Shedding Light on Consumer Sentiments: Evidence from India

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Abstract

This paper shows how location-based indicators can influence consumer confidence in India. We capture local economic activity using city-wise night-time luminosity (NTL) data. Using data on unit-level observations on consumer confidence from the Consumer Confidence Survey (CCS) by the Reserve Bank of India from June 2016 to November 2021, we find that night-time luminosity positively impacts the perception and future outlook of Indian households. Our results are robust even after controlling for state-wise urban inflation. We also find the dynamic effect of NTL on consumer sentiments. Finally, we extend our study to analyze the impact of NTL on several individual components of household sentiments from the RBI survey, such as household perception and outlook on household income, spending, employment, and general price levels. Overall, our results provide fascinating insights about using NTL as a measure of local economic indicators and its implications on households' sentiment indicators.

1. Introduction

Forecast of economic activities plays a pivotal role in the decision-making process of policymakers and market players (Galimberti, 2020). Consumer confidence (CC) in the economy is widely recognized as one of the driving forces behind several economic decision-making processes. These sentiments are often measured using perceptions and expectations about the state of the economy. On one hand, CC influences investment decisions in financial markets (Jansen & Nahuis, 2003), and on the other hand, it also reflects the prevailing animal spirits (Keynes, 1936). According to European Commission (2016), CC is a leading indicator of consumer spending. CC is also often used as a forward-looking indicator of the overall economic environment (Acemoglu & Scott, 1994). Ludvigson (2004) argues that CC is an important source of information about economic activity. Carroll et al. (1994) show that CC can forecast household spending. For instance, Barsky & Sims (2012) use data from Michigan Survey Index and show that the impact of unexpected shocks on responses to questions measuring consumers' confidence about future economic conditions can predict the movement of macro variables. Furthermore, Dees (2017) finds that consumer confidence shocks are important drivers of real economic activity.

Nevertheless, what drives consumer confidence? Literature documenting how consumers form such confidence about the real economy is primarily available in the backdrop of advanced economies and mostly based on aggregate data (Edelstein & Kilian, 2009; Fuhrer, 1993; Güntner & Linsbauer, 2018; Lahiri & Zhao, 2016). For instance, Fuhrer (1993) argues that variables like national income, unemployment rate, inflation, and real interest rates explain most of the variations in Michigan’s Index of Consumer Sentiments. In a similar study, Güntner & Linsbauer (2018) finds that besides oil supply shocks, other ancillary factors (like future inflation expectations, variation in household income, and perceived vehicle and home buying condition) also significantly impact the responsiveness of Michigan’s Index of Consumer Sentiments. Lahiri and Zhao (2016) argue that macroeconomic aggregates propel household sentiments, like perception and expectation about the economic conditions, such as their financial position and employment likelihood. Their findings also highlight that news-based channels significantly drive such household sentiments. However, these studies are primarily based on aggregate indicators of consumer confidence. A notable exception is Binder & Makridis (2020). Using household-level microdata, Binder & Makridis (2020) show that local gas prices can successfully predict consumer perceptions and expectations about the real economy in the U.S. Makridis (2019) also argues that local shocks related to housing prices affect individual perceptions about the economy and thereby drives individual beliefs about the national state of the economy. Makridis (2019) shows that changes in local economic conditions on labor and housing market activity have statistically and economically significant impact on individual beliefs about the economy's current and future state, conditional on demographic characteristics and location fixed effects. In a recent study, Makridis (2022) primarily explores the impact of local factors on an individual's perceived belief and quantifies the conducive effect of economic sentiments on consumption, using a newly licensed micro-data from Gallup between 2008 and 2017 for the U.S. The author also compares this new measure of economic sentiment vis-à-vis the Michigan Survey, the volatility index, and the EPU index of Baker et al. (2016) and finds that a rise in the economic sentiments significantly elevates consumption of non-durables. Modern macroeconomists argue that expectations about current and future economic developments are at the root of the decision-making process of the agents. Expectations, in turn, are formed based on the agent's information set, with different sets inducing potentially different economic behaviors (Gambetti et al., 2021). Moreover, Das et al. (2019) find that local economic condition variables such as unemployment level and the level of personal income can explain the cross-sectional variation in macroeconomic beliefs.

We augment the literature by examining the causal relationship between economic activity and consumer confidence using geographically disaggregated data on economic activity and sentiments at the city level for India. Our data on sentiments come from the Consumer Confidence Survey (CCS) conducted by the Reserve Bank of India (RBI) across several rounds on a bi-monthly basis. The survey is conducted across 13 major cities in India. We proxy the impact of local economic activity at the city level through data on night-time luminosity (NTL). The proxy measure of the local economy at the city level was derived using night-time light intensity provided by VIIR/Night Band (DNB) data from the Suomi NPP satellite.[1]

In Fig. 1, we plot the time series observations for the Current Situation Index (CSI) and the Future Expectation Index (FEI) based on RBI's Consumer Confidence Survey (CCS). Furthermore, we also establish a close interlinkage between CC and GDP in Fig. 1. Additionally, Figs. 2 to 5 show the variations in CC among the households across the Indian cities between March 2016 and March 2021. We observe significant variations in sentiments across the cities over the survey rounds. We also observe a high degree of heterogeneity in NTL across the cities (Fig. 6). The availability of such disaggregated data allows us to examine how NTL can impact consumer perceptions and expectations about the real economy.

The primary objective of this paper is, therefore, to quantify the effects of local economic activity on consumer sentiments using NTL as a direct measure of local economic activity. We argue that economic activity in a city is a localized event and more visible compared to aggregate economic activities. Moreover, unlike the existing studies that study the impact of economic factors on the aggregate movement in consumer sentiments, we explore these dynamics using household-level data on a set of consumer sentiment variables. We find that a rise in local economic activity (as measured by NTL) significantly elevates respondents' perceived and expected macroeconomic sentiments. Our results are consistent with several model specifications and robust to state-level controls. Furthermore, our estimated impact of NTL on other disaggregated indicators provides an interesting mix of results.

The rest of the paper is organized in the following manner. Section 2 presents a brief review of existing works done so far, and section 3 describes the data and methodology used for our analysis. We present our findings in Section 4, and finally, in section 5, we conclude.

[1] They are explained in detail in the data and methodology section.

2. Literature Review

Existing studies provide evidence that NTL is a potential location-based economic indicator that can influence economic sentiments. Location-based activities such as factories, infrastructure, and human activities generate light. The variation of such geo-located lights can indicate current economic outcomes and signal changes in anticipated broader regional economic development (Galimberti, 2020). NTL data can also act as a good proxy indicator of national, regional, and urban Gross Domestic Product (Mellander et al., 2015; Florida et al., 2012; Henderson et al., 2011; Doll et al., 2000). Moreover, it has been extensively used as a measure of urbanization and population density (Zhang & Seto, 2011; Zhuo et al., 2009; Elvidge et al., 1999; Elvidge et al., 1997). In their pioneering works, Henderson et al. (2012) developed a statistical framework to use satellite night-light data to capture changes in night lights to changes in measured income growth to improve estimates of actual income growth. They show that satellite night-light data are a valuable proxy for economic activity in places with poor or non-existent records on economic activities.

Moreover, artificial lights during the night, when measured through satellites, indicate not only growth of urban extents but also is tightly linked with local commercial activities, population density changes, and industrial sectors (Addison & Stewart, 2015; Baragwanatha et al., 2021; Ch et al., 2021; Chanda & Cook, 2019; Dingel et al., 2021; Elvidge et al., 2017; Jing et al., 2016; Prakash et al., 2019). Galimberti (2020) argues that, unlike the GDP statistics that may suffer from measurement errors due to increased informal activities or lack of developed economic agencies, data on night-time light can provide an error-free alternative proxy to such statistics. Several studies further confirm a strong relationship between NTL and local economic activity (Chodorow-Reich et al., 2020; Chen & Nordhaus, 2011; Doll et al., 2006; Ebener et al., 2005; Sutton et al., 2007; Sutton & Costanza, 2002). Further, Weidmann & Schutte (2016) find that night-light data considerably correlates with household wealth. Therefore, NTL is an excellent measure of capturing the performance of the local economy (Prakash et al., 2019).

