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Studying the Economic Impact of the Demonetization Across Indian Districts

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ABSTRACT: This thesis studies the economic impact of the Indian demonetization which was a unique monetary event that made 86.9 percent of the total currency in circulation illegal tender overnight. The decision to demonetize high-value currency notes was taken by the Indian government on November 8th, 2016, leading to a severe shortage of cash. This thesis tries to analyze how the impact of the demonetization differed across districts in India and how the characteristics of those districts pertaining to education, electricity and tap water access, employment, and technology access can help explain these differences. The thesis uses satellite data on human-generated night light activity to quantify the impact of the demonetization on economic activity. It is found that districts that had a higher literacy rate and a higher percentage of households with access to electricity experienced a less severe economic impact of the demonetization. The economic impact due to the demonetization was more severe in districts with a higher percentage of marginal workers in their workforce. Amongst the various sectors of employment, agriculture, manufacturing, and construction were affected less severely by the demonetization compared to wholesale and retail trade. These insights have the potential to help policymakers minimize the negative economic impacts of a policy like the demonetization by understanding which districts or sub-geographical regions are more susceptible to these impacts.

Introduction

On November 8th, 2016 the government of India decided to demonetize high-value currency notes of denomination Rupees 1000 and Rupees 500, which constituted 86.9 percent of the total currency in circulation. The decision was taken by the Government of India to eliminate corruption, black money, counterfeit currency, and terror funding. The decision was also guided by the aim of reaping potential medium-term benefits in the form of reduced corruption, greater digitization of the economy, and greater formalization of the economy.[1]

The Indian public could exchange the demonetized cash by either swapping the old currency with new currency (subject to daily limits) or they could deposit the old cash in their bank accounts. Between October (the last month before the demonetization) and December 31st, 2016, (the last date for exchanging the old bills for the new ones) currency in circulation in India fell by around 8.4 trillion rupees.[2]

India has traditionally been a cash-intensive economy. According to the Report of the Committee on Digital payments[3] (2016), around 78 percent of all consumer payments in India are effected in cash. Moreover, the informal sector in India is large, contributing 43.2 percent to Gross Value Added and employing more than 80 percent of the labor force.[4] Due to these reasons, the currency squeeze during the demonetization hurt economic activity.

The liquidity shock caused by the demonetization had an impact on the growth of gross value added (GVA) in India. This impact was the result of a decline in demand due to a shortage of cash for discretionary spending and disruption in productivity due to workers, who get their wages paid in cash, experiencing temporary loss of work. The gross value added (GVA) growth for 2016-17 as a whole was estimated by the Reserve Bank of India at 6.9 percent, as against the 7.6 percent communicated by the Reserve Bank of India before demonetization.

The demonetization adversely impacted organized manufacturing leading to a decline in the sales of fast-moving consumer goods (FMCG), contraction in the manufacturing purchasing manager’s index (PMI), and a deceleration in export growth. It also resulted in a slowdown in domestic demand for automobiles, consumer durables, and apparel, and textiles. The service sector was also affected, with the services PMI and service tax collection - an indicator for unorganized services- falling sharply. The impact of the demonetization on agricultural production, however, was muted and transient due to healthy progress in Rabi (crops are sown in winter) sowing with food-grain production increasing by 8.1 percent in 2016-17.

This thesis aims to understand the economic impact of the demonetization by using district-wise cross-sectional data. The objective of the thesis is to study how different characteristics of districts in India can help explain the economic impact of the demonetization in those districts. The thesis will analyze the characteristics of districts related to education, electricity and tap water access, employment, and technology access and will use satellite data on human-generated night light activity to quantify the economic impact of the demonetization.

The data for district characteristics are obtained from the NITI Aayog District Statistics and the Indian National Census of 2011. The nightlight intensity data is obtained using the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) on board the Joint Polar-orbiting Satellite System (JPSS) satellites. A linear regression model is then used to identify how the change in night-light activity varies across districts and which characteristics of these districts help explain this change.

It is found that the total population of a district and the percentage of households with mobile phones are not statistically significant variables in the regression model. Districts with a higher literacy rate and a higher percentage of households using electricity or solar energy as the main source of lighting experienced a less severe impact of the demonetization. Surprisingly, districts with a higher percentage of households receiving tap water experience a more severe economic impact of the demonetization.

Districts with a higher percentage of marginal workers face a more severe economic impact of the demonetization, while the opposite holds for districts with a higher percentage of non-workers. Amongst the different sectors of employment, the economic impact of the demonetization is less severe in districts with a higher percentage of workers in agriculture, forestry, or fishing; manufacturing, and construction. Districts with a higher percentage of workers working in wholesale and retail trade faced a more severe economic impact of the demonetization.

Literature Review

A) Past Experiences with Demonetization in India

Demonetization as a tool of fighting crime, tax evasion, and activities in the underground economy has been advocated in the past, and analyzing literature about past experiences with demonetization in India is insightful.

In 1946, bills of denomination 500 rupees or above were demonetized in India to fight against black market money and tax evasion.[5] However, the scheme was generally regarded as a failure as 94 percent of the demonetized currency was returned to the Reserve Bank of India and it caused considerable hardship to the general public. The Indian government also demonetized currency bills of denomination 1000 rupees and above in 1978. This move was marginally more successful than the one in 1946 as 86 percent of the demonetized currency was exchanged for lower denomination bills.

