennaioli, Ma and Shleifer (2016), we construct the forecast error as the difference between the state-average of firm expectations from a forecast of the expectations based on a regression model. Consistent with the evidence from the psychology literature, we find that the forecast errors related to the economy are the highest during sunny (low cloudiness) months.

Taken together, these findings confirm our conjecture that mood affects managerial expectations. In the next set of tests, we examine our second hypothesis, which posits that mood affects managerial decisions through its impact on managerial expectations. For this analysis, we again use data from the SBET survey and extract information related to the future hiring and capital expenditure decisions of small business managers. We demonstrate that the *component* of managerial expectations related to mood is related to their hiring and investment plans. Specifically, we use an instrumental variable approach where we instrument manager's economic expectations using the sky-cloud-cover mood proxy. We find that mood-instrumented expectations are strongly related to firm-level hiring and investment decisions of small business managers. Thus, mood effects are strong enough to affect firm-level decisions via its impact on expectations.

Our third hypothesis posits that if mood effects are systematic, they would have an impact on the aggregate macroeconomy. In particular, since sky-cloud-cover is our proxy for mood, this hypothesis implies that weather in one geographical region may affect the mood of all managers in that area. And if managers in a certain geographical area are all affected by the weather in a similar manner, their decisions might be correlated and biased in the same direction. Consequently, the average level of sunshine at a location, which is our proxy for local mood, could affect the local macroeconomic conditions.

To test this hypothesis, we shift our point of view from the firm-level to the U.S. state-level. Specifically, we aggregate the mood measure to the U.S. state-level and test whether state-level mood is related to state-level employment and investment outcomes. We measure aggregate employment using the net proportion of establishment reporting job gains versus losses. We also compute aggregate investments using the net proportion of establishment starts versus deaths. Our evidence indicates that net job creation and net establishment starts increase when the average state weather is relatively sunnier.

We also examine whether the aggregate mood effects depend upon the overall market-wide business climate. This test is motivated by the evidence from the social psychology literature that judgment biases induced by mood are amplified in more complex environments. Based on this finding, we expect that mood-induced biases would be stronger during periods of high macroeconomic uncertainty when forecasting is likely to be more difficult. We identify such periods of high economic uncertainty using the dispersion in one-year real GDP forecasts of professional economists from the Livingston Survey.

We find that during periods of high forecast dispersion, the effects of mood are stronger for both state-level job creation and establishment starts measures. These results provide indirect support for Shiller's (2010) conjecture, which posits that pessimism could inhibit economic activity. Periods of economic uncertainty generally correspond with economic downturns, and we find that during those periods the effects of mood on the aggregate macroeconomy are the strongest.

Collectively, our results complement the findings in the recent finance and economics literature that examines the link between mood and economic decisions. Most previous studies examine the impact of mood on individual-level decisions and stock market returns. We extend this literature and show that weather-induced mood can affect managerial decisions and aggregate macroeconomic outcomes. Further, in contrast to existing studies that are unable to directly identify the mechanism through which mood affects economic decisions, we show that *biased expectations* is the dominant channel through which mood operates and affects managerial decisions. And, through this expectations channel, we show that mood can affect even aggregate economic outcomes.

In broader terms, our findings contribute to the literature on optimism and economic decisions. Malmendier and Tate (2005) show that CEO optimism affects cash flow-investment sensitivities. Frey and Stutzer (2002) find that extreme optimism generates inferior economic decisions. Similarly, Puri and Robinson (2007) show that moderate optimism has positive effects on economic decisions. Nes and Segerstrom (2006), and Seligman (2003, 2006) find that dispositional optimism generates a positive outlook toward future outcomes and allows individuals to adjust to stressful events more effectively. Our results are consistent with the evidence from these studies since we show that mood affects economic outcomes through its impact on economic expectations.

The rest of the paper is organized as follows. Section 2 describes the data and the main variables. We present the main empirical results in Sections 3 – 5 and examine the robustness of these results in Section 6. Section 7 concludes with a brief discussion.

2. Data and Measures

2.1 Small Business Survey Data

Our firm-level data are from the Small Business Economic Trends (SBET) survey for the period from July 1993 to December 2012. The start of the sample period is dictated by the availability of the firm location information. The data are collected by the National Federation of Independent Businesses (NFIB), the largest small business organization in the U.S. The NFIB has approximately 350,000 members. These firms have an average of 10 employees, and their average annual gross sales is $500,000. The survey respondents are randomly selected from the

NFIB member firms. While the identity of the firm is confidential, the data set provides the 3-digit ZIP code of the firm's location. We describe all relevant variables, extracted from the SBET in Panel A of Table 1.

2.2 Perceived Economic Outlook (PEO) Measures

We measure managerial expectations with questions designed to extract the reasons why managers view general economic conditions as favorable or unfavorable to expand. Managers are asked if they believe it is a "good time to expand," and they can respond by answering "yes," "no," or "uncertain." Then, managers are asked to identify the factors influencing their response, which are: economic conditions, sales prospects, financing costs, expansion costs, political climate, and other. Most managers (approximately 53%) cite economic conditions as the main reason behind their decision to expand or not. This is not surprising because small, private firms are especially susceptible to macroeconomic shocks (e.g., Cochrane (2005), Korteweg and Sørensen (2010)).

Based on these two questions, we define a categorical variable that we call perceived economic outlook (PEO). PEO is +1 (-1) if the manager responds "yes" ("no") to the expansion question, conditional on citing *general economic conditions* as the explanation. PEO is zero even if they were optimistic for reasons other than general economic conditions. We focus on responses related to general economic conditions because forecasting the macroeconomy is likely to be difficult for small business managers who may not have the background or expertise to do so. Consequently, their expectations about the overall economy would be more susceptible to mood-induced biases.

2.3 Managerial Decisions

To examine the impact of mood on managerial decisions, we focus on two decision variables, namely hiring and capital investments. The planned capital expenditures variable CAPEX takes the value of 1 if the firm plans to undertake capital expenditures over the next 3 to 6 months, and 0 otherwise. The planned hiring variable HIRE takes the value of 1 (-1) if the firm plans to increase (decrease) its labor force, and 0 otherwise. Both measures are forward-looking, so that they should be related to expectation of economic conditions as captured by the PEO variable.

2.4 Main Control Variables

There are other factors that can affect managerial expectations beyond mood. We include those factors as control variables in our regression analysis. These factors are related to consumer behavior, labor market conditions, financing conditions, and seasonal operations.

One key advantage of the survey data is that we are able to observe the respondents' perceptions on each of these factors. In the case of consumer-related factors, we have information about past sales and changes in sales. The survey also provides information about expectations of consumer behavior through managerial forecasts of future sales and responses to questions related to whether the firm's most important problem is poor sales.[3] Labor market conditions are captured by the size of the total labor force in the local area and managerial perceptions on availability of qualified job applicants. Financial conditions are based upon whether the firm has experienced increased or decreased difficulty in obtaining financing.

In addition, we control for responses by managers on whether the firm's operations are seasonal and include state-quarter fixed effects in all regressions. For further robustness, we use

[3] When examining the influence of the mood proxy on the consumer-related variables, we also find evidence of mood effects on consumer behavior. Inclusion of these variables as controls should mitigate potential concerns that the tests driven by consumer, rather than managerial, mood. We provide several robustness checks to confirm this, and provide extended discussion in Section 6.2.

controls for extreme weather conditions. These variables are the average rainfall and snowfall for all weather stations within 50 km radius around the 3-digit ZIP code of the firm. To account for local business environment, we use the returns of value-weighted portfolios of listed firms headquartered in the state where the firm is located. Finally, we use the CRSP value weighted returns to capture national economic conditions.

2.5 Sample Representativeness

One potential concern with our survey data is that they may not be representative of U.S. small businesses. We assess the representativeness of our sample by assessing how closely the survey responses on hiring plans and investment decisions relate to the national unemployment rate and national proxies of investment activity, respectively.

Figure 1 plots the time-series trend of a net hiring index from 1993 to 2012 constructed using the survey data (solid black line, left-axis), and the national unemployment rate (dashed red line, right-axis) from the Bureau of Labor Statistics (BLS). The net hiring index is the difference between managers planning to hire minus those who planning to fire, scaled by the number of managers in each month. We remove the cyclical component in the net hiring index using the filter proposed in Hodrick and Prescott (1997) (hereafter, HP). The plot indicates that the net hiring index and the unemployment rate correspond closely with each other. The Pearson correlation coefficient is –0.84.

Next, we consider whether the responses on investment plans are related to proxies of national investments. Specifically, Figure 2 displays the time trend of a net investment index from 1993 to 2012, which is constructed using the survey data. The net investment index is the proportion of firms reporting expected increases in capital expenditures. To capture national investment activity, we use net firm expansions versus contractions and net firm starts versus closures from the Business Economic Dynamics (BED) data. In Figure 2, we plot the survey-based index and its trend component on the left axis (dotted black line), and the national net firm expansions (dashed blue line) and national net firm starts (solid blue line) on the right axis.

Figure 2 indicates that the survey-based index closely tracks the BED indices. Consistent with the graphical evidence, we find that the Pearson correlation coefficient between the net investment index and the net firm expansions is 0.635. The Pearson correlation coefficient between the net investment index and the net firm starts is 0.648.

Overall, the graphical evidence in Figures 1 and 2 suggests that the small business survey does a reasonable job in capturing nationwide trends in employment and firm investments.

2.6 Mood Proxy

Our measure of mood is based on sky-cloud-cover. We obtain hourly sky-cloud-cover data from all U.S. weather stations from 1990 to 2012 using the Integrated Surface Database (ISD). Cloud cover takes values from zero (clear sky) to eight (full cloud cover). A similar data set has been used by Hirshleifer and Shumway (2003), Goetzmann and Zhu (2005), and Goetzmann, Kim, Kumar and Wang (2015) as a mood instrument. The SBET data are merged with the weather data using the Haversine distance formula. The coordinates for the firm is the centroid of the 3-digit ZIP code of the firm. The exact coordinates are available for each weather station.

Because the SBET survey is at a monthly frequency, we calculate monthly sky-cloud-cover (SKC) by averaging over the daily estimates over the prior month.[4] The average daily, sky-cloud-cover is calculated using values from all weather stations within a 50-kilometer radius of

[4] The average daily sky-cloud-cover is based on hourly values during daylight hours (i.e., from 6 AM to 6 PM), the time when managers are likely to observe outdoor weather conditions. Our results are similar even if we use the full 24-hour period in each day.

the firm's 3-digit ZIP code centroid. In our analysis, we use SKC from the previous month as we do not know the exact point in the month that a firm is being surveyed in the SBET.

Following the literature, we also deseasonalize the sky-cloud-cover to mitigate the impact of seasonal and regional factors. A common approach in the literature is to take the difference between current period SKC and average SKC for the same month over the entire sample period. Because we use a 20-year sample period, this approach is susceptible to long-term trends in cloud cover.[5] For example, Eastman and Warren (2013) document a decreasing trend in cloud cover from 1971 to 2009. This trend would leave the earlier (latter) part of the sample period with systematically higher (lower) values if cloud cover were to be deseasonalized using full-sample monthly averages.

Therefore, we calculate deseasonalized SKC (DSKC) for a particular ZIP code as the difference between average SKC in the current month and the moving average of SKC from the same month over the previous three years. We consider other approaches to deseasonalize SKC and find that they do not materially change our main results. Specifically, we deseasonalize using the SKC from the previous year as well as the moving average over the previous five years over the same month. We also use a deseasonalized measures based upon the residuals from a regression model of SKC on separate time trends and intercepts for each ZIP code.