Again, the use of cities as our observational unit is also helpful. Krugman (1991) highlights the interlinkages between economic growth and different urban centers. Further, using city-level data from the U.S, Glaeser et al. (1995) show that different city-level factors contribute to urban growth, which consequently contributes to aggregate economic growth. The authors also argue that analysis of city-level data provides a more systematic measure of cross-sectional differences since cities are more specialized areas than the entire state mainly because of free mobility of labor, capital, and new ideas between the cities. In India, cities contribute almost half of the GDP (Tripathi, 2013). A growing body of literature also highlights the flourishing importance of industrialization in urban centers and its subsequent contribution to our nation's economic growth (Lall et al., 2003, 2004; Lall & Mengistae, 2005; Lall & Rodrigo, 2001). This geographical spread of these production centers also favors the utilization of location-based economic indicators.

On one hand, literatures suggest that economic variables such as income, unemployment rate, inflation, and energy prices are significant predictors of consumer sentiments. On the other hand, we also find studies that argue the role of city-level local indicators on aggregate economic activity. The larger integration of the cities compared to other locations also indicates that changes in economic activity in one city can signal further changes to economic outcomes in a different city, impacting future aggregate measures of economic activity. Moreover, personal experience also drives belief formation (Malmendier & Nagel, 2016; Kuchler & Zafar, 2019; Bailey et al., 2018). Night light data can be a proxy for capturing the personal experience at the city level. Finally, a significant part of India's economic activity is informal and is often excluded from formal GDP measures. The NTL thus provides an alternative way of capturing the spatial distribution and magnitude of the informal economy (Chodorow-Reich et al., 2020).

To our knowledge, we are the first to examine the linkage between economic activity and consumer sentiment at the city level. Thus, the contribution of this paper is manifold. First, we analyze the impact of city-level economic indicators on consumer confidence in an emerging economy using household-level data. The second contribution of our paper is to use night-time lights as a proxy of economic growth at the city level for which formal data is unavailable. We combine the unit-level observational data and the NTL using the city as the common identification unit. Third, we also establish the role of personal socioeconomic conditions in shaping the beliefs about macro-level economic conditions. Fourth, we explore the dynamic impact of NTL to provide deeper insights into macroeconomic sentiment. We also check the robustness of our baseline results by including the state-wise urban consumer price index as an additional control variable in our analysis. Finally, we extend our analysis to examine the impact of NTL on the perception and expectation on household income, spending, employment scenario, and price level.

3. Data And Methodology

This section briefly explains the data and variables used in this study. The data on consumer confidence comes from unit-level observations of the Consumer Confidence Survey (CCS) conducted by the Reserve Bank of India (RBI). RBI has conducted the CCS survey since June 2010, every quarter. However, from December 2016 onwards, RBI conducts the survey on a bi-monthly basis. Primarily the survey covered six cities, but in 2017 it incorporated thirteen major cities in India.[2] The sample period of this analysis is from June 2016 (Round 31) to November 2021 (Round 63). In every round, about 5000 respondents are asked to express their sentiments towards the present economic situation compared to a year ago and their outlook a year ahead[3].

Further, besides the respondents' opinion towards their economic conditions, they are also asked about their present perception and outlook on different household circumstances, including household income, spending (on essentials and non-essential), employment, and the current and future rate of increased prices. The responses were captured on a three-point scale, i.e., improve, remain the same, or worsen. Moreover, the survey also recorded certain demographic information of the respondents, such as age, gender, occupation, income, educational qualification, family size, and the number of earning members.

Here, it is necessary to mention that the survey is conducted for each round separately. A fresh list of polling booths from the cities is sampled, and respondents are then sampled from these polling booths. Thus, it is unlikely that respondents will be repeated in any survey rounds. The survey covers major cities across the country, and the targeted sample size for each city is based on the number of households in each city, as per Census 2011. Therefore, the survey results can be considered representative of consumer confidence in urban India. The data on CCS is publicly available from the RBI website[4].

3.1 Dependent Variables:

The two key variables representing consumer confidence are present perception on general economic condition compared to a year ago (PGEC) and outlook on future general economic condition a year ahead (FGEC). PGEC = 1 if the respondent's perception on the present general economic condition compared to a year ago has improved, 0 if it remained the same, and − 1 if it worsened (Andrade et al., 2021; Buchheim et al., 2020; Das et al., 2019). Similarly, FGEC = 1 if the respondent's outlook towards future general economic conditions will improve, 0 if it will remain the same, and − 1 if it will worsen.

3.2 Night Light Data

Traditionally, NTL data was available from the U.S. Air Force Defence Meteorological Satellite Program (DMSP) based on the Operational Linescan System (OLS). Even though this data has been used in human settlement mapping and economic growth exploration, it is known for exaggerating brightness values and coarse spatial resolution (Levin, 2017). The DMSP-OLS data was based on an algorithm and provided better estimates of economic activity by eliminating stray lights like a forest fire, movement of ship fleet, gas flares, etc., but with an upper luminosity limit of 63 only based on a linear scale from 0 to 63 (Addison & Stewart, 2015). To counter this problem from April 2012 onwards, the data is captured with nanowatt as a unit of measurement using the Suomi National Polar Partnership Satellite with a Visible Infrared Imaging Radiometer Suit (SNPP-VIIRS) launched by the Earth Observation Group (Jing et al., 2016; Prakash et al., 2019). Subsequently, the Day-Night Band (DNB) within VIIRS emerged as a better source for NTL data. Therefore, our study uses Suomi NPP satellite data that captures night-time light using the Visible Infrared region of the electromagnetic spectrum (VIIRS/DNB). This data has been available since 2012. As our study covers different cities in India, we use the first configuration[5] (from the Version 1) to obtain monthly NTL data (Elvidge et al., 2017). Also, to ensure the accuracy of DNB Composites data, we resort to cloud-free observations as an alternative, mainly for tropical regions and during monsoon months (Chanda & Cook, 2019; Elvidge et al., 2017). Then we follow the data retrieval method as proposed by Li et al. (2020). Finally, we use Google Earth Engine Monthly composites for Night-time Light

Data from the Day-Night Band (DNB) from April 2012 to November 2021 to analyze the city-level night lights. However, we do not claim any modifications in the methodological literature that already exists on remote sensing. A detailed description of the data and variables considered in our analysis is provided in Appendix A.

3.3 Identification Strategy:

CCS dataset is primarily a city-wise survey published by RBI, where the observational units are the households. However, the smallest identifiable unit is a particular individual's city of residence. Therefore, we align confidence indicators with NTL from the cities where the surveys were conducted. We exploit the variations in NTL, conditional on household covariates, and identify the causal effect of NTL on consumer perception and expectations using the following Eq. (1) (Bertrand et al., 2004; Bhalotra et al., 2020; Binder & Makridis, 2020 and Gillitzer et al., 2021):

$$Y_{ijt} = \alpha + \beta LNTL_{js} + \gamma X_{ijs} + c_j + \lambda\_t + \epsilon_{ijs}$$

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where Y_{ijs} are measures of consumer confidence, whereby, the subscript i represents an individual, j indicates the city, and t refers to the survey period. X is a vector of individual and location level control variables such as age group, gender, household income levels, occupation, education, family size, state-level urban inflation, and urban employment. Moreover, $c_j$and λ_t are fixed effects on city and time, respectively. All standard errors are clustered at the city level to allow for arbitrary degrees of autocorrelation in the errors over time in the same location (Bertrand et al., 2004).

