Spillovers of India’s Demonetization on Economic Activity and Household Welfare in Nepal

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Abstract

On November 8, 2016, the government of India demonetized the highest denomination bills in its economy, which accounted for 86% of currency-in-circulation. Although the domestic effects of the resulting cash crunch have been explored, its impact on neighboring countries is an open question. My thesis focuses on the impact of this demonetization on Nepal, a country with strong migrant and trade ties with India that facilitate inflow of Indian rupees.

I employ Difference-in-Difference (DD) strategies to gauge the policy's effect on Nepal's economy at the macro and micro-levels. First, I exploit variation in time and share of a district's population that are migrants to India to estimate the impact on monthly Night-Time Light (NTL) intensity by district, a proxy for aggregate economic activity. I find statistically insignificant effects associated with a one standard deviation increase in migrant to India share after the announcement of the policy and the implementation period.

Second, using panel data on non-metropolitan households in Nepal, I exploit variation in time and whether a household has migrant income from India, a measure of exposure to the demonetization. I estimate significant declines in non-food, infrequent expenditures by 33.1% in 2017 and 35.1% in 2018 for exposed households. These declines are driven by households with above median asset holdings. Food and other frequent expenditures increased or were unchanged following the shock. I also find that informal borrowing more than doubled in 2017, which suggests that informal credit systems played an important role in smoothing frequent expenditures for exposed, non-metropolitan households.

JEL Classification: E2, E5, F2, O40, O57, R12

Keywords: Cross-border Spillovers, Nepali Economy, Monetary Policy, Economic Growth, Night Lights, Household Expenditure, Credit, Difference-in-Difference.

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1. Introduction

Cash plays an integral role in developing countries. When individuals and businesses do not have access to well-developed banking and electronic payment infrastructure, they rely on cash to finance day-to-day transactions. In such contexts, policies that affect currency supply can have far-reaching consequences. On November 8, 2016, the Indian government announced that the highest denomination bills in its economy, the 1000 and 500 Indian rupee bills (~$14 and ~$7, respectively), were to be considered illegal tender, or demonetized, by the end of the day. As a result of this policy, 86% of the currency-in-circulation in India was rendered obsolete. The demonetized notes were to be replaced by new Rs. 2,000 and Rs. 500 bills. In India, where around 72% of consumer transactions were conducted in cash prior to the demonetization, the abrupt announcement of the policy and the shortage of new notes for exchange caused a severe cash crunch in the short-term, which is generally believed to have decreased economic growth (Chodrow-Reich et. al. 2020; Beyer et. al. 2018; Chanda and Cook 2020) and household expenditure (Karmakar et. al. 2020; Wadhwa 2019) in the short-term. While the domestic effects of the policy have been studied, its impact on related economies is largely unexplored.

I study the spillovers effects of India's demonetization policy on district-level aggregate economic activity and household expenditures in Nepal. Nepali businesses and individuals, particularly those closer to the border with India, use Indian rupees for transactions. In addition, the Nepali economy is heavily reliant on cash, with over 95% of transactions being cash-based. These economic agents accumulate Indian rupees through two primary channels: migrant work and sale of export goods in India. Nepali migrant workers view India as an attractive destination for employment due to the open border, which grants free flow of labor between the two countries. Further, around 56% of exports from Nepal are sold in India, which is facilitated by the open border and the currency peg that provides a stable basis for trade. I hypothesize that the demonetization had a similar, likely attenuated, impact to that of India through these mechanisms.

Although the focus of my research is relatively novel, the structure, methodology and data are similar to previous studies on the demonetization's effects in India (Beyer et. al. 2018; Chanda and Cook 2020; Karmakar et. al. 2020). First, I study changes in economic activity at the district level, proxied by the natural log of Night-Time Light (NTL) intensity. Then, I use household data to study the impact on per capita household expenditures and borrowing. My main estimation strategy relies on the interaction between two sources of variation in a Difference-in-Difference (DD) framework. As my first source of variation, I exploit the panel structure of my data and use variation in time by splitting the sample into pre and post-demonetization observations. The demonetization policy yields itself well to such an analysis as it was completely unexpected, implying that the timing of the policy was plausibly exogenous. As my second source of variation, I use differences in Nepal-India migrant links at the district and household levels. I use migrant links as the source of variation due to the large scale of migration from Nepal to India for work, which is one of the primary mechanisms through which households in Nepal obtain Indian rupees. At the district-level, I measure this using migrants to India as a share of a district's population prior to the demonetization. At the household-level, if a household had migrant income from India before the policy was announced, they are deemed dependent on Indian rupees and, consequently, exposed to the shock.

The results at the district-level are statistically inconclusive. I find that there are insignificant, positive effects of the demonetization on NTL growth during the implementation period of the demonetization (November 2016-March 2017) associated with a 1% or one standard deviation increase in migrant to India share of the population. This effect is negative and insignificant in the post-demonetization period (April 2017-December 2017). Based on this evidence, we cannot assert that economic activity changed in Nepal after the announcement of the policy despite the documented reductions in India during the same period. However, in the post-demonetization period, while the results are statistically insignificant, I cannot prove the absence of economically meaningful effects. The point estimate implies that an increase of around one standard deviation in migrant share by district decreases NTL intensity by 1.59%, and local GDP by 0.56%.[1] This effect on NTL intensity could lie in the range -5.65%–2.47% (95% confidence interval), corresponding to a range of -2%–0.8% in real GDP in the post period.