2.7 Summary Statistics

We present summary statistics for all our variables in Panel B of Table 1. On average, managers have a negative outlook toward the economy. The average PEO during the sample period is -0.486. However, there is considerable variation in managerial expectations. The

[5] The sample period is much shorter in previous studies. In Goetzmann and Zhu (2005), the sample period is 1991-1996. In Goetzmann, Kim, Kumar and Wang (2015), the sample spans 1999-2010. And in the Hirshleifer and Shumway (2003) study, the sample period is 1982 – 1997.

standard deviation of PEO is 0.707. Focusing on managerial decisions, we find that, on average, managers do not plan to increase their hiring considerably (mean HIRE is 0.071). However, they do report an intent to increase capital investments (mean CAPEX is 0.311). Further, both hiring and investment decisions exhibit significant variation (the standard deviation for HIRE and CAPEX is 0.491 and 0.857, respectively). Overall, the descriptive statistics suggest that managers in our sample are pessimistic and their decisions exhibit considerable heterogeneity.

3. Mood and Managerial Expectations

In this section, we present our main empirical results. First, we conduct univariate tests to examine whether our mood proxy (DSKC) is related to our proxy for managerial expectations (PEO). Next, we estimate a series of multivariate regressions to assess the robustness of these findings. Last, we perform additional robustness checks to ensure that our results reflect the effects of mood.

3.1 Mood and PEO: Univariate Tests

To relate our mood proxy to managerial perceptions about future economic conditions, we create a ranking of DSKC using the full sample. We classify periods in which DSKC is in the highest and lowest x^{th} percentile as Cloudy and Sunny, respectively. We consider the 10^{th}, 25^{th}, and 50^{th} percentile thresholds. The results are reported in Table 2.

In Panel A, for each of the Sunny and Cloudy months, we report the average of PEO, the average number of cases where PEO is +1 (*D*(PEO = +1)), and the average number of cases where PEO is -1 (*D*(PEO = -1)). In all cases, we find that relatively sunnier weather is associated with more positive assessments of economic conditions. The differences in PEO between sunny and cloudy days are also higher when the thresholds for the DSKC splits are tighter.

The DSKC rankings in Panel A are based on the full sample. But, some regions are systematically exposed to cloudier weather. The link between cloudy weather and mood could vary geographically. To account for this possibility, we obtain the DSKC ranking within each state and report the results in Panel B. The results in Panel B show that the differences in PEO levels between optimistic and pessimistic periods remain statistically significant. For example, using the 10^{th} percentile threshold, the difference in PEO between the Sunny and Cloudy months is -0.135 (*t*-value = 12.81).

3.2 Mood and PEO: Multivariate Regression Results

The univariate test results suggest that mood has a significant effect on managerial expectations. However, the univariate tests do not account for other non-mood factors related to weather that may influence these results. We estimate multivariate regressions to account for the effects of non-mood factors on managerial expectations.

Specifically, we regress DSKC on PEO by conditioning on a large set of variables, which account for the potential impact of consumer behavior, labor market conditions, financing conditions, and seasonal operations on managerial expectations. These regression results are reported in Table 3. We account for dependence across regions and time by double-clustering the standard errors on location and year-month.

In model 1, PEO is regressed on DSKC without any control variables. In model 2, we add our control variables, and in model 3, we include state fixed effects. In model 4, we replace the state fixed effects with state-quarter fixed effects. We account for seasonality with a dummy variable if a manager reports that the firm has seasonal operations.

In all specifications, we find that the mood proxy, DSKC, is negatively related to PEO. That is, relatively sunnier weather is associated with more optimistic economic expectations.

When we include the control variables, the estimate for DSKC attenuates slightly but its significance remains high. In particular, in the univariate model 1, DSKC has an estimate of -0.039 (*t*-value = -4.07). In model 2, we include all control variables. We account for the confounding effects of consumer mood by including manager's expectations on sales volume over the next quarter, a dummy related to whether sales is the biggest problem that the firm is facing, and changes in sales over the past quarter. The estimate on DSKC remains statistically significant. In model 4, we include all control variables and state-quarter fixed effects, and find that the DSKC estimate is -0.026 (*t*-value = -4.03).

Although the DSKC estimate decreases almost by one-third between model 1 and model 4, the difference in the estimates is statistically insignificant (difference = 0.008, *t*-value = 1.59). The absence of significant changes in the estimates of DSKC after including all the control variables suggests that our mood proxy has an independent influence on managerial expectations.

The dependent variable in the baseline regressions combines information on whether managers view economic conditions as favorable or unfavorable. We next evaluate whether the DSKC estimates differ when we use binary variables to capture each response separately. The variable *D*(PEO = +1) takes the value of 1 if PEO equals one, and zero otherwise. The variable *D*(PEO = -1) takes the value of 1 is PEO equals negative one, and zero otherwise.

We present the regression estimates based on *D*(PEO = +1) and *D*(PEO = -1) in specifications 1 to 4 and 5 to 8 in Table 4, respectively. Because the dependent variables are binary, we estimate both OLS and probit regressions. For probit models, we report the estimated marginal effects. Models 1, 2, 5 and 6 include the full sample of firms for which PEO is available. For robustness, the sample in specifications 3 and 4 exclude managers with negative

PEO. For robustness, in models 7 and 8, we exclude managers with positive PEO (i.e., +1) when we estimate the regression with *D*(PEO = -1) as the dependent variable . The DSKC coefficients are again statistically significant and are consistently signed across all the specifications. These results suggest that our choice of PEO as a categorical variable does not materially affect our findings.

3.3 Mood and PEO: Persistence

Next, we consider additional tests motivated by the evidence in the literature on the persistence of mood. In particular, existing studies find that the information gathering process is slow for complex tasks, which can generate persistence in mood effects.[6] Goetzmann, Kim, Kumar and Wang (2015) provide direct evidence, showing that greater persistence in cloud cover has a stronger effect in influencing institutional investor beliefs about the stock market. In addition, Goetzmann, Kim, Kumar and Wang (2015) find that the effects of weather-induced mood on stock prices do not persist for more than three months. Based on the findings from these prior studies, we expect that the effect of weather on managerial expectations would persist, but only for a few months.

In Table 5, Panel A, we test the persistence hypothesis by adding lagged values of DSKC to the baseline specifications. In addition to current period DSKC ($DSKC_t$), we use DSKC from the previous month ($DSKC_{t-1}$) and DSKC from two months prior ($DSKC_{t-2}$). In specification 1, we obtain the estimates without any of the control variables, while model 2 includes all the control variables from model 4 of Table 3.

[6] Kida, Smith and Maletta (1998) show that managers recall their reaction to old news better than recalling the news themselves. Adaval (2001) provides experimental evidence supporting the conjecture by Fishbein (1963) that mood effects are persistent in consumer related decisions. In a finance context, Goetzmann, Kim, Kumar and Wang (2015) provide direct evidence, showing that greater persistence in cloud cover has a stronger effect in influencing institutional investor beliefs about the stock market.

The results show that $DSKC_t$ estimates are significant in models 1 (estimate = -0.030, *t*-value = -3.15) and 2 (estimate = -0.020, *t*-value = -3.15). When we consider one-month lagged values of mood proxy, the $DSKC_{t-1}$ estimates are significant at the 10% level, but they are smaller in magnitude. And when we consider two-month lagged mood proxy, the $DSKC_{t-2}$ estimates are not statistically significant. These results suggest that our mood proxy does not have long-lasting effects, which supports our key assumption that DSKC is likely to capture mood effects.

In Panel B of Table 5, we examine the robustness of the mood effect to changes in the estimation window used to construct the DSKC measure. For this analysis, we create new DSKC measures based on the first and last two weeks of the estimation month used in the original DSKC measure. We choose the two-week estimation window because we do not observe the exact date when the survey was filled out by the firm. We know that the surveys are mailed to the firm at the beginning of the month. As such, we would expect the effects to be slightly stronger for the DSKC measure based upon the most recent data (i.e., last two weeks of the month prior to the survey).[7]

We find that the DSKC coefficient estimates are statistically significant in all the specifications. Moreover, the coefficient estimates are slightly larger for the DSKC measure based upon the last two weeks of the month before the survey was sent. We also find similar effects when aggregating the survey data to the state-level in Table A.1.[8] Together with the

[7] The choice of the two-week estimation window is also motivated by Goetzmann, Kim, Kumar, and Wang (2015). They use a similar two-week estimation window the same reasons.

[8] Specifically, we calculate the weighted-average of PEO on the state-level (State PEO) based upon the 3-digit ZIP code population of the firm's location. State DSKC is calculated as the weighted-average of DSKC on the state-level based upon the 3-digit ZIP code population of the firm's location where the survey data is available. Quarterly versions are the average across the monthly values within the same quarter.

results from Panel A, these findings suggest that mood effects are persistent at the monthly frequency.

Overall, the results in Table 5, Panel B suggest that mood effects are strong at the monthly frequency. This evidence is consistent with existing studies, which suggest that information used in forming beliefs related to complex tasks (e.g., forming expectations about general economic conditions by non-professional forecasters) is likely to be gathered over time. Such a slow information gathering process can generate the persistence we observe.

3.4 Mood and Alternative Measures of Expectations

We next consider how mood effects vary in settings with different levels of forecasting complexity. Based on findings from the psychology literature, we conjecture that mood would affect managerial expectations of macroeconomic conditions and not so much expectations about firm-specific factors, such as sales prospects. Forming expectations about firm-specific factors is likely to be relatively less complicated since these firm-level factors are more tangible and may depend on past decisions of the manager. In contrast, forming expectations about the general state of the U.S. economy is likely to be complicated for a small business manager, given that the process is more abstract and depends on information that may not be readily available to the firm.

To test this hypothesis, we consider alternative measures of expectations for respondents who cite reasons *other* than economic conditions as the explanation for wanting to expand or not. These expectation measures are based on the following explanations: non-economic (Non-Econ EXP), which include five factors (i.e., sales prospects, financing, expansion costs, political, or other), only sales prospects (Sales EXP), only political (Political EXP), only financing, expansion costs, and other factors (Other EXP). The Sales EXP and Other EXP are related to firm-specific factors and have low forecasting complexity. Responses associated with the Political EXP are likely to refer to regulation rather than political uncertainty given that respondents are small business owners. The managers might be familiar with the regulatory framework of their industry and, therefore, Political EXP would also have low forecasting complexity.

We present the results with the alternative expectation measures in Table 6. All specifications include controls that are related to consumer behavior, labor market conditions, financing conditions, and seasonality in operations, as in Table 3. We find that the DSKC coefficient is statistically insignificant in all regressions. Model 1 shows the results for the entire subsample of responses not citing economic conditions as the explanation for expanding. In this case, the DSKC estimate is negligible and statistically insignificant at the 10% level (estimate = -0.006, *t*-value = -1.47). When examining the individual explanations for expansion in models 2 through 4, the results remain statistically insignificant.

Overall, the findings in Table 6 support our key assumption that the DSKC variable captures mood effects on the manager's expectations of general economic conditions. The insignificant results in the Sales EXP model also suggest that the effects we captured in the PEO regression are unlikely to be affected by consumer related factors. More importantly, the results from the Sales EXP regression are consistent with evidence in the previous literature which finds that mood biases are weaker for tasks that are less complex.

3.5 Asymmetry in Mood Effects

Next, we test for asymmetric effects of good mood (optimism) and bad mood (pessimism) on managerial expectations. This test is motivated by findings in the social psychology literature which finds biases due to good mood are stronger than those due to bad mood. For example, Schwarz (1991) suggests that good mood may induce reliance on non-systematic cognitive systems that cause individuals to pay less attention to details. In contrast, bad mood may induce individuals to pay more attention to the details of a task and, subsequently, they may be less affected by mood heuristics.