The unique aspect of the demonetization in India in 2016 was that it was carried out during a period of economic stability, but with very little time given to the public to exchange their demonetized bills. This led to a cash shortage that hurt economic activity. Much like the previous instances of demonetization in India, people found ways to effectively and swiftly launder money, and 99.3% of the revoked currency was returned within the sixty-day window provided by the government.[6]

B) Descriptive Statistics and Time Series Methods

The existing literature on the economic impact of the demonetization in India consists of research that analyzes the macroeconomic impact of the demonetization at the national level using descriptive statistics. The Reserve Bank of India's (RBI) preliminary assessment of the macroeconomic impact of the demonetization, for instance, states that the demonetization led to a transient disruption in nation-wide economic activity. RBI's assessment looks at nationally aggregated data and concludes that the impact of the demonetization on gross value added growth, albeit modest, was felt in November and December of 2016-17.

While this assessment gives a good picture of the macroeconomic conditions at the national level, it fails to capture regional variations in the economic impact of the demonetization. As hard data on the unorganized sector are collected infrequently, it also fails to accurately capture the impact of the demonetization on the unorganized or informal sector. This thesis will try to capture regional variations of the economic impact by using district-wise cross-sectional data. It will also better capture the impact on the unorganized sector by utilizing night light intensity data to quantify economic costs.

There have also been studies that use time series methods to analyze the macroeconomic impact of the demonetization at the national level. Aggarwal and Narayanan[7] estimate the impact of the demonetization on domestic trade in agricultural commodities. They analyze data on arrivals and prices from close to 3000 regulated markets in India for 35 major agricultural commodities. They use a combination of difference in differences techniques and synthetic control methods to identify the causal impact of the demonetization. They find that the demonetization displaced domestic agricultural trade in regulated markets by over 15% and the trade in perishables by around 23% in the short run.

The paper by Aggarwal and Narayanan[7] provides insight into the impact that the demonetization had on agriculture, which accounts for the largest share of the informal workforce[8]. However, national time-series aggregates cannot alone provide empirical evidence of the effects of the demonetization as the episode constitutes only a single observation and because other economic shocks occurred during the period[9]. This is one of the reasons why this thesis studies the consequences of the demonetization using cross-sectional data instead of time series aggregates.

C) Survey Based Methods

Several studies also use survey-based data to examine the economic impact of the demonetization. Zhu et al.[10] analyze the short-run responses of poor rural households to the demonetization. They collect data from four villages in the Sundarbans region of West Bengal and estimate a household income loss of 15.5% over the two months after the demonetization. In a similar study, Krishnan and Siegel[11] survey around 200 families in urban slums in Mumbai and find that household incomes fell by about 10%.

Kurosaki[12] uses a panel dataset on registered and unregistered manufacturing firms to show that even after the demonetization shock, both types of firms remain cash-dependent. Karmarkar and Narayanan[13] use panel data on more than 100,000 households from the Consumer Pyramids (CP) survey of households carried out by the Centre for Monitoring the Indian Economy (CMIE). They find that the demonetization had a transient impact on household income and expenditure with significant heterogeneity in the impact across households in different asset quartiles.

This thesis is similar to the above-mentioned papers in that it can capture the household level characteristics of different districts that led to the varied economic impact of the demonetization. However, unlike some of the above-mentioned papers, the data used in the thesis spans the entire nation and is not limited in terms of geographical scope.

D) Using Cross-Sectional District-wise Data

This thesis builds primarily on the paper written by Chodorow-Reich et al.[9] which uses district-wise cross-sectional data to analyze the impact of the demonetization on economic activity. Methodologically, this approach relates to a burgeoning literature using cross-sectional, regional variation to study macroeconomic topics as reviewed in Nakamura and Steinsson[14] and Chodorow-Reich.[15]

The paper by Chodorow-Reich et al.[9] uses data from the Reserve Bank of India to construct a local area demonetization shock which is the ratio of post-demonetization to pre-demonetization currency in an area. The paper also uses survey data on household employment and satellite data on human-generated night light activity to measure the demonetization's effects at the district level. Both household employment and night light activity reveal economically sharp, statistically highly significant contractions in areas experiencing more severe demonetization shocks.

This thesis builds on the paper written by Chodorow-Reich et al.[16] by utilizing data on characteristics of districts pertaining to education, electricity and tap water access, employment, and technology access. This will provide insight into what characteristics made certain districts more susceptible to the negative economic impacts of the demonetization.

In summary, the thesis builds on the existing literature by capturing regional variations despite being national in scope. It uses cross-sectional data instead of time series aggregates and analyzes the impact on the formal and informal sectors by looking at satellite data on human-generated night light activity. It builds on the paper written by Chodorow-Reich et al.[16] by taking into account data on district characteristics to examine what made certain districts more susceptible to the negative economic impacts of the demonetization.

Night Light Intensity: A Proxy for Economic Activity

Nightlight data serves as a good proxy for economic activity because consumption and production during the evening require some form of lighting.[17] The correlation between nightlight intensity, which is the sum of nightlights divided by the area, and GDP levels has been well established. Henderson et al.[18] introduce a comprehensive framework to help increase the reliability of GDP estimates for developing countries using nightlight data. One of their key findings is that the estimated elasticity between nightlight growth and measured GDP growth is roughly 0.3. Chen and Nordhaus[19] use a similar framework and find that nightlight intensity data is a good proxy for GDP especially for countries where no national economic information is available or the quality of statistical systems is poor.

The high correlation between nightlight intensity and GDP also holds at the subnational level. Doll et al.[20] find that nightlight intensity is correlated with the Gross Regional Product across eleven European countries and the United States. Bhandari and Roychowdhury[21] find that GDP at the district level in India is significantly explained by nightlight intensity.