The coefficient of interest in Eq. 1 is β. We expect β to be positive according to local economy effects and/or leading indicator channels. The identifying assumption is that unobserved shocks to confidence indicators are uncorrelated with NTL fluctuations, conditional on individual controls. The inclusion of city and time fixed effects controls for the non-random sorting of individuals with different perceptions and expectations about the economy into cities with different economic growth rates.
[2] Ahmedabad; Bengaluru; Bhopal; Chennai, Delhi; Guwahati; Hyderabad; Jaipur; Kolkata; Lucknow; Mumbai; Patna; and Thiruvananthapuram.

[3] Based on the correspondence with the Department of Statistics and Information Management, RBI, we have been informed that the survey targets a sample size of 6100, and mostly, over 95 percent of the target sample size is achieved. Investigators approach sampled households for face-to-face interviews, and the response rate for the survey is not calculated separately.

[4] www.rbi.org.in.

[5] The first configuration excludes data affected by stray lights, while the second one provides radiance values only after stray light corrections. The latter is of reduced quality and is used for effective estimation at poles.

4. Empirical Results

4.1 Impact of NTL on macroeconomic sentiments

Table 2 provides the results from our regression analysis represented in Eq. 1 of the previous section. The first two columns present the results from the respondent's present perception, followed by their outlook toward future economic conditions. In column one, the estimated coefficient of NTL is positive and statistically significant. Here the estimated coefficient on NTL is 0.055, indicating that a one-unit increase in the local economic activity (as proxied by LNTL) elevates the respondents' perception towards their present economic condition by 5.5 percent. We present the estimated coefficient of NTL by including individual controls in Column 2 of the table. The estimated coefficient for this specification is also positive and statistically significant, showing that with the inclusion of individual controls, the respondents' perception towards their present economic condition changes approximately by five percent. The results thus suggest that when local economic activity rises, consumers become optimistic about the current state of the economy. The following two columns (columns 3 and 4) provide the results for the impact of NTL on the expectations about the future state of the economy. The results show that for both the specifications (columns 3 and 4), the estimated coefficient of NTL is approximately seven percent, and it is statistically significant. This finding, therefore, indicates that the coefficient estimate is larger for future expectations than the present perception. Thus, our results are consistent with the studies of Kuchler & Zafar (2019) and Binder & Makridis (2020) that reveal similar outcomes for the U.S. While the former study showed that recent local house price movements significantly affect expectations about future U.S. house prices and experiencing unemployment leads respondents to become pessimistic about nationwide unemployment, the later study showed that consumers' sentiment becomes more pessimistic about the national economy with rising gas prices. In our study using NTL as a measure of local economic activity, we show that a rise in NTL positively affects consumers' perception about the current and future state of the Indian economy.

4.2 Impact of NTL on macroeconomic sentiments over time

The analysis in Table 3 implicitly assumes that engagement in economic activity and response to economic sentiments are contemporaneous. This is achieved by aligning the survey month with the NTL of the same month. However, Galimberti (2020) argues that lagged changes in NTL can forecast current changes in a country's GDP. Casey & Owen (2013) also favor using lagged values of economic fundamentals. They reflect the economic conditions already experienced by the respondents when they are surveyed. Therefore, we explore this potential channel in the economic sentiment by using the lagged time variations in the intensity of NTL across the cities and quantify their impact on household macroeconomic sentiments. We test this hypothesis by examining the role of lag NTLs on PGEC and FGEC. Models I to IV in Table 3 present our estimated coefficients of NTL with contemporaneous (same as Table 2), one-month lag, two-month lag, and three-month lag for PGEC and FGEC separately. We find that the estimated coefficient of NTL for the one-month lag is 0.061, and it is statistically significant. This value is higher than the contemporaneous impact of 0.054. However, the estimated value drops to 0.044 for the second month and increases to 0.051 during the third month. The impacts are smaller than that in the first month but still statistically significant.

We also observe that for FGEC, the estimated coefficient of NTL for the first month is 0.076, which is higher than the contemporaneous value of 0.065. Interestingly, the impact is positive but statistically insignificant for the second month. However, for the third month, the impact becomes 0.071 and is statistically significant. Therefore, the result indicates significant persistence of the local economic activity on macroeconomic sentiments. The findings can be explained by the fact that NTL is a leading indicator of aggregate economic activity (Galimberti, 2020).

4.3 Exploring Heterogeneity Effects

It is argued that people with different demographic attributes can have different distributions of expectations. Therefore, the heterogeneous impact of NTL on consumer confidence indicators based on the socioeconomic characteristics of the survey respondents is explored. Based on our findings from the previous section, the discussion is purely based on the estimated values of the LNTL.

4.3.1 Heterogeneous effect based on education

There is a general belief that economic optimism increases with education. However, the role of night-time light on economic conditions based on levels of education is unexplored. Table 4 presents the estimated coefficients of LNTL for both PGEC and FGEC, based on the sub-sample analysis of education. Our findings reveal some interesting observations. The estimated coefficients of PGEC are primarily positive and statistically significant for all levels of education. However, the magnitude of the estimated coefficient of NTL is higher for lower education levels when compared to graduates (except for the below primary group). Moreover, for FGEC, the maximum impact of NTL is for the group with an education level below standard is below standard 5. Our results, therefore, show that for both PGEC and FGEC, the estimated coefficients of LNTL are the maximum for respondents under the lower education bracket vis-à-vis the graduates. Consistent with Kuchler & Zafar (2019), our findings also indicate that with a decrease in education level (i.e., respondents with low numeracy skills and without a college education), consumers are more likely to take decisions based on local economic activities about the national economic conditions.

4.3.2 Heterogeneous effect based on income

Consumer confidence is income-sensitive (Binder & Makridis, 2020; Coibion & Gorodnichenko, 2015). To examine the impact of night-time light on consumer confidence, we present a sub-sample analysis across the income level of the survey respondents. We define the first category of households that earn less than INR 100,000 a year as the poorest households. The next group comprises households earning between INR 100,000 and INR 300,000 a year and thus can be called the lower-middle class. The third group of households earns between INR 300,000 and INR 500,000 a year and belongs to the middle-income class. Finally, the last group, the upper middle class, and the wealthiest group, earn more than INR 500,000 a year. Table 4 lists our findings from this sub-sample analysis. Our results indicate that households under the lowest income bracket are more optimistic about their current perception on general economic conditions with one unit rise in the local economic activity, followed by lower-middle- and middle-income households. Similarly, the effect of NTL on future expectations about the economy is positive and statistically significant only for the lower-middle class. Further, we find that the estimated coefficient of NTL for this income group is greater for FGEC than for PGEC. Given that consumer sentiment is a forward-looking process (Acemoglu & Scott, 1994), lower-middle-class households are more optimistic about their future economic outlook than the present.

4.3.3 Heterogeneous effect based on occupational categories

Finally, we also estimate a subsample analysis based on the occupational categories of the survey respondents. Table 4 presents the estimated coefficients of LNTL for both PGEC and FGEC. The estimated coefficients are positive and statistically significant for most of the occupational categories for PGEC. However, the magnitudes (absolute values of the NTL) reveal some interesting observations. Firstly, for PGEC, the absolute value of the estimated coefficient for homemakers is the highest, followed by retired, daily wage earners, and self-employed groups. With respect to FGEC, the effect is once again highest for housewives than for other income categories. The findings, therefore, indicate that housewives are highly sensitive toward information about local economic activities that might impact their household income and therefore become much more optimistic compared to other occupational groups. Overall, our results from the heterogeneity analysis indicate that changes in respondents' sentiments towards local economic activities are likely to vary depending on their personal experiences across different socioeconomic characteristics. This is in contrast to Lusardi (2008) and Das et al. (2019), who argue that individuals with higher income levels and higher education are more optimistic about future macroeconomic developments compared to their other socioeconomic groups. Therefore, our results across the different socioeconomic characteristics indicate that respondents who are less sophisticated (i.e., having a lower level of education or belonging to low-income groups or lower occupational categories) tend to extrapolate more from variations in local economic activities vis-à-vis the more sophisticated counterparts (Kuchler & Zafar, 2019).