We test for the differential effects of optimism and pessimism by replacing the DSKC variable with two dummy variables associated with high (cloudy months) and low (sunny months) DSKC values. These tests are analogous to the univariate tests in Table 2. We categorize the cloudy and sunny indicators based on conditional DSKC rankings within each state. In models 1 through 3, the cloudy (sunny) month indicator takes the value of 1 if month's rank is in the top (bottom) 25th percentile of the U.S. state where the firm is headquartered. In models 4 through 6, the month indicators are constructed similarly, but they are based on the 10th percentile threshold. We estimate the effects of cloudy and sunny months when the dependent variable is either PEO or one of the two dummy variables, *D*(PEO = +1) or *D*(PEO = -1).

The results are presented in Table 7. As expected, the estimates for the sunny-month indicator are positive and statistically significant in all the specifications. In contrast, the estimates for the cloudy-month indicator are negative and statistically significant in some of the specifications. However, in absolute magnitude, they are weaker than the estimates for the sunny-month indicator.

For example, with the 25th percentile threshold, the estimates for the sunny-month indicator are 1.7 to 5.3 times stronger in absolute magnitude than the estimates for the cloudy-month indicator. With the 10th percentile threshold, the estimates for the sunny-month indicator are 2.1 to 4.7 times stronger in absolute magnitude than the estimates for the cloudy-month indicator. These differences in the coefficient estimates, reported at the bottom of the table, are also statistically significant. These results demonstrate an asymmetry in mood effects between good and bad mood, which is consistent with existing evidence on mood heuristics.

4. Does Mood Impact Firm-Level Decisions?

Our evidence so far suggests a strong association between mood and managerial expectations about broad economic conditions. In this section, we examine whether mood-induced biases in firm-level expectations are sufficiently strong to influence firm-level decisions.

4.1. Biased Expectations and Firm-level Decisions

Based on the evidence from the literature, a possible mechanism through which mood affects decisions is through its impact on expectations. We test this hypothesis using an instrumental variable (IV) approach. Constrained by the available data in the SBET survey, we focus on two firm-level decisions: hiring (HIRE) and capital investment (CAPEX) planned over the following three to six months.

In the IV estimation, the dependent variables are HIRE and CAPEX and the main independent variable is the expectation proxy PEO. The regression also includes all control variables used in Table 3. To implement the IV estimation, we use first stage regressions to estimate the component of PEO related to mood. Then, in the second stage, we assess whether hiring and investment plans are related to the component of PEO that is explained by our mood proxy DSKC. If DSKC does not explain a sufficient amount of variation in PEO, or the mood proxy does not have a strong enough effect on firm expectations, then the effect of the instrumented PEO on firm-level decisions would be small.

We examine this hypothesis in two ways. First, we run a weak instrument test to formally examine if the relation between DSKC and PEO is statistically significant. Second, we focus on the economic significance of the relation between the mood-instrumented PEO and firm-level decisions. If mood has a strong effect, the weak instrument hypothesis should be rejected and the economic significance of the instrumented-PEO should be high.

4.2. OLS and IV Regression Estimates

In Table 8, we present the second stage IV estimates. For comparison, we also present the OLS estimation results. Because the first stage regression results are similar to the results in Table 3, we only report at the bottom of the table the weak instruments Kleibergen-Paap *rk* Wald F-statistic (Kleibergen and Paap (2006)) for the DSKC variable.

In model 1 of Table 8, the OLS regression results show that firm expectations affect hiring plans (estimate = 0.090, *t*-value = 30.27). This effect is economically significant in comparison to the sample standard deviation of HIRE (= 0.487): A one-standard deviation increase in PEO (= 0.707) is related to a change in HIRE of about 0.06. In model 2, we present the IV estimation results. The weak instruments test indicates that the IV bias is low (*rk* F-stat = 16.24). This evidence suggest that our mood proxy, DSKC, explains a significant degree of the variation in PEO. The IV estimates also show that the instrumented PEO has a strong impact on HIRE (estimate = 0.247, *t*-value = 3.22). The related economic significance based on the IV estimate is again high: A one-standard deviation increase in PEO (= 0.707) is associated with a change in HIRE of about 0.175.

In models 3 and 4, we present results on the effect of firm expectations on capital investment decisions. Consistent with our conjecture, we find that PEO has a positive impact on capital expenditures in the OLS regression model (estimate = 0.093, *t*-value = 33.86). The effect of mood-instrumented PEO is also positive and significant (estimate = 0.211, *t*-value = 3.15). Further, as with the HIRE model, the weak instrument test suggests that the level of IV bias is likely to be low (*rk* F-stat = 16.24). The economic significance of PEO is strong in both OLS and IV estimation results. For example, using the OLS estimates from model 3, we find that a one standard deviation increase in PEO (= 0.707) is associated with an increase in CAPEX of about 0.066. In comparison, the increase in CAPEX based on the coefficient estimate of the instrumented PEO from model 4 is 0.149. These results suggest that mood effects are strong and influence firm decisions through their impact on managerial expectations.

For robustness, we compare the *direct* effect of DSKC on HIRE and CAPEX *with* and *without* the inclusion of PEO in the HIRE and CAPEX regression models. Our conjecture is that if mood is related to decisions through its impact on expectations, the explanatory power of DSKC on firm decisions should attenuate once we account for managerial expectations. In untabulated results, we find that the DSKC estimates are negative and statistically significant in the HIRE (estimate = -0.006, *t*-value = -2.53) and CAPEX (estimate = -0.010, *t*-value = -2.48) models when we do not include PEO in the regression specification. In contrast, when we include PEO, the DSKC estimates become statistically insignificant in both the HIRE (estimate = -0.004, *t*-value = -1.39) and CAPEX (estimate = -0.005, *t*-value = -1.37) models. These results provide further evidence of a strong link between mood and firm-level decisions through the impact of mood on managerial expectations.

5. Does Mood Affect Aggregate Macroeconomic Outcomes?

In this section, we shift our focus from firm-level analysis and investigate whether the effects of mood are detectable at the aggregate macroeconomic level.

5.1 Mood and State-Level Economic Activity

For the aggregate level analysis, we rotate our point of interest from the firm-level to the state-level. We choose to aggregate to the U.S. state-level because there is rich cross-sectional variation in weather and economic conditions across the U.S. states. Similar to the firm-level analysis, we construct state-level mood proxies using sky-cloud-cover data and focus on U.S. state level indices related to hiring and capital expenditure.

Constrained by the availability of state-level economic data, we perform our analysis at the quarterly frequency. We obtain state-level, quarterly versions of the mood proxy. The state DSKC is the average DSKC across all the ZIP codes within a state, weighted by ZIP code-level population. Similar to the firm-level analysis, we consider three state-level measures of economic activity that capture hiring and investment activities.

To construct our state-level measures, we use the Business Economic Dynamics (BED) data from the Quarterly Census of Employment and Wages. We define NETJOB as the difference between the natural logs of number of jobs gained and lost. NETEXP is defined as the difference between the natural logs of the number of establishments that are expanding and contracting. Finally, NETSTART is the difference between the natural logs of the number of establishments starting and closing. We use NETEXP and NETSTART to proxy for state-level investments because the BED data do not provide any information on state-level total investment activity.

We examine the effect of our mood proxy on these three state-level measures. We also construct analogous measures of all control variables used in the baseline firm-level regression models by aggregating the survey data to the state-level. For additional details, see Panel A of Table 1. To account for U.S.-level economic conditions, we use a dummy variable related to NBER recession dates, the U.S. unemployment rate reported by the Bureau of Labor Statistics, and the forecasted GDP rate by professional economists from the Livingston survey provided by Federal Reserve Bank of Philadelphia. Like our firm-level regressions, we include state-level portfolio returns in the regressions, which are the returns of value-weighted portfolios of listed firms in the state where the firm is headquartered. We account for changes in national market conditions using the CRSP value-weighted returns index. To control for extreme weather conditions, we use the population-weighted rainfall and snowfall for each state-quarter. We add state-quarter fixed effects in all the regression models.

The state-level regressions also include control variables related to consumer behavior, labor market conditions, and financing conditions. To obtain these control variables, we compute weighted-averages with the survey responses of firms in each state-quarter. The weights are based on the size of local population.[9] Additional control variables include state-level retail sales and change in retail sales. Finally, our regressions include the level and annual change in the University of Michigan Consumer Sentiment Index, which is available quarterly at the regional level.[10]

5.2 State-Level Regressions: Baseline Results

We report the state-level regression estimates in Table 9. At the state-level, we no longer have direct measures of managerial expectations about future economic conditions, and thus we cannot estimate regressions comparable to the survey-based regressions of Table 8. Instead, we include the mood proxy directly into the regression specifications associated with state-level hiring and investment activities.

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[9] We define local population as the total population within the 3-digit ZIP code of the firm's location.
[10] Specifically, the consumer sentiment index is available for four geographical regions South, Midwest, West and Northeast.

Consistent with the firm-level results, the State DSKC estimates are negative across all models, which suggests that a deterioration in state-level mood is associated with a decline in employment and investment activities. The State DSKC estimates are statistically significant in the NETJOB (estimate = -0.017, *t*-value = -2.61), the NETEXP (estimate = -0.013, *t*-value = -3.35), and NETSTART (estimate = -0.013, *t*-value = -2.18) regressions. In economic terms, a one standard deviation decrease in State DSKC (0.524) is related to a 0.023, 0.032, and 0.013 increase in NETJOB, NETEXP, and NETSTART, respectively.[11] The economic significance estimates are smaller compared to those from the firm-level regressions. This is not surprising, given that the DSKC variable is aggregated to the state-quarter level and thus becomes a noisy mood proxy. However, these results show that mood effects are detectable even at the aggregate level.

5.3 Mood and Macroeconomic Uncertainty

One limitation of the state-level analysis is that we do not have direct measures of expectations. Thus, it is not clear whether biased expectations is the main channel through which the aggregate effects of mood operate. To provide more direct evidence of the biased-expectations channel, we consider a test motivated by evidence from the psychology literature.

The evidence (see the Introduction and Section 2) from the social psychology literature suggests that judgment biases induced by mood are amplified in more complex environments. Therefore, mood effects should be more pronounced during periods of greater economic uncertainty. Specifically, forecasting economic conditions by firm managers should be even more difficult in periods when professional economists cannot agree on economic projections.

[11] The economic effects are expressed relative to the sample averages of the dependent variables.

Accordingly, we measure economic uncertainty with the disagreement in real GDP forecasts by professional economists from the Livingston survey.[12] In each period, the survey collects forecast information from 23 to 64 respondents. Based on their responses, the survey computes seasonally adjusted forecasts of real, gross domestic product. We use these forecasts and compute an index of economic uncertainty (Forecast Dispersion). The index is the standard deviation of the percentage difference between the forecasted GDP for the following year relative to the base period.

In Table 10, we estimate the regression models from Table 9 after including the economic uncertainty measures as additional control variables. To capture the impact of pronounced expectation biases on mood, the regressions in Table 10 also include an interaction term between State DSKC and the economic uncertainty measure. To compute the interaction terms, we center each variable to have zero mean to avoid multicollinearity issues (Wooldridge (2010)).