The correlation between nightlight intensity and GDP captures the fact that access to electricity increases as countries develop and that electricity consumption increases with income levels.[22] It is also found that nightlight intensity in South Asia is more strongly correlated with economic activity in manufacturing and services than in agriculture.[17] This is as access to electricity among farmers is low in South Asia and even when they do have access to electricity, they use it for activities such as water pumping which do not generate nightlight.[22]

Using nightlight intensity data as a proxy for economic activity is advantageous as it captures informal activity. Official GDP data cannot capture informal activity and there are several challenges to the collection of high-quality GDP data including the absence of standardized national income accounting methods, low levels of efficiency of surveyors, and the subjective response of responders in the ground survey.[23] Another issue is that in several countries, subnational estimates of GDP are not available at a reasonable frequency. Nightlight data is available at high levels of spatial disaggregation, can be obtained relatively easily in real-time, and is not subject to politically motivated interference.[24]

Nightlight intensity data have been used as a proxy for economic activity in several applications. Ghosh et al.[25] use nightlight data and find that the magnitude of Mexico's informal economy and the inflow of remittances are 150 percent larger than their existing official estimates in the gross national income. Min[26] uses nightlight data to study trends in rural electrification in India and Doll et al.[27] provide satellite-derived estimates of the rural population without access to electricity in developing countries. Pandey and Seto[28] use nightlight data to study the impact of urbanization on agricultural land loss in India and find that the land loss is concentrated in smaller cities and districts with high rates of economic growth.

Several other applications of nightlight data in economics are outlined in Donaldson and Stoneygard.[29] Donaldson and Stoneygard[30] also describe some unique challenges associated with using nightlight data. Nightlight data show spatial dependence and when using nightlight intensity as a dependent variable, the error term in a multivariate regression is not distributed independently. Potential measurement errors and the complexity of remote sensing datasets can also make them difficult to model using linear functions. It is important to keep these considerations in mind when using nightlight intensity data.

Data and Descriptive Statistics

This paper utilizes a combination of the NITI Aayog district statistics,[31] Indian National Census (2011) data,[32] and nightlight intensity data provided by the Earth Observation Group.[33] NITI Aayog or the National Institute for Transforming India is the policy think tank for the Government of India and provides directional and policy inputs. The NITI Aayog and Census data are used to understand district characteristics and the nightlight data is used as a proxy for economic activity.

The district characteristics which are used in this paper are outlined in Table 1. The descriptive statistics for the district characteristics are provided in Table 2. Appendix A shows choropleth maps of India created using some of these district characteristics. The data regarding district characteristics were recorded in 2011. It is assumed that the district characteristics in 2016 (when the demonetization took place) are closely related to those measured in 2011.

Table 1: District Characteristics

Variable	Source	Notes
TotalPopulation	Census	-
PercentMarginalWorkers	Census	People who did not work for a majority of the previous year were classified as marginal workers
PercentNonWorkers	Census	People who did not work during the previous year were classified as non-workers
LiteracyRate	NITI Aayog	-
PercentHouseholdsWithMobilePhones	NITI Aayog	-
PercentHouseholdsWithElectricityOrSolar	NITI Aayog	Percentage of households with electricity or solar energy as the main source of lighting
PercentHouseholdsWithTapWater	NITI Aayog	Percentage of households receiving treated or untreated tap water within premises
PercentAgricultureForestryFishing	Census	Percentage of main and marginal workers working in these sectors
PercentManufacturing	Census	-
PercentConstruction	Census	-
PercentWholesaleRetailTrade	Census	-

Table 2: Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Max
TotalPopulation	1,949,032.000	1,526,947.000	8,004	11,060,148
PercentMarginalWorkers	0.110	0.055	0.017	0.336
PercentNonWorkers	0.588	0.069	0.331	0.742
LiteracyRate	0.726	0.102	0.421	0.979
PercentHouseholdsWithMobilePhones	0.510	0.143	0.070	0.796
PercentHouseholdsWithElectricityOrSolar	0.661	0.282	0.061	0.997
PercentHouseholdsWithTapWater	0.238	0.202	0.004	0.929
PercentAgricultureForestryFishing	0.604	0.189	0.007	0.891
PercentManufacturing	0.081	0.067	0.006	0.707
PercentConstruction	0.055	0.033	0.004	0.237
PercentWholesaleRetailTrade	0.057	0.033	0.008	0.275

The nightlight intensity data are obtained using the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) onboard the Joint Polar-orbiting Satellite System (JPSS) satellites. The data used in this paper are obtained from a product called the Monthly Cloud-free DNB composite. This product has an image resolution of 15 arc seconds and covers latitudes ranging from 75N to 60S and longitudes ranging from 180W to 180E. This paper uses a configuration of the product that includes data impacted by stray light if the radiance values have undergone the stray light correction procedure. The data can be downloaded in GeoTIFF format and monthly data from April 2012 onwards are available. Appendix B provides an illustration of what the nightlight data product looks like.