The insignificance of results at the macro-level can be partly explained by the fact that total Indian rupees in circulation in Nepal is estimated to be only 3% of total currency-in-circulation. However, the stock of Indian rupees is concentrated in migrant households with income from India, which increases their exposure to the demonetization. Using data from the Household Risk and Vulnerability Survey (HRVS) 2016-2018, an annual panel survey of non-metropolitan (rural and peri-urban) households in Nepal, I show that being dependent on Indian rupees prior to the demonetization decreased per capita expenditures on non-food, infrequently purchased items by 33.1% in 2017 and 35.1% in 2018 relative to

[1] Conversion from changes in NTL to local GDP is done using the Inverse-Henderson elasticity of GDP to NTL intensity (Henderson et. al. 2012), calculated using a subset of South Asian Countries (Beyer et. al. 2018). The elasticity is estimated to be 0.35 (significant at 0.1%).

expenditures in 2016. These results are consistent with my initial hypothesis, as they suggest that the demonetization was a negative income shock for households dependent on Indian rupees. I further show that these declines were driven by exposed households with above median asset holdings in my 2016 sample. Per capita expenditures on frequently purchased items, however, tell a different story: food expenditures increased by 17.4% on average for households dependent on Indian currency in 2017, while the effect is insignificant in 2018; non-food, frequent expenditures were unaffected (insignificant) in 2017 and 2018. I show that the increase in food expenditures in 2017 is not due to differential changes in food prices for dependent households. The lack of an expected, negative effect on food and frequent, non-food expenses suggest household reluctance to reduce frequent, necessary expenditures.

While there is a possibility that households used spare income from reductions in infrequent expenditures to smooth (or increase) their expenditure on frequently purchased items, I find an increase in informal borrowing by 105.8% in 2017 for households dependent on Indian rupees. This provides evidence for reliance on informal credit to cope with the shock by households in my sample. Further, it suggests that the policy was viewed as a negative income shock, rather than an event that simply caused substitution between expenditure categories for non-metropolitan, exposed households in Nepal.

Given the inextricability of the Nepali and Indian economies, an overall assessment of the demonetization would ideally account for the impact on Nepal. However, the understanding of the demonetization's impact on economies with close ties to India is limited. My thesis addresses this by showing that the demonetization had significant effects on Nepal, particularly at the household-level. It also contributes to the long-standing literature on aggregate and household-level spillovers of shocks beyond country borders, since the demonetization is one of the largest monetary shocks in recent history. My district-level results cannot reject the existence of sizeable macroeconomic spillovers of monetary policy and financial shocks from more advanced to developing countries found in previous studies (Kose et. al. 2017; Gupta et. al. 2017; Kuzlok and Mehrotra 2008). On the micro side, the household-level results are strong evidence for the existence of a relationship between large-scale income shocks in foreign countries and changes to domestic household consumption (Yang 2008; Verner and Gyongyosi 2018).

Finally, my thesis is also relevant to the literature on the Life Cycle/Permanent Income Hypothesis (LCH/PIH). In a seminal paper, Hall (1978) finds a small and insignificant relationship between lagged and current consumption, which they use to conclude that consumers have a preference to smooth consumption. However, several studies since have argued for the need to account for liquidity constraints in the model (Runkle 1983, Zeldes 1989). The results of my thesis support this argument, as they suggest that consumption smoothing post-demonetization was facilitated by growth in informal borrowing. Further, the result that expenditure responses differ by consumption categories is consistent with the claim that studies testing the LCH/PIH using food consumption data should not generalize results to overall consumption (Shea 1993).

The rest of this paper is structured as follows. In section 2, I provide additional background on India’s demonetization policy. I provide an overview of the data and the empirical strategy used in sections 3 and 4. Section 5 presents the main results from my household and district-level analyses. In section 6, I test alternate specifications and conduct robustness checks for both analyses. Section 7 concludes.

2. Background

a. India’s Demonetization Policy of 2016

At 8 PM on November 8, 2016, the Prime Minister of India, Narendra Modi, made a surprise announcement of the implementation of the demonetization policy, which rendered highest denomination bills in the Indian economy (1000 and 500 Indian rupee bills; around $14 and $7, respectively) illegitimate by midnight of the same day. As a result, 86% of currency-in-circulation in India was demonetized with immediate effect (RBI 2017). The demonetized notes were to be replaced by new Rs. 2,000 and Rs. 500 bills. Indian citizens living in India were allowed to exchange or deposit old currency by December 31, 2016, and non-resident Indians were allowed to do the same by March 31, 2017. Initially, Modi’s speech on November 8 cited two motives for the implementation of the policy: to seize wealth accumulated through illicit activities and to delegitimize the majority of counterfeit notes that existed as Rs. 1000 and Rs. 500 bills. In the subsequent days, two other motives were added to the narrative: the government claimed that they saw this as an opportunity to move India toward a more modern, regulated digital economy by forcing households and businesses to conduct fewer transactions in cash. Doing so, it was hoped that a large portion of the informal economy would move to the organized sector. Lastly, forcing individuals to exchange or deposit demonetized notes for new notes would decrease the undeclared income that individuals and businesses held, ultimately increasing the tax base in India (Lahiri 2020).

The implementation of the policy was hindered by the unpreparedness of the Reserve Bank of India (RBI), the Central Bank of India, which was unable to meet the large demand of new bills in the Indian economy. As a result, individuals could not exchange demonetized bills or withdraw cash from bank accounts at will– ceilings were imposed on the amount to be exchanged or withdrawn at a given time. Figure 1 shows that while currency-in-circulation eventually returned to pre-demonetization levels, it took over a year to do so. This imposed a severe cash constraint for households in a country where 72% of consumer transactions are conducted in cash (RBI 2017). Further, industry reports mention that employees working in small and medium-sized enterprises reported job loss after the policy was announced due to sharp decrease in the supply of cash in the economy (Lahiri 2020).

b. Indian Rupees in Nepal

While the domestic impact of the policy has been documented, the effects on neighboring countries such as Nepal are less explored. As is the case in India, the Nepali economy is heavily dependent on cash. Although the use of the Nepali rupee is most prevalent, in practice, individuals and businesses in Nepal informally use Indian rupees for transactions, especially in areas close to the Indian border. An official study estimates that when the demonetization was announced, Nepali individuals and businesses held around $108 million in Indian rupees, with Nepali banks in possession of $1 million in Indian rupees (*The Financial Express* 2020).[2]

Businesses earn Indian currency primarily through trade. India and Nepal have strong trade relations, with India being the destination for 56% of exports from Nepal ("Nepal Trade" 2019). However, the primary holders of Indian rupees in Nepal are households with migrant workers in India. This is supported by the scale of migration: it is estimated that around 1 million Nepalese work as temporary/seasonal workers in India, out of a total population of Nepal of 28 million (Sharma 2013).[3] India is an attractive destination for

[2] This estimate is around 3% of currency in circulation in Nepal in 2016 ($3.7 billion).
[3] There are no official statistics for migration from Nepal to India or vice versa. The open border between the two countries implies that migrant workers do not need visas/work permits to travel/work across the border.