The evidence in Table 10 is consistent with our expectations. Specifically, the estimates on economic uncertainty are negative across all specification. More importantly, the interaction term is negative and statistically significant in the regression models for the NETEXP (estimate = -2.541, *t*-value = -1.79) and NETSTART (estimate = -5.544, *t*-value = -2.77). Though the interaction term is not statistically significant in the NETJOB (estimate = -2.605, *t*-value = -1.42) model, the magnitudes are comparable. Collectively, these results show that the mood effect is significantly stronger in periods when economic uncertainty is higher. These results are similar

[12] Additional information about the survey can be found at the Federal Reserve Bank of Philadelphia website, along with other studies using the data (http://www.philadelphiafed.org/research-and-data/real-time-center/Livingston-survey/).

when we consider interaction terms between economic uncertainty and adverse weather conditions, as shown in Table A.2.[13]

6. Robustness Tests and Alternative Explanations

In this section, we discuss evidence from additional tests where we examine the robustness of our main results.

6.1 Forecast Accuracy and Over-correction

Evidence from the psychology literature suggests that mood-related biases lead to inaccurate forecasts (Johnson and Tversky (1983)). Such inaccuracies are especially pronounced for good, rather than bad, moods (Schwarz (1991)). In this section, we test this conjecture to provide additional evidence that the DSKC variable is likely to be a reliable proxy of mood.

For this analysis, we follow Gennaioli, Ma and Shleifer (2016) and construct a measure of forecast error (Forecast Error). We first compute an "accurate" forecast of firm expectations using a regression model that includes relevant control variables. Then, we compute the forecast error as the difference between the actual forecasts made by managers and the predicted forecasts from the regression. Finally, we estimate regressions where the forecast error is the dependent variable and weather variables are the main explanatory variables. Our conjecture is that the forecast error would be higher during sunny periods.

Ideally, to compute the forecast error for each firm, we would use a long time-series of observations for each firm. Unfortunately, our firm-level data are a repeated cross-section sampling different firms in different months. As a compromise, we create a state-level pseudo

[13] For robustness we add the interaction terms of the economic uncertainty measure with rainfall and snowfall in the regression models. Table A.2 shows that the estimates on the interaction terms between State DSKC and Forecast Dispersion are quite stable and comparable to those in Table 10. In contrast, the estimates on the extreme weather interaction terms are statistically insignificant (not reported), suggesting that our results are not driven by extreme weather conditions.

panel that tracks the average forecast error of all managers in a given state and examine if it is related to our mood proxy, also aggregated at the state level. We examine forecast errors related to the general economic conditions (PEO), sales (Sales EXP), and political expectations (Poly EXP).

6.1.1 State PEO Forecasts

In the case of PEO, Forecast Error is the average difference between firm-level economic forecasts (PEO) and predicted values of PEO (Expected PEO) within the same state and date. The Expected PEO is the predicted value from a Tobit regression, where the dependent variable is PEO. The main explanatory variable is the mean probability of a decline in the U.S. GDP over the next quarter across professional forecasters.[14] This measure should be related to accurate expectations about the U.S. national economy. The Tobit regressions also include all the explanatory variables from Table 3, excluding DSKC. As shown in Table A.3, we find that the probability of a decline in GDP is negatively related to PEO.

Next, we estimate regressions where the forecast error is the dependent variable. The key explanatory variable is the State DSKC. We also create measures that distinguish between sunny and cloudy weather. Specifically, State Sunny and State Cloudy are the percentage of firms within a state and month whose DSKC is in the bottom and top 25th sample percentile, respectively.

We present the results in Panel A of Table 11. To set the stage, in model 1, we regress State PEO on State DSKC and include State Expected PEO as a control variable. As expected, the coefficient on State DSKC is negative and statistically significant. In model 2, we directly estimate the impact of State DSKC on Forecast Error. In model 3, we decompose DSKC into

[14] The professional forecasts are from the Livingston Survey, which is available at http://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey.

sunny and cloudy periods. We find that only when the weather is sunny, the forecast inaccuracy is strong. In sum, these results suggest that forecast inaccuracy is related to mood and it is larger as the forecasts become more optimistic on sunnier days.

To complement our findings with Forecast Error, we examine how the State PEO varies over time. We conjecture that mood-related forecasting inaccuracy would lead to reversal in the forecasts in the subsequent months. In particular, high and inaccurate PEOs should be followed by lower, possibly, more accurate PEOs. To test this hypothesis, we construct a new measure called Adjustment. Adjustment is the ratio of the average State PEO over the next 3 months relative to the current State PEO. We then estimate panel regressions where the Adjustment is the dependent variable and State DSKC is the main independent variable.

Consistent with our expectations, the State DSKC coefficient estimate is positive and statistically significant, i.e., future state-level economic outlooks are lower following periods when State DSKC is lower (see model 4 of in Panel A of Table 11). Model 5 displays the estimation results when we decompose the State DSKC into State Sunny and State Cloudy variables. Again, we find that the coefficient estimate for the State Sunny variable is negative and statistically significant, whereas the coefficient estimate for the State Cloudy is insignificant.

6.1.2 State Sales and Political Forecasts

For comparison, we design placebo tests to assess whether similar effects can be found for non-economic forecasts. We focus on sales and political forecasts. These measures represent scenarios where the manager might have better knowledge than their macroeconomic knowledge. We do not expect the mood proxy to be significant in these regressions. As before, we first estimate Tobit regressions to extract the forecast error. Then, we estimate regressions where the forecast error is the dependent variable and weather measures are the independent variables.

In the case of sales expectations, we conjecture that accurate expectations would be related to actual sales. We define the forecast error using Tobit regression models where the dependent variable is Sales EXP. The main explanatory variable is the actual state-level sales growth in the current quarter. The other control variables are the same as those in Table 3, excluding DSKC. As shown in Table A.3, the realized state-level sales growth has a positive and statistically significant relation with Sales EXP.

In the case of political forecasts, we posit that economic conditions would be relevant. In the Tobit regression related to political expectations, the average probability of a decline in the GDP over the next quarter of professional forecasters is the main explanatory variable. In these Tobit regressions, the dependent variable is Poly EXP. The other control variables are the same as those in Table 3, excluding DSKC. As shown in Table A.3, the probability of a recession has a negative and statistically significant relation with Poly EXP.

After we estimate the Tobit models, we obtain the forecast errors. The Forecast Error (Sales EXP) is the difference between Sales EXP and Expected Sales EXP from the Tobit regressions. The Forecast Error (Poly EXP) is the difference between Poly EXP and Expected Poly EXP from the Tobit regressions. We also compute measures related to the adjustment of expectations. The Adjustment (Sales EXP) is the ratio of the average State Sales EXP over the next 3 months relative to the current State Sales EXP. The Adjustment (Poly EXP) is the ratio of the average State Poly EXP over the next 3 months relative to the current State Poly EXP.

We present the estimation results in Panel B of Table 11. In all specifications, the State DSKC coefficient is statistically insignificant and close to zero. Combined with the results from

Panel A, our findings are consistent with the evidence from the psychology literature that domains of judgment with greater complexity are more susceptible to misattribution biases. In particular, our evidence suggests that forecast inaccuracy is more severe for forecasts related to general economic conditions than to forecasts that are more closely related to firm operations.

6.2 Control for Consumer Mood

Another potential concern with our evidence might be that our results reflect the behavior of local consumers rather than local managers. Local manages could merely respond to weather-induced changes in consumer mood. Several studies in the marketing literature find a connection between mood and consumer behavior. For example, several studies use cloud cover as a mood priming instrument and demonstrate that consumer mood affects tipping (Cunningham (1979), Rind (1996), Rind and Strohmetz (2001)), retail car transactions (Busse, Pope, Pope, and Silva-Risso (2015)), product evaluation (Gorn, Goldberg, and Basu (1993), Pham (1998), Adaval (2001) and Yeung and Wyer (2004)), and art transactions (De Silva, Pownall and Wolk (2012)).

To mitigate the potential concern that our results reflect the effect of shifts in consumer mood rather than managerial mood, all of our regressions include control variables that capture the impact of shifts in consumer mood. We further examine the impact of mood on consumer decisions with additional tests. For these tests, we construct consumer variables using the SBET survey. Specifically, we use the firm's reported changes in sales over the past quarter, the managerial expectations on the future firm sales over the next quarter, and whether the manager believes that sales is the firm's most significant problem. These sales-related variables should be related to consumer mood.

Next, we estimate regressions where the consumer behavior proxies are the dependent variables and our DSKC measure is the main explanatory variable. We report these regressions in Panel A of Table 12. When only controlling for adverse weather conditions, DSKC has a significant effect on changes in sales over the previous quarter. However, when we *include* other control variables used in the main analysis, the DSKC coefficient becomes insignificant. We find similar results for expected changes in future firm sales and for whether the manager believes that sales is the firm's most significant problem. These results suggest that control variables used in the main firm-level tests absorb the direct influence of weather on consumer mood and their economic behavior.

We perform similar tests at the state-level and report the results in Panel B of Table 12. For these tests, our state-level measure of consumer behavior is U.S. state-level retail sales. The results in Table 12, Panel A, indicate that when we only control for adverse weather conditions, State DSKC has a significant impact on consumer mood. However, State DSKC becomes insignificant when we *include* the other control variables. Again, these results suggest that our control variables used in the main state-level tests are likely to capture the influence of weather on consumer mood and their economic behavior.

6.3 Simultaneity Bias and SURE estimation

For additional robustness, we further control for the possible impact of consumer mood on managerial expectations. Specifically, we examine whether our previous estimation results are affected by any simultaneity bias between firm manager mood and consumer mood.

For this analysis, we estimate a system of two equations. In the first equation, the dependent variable is the manager's economic outlook, while in the second equation, the dependent variable is the firm's change in sales. We estimate the system using the seemingly unrelated regression (SURE) estimation framework. This estimation framework, accounts for simultaneity bias by allowing the residuals across the models to be correlated.

We present the firm-level test results in Panel A of Table 13. We find that the DSKC estimate in the PEO model remains statistically significant. The DSKC estimate in the Change in Sales model is statistically insignificant, which is not surprising given the results in Table 12. The results are similar when we use alternative specifications, where we add the Expected Sales Volume model to the system, or remove different sets of the control variables. In all cases, the DSKC coefficient in the PEO model remains negative and significant. The results are also similar when we exclude the control variables. These results from SURE estimation suggest that the OLS estimates in the firm-level tests are unlikely to be driven by potential simultaneity biases.

We repeat the SURE estimation for the state-level tests. Panel B of Table 13 presents the results. We find that the DSKC estimates are statistically significant in the NETJOB, NETEXP and NETSTART models, and are comparable to the OLS estimates. In contrast, the *DSKC* estimate in the State Retail Sales model is statistically insignificant. The results are similar when we replace the State Retail Sales with the Growth in Retail Sales model. The results are also similar when we exclude the control variables.

Collectively, the evidence from SURE tests suggests that our key results are unlikely to be driven by consumer mood. Our findings are more likely to reflect the mood effects of firm managers on their economic outlooks.

6.4 Potential Asset Pricing Implications

Our main results suggest that weather-induced mood affects the economic decisions of small business managers. This implies that mood might be affecting the decisions of managers of public firms, which in turn, might have an impact on asset returns. Also, local investors are affected by local weather, which could induce correlated trading by local investors among locally listed companies. Following Korniotis and Kumar (2013), we examine this hypothesis using the U.S. states as the unit of observation.

In Table A.4, we report estimates from panel regressions of state-level portfolio return indices on the weather variables (i.e., DSKC, Rain, and Snow). We also include the market index return as a control variable to account for any aggregate effects. We estimate both monthly and quarterly regressions. As in Korniotis and Kumar (2013), we use Driscoll-Kraay standard errors (Driscoll and Kraay (1998)) to account for potential serial and cross-sectional dependency.