For each month, the average nightlight intensity is calculated for all districts in India. The data obtained are monthly in frequency and have substantial seasonality. This paper follows a procedure similar to the one outlined in Chodorow-Reich et al.[34] to obtain seasonally adjusted data. The data are seasonally adjusted by running a regression with the nightlight intensity (in levels) as the dependent variable and district-specific linear time trends and month categorical variables as the independent variables. The regression is described in equation (1) where '$nightlight_{i,t}$' represents the nightlight intensity in the 'i'th district at time 't' with 't=1' for April 2012. Nightlight data from April 2012 to March 2016 are used to run this regression.

$$nightlight_{i,t} = \beta_0 + \beta_{1,i} * Jan + \beta_{2,i} * Feb + \cdots + \beta_{11,i} * Nov + \beta_{12,i} * t \quad (1)$$

Table 3: Seasonality and Trend Coefficients National Average

	Coefficient Values
January	-0.092
February	0.025
March	0.018
April	0.051
May	-0.130
June	-0.446
July	-0.561
August	-0.465
September	-0.232
October	0.059
November	0.167
Trend	0.008
Intercept	0.994

The national average of the coefficients obtained for the month categorical variables and the linear time trend is provided in Table 3. Appendix C graphs the values of nightlight intensity obtained using the seasonal and trend coefficients for four districts in India. The nightlight data from April 2016 onwards are adjusted by subtracting the nightlight intensity value predicted using the regression coefficients from the actual nightlight intensity value observed. Finally, the monthly data are aggregated to quarterly data to remove high-frequency volatility. The month of October is dropped from 2016Q4 so that 2016Q4 is almost entirely post demonetization.

To demonstrate that nightlight intensity can be used at the sub-national level as a proxy for economic activity, the following analyses are carried out. First, the correlation coefficient between the total nightlight intensity and total electricity supply[35] is calculated for states across

India using annual data from 2012 to 2017. The average value of the correlation coefficient is 0.48. The correlation coefficient between average nightlight intensity and Per Capita Net State Domestic Product[36] is also calculated for states across India using annual data from 2012 to 2017. The average value of the correlation coefficient is found to be 0.44. A table of correlation coefficients by state is presented in Appendix D.

The three datasets are merged by joining them on the basis of district names. After merging the three datasets and dropping out districts with missing data, data about district characteristics, and average nightlight intensity for 585 districts are available.

Model and Results

To understand how the characteristics of a district affected the economic impact of the demonetization in that district, a regression model is run with the difference in nightlight intensity between 2016Q4 and 2016Q3 as the dependent variable and the district characteristics as the independent variables. The regression model is described in equation (2), where 'i' represents the 'i'th district and 'Q3' and 'Q4' represent the third and fourth quarters of 2016 respectively. The results of this regression are provided in Table 4.

$$nightlight_{i,Q4} - nightlight_{i,Q3} = \beta_0 + \beta_1 * TotalPopulation_i + \cdots + \beta_{11} * LiteracyRate_i \quad (2)$$

To ensure that the model specification is robust, the correlation coefficients between the difference in nightlight intensity between 2016Q3 and 2016Q2 (pre-demonetization) and the district characteristics are calculated. The maximum absolute value amongst the correlation coefficients calculated is 0.29 (obtained for the variable PercentWholesaleRetailTrade). This shows that the pre-demonetization changes in nightlight intensity are not strongly correlated with the district characteristics. The correlation coefficients obtained are provided in Appendix E.

A) Total Population and Access to Mobile Phones

We find that the TotalPopulation variable is not statistically significant. The total population of a district is used as a control variable in this regression. We also find that the PercentHouseholdsWithMobilePhones variable is not statistically significant and this is somewhat surprising.

Chodorow-Reich et al.[37] find that districts that experienced sharper declines in money following the demonetization experienced sharp declines in overall economic activity and had faster growth of alternative payment mechanisms such as e-wallets. So, there should be a strong negative correlation between change in economic activity and the adoption of e-wallets. If we assume that the percentage of households with mobile phones in a district is strongly positively correlated with the adoption of e-wallets in that district, then there should also be a strong negative correlation between the change in economic activity and the percentage of households with mobile phones.

However, it is possible that districts that saw increased adoption of e-wallets had

Table 4: Results

	Dependent variable:
	Nightlight Intensity Difference 2016Q4 - 2016Q3
TotalPopulation (millions)	-0.054
	(0.044)
PercentMarginalWorkers	-4.042^{***}
	(1.476)
PercentNonWorkers	3.564^{***}
	(1.322)
LiteracyRate	1.324^{*}
	(0.793)
PercentHouseholdsWithMobilePhones	0.194
	(0.531)
PercentHouseholdsWithElectricityOrSolar	0.717^{*}
	(0.393)
PercentHouseholdsWithTapWater	-0.902^{**}
	(0.452)
PercentAgricultureForestryFishing	4.271^{***}
	(0.903)
PercentManufacturing	8.170^{***}
	(1.378)
PercentConstruction	15.090^{***}
	(2.735)
PercentWholesaleRetailTrade	-23.583^{***}
	(3.618)
Constant	-5.815^{***}
	(1.476)
Observations	585
R^2	0.250
Adjusted R^2	0.235
Residual Std. Error	1.413 (df = 573)
F Statistic	17.351^{***} (df = 11; 573)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

sharper declines in money post demonetization, but not necessarily a high percentage of households with mobile phones. The percentage of households with mobile phones may not be not strongly positively correlated with the adoption of e-wallets post demonetization. This is a plausible explanation for why the variable is not statistically significant.

B) Literacy Rates and Electricity and Tap Water Access

Prusty[38] finds that the overall literacy rate had a long-term impact on per capita personal disposable income in India during 1952-2006. Rao[39] finds that electricity access at mean supply levels is associated with at least 18 percent higher income for households in India. Therefore, districts with higher literacy rates and greater access to electricity and tap water should have households with higher incomes and a lesser percentage of workers working in the cash-intensive informal sector. The demonetization should have a less severe economic impact in these districts.