4.4 Robustness

In this section, we implement a few robustness checks for our baseline model. To verify the robustness of our baseline model arrived at (as shown in Table 1), we include urban inflation as an additional control variable for our regression equation, as shown in section 3.3 of this paper. Owing to the lack of city-level inflation data, we use the state-level (corresponding to the states where the cities are located) urban inflation as our control variable. Therefore, with the inclusion of urban inflation as an additional control variable, we estimate the following Eq. (2):

$$Y_{ijt} = \alpha + \beta LNTL_{js} + \beta LUCPI_{js} + \gamma X_{ijs} + c_j + \lambda\_t + \epsilon_{ijs}$$

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The measures of Y_{ijs}, subscript i, j, and t remain the same as that of Eq. (1). X is a vector of individual and location level control variables such as age group, gender, household income levels, occupation, education, family size, state-level urban inflation, and urban employment. Moreover, $c_j$and λ_t are the fixed effects on city and time, respectively.

Our data on the urban consumer price index comes from the National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI) with the base year 2012. LUCPI is the log of CPI (Urban) measure at the state level that we incorporate in our regression exercise. Table 5 shows our estimated coefficients of LNTL and LUCPI for both PGEC and FGEC. Our findings reveal that the inclusion of state-level urban inflation does not alter our primary model outcomes, indicating the robustness of our model results.

Furthermore, we augment our analysis by considering an alternative approach to measure the economic sentiment of the households. Following Binder & Makridis (2020), we denote ES_{ijs} as the sum of PGEC and FGEC sentiment scores of respondent i in city j, at time t. We examine the impact of NTL on E.S. by employing the following equations (3):

$$ES_{ijs} = \alpha + \beta LNTL_{js} + \gamma X_{ijs} + c_j + \lambda\_t + \epsilon_{ijs}$$

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Table 6 shows our estimated coefficients of LNTL and LUCPI for E.S. Model I consider the impact of LNTL for E.S., without controlling for LUCPI, whereas Model II includes LUCPI. Our findings reveal that the impact of NTL remains positive and statistically significant for both specifications. Therefore, the results of LNTL are robust with respect to alternative definitions of macroeconomic sentiments, even after controlling for urban inflation.

4.5 Disaggregated analysis of the other survey indicators

In this section, we extend our to examine the impact of LNTL on other survey indicators contained in the CCS survey, like perception and outlook expectations on household income (PPHI and OFHI), household spending (PPHS and OFHS), spending on essential and non-essential goods (PPES, OFES, PNESP, and ONESP), employment (PPEM and OFEM), overall price levels (PPGP and OFGP) and inflation (PPIN and OFIN). Tables 7 to 13 present the results of our regression exercise with respect to the other survey indicators.

Overall our results indicate that LNTL alone significantly elevates PPHI, PPHS, PPES, PPNES, whereas, in the presence of individual-level control variables, LNTL significantly boosts respondents' perception towards their present employment scenario but significantly lowers perception towards the present general price level. Interestingly, LNTL alone significantly elevates the respondents' future outlook toward their household spending as well as their outlook on non-essential spending.

Therefore, the findings from both sections indicate that households with higher levels of socioeconomic conditions and those residing in cities with greater economic activity have more optimistic macroeconomic beliefs. The findings, therefore, corroborate that macroeconomic beliefs are responsive to changes in individuals' perceived economic circumstances and location-based economic indicators.

5. Conclusion

In this paper, we document evidence of how local economic activity can impact the macroeconomic sentiments of Indian households. Using unit-level observations on consumer sentiments from the Consumer Confidence Survey (CCS), conducted by the Reserve Bank of India from June 2016 to November 2021, we identify two key indicators to denote the respondents' macroeconomic sentiments, present perception on economic activity, and future economic outlook (PGEC and FGEC, respectively). We proxy the local economic activity using city-level data on night-time lights (NTL). Our results indicate that increase in the magnitude of local economic activities significantly elevates the respondents' perception and outlook about their general economic conditions. Such an outcome also remains consistent even after controlling for the state-wise urban price level. Moreover, we examine the time variations in the intensity of NTL (at different lags) on the macroeconomic sentiments of respondents and find consistent outcomes for both perception (present) and outlook (future expectation) on respondents' economic conditions. This finding indicates the usefulness of night-time light data in improving the forecast accuracy of economic activity. We also explore the heterogenous impact of NTL on the macroeconomic sentiments across education, income, and occupational categories of the respondents that interestingly indicate how personal level experiences are related to consumer sentiments. For instance, households with a lower level of education or belonging to low-income groups or occupational categories tend to extrapolate more from local economic activity compared to other socioeconomic categories when forming their perceptions and expectations about macroeconomic sentiments. Finally, we also conduct a disaggregated analysis by estimating the impact of NTL on other survey indicators contained in the CCS survey. The findings indicate that apart from general economic activities, NTL has a significant influence in forming sentiments related to household income, spending, and employment opportunities.

Households form an essential part of any economic ecosystem. Therefore, households' perceptions and expectations about the variations in the economic environment are essential drivers of the household decision-making process that consequently impact the aggregate economy. We use innovative location-based night lights data to extract new insights about consumer sentiments. Overall, our results hint toward the favorable outcome for the use of NTL measures to proxy GDP statistics at a disaggregated level.

In this study, we focus on the response of the Reserve Bank of India's CCS measures of consumer sentiment. Our analysis of innovative location-based night lights provides an interesting framework for future applications of night light data for economic measurement and forecasting, especially exploring the response to personal consumption expenditures.

Declarations

Statement of Conflict of Interest

The authors hereby declare that they neither have any conflict of interest as regards to this submitted nor have any relevant financial or non-financial interests to disclose.

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Tables

Table 1: Variable Definitions and Descriptive Statistics

Variables	Measurement	Mean	SD
Dependent Variables			
PGEC	=1 if the respondents perceive that the present general economic condition has improved, 0 if it remained the same, and -1 if it worsened.	-0.234	0.866
FGEC	=1 if the respondent expects that the future general economic condition will improve, 0 if it will remain the same, and -1 if it will become worse.	0.208	0.880
Main Independent Variables			
LNTL	Log of night-time light data	3.136	0.696
LNTL1	First lag of log of night-time light data	3.189	0.604
LNTL2	Second lag of log of night-time light data	3.160	0.691
LNTL3	Third lag of log of night-time light data	3.223	0.540
LUCPI	Log of Urban Consumer Price Index	4.973	0.080
Other Controls			
AGE22T29	=1 if the age of the respondent is between 22 and 29 years, 0 otherwise	0.289	0.453
AGE30T39	=1 if the age of the respondent is between 30 and 39 years, 0 otherwise.	0.280	0.449
AGE40T59	=1 if the age of the respondent is between 40 and 59 years, 0 otherwise.	0.333	0.471
AGE60P	=1 if the age of the respondent is 60 years or above, 0 otherwise.	0.098	0.297
FEMALE	=1 if the gender of the respondent is female, 0 otherwise (Ref	0.457	0.498
INCOMEBL1	=1 if the household's annual income is < ₹1 Lakh	0.417	0.493
INCOME1TL3	=1 if the household's annual income is > ₹1 Lakh and <₹3 Lakh, 0 otherwise.	0.468	0.499
INCOME3TL5	=1 if the household's annual income is >₹3 Lakh and <₹5 Lakh, 0 otherwise.	0.082	0.274
INCOME5P	=1 if the annual income of the household is >= ₹5 Lakh, 0 otherwise.	0.030	0.171
ILLITERATE	=1 if the respondent's education qualification is illiterate, 0 otherwise.	0.064	0.244
EDUBP	=1 if the respondent's education qualification is below primary, 0 otherwise.	0.049	0.217
Other Controls			
EDUL5	=1 if the respondent's education qualification is below standard 5, 0 otherwise.	0.048	0.213
EDU5TL10	=1 if the respondent's education qualification is greater than or equal to the 5th standard but less than the 10th, 0 otherwise.	0.223	0.416
EDU10T12	=1 if the respondent's education qualification is greater than or	0.365	0.482