We find that DSKC is statistically insignificant in all specifications. Local sky-cloud-cover might not be related to local returns for various reasons. For example, as we show in Section 3.3, the effects of mood are not very persistent and, thus, the market may not respond to them. Also, publicly listed firms are considerably larger than small businesses. Managers at such large firms have many layers of management, which could hinder autonomy in decision-making. Therefore, moderate shifts in mood induced by changes in weather are less likely to affect the decisions of managers at public firms. Further, listed firms are held by both local and non-local investors. As such, if trading behavior of investors can be affected by mood, then the relevant mood is not just the mood of local investors. To this point, Goetzmann, Kim, Kumar and Wang (2015) find that trading behavior and individual stock returns are affected by the mood of investors across *different* locations on the same date. Overall, the findings in Table A.4 suggest that our mood results are distinct from those documented for stock returns of publicly-traded firms.

7. Summary and Conclusion

In this study, we use a novel data set on the economic expectations and financial decisions of small business managers to establish a link between mood and aggregate macroeconomic outcomes. Previous studies in finance and economics show that mood and economic decisions are correlated but the focus of those studies is typically on individual-level decisions or stock returns. Our study extends this literature on mood and economic decisions and examines whether mood affects the macroeconomy through its impact on firm-level economic decisions.

A key challenge we face is to identify a determinant of mood that is *not* affected by the economic environment. Motivated by the literature in psychology, we use sky-cloud-cover as a mood proxy. Our key finding is that mood systematically influences managerial decisions and has an impact on aggregate macroeconomic outcomes. Specifically, on relatively sunnier days, managers have more optimistic economic expectations and the component of their expectations related to mood influences their hiring and investment decisions. Further, we find that the effect of cloud cover on managerial expectations is short-lived and the effect of positive mood (optimism) is stronger than the effect of negative mood (pessimism). These results are robust in the presence of a rich set of control variables, like extreme weather conditions, consumer mood proxies, and stock market return indices.

Next, we show that mood affects managerial decisions *through* its impact on their expectations. Using instrumental variable regressions, we find that managerial expectations instrumented by cloud cover affect the firm's hiring and capital investment plans. The effects of mood also aggregate to the state-level and affect the business cycles of U.S. states. We show that, at the aggregate-level, mood affects U.S. state-level job creation and new business starts. This effect is especially strong during periods of greater economic uncertainty when expectations are more likely to be influenced by mood. Moreover, consistent with the psychology literature, we find that at the aggregate level, the accuracy of the forecasts of the managers is better during cloudier months.

Collectively, our results suggest that mood-induced economic expectations influence firm-level managerial decisions, which in turn affect state-level economic fluctuations. This evidence provides empirical support to Shiller's (2010) conjecture that mood can affect economic recovery during an economic recession.

In future work, it may be interesting to examine whether the impact of mood on the local state-level economy propagates to other regions. While the economic impact of mood on a given state's macroeconomic environment may be small, through the economic connections among the U.S. states, the mood effects can get amplified. Consequently, even moderate shifts in local mood can potentially generate a large impact on the aggregate U.S.-level business cycle.

It would also be interesting to examine how shifts in the political environment affect the mood and optimism level of local managers and how potential shifts in managerial expectations affect state-level macroeconomic climate. It is likely that managers in U.S. states where the local political environment is mis-aligned with the national political environment are less optimistic. This reduced optimism would affect their hiring and investment decisions, and subsequently, politics-induced optimism shifts could adversely affect state economic conditions. Further, the impact of politics and weather on managerial mood may add up. In particular, the impact of weather-induced shifts in managerial mood on state-level macroeconomy may get amplified when the state-level political climate is strongly aligned or mis-aligned with the national political climate.

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Table 1: Variable Description and Sample Summary

Panel A provides definitions of variables used in the analysis. The data sources include the Small Business Economic Trends (SBET), Business Economic Data (BED), National Oceanic and Atmospheric Administration (NOAA), Center for Research in Security Prices (CRSP), Bureau of Labor Statistics (BLS), Standard and Poors (S&P), the Federal Reserve Bank of Philadelphia (PFED), and University of Michigan Survey of Consumers (SoC). Panel B reports the summary statistics for the survey and state-level observations used in the analysis.

Panel A: Variable Definitions

Name	*Description*	*Source*
Dependent variables:		
PEO	Available for respondents citing economic conditions as explanation for answer to Q4 ("Good time to expand?"). Takes value 1 if "yes" to Q4, value -1 if "no", and value 0 otherwise.	SBET
D(PEO = +1)	Binary variable for when PEO takes value +1.	SBET
D(PEO = -1)	Binary variable for when PEO takes value -1.	SBET
Firm HIRE	Based upon Q14 ("Employee changes in next 3 months"), takes value 1 if answer is "INCREASE", -1 if "DECREASE", 0 otherwise.	SBET
Firm CAPEX	Based upon Q22 ("Capital expenditures next 3 to 6 months"), and takes value 1 if "INCREASE", and 0 otherwise.	SBET
U.S. State NETJOB	The log difference between state-level job gains and losses.	BED
U.S. State NETEXP	The log difference between state-level number of establishments expanding and contracting.	BED
U.S. State NETSTART	The log difference between state-level number of establishment starts and closures.	BED
Mood proxy:		
DSKC	Deseasonalized SKC (DSKC) for respondent observation ending in second Tuesday of month t is defined as average SKC over month t-1 minus the average SKC over the month t-1 over the prior three years. SKC for a firm is calculated using all weather stations within 50 kilometer radius of centroid to 3-digit ZIP code of firm.	NOAA
U.S. State DSKC	Average DSKC, weighted by ZIP code-level population, for each state-quarter.	NOAA
Control variables (SBET Survey):		
Sales	Natural log of one plus the lower bound of firm's size category in Q6: "$0K - $12.5K", "$12.5K - 24.9K", "$25K - $49.9K", "$50K - $87.49K", "$87.5K - $199.9K", "$200K - $374.9K", "$375K - $749.9K", "$750K - $1,249.9K", and "$1,250K or more."	SBET
Change in Sales	Coded on 5-point scale based upon Q6A ("Change in gross sales in the current period versus the prior quarter") increasing in actual change in sales volume: 2 if "Much higher", 1 if "higher", 0 if "stayed the same", -1 if "lower", and -2 if "much lower."	SBET
Expected Sales Volume	Coded on 5-point scale based upon Q8 ("Real volume expectation in next 3 months") increasing in expected change in sales volume: 2 if "Go up a lot", 1 if "go up a little", 0 if "stays the same", -1 if "go down a little", and -2 if "go down a lot."	SBET
Problematic Sales	Binary variable taking value 1 if response to Q3 ("Single most important problem") is poor sales, and zero otherwise.	SBET
Financing Difficulty	Coded on a 3-point scale to Q18A ("Easier, harder to get [financing] now versus 3 months ago"), taking value 1 if "Easier", -1 if "harder", and 0 otherwise.	SBET
Labor Available	Coded on 4-point scale based upon Q13 ("Qualified job applicants") increasing in labor availability: 3 if "lots", 2 if "some", 1 if "few", and 0	SBET

	otherwise.	
ln(Labor force)	Natural log of one plus the county labor force.	BLS
Seasonal Operations	Binary variable based upon Q12A ("Employees changed due to seasonal factors"): 1 if "yes", and 0 otherwise.	SBET
Rain	Average rainfall (in centimeters) for a firm in month t-1 is calculated using all weather stations within 50 kilometer radius of centroid to 3-digit ZIP code of firm.	NOAA
Snow	Average snowfall (in centimeters) for a firm in month t-1 is calculated using all weather stations within 50 kilometer radius of centroid to 3-digit ZIP code of firm.	NOAA
State Returns	The returns on a value-weighted portfolio of listed firms located in the same state in month t-1.	CRSP
Market Returns	The returns on a CRSP value-weighted portfolio in month t-1.	CRSP
Control variables (U.S. State):		
Retail Sales	The quarterly state-level retail sales-per-capita.	S&P
Change in Retail Sales	The quarterly percentage change in state-level retail sales-per-capita.	S&P
Expected Sales Volume (Survey)	State-level index based upon (# "Go up a lot" - # "Go down a lot")/# respondents to Q8. Index calculated first on ZIP code level, and the state-level version is average index weighted by ZIP code-level population.	SBET
Change in Sales (Survey)	State-level index based upon (# "Much higher" - # "Much lower")/# respondents to Q6A. Index calculated first on ZIP code level, and the state-level version is average index weighted by ZIP code-level population.	SBET
% Sales Problem (Survey)	Percentage of firms responding "poor sales" to Q3 in the state.	SBET
Finance Availability (Survey)	State-level index based upon (# "Easier" - # "Harder")/# respondents to Q18A. Index calculated first on ZIP code level, and the state-level version is average index weighted by ZIP code-level population.	SBET
Labor Availability (Survey)	State-level index based upon (# "Lots" - # "None")/# respondents to Q13. Index calculated first on ZIP code level, and the state-level version is average index weighted by ZIP code-level population.	SBET
% Seasonal Operations (Survey)	Percentage of firms have have seasonal operations based upon Q12A in the state.	SBET
log(State Workforce)	Natural log of one plus the state-level labor workforce.	BLS
Rain	Average rainfall (in centimeters), weighted by ZIP code-level population, for each state-quarter.	NOAA
Snow	Average snowfall (in centimeters), weighted by ZIP code-level population, for each state-quarter.	NOAA
State Returns	The returns on a value-weighted portfolio of listed firms for each state-quarter.	CRSP
Market Returns	The returns on a CRSP value-weighted portfolio for each quarter.	CRSP
Forecast Dispersion	Standard deviation of percentage change based upon 12-month real GDP forecasts over base period from Livingston survey.	PFED
Forecasted GDP Growth	Median percentage change based upon 12-month real GDP forecasts over base period from Livingston survey.	PFED
NBER Recession	Binary variable based upon NBER recession period.	
Unemployment	National unemployment rate.	BLS
Consumer Sentiment	Quarterly Index of Consumer Sentiment for region	SoC
Change in Consumer Sentiment	Change in quarterly Index of Consumer Sentiment for region	SoC