It is found that the LiteracyRate variable is statistically significant at the 10% level with a coefficient of 1.324, the PercentageHouseholdsWithElectricityOrSolar variable is statistically significant at the 10% level with a coefficient of 0.717, and the PercentageHouseholdsWithTapWater variable is statistically significant at the 5% level with a coefficient of -0.902. These results show that districts with higher literacy rates and greater access to electricity had a less severe economic impact due to the demonetization. The negative coefficient associated with the PercentageHouseholdsWithTapWater is surprising, as it indicates that districts that had a greater percentage of households with access to tap water faced a greater economic impact due to the demonetization. Apoorva et al.[40] find that household surveys in India do not reliably estimate household tap water use and this might be a reason why the surprising result associated with the percentage of households receiving tap water is obtained.

C) Marginal workers and Non-workers

The Indian National Census of 2011 divides workers into main workers (who worked for a majority of the previous year), marginal workers (who worked for less than the majority of the previous year), and non-workers (who did not work during the previous year). The PercentMarginalWorkers and PercentNonWorkers variables are statistically significant at the 1% level with coefficients -4.402 and 3.564 associated with them respectively.

This result shows that districts with a higher percentage of marginal workers faced a more severe economic impact due to the demonetization. Marginal workers are more likely to be on the lower rungs of the economic strata and are mostly employed by the cash-intensive informal sector, which helps explain this result. Districts with a higher percentage of non-workers, however, faced a less severe economic impact. Non-workers consist of students, dependents, people performing household duties, pensioners, and rentiers. The result shows us that the impact that the demonetization had on non-workers was lesser compared to marginal workers.

D) Occupation Data

The 2011 Census also provides data about the occupations of main and marginal workers in each district. The four categories of occupations chosen for this regression analysis - agriculture, forestry and fishing; manufacturing; construction; and wholesale and retail trade account for 80% of the main and marginal workers in a district on average. The PercentAgricultureForestryFishing, PercentManufacturing, PercentConstruction, and PercentWholesaleRetailTrade variables have coefficients 4.271, 8.170, 15.090, and -23.583 associated with them respectively, and are all statistically significant at the 1% level.

These coefficients show us that wholesale and retail trade was a sector that was heavily affected by the demonetization. Districts with a higher percentage of workers in agriculture felt a less severe impact of the demonetization. The impact of the demonetization on agriculture was muted due to healthy progress in Rabi sowing.[41]

Nationally aggregated statistics show that the index of industrial production which is a proxy indicator for unorganized manufacturing contracted by 1.7% in December 2016 and the organized manufacturing sector was also adversely affected. They also show that the production of cement which is an indicator for the construction sector contracted by 13.3% in December 2016.[41] As a result, it is surprising to see that districts with a higher percentage of workers employed by the manufacturing and construction sectors were less severely affected by the demonetization. The manufacturing and construction sectors could have performed better compared to the wholesale and retail trade sectors and other sectors excluded from the regression such as services, accommodation, and food, etc. This might be a plausible explanation for the positive coefficients associated with these variables.

E) Spatial Correlation

The district characteristics used as independent variables in this regression model may be spatially correlated. According to Donaldson and Stoneygard[42] nightlight data also show spatial dependence when using nightlight intensity as a dependent variable. To account for spatial correlation, standard errors in the regression model are clustered by state, resulting in 35 clusters. The standard errors are adjusted by implementing the Imbens and Kolésar[43] and Bell and McCaffrey[44] degrees of freedom adjustments.

On accounting for spatial correlation, it is found that the PercentMarginalWorkers variable is statistically significant at the 10% level, the PercentManufacturing and PercentWholesaleRetailTrade variables are statistically significant at the 5% level and the other variables are not statistically significant. This method only adjusts the standard errors and the coefficient estimates for all the variables remain the same. This is a good check of the robustness of the model and even after accounting for spatial correlation, some of the district characteristics are statistically significant in explaining the economic impact of the demonetization. The p-values obtained for all the independent variables are presented in Appendix F.

Conclusion

This thesis examines the economic impact of the demonetization in India, by using cross-sectional data at the district level. It adds to the existing literature by capturing regional variations in the economic impact of the demonetization while being national in scope. Satellite data on human-generated night light activity are used as a proxy for economic activity at the district level. The results provide insight into what characteristics made certain districts more susceptible to the negative economic impacts of the demonetization.

There are several opportunities to refine and expand the analysis presented in this thesis. The nightlight intensity data can be cleaned using more sophisticated techniques, before aggregating it at the district level. Individual nightlight observations below a certain threshold can be removed, outlier observations can be removed from each location, or observations from locations with background noise can be removed as described in Beyer et al.[45] Data about unemployment at the district level can also be used to examine the impact of the demonetization on economic activity.

It is also important to remember that there were other economic events and policies that affected the Indian economy during the period in which the demonetization took place. Some salient examples include the election of President Donald Trump on the same day as the demonetization was announced, a 60% rise in global prices of crude oil from January to October 2016 and a better monsoon rainfall than in the previous year.[46] While future improvements are possible, this thesis provides policymakers an understanding of what made certain districts in India more susceptible to the negative economic impacts of the demonetization. Hopefully, these findings will help policymakers in India and other countries make informed policy decisions in the future.