Nepali workers due to the stability of employment: migrant worker wages are not subject to exchange rate variability due to currency peg and workers from both countries do not need permits to work in the other due to the open border. The lack of restrictions on work leads to two types of labor from Nepal in India: workers near the border who commute to India for work and migrant workers who remit part of their earnings in India to their household. While formal remittance channels convert foreign currency to its local equivalent as part of their service, informal channels of remittances, or *hundi,* include transporting money across borders by the migrants themselves, their friends, their family or unregistered cross-border money transfer agencies. Overall, it has been estimated that only 52% of total remittances flowing into Nepal are transferred through formal channels (Maher 2018). Further, informal channels are reported to be the more common method of remittance from India due to the open border (*The Kathmandu Post* 2016).

c. Conceptual Framework

Remittances from India form a large portion of disposable income for migrant households in Nepal. Households that received migrant worker earnings through *hundi* or have migrant workers who commute to work in India hold Indian currency as part of their liquid assets. Consequently, these households are exposed to the effects of the demonetization. The constraint on expenditure faced by migrant households in Nepal are documented in several newspaper articles (Leudi 2016). Exposure to the demonetization differs between households in India and Nepal as Nepali households do not exclusively hold liquid assets in Indian rupees and can use Nepali rupees as a buffer against the shock. Another key distinction is that households in India had access to official exchange facilities to convert demonetized notes, while Nepali households did not.[4] Thus, in order to assess the effects of the policy in Nepal, I use a conceptual framework that borrows from Chanda and Cook (2020) and Beyer et. al. (2018) that use variation in exposure by district in India to assess policy impact.

With the advent of demonetization, demonetized Indian rupee bills that were accepted as a form of payment previously were no longer accepted in Nepal. This would lead to a decrease in disposable income for individuals/households holding demonetized bills. Given the sheer scale of migration from Nepal to India for work and the fact that migrants are primary holders of Indian rupees in Nepal, districts with higher share of the population who are migrants to India could experience reduced aggregate demand and, consequently, reduced economic activity.

At the household level, I take a more granular look at the effects of this mechanism by exploring the impact of the demonetization on expenditure of households with migrant income from India, i.e. households dependent on Indian rupees. Expenditures are hypothesized to decrease for such households. However, the relationship is not clear if households view demonetization as a temporary, idiosyncratic shock, as borrowing to finance household expenditure could be a viable solution in such a case. I claim this to be unlikely for formal borrowing specifically, as formal credit is difficult to access for rural households due to underdeveloped banking and transport infrastructure. Households facing such binding credit constraints would not be able to smooth consumption completely following the demonetization. For this reason, I have used a household dataset that exclusively sampled households from non-metropolitan (or rural and peri-urban) areas in Nepal for whom formal

[4] Although the Nepal Rashtra Bank (NRB), the central bank of Nepal has been lobbying the RBI to open exchange facilities in Nepal, no development has been made on this front (*The Economic Times* 2019).

credit and liquidity constraints are likely binding. Referring to the LCH/PIH literature, regardless of credit constraints, I expect infrequent expenditures to decrease following the shock due to the lower decrease in utility of reducing spending in this category, as such items are usually luxury goods or, at the very least, not necessary goods. On the other hand, I expect to see consumption smoothing of frequently purchased items, food or otherwise, either through expenditure substitution from infrequently purchased items or through reliance on informal credit.

3. Data

a. Night Lights

Night-Time Light (NTL) intensity has been widely used as a proxy for aggregate economic activity in developing countries, particularly in South Asia (Chanda and Cook 2020, Beyer et. al. 2018). This is primarily due to the fact that NTL intensity attempts to capture the informal economy and is available at high-frequencies. Since 2012, the Earth Observation Group (EOG) has been processing and sharing monthly, light imaging data from the Visual Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) from around the world. Compared to the yearly data produced prior to 2012, the VIIRS produces images with higher resolution, wider dynamic range and smaller pixel footprints (Elvidge et. al. 2017). The data for NTL intensity distribution is heavily skewed to the right, hence I follow the literature and use the natural log of NTL intensity as my outcome.

I also follow the literature and correct NTL observations for sunlight, moonlight, stray lights and lightening contamination. Then, I average the monthly NTL data by district in Nepal over the period January 2014–December 2017. This leads to a total sample size of 3,600 (75 districts over 48 months). Figure 2 plots the residual variation in log of NTL for

Nepal. We can see substantial residual variation in the data after accounting for month-year fixed effects.

b. District Level Demography and Climate

To construct time-invariant, pre-demonetization controls, I use the Nepal Demographic Health Survey (NDHS) 2011 and the Nepal Census of 2011. The NDHS is a household dataset that contains data on whether a household member is a migrant to India. This data is aggregated by district using sample weights, and used as the treatment variable in my analysis. The NDHS did not have data on four districts out of 75 and, as a result, these districts have been dropped from the analysis. I use variables for population, literacy rate, rural population and population working in agriculture by district from the 2011 census. Geo-climatic variables such as cloud cover induce measurement error in NTL observations (Elvidge et. al. 2017), hence, rainfall data sourced from the Nepal Department of Hydrology and Meteorology is controlled for in my econometric specification as a proxy for the number of days with cloud cover. Table 2 provides summary statistics on the district data. Districts in the Himalayan region are starkly worse-off than the rest of the country in variety of socio-economic indicators, generally due to difficulty in accessing high-altitude areas. Consequently, I have restricted the sample to districts in the Hill and Terai regions (refer to Figure 3) to ensure that the treatment and control groups are conducive to comparison. This leads to a sample size of 2,496 (52 districts over 48 months).