Panel B: Summary Statistics

Variable	N	Mean	StDev	25th	50th	75th
Dependent variables:						
PEO	95465	-0.486	0.707	-1.000	-1.000	0.000
D(PEO = +1)	95465	0.125	0.331	0.000	0.000	0.000
D(PEO = -1)	95465	0.611	0.487	0.000	1.000	1.000
Hiring plans	95465	0.070	0.487	0.000	0.000	0.000
Capex plans	95465	-0.314	0.857	-1.000	-1.000	1.000
U.S. State NETJOB	3905	0.038	0.341	-0.184	-0.010	0.215
U.S. State NETEXP	3905	0.004	0.227	-0.154	-0.048	0.132
U.S. State NETSTART	3905	0.054	0.333	-0.173	0.067	0.266
Mood instrument:						
DSKC	95465	-0.103	0.950	-0.680	-0.085	0.502
State DSKC	3905	-0.130	0.524	-0.470	-0.117	0.220
Control variables (Respondent):						
Sales	92034	4.467	1.734	3.258	4.483	5.930
Change in Sales	94248	-0.127	0.894	-1.000	0.000	0.000
Expected Sales Volume	95465	0.052	0.973	-1.000	0.000	1.000
Problematic Sales	95465	0.190	0.392	0.000	0.000	0.000
Financing Difficulty	95465	-0.068	0.293	0.000	0.000	0.000
Labor Available	95465	0.484	0.775	0.000	0.000	1.000
ln(Labor force)	95465	11.021	1.550	9.761	10.742	12.132
Seasonal Operations	95465	0.056	0.230	0.000	0.000	0.000
Rain	95465	0.553	1.275	0.131	0.324	0.665
Snow	95465	0.246	1.238	0.000	0.000	0.000
State Returns	95442	0.007	0.064	-0.024	0.012	0.043
Market Returns	95442	0.006	0.049	-0.018	0.015	0.039
Control variables (U.S. State):						
Retail Sales	3905	6752.207	881.425	6174.705	6664.742	7209.545
Change in Retail Sales	3905	0.002	0.014	-0.007	0.003	0.011
Change in Sales (Survey)	3905	-0.032	0.271	-0.187	-0.021	0.132
Expected Sales Volume (Survey)	3905	0.704	0.161	0.611	0.711	0.802
% Sales Problem (Survey)	3905	0.144	0.122	0.052	0.114	0.212
Finance Availability (Survey)	3905	0.583	0.307	0.553	0.701	0.777
Labor Availability (Survey)	3905	0.189	0.134	0.107	0.186	0.268
% Seasonal Operations (Survey)	3905	0.068	0.074	0.000	0.056	0.101
log(State Workforce)	3905	14.406	0.999	13.589	14.493	15.046
Rain	3905	0.593	0.559	0.280	0.494	0.755
Snow	3905	0.252	0.756	0.000	0.001	0.116
State Returns	3905	0.010	0.064	-0.021	0.011	0.044
Market Returns	3905	0.008	0.043	-0.011	0.015	0.038
Forecast Dispersion	3905	0.008	0.003	0.006	0.008	0.009
GDP Forecast	3905	0.035	0.013	0.028	0.034	0.039
NBER Recession	3905	0.141	0.348	0.000	0.000	0.000
Unemployment	3905	0.055	0.020	0.042	0.052	0.065
Consumer Sentiment	3905	87.446	13.603	76.200	88.950	96.700
Change in Consumer Sentiment	3905	-0.367	9.776	-4.400	1.000	5.300

Table 2: Mood and Managerial Perceptions: Results From Univariate Tests

The table displays sample averages of *D*(PEO = +1), *D*(PEO = -1), and PEO for subsamples based upon DSKC rankings. For each column, the split percentile (DSKC % Split) corresponds with the top and bottom 10^{th}, 25^{th} and 50^{th} percentile used for the Cloudy and Sunny subsamples, respectively. Panel A uses the full sample to calculate the DSKC rankings, while Panel B conditions DSKC rankings within each state. The difference in the sunny and cloudy sample averages are displayed at the bottom, and the paired t-statistics in the group means are displayed in parentheses. Statistical significance of the differences are denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample Rankings

Dependent Variable:	*D*(PEO = +1)			*D*(PEO = -1)			PEO		
DSKC % Split	50th	25th	10th	50th	25th	10th	50th	25th	10th
Sunny	0.135	0.149	0.167	0.595	0.578	0.556	-0.460	-0.430	-0.389
Cloudy	0.115	0.114	0.113	0.627	0.631	0.639	-0.512	-0.517	-0.526
Cloudy-Sunny	-0.019***	-0.034***	-0.054***	0.032***	0.053***	0.083***	-0.052***	-0.088***	-0.137***
	(9.09)	(11.07)	(10.67)	(-10.25)	(-11.82)	(-11.64)	(11.32)	(13.30)	(12.96)

Panel B: State Rankings

Dependent Variable:	*D*(PEO = +1)			*D*(PEO = -1)			PEO		
DSKC % Split	50th	25th	10th	50th	25th	10th	50th	25th	10th
Sunny	0.134	0.148	0.164	0.595	0.580	0.559	-0.461	-0.432	-0.394
Cloudy	0.116	0.113	0.111	0.627	0.633	0.640	-0.511	-0.520	-0.529
Cloudy-Sunny	-0.019***	-0.035***	-0.053***	0.032***	0.053***	0.081***	-0.050***	-0.088***	-0.135***
	(8.69)	(11.42)	(10.67)	(-10.04)	(-11.82)	(-11.40)	(10.99)	(13.47)	(12.81)

Table 3: Mood and Managerial Perceptions: Results From Multivariate Tests

The table displays the OLS regression model estimates using PEO as the dependent variable for respondents citing economic conditions as their explanation to question 4 of the survey. Robust standard errors clustered at the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance of the differences are denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	PEO	PEO	PEO	PEO
DSKC	-0.039***	-0.027***	-0.026***	-0.026***
	(-4.07)	(-4.06)	(-3.91)	(-4.03)
Sales		0.004**	0.004**	0.004**
		(2.46)	(2.34)	(2.36)
Changes in Sales		0.137***	0.137***	0.139***
		(25.03)	(25.18)	(26.05)
Expected Sales Volume		0.200***	0.199***	0.197***
		(32.83)	(33.13)	(33.61)
Problematic Sales		-0.234***	-0.235***	-0.234***
		(-23.49)	(-23.32)	(-23.39)
Financing Difficulty		0.149***	0.150***	0.150***
		(17.35)	(17.40)	(17.30)
Labor Available		0.033***	0.031***	0.032***
		(10.61)	(10.22)	(10.35)
ln(Labor force)		0.013***	0.016***	0.017***
		(5.25)	(6.56)	(6.70)
Seasonal Operations		0.075***	0.079***	0.079***
		(4.73)	(4.99)	(4.97)
Rain		0.003	0.003	0.004
		(1.03)	(1.00)	(1.36)
Snow		0.000	0.003	-0.001
		(0.15)	(0.81)	(-0.33)
State Returns		-0.096	-0.082	-0.098
		(-1.11)	(-1.00)	(-1.19)
Market Returns		0.984***	0.978***	0.960***
		(3.49)	(3.47)	(3.40)
State FE	NO	NO	YES	NO
State × Quarter FE	NO	NO	NO	YES
N	91204	91204	91204	91204
Adjusted R^2	0.27%	16.99%	17.34%	17.38%

Table 4: Mood and Managerial Perceptions: Separating Good and Bad Time to Expand

The table displays the OLS and probit regression model estimates using *D*(PEO=+1) and *D*(PEO=-1) as the dependent variables. The odd-numbered models present the OLS estimates, while the even-numbered models present the marginal effects calculated from the probit estimates. Each model includes the full set of control variables from model 4 of Table 3, though the probit models do not include state-quarter fixed effects. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance of the differences are denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	D(PEO=+1)				D(PEO=-1)			
Estimator:	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit
Excluded Subsample:			PEO=-1	PEO=-1			PEO=+1	PEO=+1
DSKC	-0.010***	-0.010***	-0.013**	-0.013**	0.016***	0.016***	0.012***	0.012***
	(-3.11)	(-3.32)	(-2.44)	(-2.48)	(4.49)	(4.57)	(4.49)	(4.49)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
State × Quarter FE	YES	NO	YES	NO	YES	NO	YES	NO
N	91204	91204	35510	35510	91204	91204	79707	79707
Adjusted / Pseudo R^2	11.97%	17.42%	12.43%	10.19%	14.03%	11.22%	7.52%	6.37%

Table 5: Persistence and Decomposition of Mood Effects on Managerial Expectations

Panel A displays the OLS regression models estimates using PEO as the dependent variable. DSKC applicable to the current period (t), one month prior (t-1) and two months prior (t-2) are included in the models. The models include the full set of control variables from model 4 of Table 3 where indicated. The table displays the OLS regression models estimates using PEO as the dependent variable. The DSKC measure is decomposed into the first and last two weeks of the month that it is estimated in. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Persistence of Mood Effects

Model:	(1)	(2)
Dependent Variable:	PEO	PEO
$DSKC_t$	-0.030***	-0.020***
	(-3.15)	(-3.15)
$DSKC_{t-1}$	-0.017*	-0.014**
	(-1.72)	(-1.98)
$DSKC_{t-2}$	-0.017	-0.012
	(-1.58)	(-1.52)
Control Variables	NO	YES
State × Quarter FE	NO	YES
N	95427	91168
Adjusted R^2	0.38%	17.45%

Panel B: Decomposition of Mood Effects

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	PEO	PEO	PEO	PEO
Last 2 Weeks DSKC	-0.026***		-0.023***	-0.016***
	(-3.09)		(-2.73)	(-2.79)
First 2 Weeks DSKC		-0.020***	-0.017**	-0.011**
		(-2.72)	(-2.24)	(-2.25)
Control Variables	NO	NO	NO	YES
State × Quarter FE	NO	NO	NO	YES
N	95362	95312	95212	90966
Adjusted R^2	0.18%	0.13%	0.27%	17.37%

Table 6: Mood Effects When Forecasting Complexity is Low

The table displays the OLS regression model estimates for the placebo tests using measures analogous to PEO but based upon subsamples that do not cite economic conditions as the explanation. The dependent variables are coded as 1 if “yes” to question 4, -1 if “no”, and 0 otherwise. The subsamples based upon the explanation include: non-economic (Non-Econ EXP), sales prospects (Sales EXP), political (Political EXP), and other (Other EXP). The “other” group is defined as respondents who do not cite “economic conditions,” “sales prospect,” or “political” as the explanation. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	Non-Econ EXP	Sales EXP	Political EXP	Other EXP
DSKC	-0.006	-0.005	-0.007	0.001
	(-1.47)	(-1.06)	(-1.04)	(0.24)
Control Variables	YES	YES	YES	YES
State × Quarter FE	YES	YES	YES	YES
N	72778	21639	21899	29240
Adjusted R^2	12.92%	29.67%	8.42%	5.32%

Table 7: Asymmetric Effects of Optimism and Pessimism on Managerial Expectations

The table displays the OLS regression models estimates using *D*(PEO = +1), *D*(PEO = -1), and PEO as the dependent variables. DSKC rankings based upon the full sample and conditioned within state are used to calculate indicator variables that correspond with DSKC values in the top (Cloudy) and bottom (Sunny) 25th percentile for models 1 through 3, and 10th percentile for models 4 through 6. Differences in Sunny and Cloudy coefficients and absolute value of coefficients for each model are displayed at the bottom of the table. Each model includes the full set of control variables from model 4 of Table 3. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	D(PEO=+1)	D(PEO=-1)	PEO	D(PEO=+1)	D(PEO=-1)	PEO
Ranking Criteria:	25th percentile			10th percentile		
Cloudy	-0.004	0.014**	-0.018*	-0.007	0.019**	-0.025*
	(-0.88)	(2.12)	(-1.66)	(-0.99)	(2.21)	(-1.76)
Sunny	0.021***	-0.024***	0.045***	0.033***	-0.040***	0.073***
	(3.67)	(-3.54)	(3.83)	(3.66)	(-3.71)	(3.90)
Control Variables	YES	YES	YES	YES	YES	YES
State × Quarter FE	YES	YES	YES	YES	YES	YES
N	91204	91204	91204	91204	91204	91204
Adjusted R^2	11.97%	14.01%	17.36%	11.97%	14.01%	17.36%
coef(Sunny) - coef(Cloudy)	0.025***	-0.037***	0.062***	0.039***	-0.059***	0.098***
	(4.71)	(-5.70)	(5.57)	(4.99)	(-6.05)	(5.89)
|coef(Sunny)| - |coef(Cloudy)|	0.016***	-0.010	0.027**	0.026***	-0.021**	0.047***
	(3.06)	(-1.57)	(2.37)	(3.32)	(-2.18)	(2.84)