Appendices

Appendix A:

Figure A.1: Literacy Rate Choropleth Map

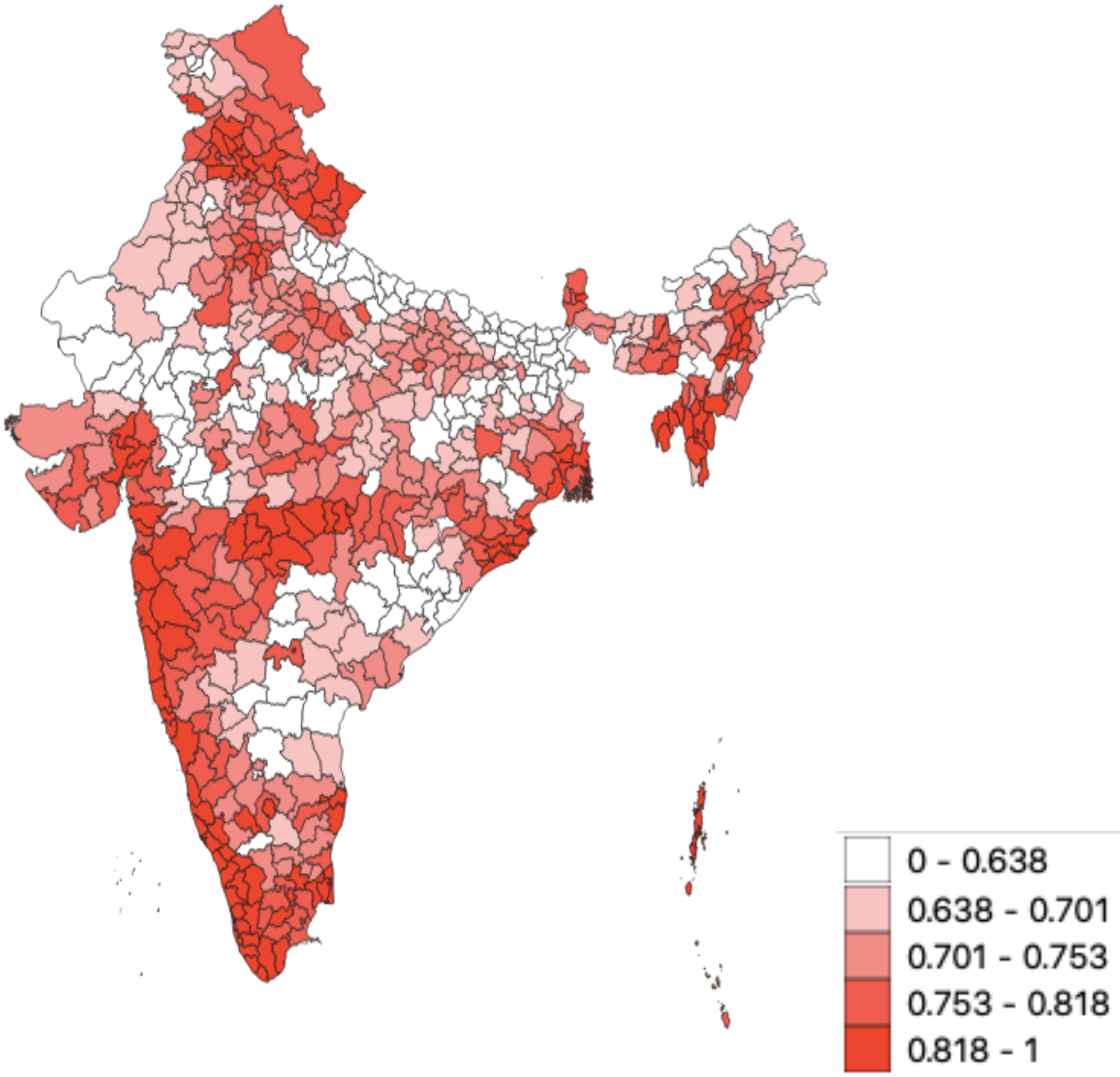
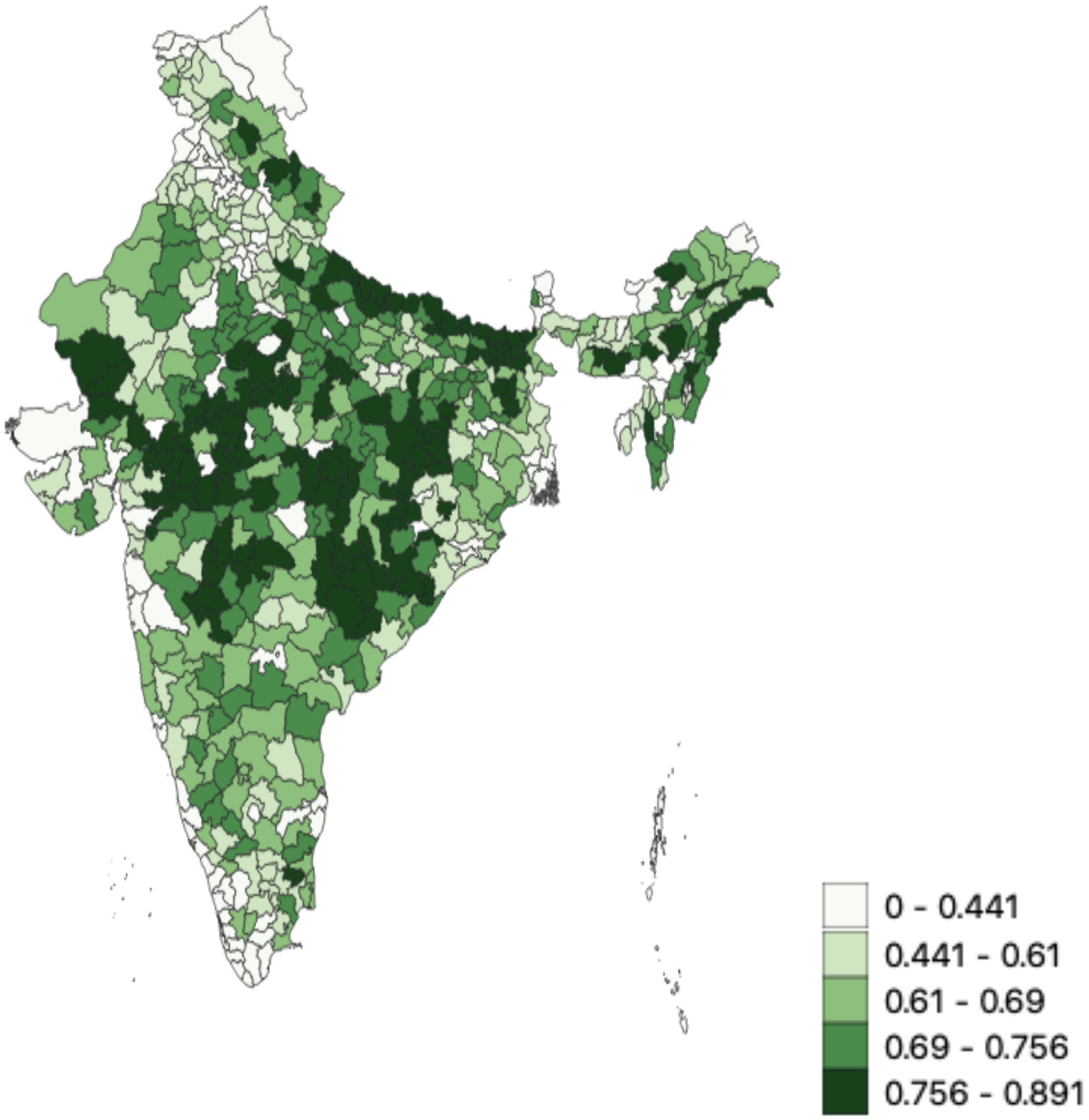