	equal to 10^{th} standard but less than 12^{th} standard, 0 otherwise.		
EDUGRADP	=1 if the respondent's education qualification is graduate or above, 0 otherwise.	0.251	0.434
FAMSZ1T2	=1 if the number of family members is 1 to 2, else 0	0.084	0.277
FAMSZ3T4	=1 if the number of family members is 3 to 4, else 0	0.480	0.500
FAMSZ5P	=1 if number of family members is 5 or more, else 0	0.437	0.496
RETIRED	=1 if the respondent is retired or unemployed, 0 otherwise.	0.149	0.356
HOUSEWF	=1 if the respondent is housewife, 0 otherwise.	0.313	0.464
SALARIED	=1 if the respondent is a salaried employee, 0 otherwise.	0.248	0.432
DAILYWG	=1 if the respondent is a daily wage earner, 0 otherwise.	0.096	0.294
SELFEMP	=1 if the respondent is self-employed or has a business, 0 otherwise.	0.193	0.395
NEARMW1	=1 if the number of earning members is equal to 1, 0 otherwise	0.595	0.491
NEARNMG1	=1 if the number of earning members is greater than 1, 0 otherwise	0.405	0.491

Source: Authors' own calculations.

Table 2: Impact of NTL on macroeconomic sentiments

Variables	**Dep Var- PGEC**		**Dep Var- FGEC**	
	Model I	**Model II**	**Model I**	**Model II**
	Coeff. (Std. Error)	**Coeff. (Std. Error)**	**Coeff. (Std. Error)**	**Coeff. (Std. Error)**
LNTL	0.055**	0.054**	0.067*	0.066*
	(0.024)	(0.024)	(0.036)	(0.036)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 3: Impact of NTL on macroeconomic sentiments over time

Variables	Dep Var- PGEC				Dep Var- FGEC			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)
LNTL	0.054**				0.066*			
	(0.024)				(0.036)			
LNTL1		0.061**				0.076*		
		(0.024)				(0.035)		
LNTL2			0.044*				0.039	
			(0.023)				(0.035)	
LNTL3				0.051*				0.071*
				(0.024)				(0.039)
CITY FE	YES	YES	YES	YES	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES
Nobs	184701	184701	184701	184701	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors are in parentheses.

Source: Authors' own calculations

Table 4: Heterogeneity with respect to socio-economics variables- Perception of Present and Outlook on Future General Economic Conditions

Variables		LNTL							
		PPGEC	OFGEC	CITY FE	ROUND FE	Individual Controls	Rsq		Nobs
		Coeff.	Coeff.				PPGEC	OFGEC	
		(Std. Error)	(Std. Error)						
EDUCATION	ILLITERATE	0.059***	0.037	YES	YES	YES	0.155	0.073	11767
		(0.019)	(0.039)						
	EDUBP	-0.345	-0.045	YES	YES	YES	0.104	0.057	9115
		(0.336)	(0.926)						
	EDUL5	0.083**	0.082**	YES	YES	YES	0.148	0.089	8811
		(0.029)	(0.037)						
	EDU5TL10	0.075*	0.097	YES	YES	YES	0.151	0.069	41209
		(0.037)	(0.055)						
	EDU10T12	0.050*	0.063	YES	YES	YES	0.181	0.084	67465
		(0.024)	(0.035)						
	EDUGRADP	0.058*	0.060*	YES	YES	YES	0.192	0.083	46334
		(0.027)	(0.031)						
INCOME	INCOMEB1L	0.071**	0.065	YES	YES	YES	0.177	0.082	77071
		(0.023)	(0.044)						
	INCOME1TL3	0.045*	0.079**	YES	YES	YES	0.176	0.076	86445
		(0.064)	(0.034)						
	INCOME3TL5	0.044**	0.009	YES	YES	YES	0.175	0.070	15094
		(0.017)	(0.022)						
	INCOME5P	0.007	-0.001	YES	YES	YES	0.176	0.071	5584
		(0.035)	(0.027)						
OCCUPATION	RETIRED	0.053**	0.037	YES	YES	YES	0.186	0.094	27584
		(0.019)	(0.133)						
	HOUSEWF	0.062*	0.079*	YES	YES	YES	0.167	0.075	57879
		(0.030)	(0.043)						
	SALARIED	0.046	0.063*	YES	YES	YES	0.182	0.080	45874
		(0.028)	(0.033)						
	DAILYWG	0.056**	0.087	YES	YES	YES	0.178	0.087	17645
		(0.021)	(0.053)						
	SELFEMP	0.057**	0.062	YES	YES	YES	0.172	0.077	35719

	(0.259)	(0.037)

Note: ***p<0.01; **p<0.05; *p<0.10. We only provide the estimated coefficients for the LNTL. All the other control variables remain the same as the baseline model. Standard errors are in parenthesis.

Source: Author's own calculations.

Table 5: Robustness Analysis

Variables	Dep Var- PPGEC		Dep Var- OFGEC	
	Model I	Model II	Model I	Model II
	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)	Coeff. (Std. Error)
LNTL	0.054**	0.054**	0.066*	0.069*
	(0.024)	(0.023)	(0.036)	(0.035)
LUCPI		0.258		-1.121
		(0.804)		(0.701)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	YES	YES	YES	YES
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 6: Robustness Analysis (with combined macroeconomic sentiment)

Variables	Dep Var- CMES			
	Model I		Model II	
	Coeff.	(Std. Error)	Coeff.	(Std. Error)
LNTL	0.120*		0.123*	
	(0.058)		(0.057)	
LUCPI			-0.862	
			(1.189)	
CITY FE	YES		YES	
ROUND FE	YES		YES	
Individual Controls	YES		YES	
Rsq	0.152		0.152	
Nobs	184701		184701	

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 7: Empirical Results: Perception of Present and Outlook on Future Household Income

Independent Variables	PPHI		OFHI	
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)
LNTL	0.118**	0.030	0.004	0.029
	(0.051)	(0.112)	(0.035)	(0.020)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Rsq	0.012	0.174	0.000	0.046
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 8: Empirical Results: Perception of Present and Outlook on Future Household Spending

Independent Variables	PPHS		OFHS	
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)
LNTL	0.102***	-0.002	0.051**	-0.001
	(0.032)	(0.018)	(0.020)	(0.026)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Rsq	0.013	0.131	0.004	0.061
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 9: Empirical Results: Perception of Present and Outlook on Future Essential Spending

Independent Variables	PPES		OFES	
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)
LNTL	0.062**	0.003	0.031	-0.001
	(0.025)	(0.019)	(0.018)	(0.023)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Rsq	0.006	0.066	0.002	0.031
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 10: Empirical Results: Perception of Present and Outlook on Future Non-essential Spending

Independent Variables	PPNES		OFNES		
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. err)	(Std-
LNTL	0.202***	0.012	0.108**	0.020	
	(0.034)	(0.025)	(0.046)	(0.053)	
CITY FE	YES	YES	YES	YES	
ROUND FE	YES	YES	YES	YES	
Individual Controls	NO	YES	NO	YES	
Rsq	0.030	0.027	0.009	0.164	
Nobs	184701	184701	184701	184701	

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 11: Empirical Results: Perception of Present and Outlook on Future Employment Scenario