Table 8: Mood and Firm-Level Decisions: Hiring and Investment Plans

The table presents the OLS and IV regression models using HIRE and CAPEX as the dependent variables. Each model includes the full set of control variables from model 4 of Table 3. The IV specifications use DSKC as an instrument for the PEO variable. Weak instruments tests are reported at the bottom of the panel from the first stage regressions. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	HIRE	HIRE	CAPEX	CAPEX
Estimator:	OLS	IV	OLS	IV
Instrument for PEO:		DSKC		DSKC
PEO	0.090***	0.247***	0.093***	0.211***
	(30.27)	(3.22)	(33.86)	(3.15)
Control Variables	YES	YES	YES	YES
State × Quarter FE	YES	YES	YES	YES
N	91204	91204	91204	91204
Adjusted R^2	11.75%	7.47%	9.31%	6.32%
rk Wald Statistic		16.24		16.24

Table 9: Mood and State-level Economic Outcomes

The table displays OLS regression model estimates using quarterly, state-level values of NETJOB, NETEXP, and NETSTART as the dependent variables. Robust standard errors clustered on the state and year-quarter levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)
Dependent Variable:	NETJOB	NETEXP	NETSTART
State DSKC	-0.017***	-0.013***	-0.013**
	(-2.61)	(-3.35)	(-2.18)
State Retail Sales	-0.062*	-0.057**	0.008
	(-1.66)	(-2.48)	(0.24)
Change in Retail Sales	-0.246***	-0.231***	-0.127*
	(-3.41)	(-4.65)	(-1.86)
Change in Sales (Survey)	1.634***	1.350***	1.643***
	(3.84)	(5.07)	(3.88)
Expected Sales Volume (Survey)	0.050***	0.035***	0.031**
	(5.08)	(4.86)	(2.52)
% Sales Problem (Survey)	0.039*	0.031*	0.016
	(1.67)	(1.77)	(0.60)
Finance Availability (Survey)	-0.057**	-0.042***	-0.068***
	(-2.30)	(-2.56)	(-3.40)
Labor Availability (Survey)	-0.013	0.018	0.036
	(-0.48)	(1.20)	(0.97)
% Seasonal Operations (Survey)	0.008	0.005	0.014
	(0.54)	(0.63)	(1.03)
log(Workforce Population)	-0.158***	-0.129***	-0.269***
	(-2.74)	(-3.31)	(-3.55)
Rain	-0.013**	-0.008	-0.002
	(-2.08)	(-1.51)	(-0.39)
Snow	-0.011**	-0.008**	-0.014***
	(-2.43)	(-2.44)	(-3.30)
State Returns	-0.011	0.004	0.092***
	(-0.29)	(0.16)	(3.54)
Market Returns	-0.236	-0.193	-0.297**
	(-1.23)	(-1.58)	(-2.33)
Forecasted GDP Growth	1.465***	1.105***	1.088***
	(2.60)	(2.62)	(2.83)
NBER Recession	-0.126***	-0.071***	-0.067***
	(-4.46)	(-4.00)	(-3.43)
Unemployment	-1.813***	-1.293***	-1.842***
	(-4.22)	(-4.90)	(-4.15)
Consumer Sentiment	-0.002***	-0.001**	-0.002***
	(-3.31)	(-2.13)	(-3.56)
Change in Consumer Sentiment	0.001*	0.000	0.001
	(1.92)	(1.04)	(1.58)
State × Quarter FE	YES	YES	YES
N	3905	3905	3905
Adjusted R^2	93.79%	94.96%	81.98%

Table 10: Mood and State-level Economic Outcomes: Role of Economic Uncertainty

The table displays OLS regression model estimates using NETJOB, NETEXP, and NETSTART as the dependent variables. Variables are mean-centered before the interaction terms are calculated. All control variables from models in Table 9 are included in the models, but not reported. Robust standard errors clustered on the state and year-quarter levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)
Dependent Variable:	NETJOB	NETEXP	NETSTART
State DSKC	-0.016***	-0.013***	-0.012**
	(-2.64)	(-3.47)	(-2.20)
Forecast Dispersion	-2.792	-2.340*	-0.434
	(-1.30)	(-1.72)	(-0.17)
State DSKC × Forecast Dispersion	-2.605	-2.541*	-5.544***
	(-1.42)	(-1.79)	(-2.77)
Control Variables	YES	YES	YES
State × Quarter FE	YES	YES	YES
N	3905	3905	3905
Adjusted R^2	93.84%	95.04%	82.03%

Table 11: Managerial Forecast Accuracy and Mood

Panel A displays OLS regression model estimates of the tests on managerial forecast error. State PEO is the average PEO across firms within the same state and date. Forecast Error is calculated as the average difference between PEO and Expected PEO. Expected PEO is the predicted values of a Tobit regression model whose dependent variable is PEO and explanatory variables include the mean probability of a decline in the GDP in the upcoming quarter by professional economists and the control variables, excluding the weather variables, from Table 3. The Tobit regression model is censored according the range on PEO. Adjustment is calculated as the ratio of the average state-level managerial forecasts over the next three months relative to the state-level managerial forecasts in the current period. The managerial forecasts used are for the economy (PEO), and the state-level estimates are measured as the average managerial forecast for a given month. Panel B displays OLS regression model estimates of the tests on managerial forecast error on non-economic projections. State Sales EXP (State Poly EXP) is the average Sales EXP (Poly EXP) across firms within the same state and date. Forecast Error (Sales EXP) is calculated as the average difference between Sales EXP and Expected Sales EXP for each state and date, while Forecast Error (Poly EXP) is calculated as the average difference between State Poly EXP and Expected Poly EXP for each state and date. Expected Sales EXP is the predicted values of a Tobit regression model whose dependent variable is Sales EXP and explanatory variables include realized state-level sales growth in upcoming quarter and the control variables, excluding the weather variables, from Table 3. Expected Poly EXP is the predicted values of a Tobit regression model whose dependent variable is Poly EXP and explanatory variables include the mean probability of a decline in the GDP in the upcoming quarter by professional economists and the control variables, excluding the weather variables, from Table 3. The Tobit regression models are censored according the range on State Sales EXP and State Poly EXP. Adjustment is calculated as the ratio of the average state-level managerial forecasts over the next three months relative to the state-level managerial forecasts in the current period based upon Sales EXP or Poly EXP. The state-level estimates are measured as the average managerial forecast for a given month. State DSKC is a monthly average of DSKC of firms within a particular state. State Sunny and State Cloudy are the percentage of firms in a particular month whose DSKC is in the bottom and top 25th sample percentile, respectively. The other explanatory variables from Table 3 are aggregated to the state-level and included as control variables in all of the models. Robust standard errors clustered on the state and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels.

Panel A: Forecasts of General Economic Conditions

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	State PEO	Forecast Error	Forecast Error	Adjustment	Adjustment
State DSKC	-0.022***	-0.025***		0.036**	
	(-2.95)	(-3.10)		(2.01)	
State Sunny			0.062***		-0.124***
			(3.44)		(-3.53)
State Cloudy			0.013		-0.034
			(0.74)		(-0.83)
Expected State PEO	2.886***				
	(8.66)				
Control Variables	YES	YES	YES	YES	YES
State × Quarter FE	YES	YES	YES	YES	YES
N	9510	9510	9510	8775	8775
Adjusted R^2	33.55%	20.90%	20.89%	3.67%	3.72%

Panel B: Placebo Tests on Non-Economic Forecast

Dependent Variable:	(1) Forecast Error (Sales EXP)	(2) Forecast Error (Poly EXP)	(3) Adjustment (Sales EXP)	(4) Adjustment (Poly EXP)
State DSKC	-0.004	0.006	0.022	-0.010
	(-0.44)	(0.65)	(1.50)	(-0.54)
Control Variables	YES	YES	YES	YES
State × Quarter FE	YES	YES	YES	YES
N	7249	7249	6860	6860
Adjusted R^2	0.86%	8.98%	7.17%	2.41%

Table 12: Consumer Mood and Sky-Cloud-Cover

Panel A displays the OLS regression models estimates using Change in Sales, Expected Sales Volume, and Problematic Sales as the dependent variables. The control variables included in each model are indicated at the bottom of the table, but are not reported. Control variables from model 4 of Table 3 are included in models 2 through 4, with exception of Change in Sales, Expected Sales Volume, and Problematic Sales. Robust standard errors clustered on the ZIP code and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Panel B displays state level OLS regression model estimates using State Retail Sales, Retail Sales Growth, Change in Sales (Survey), Expected Sales (Survey), and % Sales Problem (Survey) as the dependent variables. State-quarter fixed effects and adverse weather variables are included in all specifications. Robust standard errors clustered on the state and year-quarter levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm Sales

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	Change in Sales	Change in Sales	Expected Sales Volume	Problematic Sales
DSKC	-0.016**	-0.008	-0.010	0.003
	(-2.25)	(-1.43)	(-1.42)	(1.15)
State x Quarter FE	Y	Y	Y	Y
Adverse Weather Conditions	Y	Y	Y	Y
Change in Sales	N	N	N	N
Expected Sales Volume	N	N	N	N
Problematic Sales	N	N	N	N
Other Control Variables	N	Y	Y	Y
N	56380	56380	56380	56380
Adjusted R^2	0.92%	7.31%	6.26%	5.33%

Panel B: State level Retail Sales

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	State Retail Sales	State Retail Sales	Retail Sales Growth	Change in Sales (Survey)	Expected Sales (Survey)	% Sales Problem (Survey)
State DSKC	-0.012**	-0.000	-0.001	0.013	-0.000	0.004
	(-2.11)	(-0.10)	(-0.92)	(1.30)	(-0.06)	(0.96)
State × Quarter FE	YES	YES	YES	YES	YES	YES
State Retail Sales	NO	NO	NO	NO	NO	NO
Retail Sales Growth	NO	NO	NO	NO	NO	NO
Change in Sales (Survey)	NO	NO	NO	NO	NO	NO
Expected Sales (Survey)	NO	NO	NO	NO	NO	NO
% Sales Problem (Survey)	NO	NO	NO	NO	NO	NO
Other Control Variables	NO	YES	YES	YES	YES	YES
N	3905	3905	3905	3905	3905	3905
Adjusted R^2	73.58%	85.73%	29.17%	32.46%	22.30%	50.05%

Table 13: Seemingly Unrelated Regression Results

Panel A displays the seemingly unrelated regression models estimates using model 4 of Table 3 and model 2 of Panel A of Table 12. PEO is included as an additional explanatory variable in model 2 only. Panel B displays the seemingly unrelated regression models estimates using models 1 through 3 of Table 9 and model 2 of Panel B of Table 12. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm Level Results

Model:	(1)	(2)
Dependent Variable:	PEO	Change in Sales
DSKC	-0.024***	-0.001
	(-10.76)	(-0.49)
State × Quarter FE	YES	YES
PEO	NO	YES
Change in Sales	YES	NO
Other Control Variables	YES	YES
N	91204	91204
Adjusted R^2	15.10%	8.21%

Panel B: State Level Results

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	NETJOB	NETEXP	NETSTART	State Retail Sales
State DSKC	-0.016***	-0.013***	-0.013***	-0.000
	(-6.11)	(-8.21)	(-2.93)	(-0.18)
State × Quarter FE	YES	YES	YES	YES
State Retail Sales	YES	YES	YES	NO
Other Control Variables	YES	YES	YES	YES
N	3904	3904	3904	3904
Adjusted R^2	94.17%	95.25%	83.01%	86.53%

Figure 1: Survey Hiring Index and Nationwide Unemployment Rates

The figure displays nationwide estimates for the survey-based hiring index (solid black, left-axis), the trend component of the survey index (dotted black, left-axis), and the national unemployment rate (red, right-axis). The hiring index is calculated by subtracting the number of respondents that indicate that they will increase and decrease the number of employees over the next three months, scaled by the number of respondents. The Pearson correlation coefficient between the trend hiring index and the unemployment rate is -84%.