c. Household Surveys

The household data is from the Household Risk and Vulnerability Survey (HRVS) 2016-2018. This panel dataset was collected to provide the government of Nepal with empirical evidence to understand patterns of household exposure to various kinds of shocks and to assess vulnerability of household welfare to such shocks. The survey interviews and follows 5,654 households in 400 communities in rural and peri-urban areas in Nepal over three years.[5] As a result, conclusions from the household analysis may not be applicable to households in metropolitan areas. Outcomes of interest from the dataset are per capita household expenditure and borrowing. Table 2 presents summary statistics for the dataset. The mean log of per capita expenditure on food items in the seven days prior to the interview for households in 2017-2018 is lower than the same statistic for the 2016 sample. However, the mean log of per capita expenditure on non-food items, purchased frequently or not, is higher in 2017-2018. The statistics also indicate that there was a decrease in borrowing from formal and informal channels from 2016 to 2017-2018. These statistics represent the overall trends in the outcome variables, as they do not yet account for differences in household exposure to the shock.

The survey contains detailed data on household income and assets, migrant members and their economic contributions to the household, experience with shocks in the past at the community level, dwelling characteristics and access to services. Data on income for each household member and where they work is provided, allowing differentiation between income earned domestically, in India and elsewhere. Summary statistics for these variables are included in Table 2.[6] Over the three years, 903 unique households (2,709 observations) had complete data for the outcomes and covariates relevant for my analysis due to non-responses or not knowing the answers to questions asked.

[5] 5,654 households were present in all three rounds. The year-by-year attrition rate of the sample was around 3%, and certain households were only interviewed in 2016 and 2018.

[6] Table 2 includes households with data in 2017 and 2018 only as well.

Since the HRVS dataset only contains data for one year prior to the demonetization (2016), the pre-trends check for this analysis will be conducted with the Nepal Living Standard Survey (NLSS), a panel dataset available for 1996, 2004 and 2011. The NLSS and the HRVS share a sample frame and ask similar questions, making them compatible to use in the same analysis even though individual households cannot be matched across datasets.

4. Empirical Strategy

a. District-Level Analysis:

i. Empirical Specification

There are two sources of variation in this analysis: the first difference is in time and the second difference is in migrant to India share of the population of district *d* in development region *s*, given by $share_{d,s}$. The district analysis leverages these sources of variation in a Difference-in-Difference (DD) model. The high frequency of the data allows the estimation of effects by two time periods, during and post demonetization, with pre-demonetization being the baseline. The during period covers November 2016 – March 2017, the period in which non-resident Indians could exchange demonetized notes at official exchange facilities in India. The post period covers April 2017 – December 2017, during which exchange facilities in India were closed. This is formally given by the equation:

$$\begin{aligned} \ln\left(lights_{d,s,my}\right) &= \gamma_0 + \gamma_1 I_{During,my} \,.\, share_{d,s} \\ &+ \gamma_2 I_{Post,my} . share_{d,s} + \gamma_3 I_{During,my} + \gamma_4 I_{Post,my} + share_{d,s} \\ &+ \boldsymbol{\beta'}_{\boldsymbol{During}} I_{During} . \boldsymbol{X_{d,s}} + \boldsymbol{\beta'}_{\boldsymbol{Post}} I_{Post} . \boldsymbol{X_{d,s}} + \rho_{d,s} + \delta_{s,my} \\ &+ \mu_{d,s,my} \end{aligned} \tag{1}$$

Where $\ln(lights_{d,my})$ is the natural logarithm of monthly Night-Time Light intensity of district d in development region s at month-year my, $I_{During,\ my}$ and $I_{Post,\ my}$ are indicators for observations during and post-demonetization and $\delta_{s,my}$ and $\rho_{d,s}$ are development region-month-year fixed effects and district fixed effects respectively. The sample covers observations from January 2014–December 2017. The parameters of interest are γ_1 and γ_2, which represent the average treatment effect of the policy in the during and post-demonetization periods after accounting for differential effects of household covariates and district and development region-month-year fixed effects. This identification strategy is contingent on parallel trends in the outcome for districts with varying migrant to India shares in the absence of demonetization.

It is important to note that variation in export production by district could be a threat to identification. This is because the majority of the goods exported from Nepal are sold in the Indian market, and it has been widely documented that the demonetization led to a decrease in aggregate demand in India in the short-run. If pre-demonetization levels of export production to India by district is highly correlated with migrant share, then the impact estimated by the above specification will capture the effect of the demonetization policy on Nepal through the migrant and the export production channels. Due to the unavailability of detailed export production data at the district-level, this will remain limitation that can affect the interpretation of the results.

ii. Pre-trends Checks

Before proceeding with this analysis, it is important to establish that the source of variation, migrant to India share by district, is not related to trends in NTL intensity prior to the demonetization policy. I first test for differential linear trends associated with migrant to

India share in the pre-demonetization period (before November 2016). This is given by the regression specification below:

$$\ln\left(lights_{d,my}\right) = \beta_0 + \beta_1 trend_{my} + \beta^* trend_{my} \,.\, share_{d,s} + \boldsymbol{\beta}' trend_{my} . \boldsymbol{X_{d,s}} + \rho_d + \delta_{s,my} + \epsilon_{d,my} \quad (2)$$

Where $trend_{my}$ is the linear time trend the coefficient of interest is β^* which estimates whether there are differential linear trends associated with migrant to India share by district in 2011. Columns (1) presents the results for the baseline specification that only includes district and development region-month-year fixed effects. The specification for column (2) further includes log of the population in 2011 interacted with the linear time trend. The specification for columns (3) and (4) include time-invariant demographic controls and geo-climatic controls interacted with the linear time trend, respectively. In all four columns, since no statistically significant coefficients are estimated, we fail to reject that there are no differential linear trends in NTL intensity by district associated with migrant to India share.