Independent Variables	PPEM		OFEM	
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)
LNTL	0.110	0.059*	0.016	0.056
	(0.074)	(0.030)	(0.064)	(0.039)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Rsq	0.008	0.145	0.000	0.062
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 12: Empirical Results: Perception of Present and Outlook on Future General Price levels

Independent Variables	PPGP		OFGP	
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)
LNTL	-0.023	-0.017**	0.020	-0.023
	(0.024)	(0.008)	(0.016)	(0.014)
CITY FE	YES	YES	YES	YES
ROUND FE	YES	YES	YES	YES
Individual Controls	NO	YES	NO	YES
Rsq	0.001	0.044	0.001	0.02
Nobs	184701	184701	184701	184701

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Table 13: Empirical Results: Perception of Present and Outlook on Future Inflation

Independent Variables	PPIN		OFIN		
	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. (Std-err)	Coeff. err)	(Std-
LNTL	-0.009	0.022	-0.027	-0.023	
	(0.028)	(0.016)	(0.022)	(0.015)	
CITY FE	YES	YES	YES	YES	
ROUND FE	YES	YES	YES	YES	
Individual Controls	NO	YES	NO	YES	
Rsq	0.000	0.068	0.001	0.055	
Nobs	184701	184701	184701	184701	

Note: ***p<0.01; **p<0.05; *p<0.10. Following the same order as that of Table 1, the reference group for age is 20-29 years, for gender, it is male; for income: annual income less than INR 1 lakh; for education: no education; for family size: family size between 2 to 3; for the type of employment: housewives, retired and unemployed; for the number of earning members: 1 earning member. Standard errors in parentheses.

Source: Authors' own calculations.

Figures

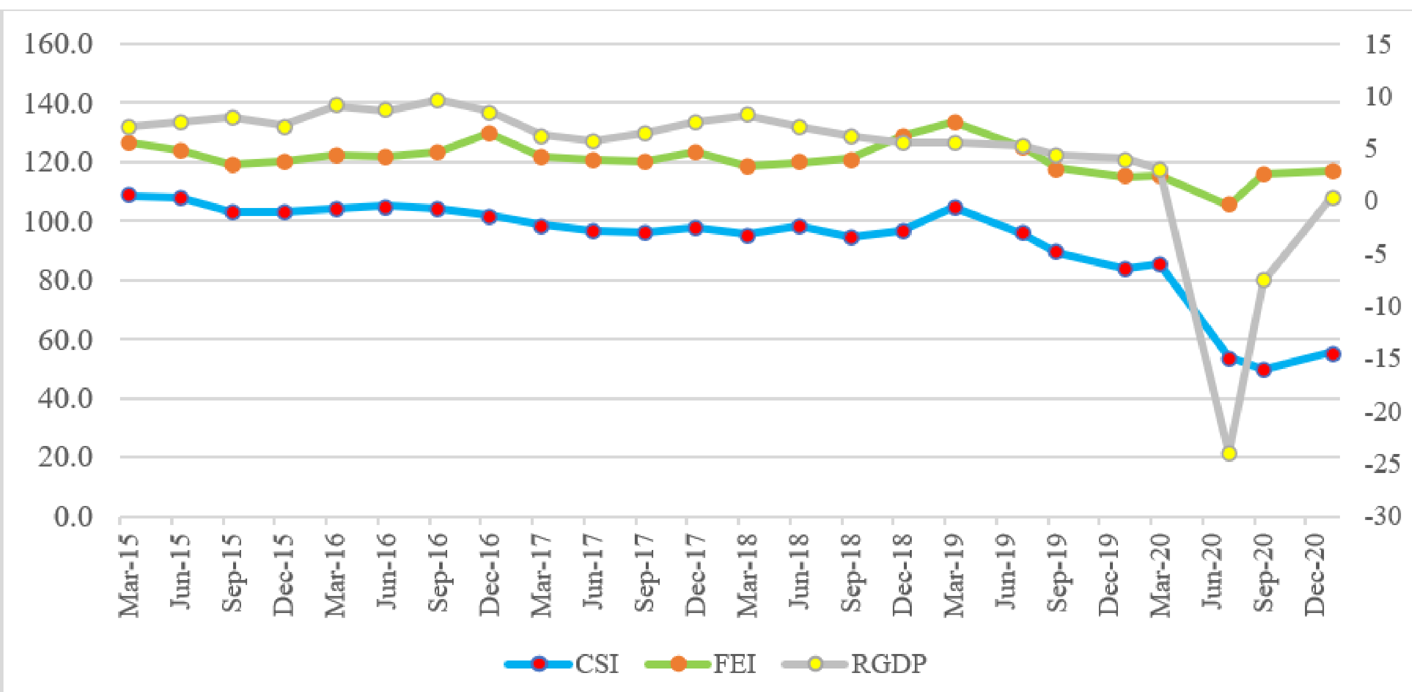

Figure 1

Time series plot of CSI, FEI, and RGDP

Note: Current Situation Index (CSI), Future Expectation Index (FEI) are from the Consumer Confidence Survey

(CCS) released by the Reserve Bank of India (RBI). The right-hand scale represents the growth rate (quarterly) of the real gross domestic product (RGDP).

Source: Authors' own calculations.

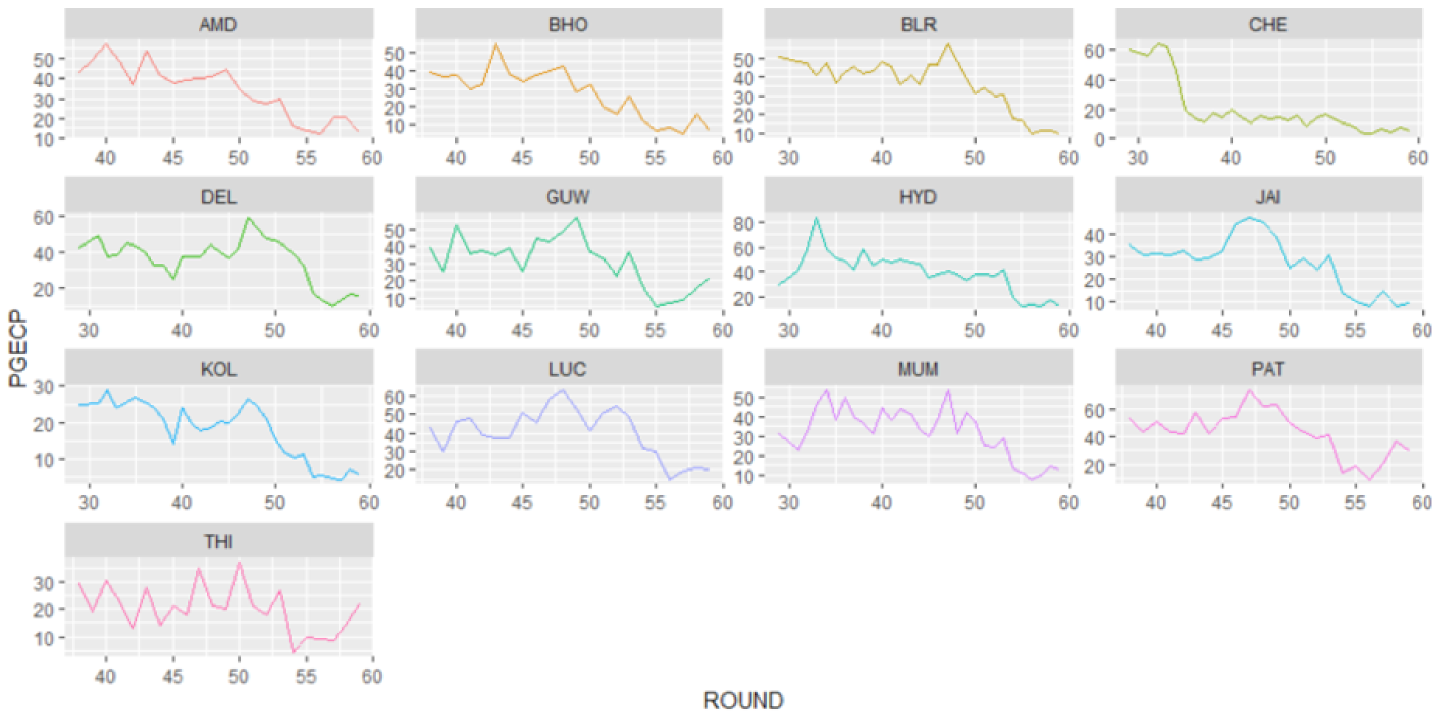

Figure 2

City-wise distribution of perception of present General Economic Condition (Positive Sentiment)

Note: PPGECP captures the percentage of respondents with a positive perception of the general economic condition (PPGEC=1) in each city over the rounds. The city abbreviations are explained in Appendix A2.