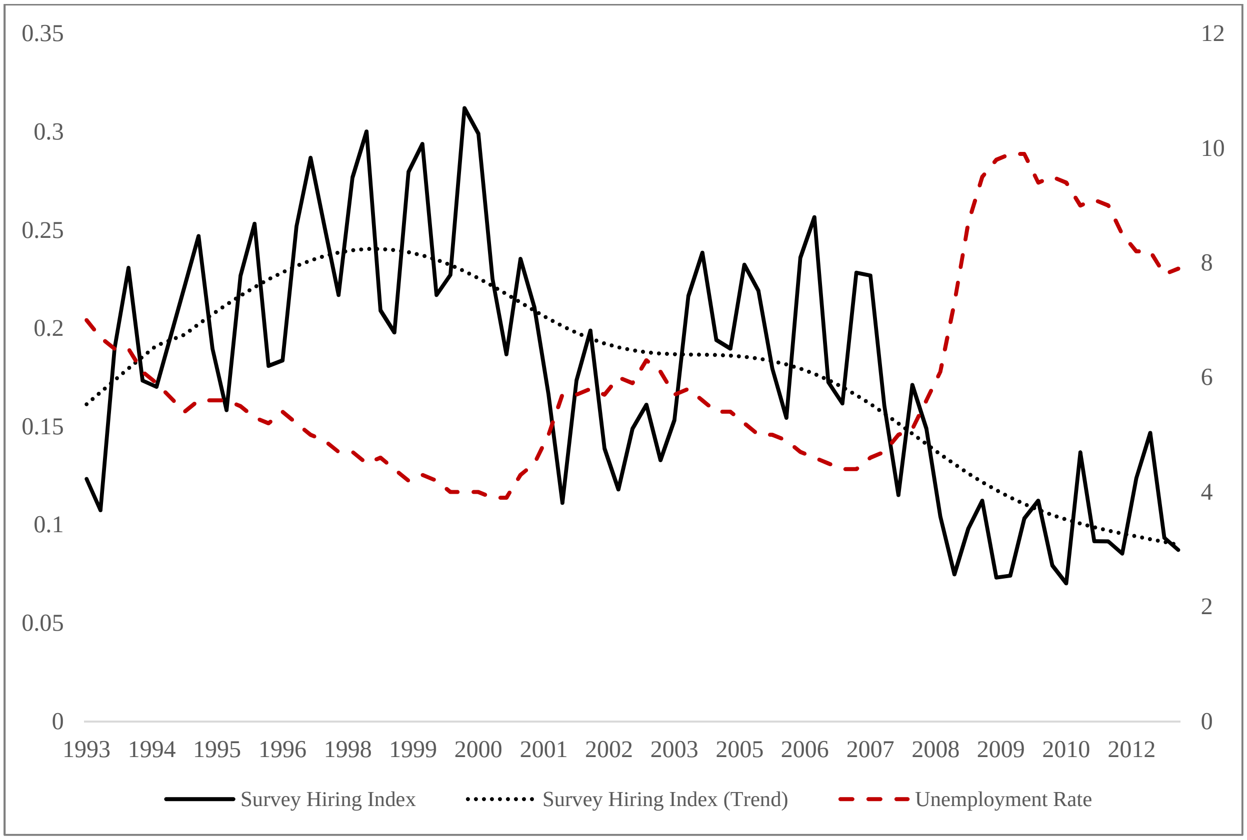
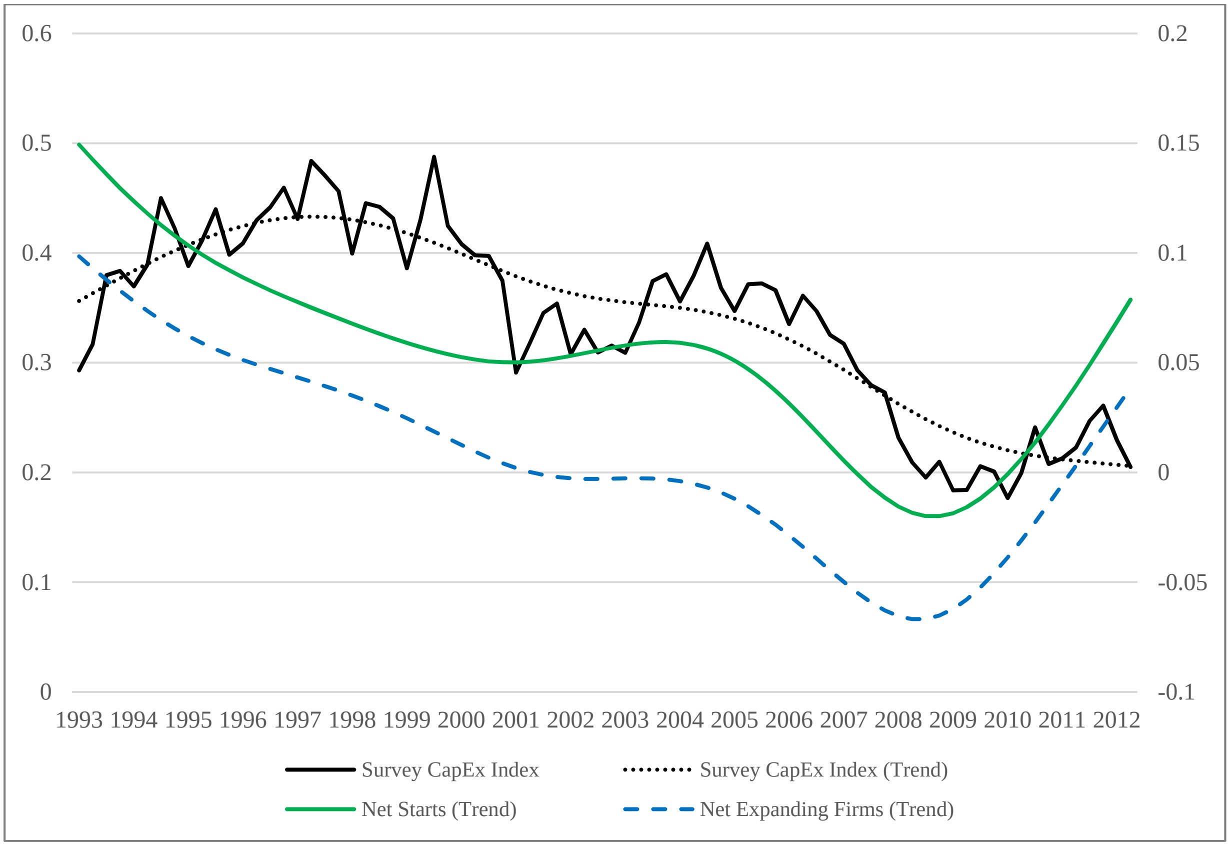


Figure 2: Survey Investment Index and Nationwide Index of Firm Expansions and Starts

The figure displays nationwide estimates for the survey-based investment index (solid black, left-axis), the trend component of the survey index (dotted black, left-axis), the trend component of the net number of firms expanding versus contracting (blue, right-axis), and the net number of firm births versus deaths (green, right-axis). The survey-based investment index is defined as the number of survey firms reporting expected increases in capital expenditures within the next six month scaled by the number of respondents. The net number of firms expanding versus contracting is defined as the difference in the natural log of the number of establishments reporting expansion and contraction in employee size. The net number of firm births versus deaths is defined as the difference in the natural log of the number of establishment starts and closures. The Pearson correlation coefficient between the trend hiring index and trend net expanding firms is 63.5%, and that between the trend hiring index and trend net starts is 64.8%.



Appendix

This appendix includes results of various tests referenced in the main text.

Table A.1: Aggregated Survey Tests

The table displays the OLS regression models estimates using PEO aggregated on the state-level, or State PEO, as the dependent variable. The explanatory variables of Model 4 of Table 3 are aggregated to the state-level. Models 1 and 2 are aggregated to a monthly frequency. Models 3 and 4 are aggregated to a quarterly frequency. Robust standard errors clustered on the state and date levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)	(4)
State Aggregation:	Monthly	Monthly	Quarterly	Quarterly
Dependent Variable:	State PEO	State PEO	State PEO	State PEO
State DSKC	-0.050***	-0.025***	-0.084***	-0.030**
	(-4.09)	(-3.07)	(-3.60)	(-2.53)
Control Variables	NO	YES	NO	YES
State x Quarter FE	NO	YES	NO	YES
N	10105	10105	3866	3866
Adjusted R^2	0.76%	30.86%	1.87%	45.80%

Table A.2: Mood, Economic Uncertainty and Adverse Weather Conditions

The table displays OLS regression model estimates using NETJOB, NETEXP, and NETSTART as the dependent variables. Variables are mean-centered before the interaction terms are calculated. Forecast Dispersion interaction terms with Rain and Snow are included in all the models, but not reported. All control variables from models in Table 9 are included in the models, but not reported. Robust standard errors clustered on the state and year-quarter levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)
Dependent Variable:	NETJOB	NETEXP	NETSTART
State DSKC	-0.015**	-0.013***	-0.011**
	(-2.46)	(-3.30)	(-2.13)
Forecast Dispersion	-2.945	-2.302*	-0.686
	(-1.35)	(-1.65)	(-0.27)
State DSKC × Forecast Dispersion	-2.876	-2.890*	-5.719***
	(-1.55)	(-1.92)	(-3.00)
State × Quarter FEs	YES	YES	YES
Adverse Weather × Forecast Dispersion Interaction Terms	YES	YES	YES
Control Variables	YES	YES	YES
N	3905	3905	3905
Adjusted R^2	93.74%	94.92%	82.00%

Table A.3: Tobit Regression Estimates

The table displays Tobit regression model estimates using PEO, Sales EXP and Poly EXP as the dependent variables. The Tobit regressions censor values according to the range of the dependent variables. Probability GDP Decline is the mean probability of professional economic forecasters of a decline in the GDP over the next quarter. State Sales Growth is the realized state-level sales growth rate. All control variables from models in Table 3 are included in the models with the exception of the mood proxy, but not reported. Robust standard errors clustered on the state and year-quarter levels are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)	(3)
Dependent Variable:	PEO	Sales EXP	Poly EXP
Probability GDP Decline	-0.787***		-0.165***
	(-41.56)		(-6.54)
State Sales Growth		5.688***	
		(7.80)	
State × Quarter FEs	YES	YES	YES
DSKC	NO	NO	NO
Other Control Variables	YES	YES	YES
N	91204	21639	21899
Adjusted R^2	9.90%	14.80%	4.60%

Table A.4: Weather Conditions and Local Stock Returns

The table displays OLS regression model estimates using value-weighted state-level portfolio returns as the dependent variable. Model 1 displays the results for monthly frequency, while Model 2 displays the results for quarterly frequency. The control variables included in each model are State SKC, State Rain, State Snow, and the value-weighted market portfolio returns measured using same frequency as the dependent variable. Driscoll-Kraay standard errors are used to estimate the *t*-statistics, which are displayed in parentheses. Statistical significance is denoted by ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

Model:	(1)	(2)
Estimation Period:	Monthly	Quarterly
Dependent Variable:	State Returns	State Returns
State DSKC	0.000	0.001
	(0.67)	(0.48)
State Rain	-0.000	-0.003
	(-0.46)	(-1.58)
State Snow	-0.004***	-0.030***
	(-4.94)	(-2.97)
Market Returns	0.966***	0.975***
	(45.20)	(55.24)
N	11367	3905
Adjusted R^2	76.71%	77.75%