I further test for parallel trends using an event study. The following specification is used to test for differential monthly effects of migrant to India share by district:

$$\ln\left(lights_{d,s,my}\right) = \gamma_0 + \sum_{t=Jan\,2014}^{Sept\,2016} \alpha_t month_{t,my} share_{d,s} + \sum_{t'=Jan\,2014}^{Sept\,2016} \boldsymbol{\tau}'_t month_{t,my} \boldsymbol{X_{d,s}} + \rho_d + \delta_{s,my} + \epsilon_{d,s,my} \quad (3)$$

Where $month_{t,my}$ is an indicator equal to 1 if the month-year of an observations is the month-year *t*, 0 otherwise. The vector of time-invariant covariates $\boldsymbol{X_{d,s}}$ are interacted with each $month_{t,my}$ indicator. If it is the case that migrant to India share by district only accounts for differences between the control and treatment groups post-demonetization, then the α_t

coefficients should not be estimated as significantly different from 0 in the period prior to the policy. Figure 4 plots the α_t coefficients for each month prior to the demonetization, using October 2016 as a reference. The coefficients estimated for early 2015 are significantly different from zero, but there does not seem to be clear and consistent patterns of such significant deviations from the null hypothesis in the pre-demonetization period.

b. Household-Level Analysis:

i. Empirical Specification

An experimental approach to the household-level analysis would include randomly exposing certain households to the demonetization by endowing them with Indian rupees and comparing their responses in the outcomes to households randomly selected to not be treated. In such a hypothetical setting, the following first-differenced regression specification on cross-sectional data would yield an unbiased estimate of policy impact:

$$y_i = \beta_0 + \beta^* exp_i + \epsilon_i \qquad (4)$$

Where y_i is the outcome for household i, exp_i is an indicator for the assignment of exposure and β^* is the parameter of interest.

Since exposure to demonetization at the household-level is determined by the amount of liquid assets in Indian rupees, such variation cannot be deemed random. Instead, with the panel dataset at hand, I plan to leverage correlation of observations across time. First, due to data limitations, I proxy for the exposure to demonetization by an indicator for whether a household *I* in district *d* has income from migrant work in India, i.e.,

$$dep_{i,d} = \begin{cases} 1\, if\ migrant\ income_{i,d} > 0 \\ 0\, otherwise \end{cases} \qquad (5)$$

Since migrant income from India is the primary way in which households accumulate Indian rupees in Nepal, this measure should be correlated with variation in dependency on Indian rupees for households. The choice to use an indicator for this variable is supported by the bimodal distribution of migrant income from India as a fraction of total household income for households in the sample (figure 5).[7] The two modes of the distribution are situated at 0 and 1, which can be interpreted as there being households with very high or very low dependence on Indian rupees. A Difference-in-Difference (DD) specification with time and dependency on Indian rupees as the sources of variation is used. This is formally given by the following regression equation for my baseline specification:

$$ln\ (y_{i,d,y}) = \beta_0 + \beta_1 I_{2017,y} . dep_{i,d} + \beta_2 I_{2018,y} . dep_{i,d} + \beta_3 dep_{i,d} + \boldsymbol{\beta' X_{i,d,y}} + \rho_d + \delta_y + \mu_{i,d,y} \quad (6)$$

Where $y_{i,d,y}$ are the outcomes of interest for household *i* in district *d* at year *y*, $I_{2017,y}$ and $I_{2018,y}$ are indicators for observations collected after the demonetization (2017 and 2018), $\boldsymbol{X_{i,d,y}}$ are household level covariates for household *i* in district *d* at year *y*, and ρ_d and δ_t are district and year fixed effects. I divide the post period into 2017 and 2018 to assess the short-term (in 2017) and the long term (in 2018) impact of the policy. β_1 ad β_2 are the parameters of interest. The identifying assumption is that in the absence of demonetization, households with varying degrees of dependency of Indian currency trend parallel to each other in the outcome.

ii. Pre-trends Check

For the pre-trends check at the household level, I first subset the NLSS sample to households in non-metropolitan areas to make the two samples comparable. The test checks

[7] Estimates of this analysis using a continuous dependence variable, measured using migrant income as a fraction of total household income are reported in Tables A1 and A2. The significance and direction of the estimates for borrowing and food and non-food, infrequent expenditures remain unchanged. The estimated elasticity of per capita expenditures on non-food frequently purchased items is positive and significant in 2018.

for differential time effects associated with the measure for dependency on Indian currency and is given by the event study regression equation below:

$$ln(y_{i,d,y}) = \lambda_0 + \lambda_1 year_{1996,\mathrm{t}}.dep_{i,d} + \lambda_2 year_{2004,y}.dep_{i,d} + \lambda_3 dep_{i,d} \qquad (7)$$
$$+ \boldsymbol{\lambda}'.\boldsymbol{X_{i,d,y}} + \rho_d + \delta_y + \epsilon_{i,d,y}$$

Where $y_{i,d,y}$ is the outcome variable for household *i*, in district *d*, at year *y*, $dep_{i,d}$ is the dependency on Indian currency measure for household *i* in district *d* calculated using the 2011 NLSS sample, ρ_d and δ_y are district and year fixed effects and X_i is a vector of household controls. An interaction for the year 2011 is not included in the specification and is treated as a reference year. If coefficients of interest, $\lambda_1$and λ_2 are not significantly different from 0, then we fail to reject the pre-trends assumption at the household-level.