Source: Authors' own calculations.

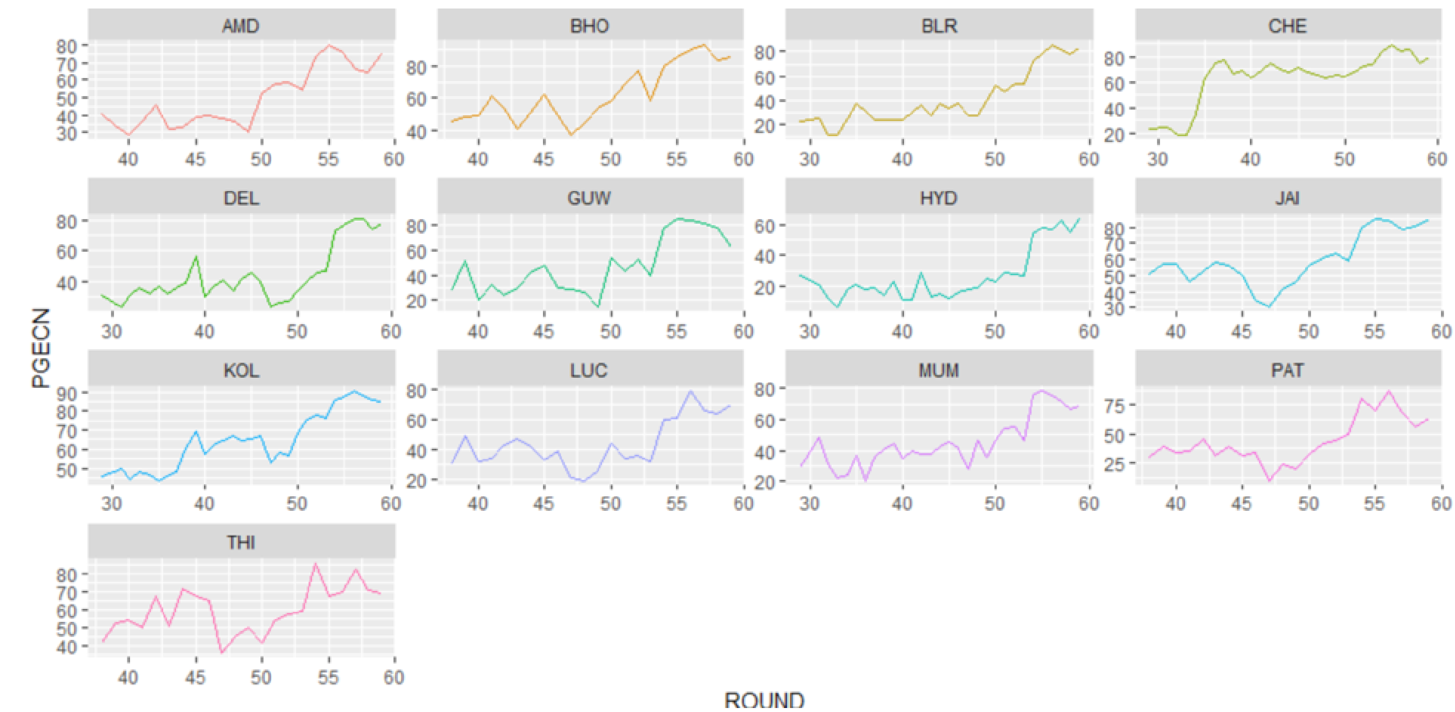

Figure 3

City-wise distribution of perception of Present General Economic Condition (Negative Sentiment)

Note: PPGECN captures the percentage of respondents with a negative perception of the general economic condition (PPGEC=-1) in each city over the rounds. The city abbreviations are explained in Appendix A2.

Source: Authors' own calculations.

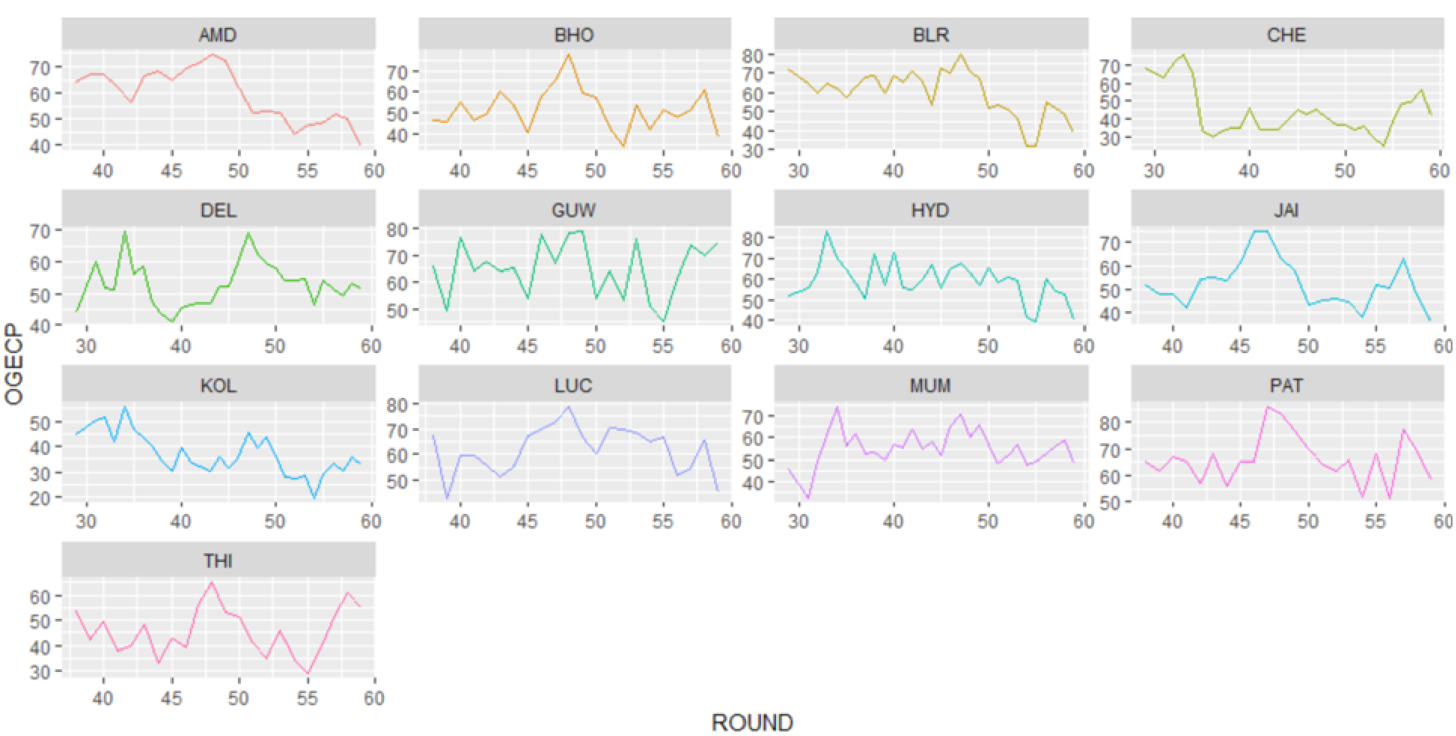

Figure 4

City-wise distribution of Outlook on Future General Economic Condition (Positive Sentiment)

Note: OFGECP captures the percentage of respondents with a positive outlook on the general economic condition (OFGEC=1) in each city over the rounds. The city abbreviations are explained in Appendix A2.