Figure A.2: Percentage of Workers Employed in Agriculture/Forestry/Fishing Choropleth Map



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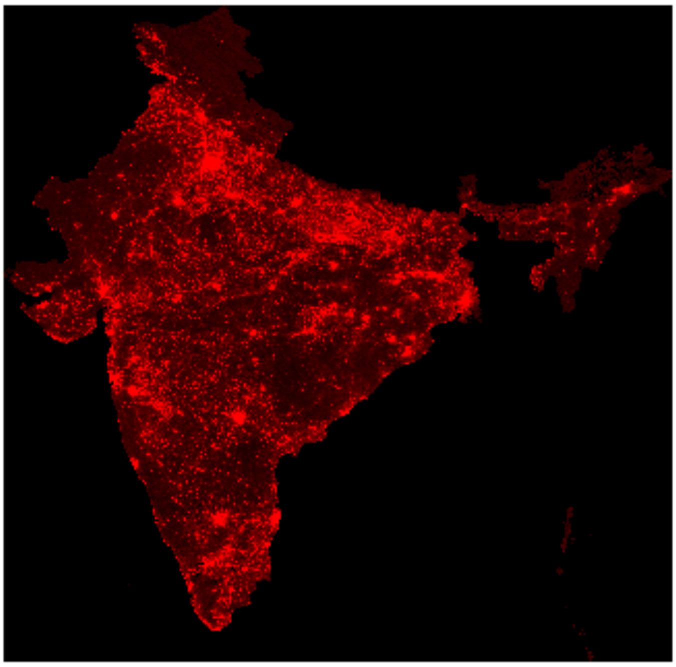
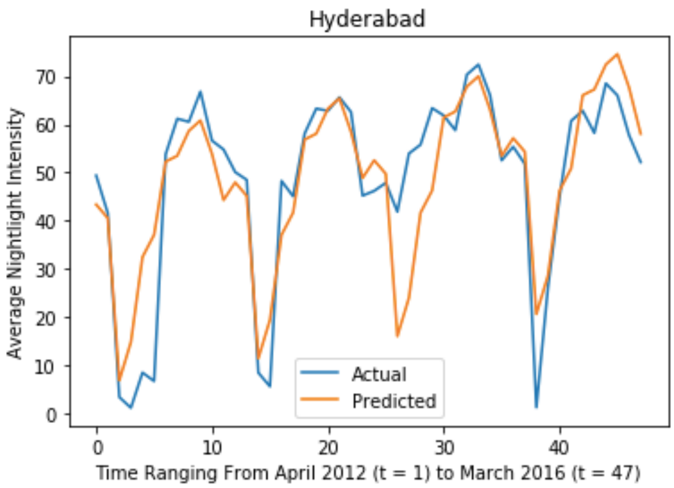
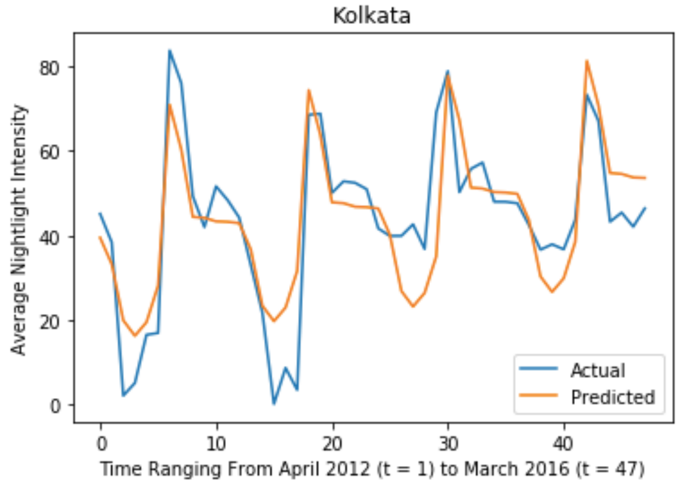
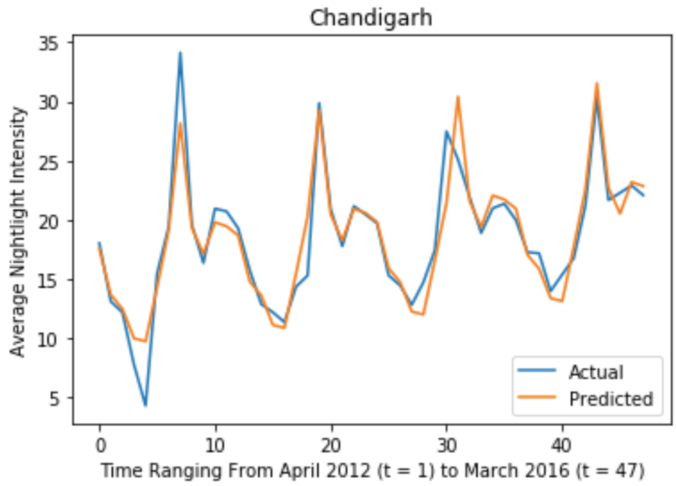
Appendix B: Nightlight Data Example