To make this comparable to the HRVS sample, I further subset the sample to households in the hill and terai regions of Nepal (figure 3). Table 4 presents the results from this specification with household expenditure as the outcome. All three specifications in the table include district fixed effects and household controls. Each column has a different outcome variable: per capita expenditure on food items is the outcome in column (1), on frequently purchased non-food items is the outcome in column (2) and on non-food items is the outcome in column (3). In each of the columns, the effects associated with the dependency on Indian rupees in 1996 and 2004 are not statistically significant. Similarly, Table 5 presents results from the specification with the natural log of borrowing as the outcome. The outcomes in column (1) is overall borrowing, in column (2) is borrowing through informal channels and in column (3) is borrowing through formal channels. Again, the effects associated with dependency on Indian rupees in 1996 and 2004 for borrowing outcomes are not statistically significant.

5. Main Results

a. Night lights

Table 6 presents the results for the district-level DD regression on NTL intensity presented in Equation 1. The specification in: column (1) includes district and month-year fixed effects; column (2) further adds the interaction between the natural log of district population in 2011 and the during and post indicators to the baseline specification; column (3) adds the interaction between district level controls and the during and post indicators; column (4) is preferred due to the inclusion of geo-climatic controls, which accounts for measurement error in night-time light intensity. In the first two columns, we can see a strong, positive effect of the demonetization on districts with higher migrant share to India in the during period. As we include more controls, the results become more attenuated and are not significant at conventional levels in columns (3) and (4). In the post period, we see a negative effect of higher migrant share to India. The coefficient is significant at 10% in column (1), but is attenuated further as more controls are added. As a result, the coefficients are not significant at conventional levels in columns (2), (3) and (4).

Although the estimates are insignificant, the estimated changes in terms of real GDP are still important to discuss. Beyer et. al. (2018) use a sample of South Asian countries including Nepal[8] to estimate the Inverse-Henderson elasticity of the natural log of GDP to the natural log of NTL intensity (Henderson et. al. 2012), which they find to be 0.35 (significant at 0.1%). Using this result, we can interpret the results in Table 1 in terms of real GDP. The results from the final specification (column (4)) imply that during the demonetization period (November 2016 – March 2017) a 1% or one standard deviation increase in migrant to India

[8] The subset includes Nepal, Bhutan, Pakistan and Sri Lanka.

share by district led to an increase of 0.07% in GDP, equivalent to a change of around Nepali Rs. 1.5 billion in terms of Nepal's real GDP in 2016. In the post period (March 2017-December 2017), a one standard deviation increase in the migrant to India share of a district led to a decrease of 1.59% in NTL intensity, which corresponds to a decline of 0.56% in local GDP. The 95% confidence interval of this point estimate is -5.65%–2.47& in NTL intensity and -0.8%–2% in real GDP, the lower and upper bounds of which are sizeable effects on local GDP. This implies that the results of this analysis do not provide sufficient evidence to rule out economically meaningful effects.

b. Household Expenditure

The insignificance of the district-level results is not surprising given that total Indian rupees in circulation in Nepal is estimated to be a small portion of total currency-in-circulation (around 3%). However, it is important to note that the endowment of Indian rupees is not uniform across Nepal– for example, households with migrants to India have higher liquid asset holdings in Indian rupees, increasing their exposure to the shock. In this section, I will explore the effects at the household-level determined by this exposure.

Table 7 presents results with household expenditure as the outcome. Household expenditure has been divided into three categories: food expenditure (past 7 days), non-food, frequent expenditure (past 7 days) and non-food, infrequent expenditure (past year). The first two columns show results from the specification with food expenditure as the outcome—column (1) includes district fixed effects and column (2) adds household controls. Per capita food expenditure is estimated to have increased by 15.9% in 2017 and 6.68% in 2018 in column (1). The results in column (2) imply that being dependent on Indian rupees leads to an increase of 17.4% in 2017, which is significant at the 10% level. I show in section 6 that this increase is not driven by changes in prices of food items. I also estimate an increase of 7.69% in food expenditures in 2018 for households dependent on Indian rupees, but this effect is not significant. In column (3) and (4), the estimated changes to frequent, non-food expenditures in 2017 and 2018 are positive as well, but these estimates are not significant at conventional levels. On the other hand, infrequent non-food expenditures decreased in 2017 and 2018. The decrease in infrequent, non-food expenditures are 33.4% and 33.1% in 2017, significant at the 5% level, and 35.1% and 35.1% in 2018, significant at the 1% level, in columns (5) and (6) respectively.

The estimated changes are in accordance with the initial hypothesis– households are more likely to reduce infrequent expenditures over frequent, necessary expenditures when faced with an income shock. However, it is difficult to fully rationalize the reason for increased expenditure on food items in 2017. Further, it is not clear how households financed increases in food expenditure in 2017 and kept other expenditures unchanged following the demonetization. There is a possibility that households used spare income from lower consumption on infrequent, non-food items in both periods, implying a possible substitution effect between expenditure categories. However, if the income shock is sufficiently large, households could have relied on credit channels as a coping mechanism.

c. Household Credit

In this subsection, I formally test for the effect of dependency on Indian rupees on new household borrowing after the demonetization. Table 8 presents results from the household level regression with the natural log of borrowing as the outcome. As in Table 7, the post-demonetization period has been divided into observations from 2017 and 2018. First, we focus on overall borrowing in columns (1) and (2). Column (1) represents the baseline specification with district fixed effects, and column (2) further adds household level controls, which is preferred over the baseline specification. The estimated increase in 2017 for dependent households is 103.6%, which is significant at the 10% level.

I divide borrowing by type of channel used by household (formal or informal). Informal borrowing includes borrowing through family/relatives/friends, shopkeepers, loan sharks and community-based credit systems. With log of borrowing through formal channels as the outcome, the estimates are small and not significant in the baseline specification (column (3)) and with the inclusion of household controls (column (4)) in 2017 and 2018. This is consistent with my hypothesis given that non-metropolitan households face formal credit constraints due to poor banking and/or transport infrastructure. Informal borrowing, on the other hand, increases for households with higher dependency on Indian currency in 2017. Columns (5) and (6) present results from the baseline specification (with districts fixed effects) and with household controls, respectively. Informal borrowing is estimated to increase for households dependent on Indian rupees by in 2017 of 105.5% (significant at 10%) in the baseline specification. The estimates and standard errors are fairly robust to the inclusion of household controls, as this effect in column (6) is 105.8% and also significant at the 10% level. The increases in overall borrowing seem to be entirely driven by increases in informal borrowing, as the estimates for the two categories are close to equal. The estimated coefficient is negative in 2018 (-0.525) relative to 2016, but insignificant at conventional levels. These results suggest that in 2017, households in the sample relied on informal credit to finance expenditures on frequently purchased items. The return to pre-demonetization levels of informal borrowing in 2018 is expected given the increase in new credit in 2017—

access to credit, formal and informal, is limited by reluctance to borrow and/or to lend more when a household already has debt on its balance sheet.