Source: Authors' own calculations.

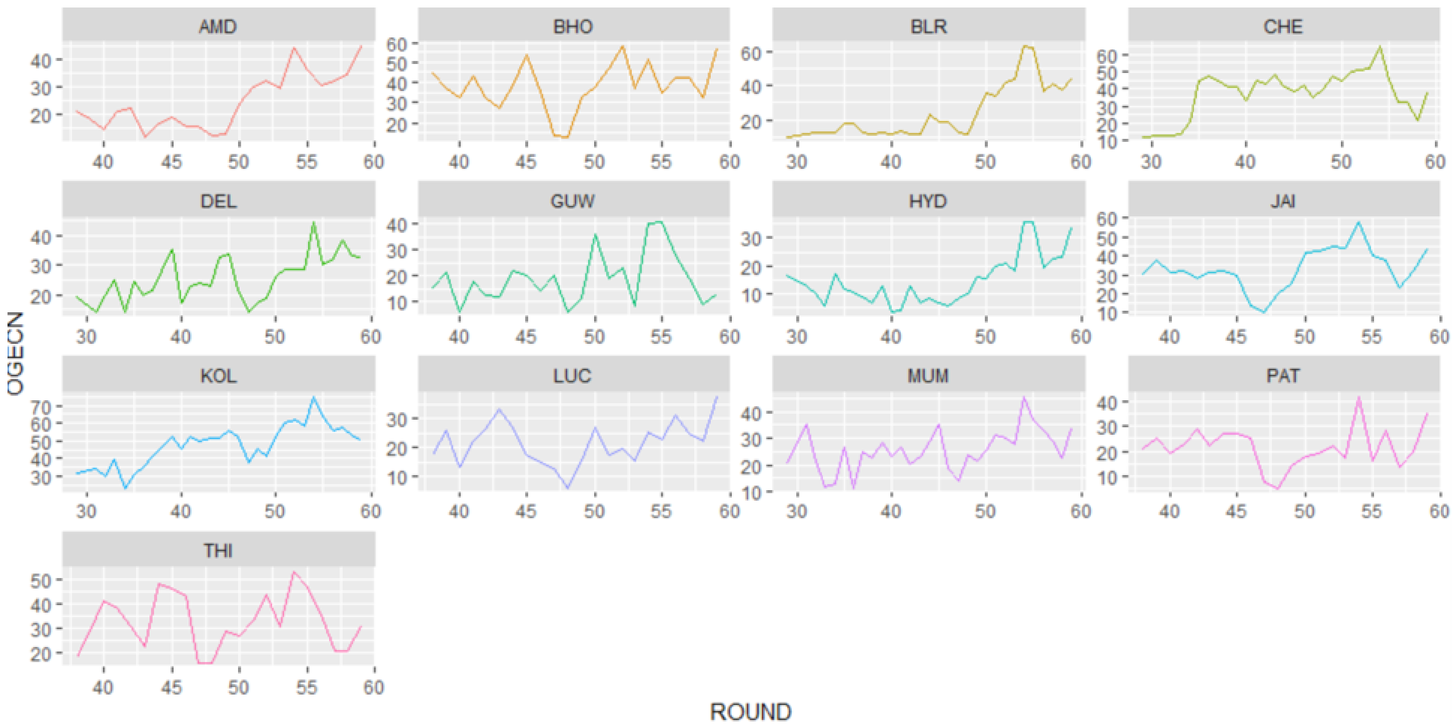

Figure 5

City-wise distribution of Outlook on Future General Economic Condition (Negative Sentiment)

Note: OFGECN captures the percentage of respondents with a negative outlook on the general economic condition (OGEC=-1) in each city over the rounds. The city abbreviations are explained in Appendix A2.

Source: Authors' own calculations

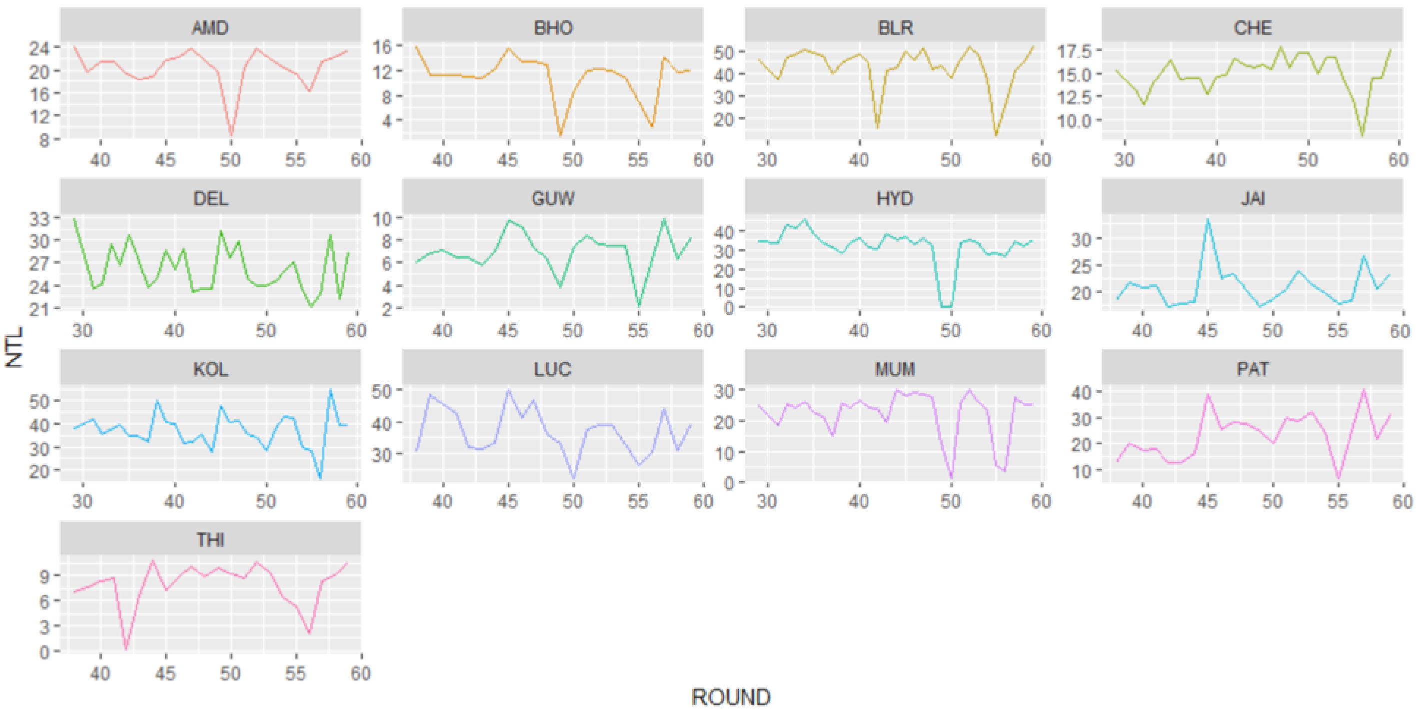

Figure 6

City-wise distribution of Night-Time Luminosity

Note: NTL captures the percentage of night-time luminosity in each city across the survey rounds. The city abbreviations are explained in Appendix A2.

Source: Authors' own calculations

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- D.ResultsApendixCCSNTL.docx