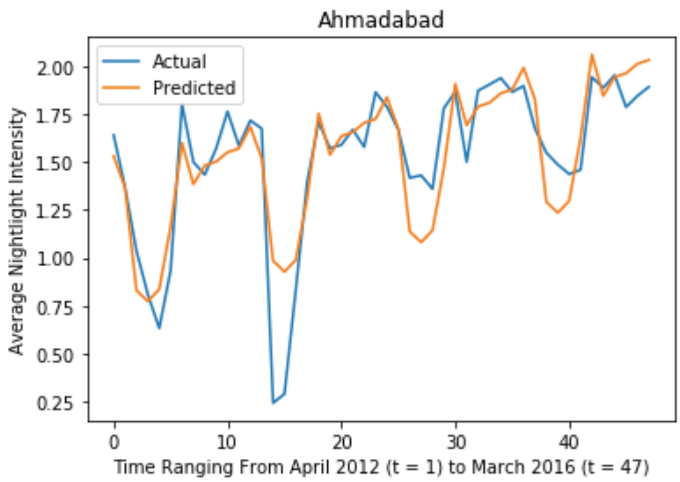


Appendix C: Regression Results Using Seasonality and Trend Coefficients




Kolkata
Average Nightlight Intensity
0
20
40
60
80
0
10
20
30
40
Time Ranging From April 2012 (t = 1) to March 2016 (t = 47)
Actual
Predicted


Chandigarh
Average Nightlight Intensity
5
10
15
20
25
30
35
0
10
20
30
40
Time Ranging From April 2012 (t = 1) to March 2016 (t = 47)
Actual
Predicted


Ahmadabad
Average Nightlight Intensity
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0
10
20
30
40
Time Ranging From April 2012 (t = 1) to March 2016 (t = 47)
Actual
Predicted

Appendix D:

Correlation Coefficients

State	Electricity Supply and Nightlight	NSDP and Nightlight
Andaman- Nicobar	-0.68	0.64
Andhra Pradesh	0.89	0.84
Arunachal Pradesh	-0.46	-0.02
Assam	0.92	0.66
Bihar	0.99	0.95
Chandigarh	0.16	0.86
Chhattisgarh	0.68	0.65
Dadra and Nagar Haveli	0.84	-
Daman and Diu	0.33	-
Delhi	0.61	0.46
Goa	0.83	0.62
Gujarat	0.86	0.94
Haryana	0.26	-0.18
Himachal Pradesh	0.25	-0.42
Jammu and Kashmir	-0.01	-0.36
Jharkhand	0.96	0.7
Karnataka	0.84	0.9
Kerala	0.99	0.97
Lakshadweep	0.55	-
Madhya Pradesh	0.86	0.86
Maharashtra	0.97	0.95
Manipur	0.28	0.61
Meghalaya	0.25	-0.65
Mizoram	-0.41	-0.47
Nagaland	0.06	0.32
Odisha	0.92	0.72
Puducherry	0.88	-0.07
Punjab	-0.02	0.04
Rajasthan	0.86	0.66
Sikkim	-0.48	-0.46
Tamil Nadu	0.97	0.93
Telengana	-	0.73
Tripura	0.27	0.79
Uttar Pradesh	1	0.98
Uttarakhand	-0.32	-0.43
West Bengal	0.98	0.84

Appendix E:

Change in Nightlight Intensity Pre-Demonetization

Variable	Correlation with Nightlight Intensity 2016Q3-2016Q2
TotalPopulation	0.12
PercentMarginalWorkers	-0.07
PercentNonWorkers	0.12
LiteracyRate	0.07
PercentHouseholdsWithMobilePhones	0.1
PercentHouseholdsWithElectricityOrSolar	0.03
PercentHouseholdsWithTapWater	0.17
PercentAgricultureForestryFishing	-0.23
PercentManufacturing	0.01
PercentConstruction	0.06
PercentWholesaleRetailTrade	0.29

Appendix F:

Accounting For Spatial Correlation

Variable	p-value
TotalPopulation	0.45
PercentMarginalWorkers	0.08*
PercentNonWorkers	0.18
LiteracyRate	0.13
PercentHouseholdsWithMobilePhones	0.65
PercentHouseholdsWithElectricityOrSolar	0.17
PercentHouseholdsWithTapWater	0.26
PercentAgricultureForestryFishing	0.11
PercentManufacturing	0.04**
PercentConstruction	0.11
PercentWholesaleRetailTrade	0.04**
Note:	*p<0.1; **p<0.05; ***p<0.01

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