6. Robustness

This section focuses on testing alternate hypotheses at the district-level (Section 7a) and assesses the robustness of results to behavioral assumptions at the household-level (Section 7b). At the district-level, I test for the effects of the demonetization transmitted though the tourism sector. At the household-level, tests for heterogenous changes in expenditure by asset holdings, differential changes in household composition and differential reporting of prices of staple foods are included.

a. District Level Analysis

i. Tourism Effects

The Nepali tourism sector is heavily reliant on India. Although there are no official and reliable statistics for the number of tourists from India, Indians are regularly estimated to be the largest tourist group to visit Nepal in a given year. Given the cash shortage introduced by the demonetization, Indian households could cut back on their trips to Nepal in the short-term. This effect could, however, be offset if tourists in India traveled to Nepal after the announcement of the demonetization that led to domestic turmoil. Given the statistically insignificant effects through the migrant channel at the district-level, I plan to test whether demonetization affected light-based economic activity in Nepal through the tourism channel.

Ideally, I would test for differential changes in the number of tourists from India by district associated with migrant to India share of the population. Unfortunately, tourism-related, high-frequency panel datasets are not publicly available. Due to this limitation, I test for whether the tourism channel facilitated spillovers to NTL intensity in the period following the demonetization by conducting a DD analysis similar to the one given my district level specification in Equation 1. Instead of using migrant to India share as my source of variation, I use estimates calculated by the World Bank on GNI per capita from the Hotel and "tourist-quality" restaurant sectors by district in 2014 (referred to as Tourism GNI, or $TourGNI_{d,s}$). Ideally, I would use the number of Indian tourist visits by district prior to the demonetization as the source of variation, but reliable statistics for such are not available. An identifying assumption for this analysis is that Tourism GNI should strongly and positively predict the number of tourist visits by district, which in turn should be correlated with Indian tourist visits by district. I deem this to be a plausible assumption because of the sheer volume of tourists from India. An event study figure that serves as a pre-trends check is included as Figure 6. There seems to be a significant differential effect estimated for February 2014, but such effects are not consistently estimated in the pre-demonetization period.

The results from this specification are included in Table 9. Column (1) presents the baseline specification which includes district and development region-month-year fixed effects; column (2) adds the interaction between the during and post-demonetization indicators and the natural log of population in 2011; column (3) adds district-level controls in a similar manner; and column (4) adds geo-climatic controls to the specification. The results in column (1) and (2) are significant at 0.1%, and are positive for the during-demonetization period (November 2016–March 2017) and negative in the post-period (April 2017–December 2017). The inclusion of the district controls in column (3) attenuates the estimated impact, and renders the estimate for the post-period insignificant. By column (4), both estimates are insignificant at conventional levels. It is possible that while the association between Tourism GNI and number of Indian tourists by district is positive, the relationship is weak, since foreign tourists from the west have a higher propensity to spend when traveling in Nepal. This would bias the estimates since Tourist GNI would be higher for districts that are popular destinations for western tourists, which may not necessarily be popular amongst Indian tourists, the majority of whom travel to Nepal for religious motivations. However, with these limitations in mind, I conclude with caution that the results in column (4) do not provide evidence that the demonetization affected Nepal through the tourism channel.

b. Household Level Analysis

i. Expenditure Growth by Asset Holdings

Wealth could be an important source of heterogeneity in the expenditure responses documented in the main results section. Households with larger asset holdings could liquidate assets to deal with the demonetization. This would lead to smaller changes in expenditure for such households. Conversely, households with larger asset holdings likely indulged in more discretionary spending prior to demonetization, making it easier for them to decrease expenditures following the shock. To test these hypotheses, I modify my household specification (equation 6) to a Triple difference (DDD) specification with above/below median asset holdings as the third source of variation. This is given formally by the regression equation below:

$$\begin{aligned} ln\ (y_{i,d,t}) &= \beta_0 \\ &+ \beta_1 I_{2017,t} . low\_asset_{i,d} . dep_{i,d} + \beta_2 I_{2018,t} . low\_asset_{i,d} . dep_{i,d} \\ &+ \beta_3 I_{2017,t} . dep_{i,d} + \beta_4 I_{2018,t} . dep_{i,d} \\ &+ \beta_5 low\_asset_{i,d} . dep_{i,d} + \beta_6 I_{2017}, t . low\_asset_{i,d} \\ &+ \beta_7 I_{2018}, t . low\_asset_{i,d} + \beta_8 . dep_{i,d} + \beta_9 low\_asset_{i,d} + \boldsymbol{\beta}_X{}' \boldsymbol{X}_{\boldsymbol{i,d}} + \rho_d \\ &+ \delta_t + \mu_{i,d,t} \end{aligned} \tag{8}$$

Where $low\_asset_{i,d}$ is an indicator equal to 1 if household i in district d has below median asset holdings in my 2016 sample, and 0 otherwise.[9] The coefficients of interest are β_1 and β_2, which represent the effect of having below median assets when exposed to the demonetization in 2017 and 2018, respectively, relative to above median asset households. I use the same set of controls and fixed effects included in the main household analysis.

Table 10 presents the results from the above regression. Similar to the main analysis, columns (1) and (2) present estimated effects on log of per capita food expenditures, columns (3) and (4) on log of per capita non-food, frequent expenditures and columns (5) and (6) on log of per capita non-food, infrequent expenditures. For each of the outcomes, the first column presents results from the baseline specification, and the second includes the set of household controls, which is the preferred specification. In column (4) and (6), we see that households dependent on Indian rupees with above median assets decreased frequent, non-food expenditures by 71.1% and infrequent, non-food expenditures by 106.7% in 2017. Non-food, frequent expenditures for below median asset households increased by 112.3% in 2017 relative to above median asset households. Together with the main results in Table 7, this suggest that the reduction in non-food, frequent expenditures by above median asset households was offset by households with below median asset holdings, as the response in this expenditure category for the full sample was insignificant. While we see the same relative behavior regarding non-food, infrequent expenditures, the increase for below median asset households relative to their above median counterparts does not seem to offset declines as I find significant reductions in this category for my full sample. In 2018, above median asset households were the only group that experienced declines in non-food, infrequent

[9] Results from a similar analysis by asset quartiles are presented in Table A5 in the appendix, although the results are not easy to interpret due to the low power with which the coefficients are estimated.

expenditures, which decreased by 64.6% (significant at the 5% level). These results are generally consistent with the documented effects in India, as households with higher asset holdings were driving declines in non-food, infrequent expenditures in both years (Chanda and Cook 2020; Karmakar et. al. 2020; Wadhwa 2019).

The results also indicate significant increases in expenditure for below median asset households, relative to above median asset households, for all categories in 2017. Given that above median asset households are decreasing their expenditures, I attempt to understand whether the total effect for below median asset households, i.e. the effect not relative to above median households, is significant. I conduct F-tests to test for whether the effect of being a below median asset household in a given year on expenditures is significantly different from 0, using coefficients in columns (2), (4) and (6). The relevant joint null hypothesis for food expenditures in 2017 is given by $H_0 \colon \beta_1 + \beta_3 = 0$ (refer to Equation 8). The results of this analysis are reported in Table 11. I find that the effect on exposed, below median asset households is insignificantly for all expenditure categories in 2017 and 2018, except for food expenditures in 2017, which is positive and significant at 10%.

ii. Changes to Household Composition

Changes in household composition could have driven the significant increase in frequent expenditures. Given that the demonetization led to loss of jobs for individuals, particularly those working in small and medium sized enterprises, migrant workers in India working in such industries could have returned to Nepal after losing their jobs post-demonetization. This could bias estimates for per capita expenditure on frequently purchased items. Further, the estimates from my analysis could be unreliable if a large portion of households dependent on Indian currency that were together in 2016 branched off in 2017.

To test this hypothesis, I use my main household specification (equation 6) with number of household members living in the dwelling and the number of household members who are migrants to India as the outcomes. Table 12 reports the estimates from this specification. The results in column (1), which represents the results from the baseline specification (includes district fixed effects) with number of household members living in the dwelling as the outcome, are not significant at conventional levels. The inclusion of household controls in the specification of column (2) attenuate these estimates, which remain insignificant. The results in column (3) and (4) are from specifications with the number of household members who are migrants to India as the outcome. Again, the results are not significant at the 10% level in the baseline specification in column (3). This result is also robust to the inclusion of household controls (column (4)). As a result, we cannot attest that the results from my main specification are biased due to household compositional changes.

iii. Differential Changes in Reported Food Prices

The increase in food expenditures in 2017 could be driven by increases in the price of food items for households dependent on Indian currency. It has been reported that certain small businesses in Nepal, particularly those close to the border, were accepting Indian rupees for the sale of goods at unfavorable exchange rates after the demonetization (*My Republica* 2016). When reporting expenditure on food items in Nepali rupees, households that used Indian rupees to purchase these goods could have reported the effective price of the item, taking into account the unfavorable exchange rate, rather than the market price.

To test this hypothesis, first, I have selected a basket of staple foods (rice, lentils, onions and sugar), and estimate whether the unit prices of these items reported by households in the sample experience differential changes in 2017. I use my household DD specification

(Equation 6) to test whether the price of certain food items increased in 2017 relative to 2016 for households dependent on Indian rupees. Results for these regressions are presented in Table 13. The estimated changes in prices of all four staple food items are insignificant in the baseline specification. These results are robust to the inclusion of household controls. As a result, I fail to reject the hypothesis that households dependent on Indian rupees did not report significantly different prices for staple food items compared to households not dependent on Indian rupees. Thus, we cannot conclude that differential price reporting for food items was responsible for the increase in food expenditures in 2017 in the main analysis.

7. Conclusion

India's demonetization policy of 2016 had explicit goals for the domestic economy. The literature on the impact of the policy on India suggests that these goals were not fully met, and that there were contractionary effects on economic activity and household consumption in the short-term. This study further postulates that similar effects were seen in the closely tied Nepali economy, particularly at the household level. The estimated effect of the demonetization on NTL intensity at the district-level were insignificant; however, I estimate decreases in per capita expenditure on infrequent, non-food items in 2017 and 2018, driven by households with above median assets in both years, an increase in per capita food expenditure in 2017 and higher informal credit reliance in 2017 for non-metropolitan households exposed to the shock.

The estimates of NTL growth are statistically insignificant. The estimate for the during-period (0.00203) is small economically and relative to the standard error. However, the effect of the policy on NTL intensity in the post-period, associated with a one standard deviation increase in migrant to India share, is in the range of -5.56%–2.47%, corresponding to the range -0.8%–2% in terms of local GDP. As a result, I cannot reject the possibility of economically meaningful effects. The use of more granular data can help estimate this effect with more precision. As an example of possible improvement, future research could disaggregate NTL intensity data by smaller administrative divisions such as the Village Development Committee (VDC)[10], as aggregation by district masks important heterogeneity in NTL within-districts. Further, if data on export to India production by district prior to the demonetization is available, an assessment of the correlation between pre-demonetization levels of export production and migrant share by district will help to gauge whether the estimated effects (or lack thereof) are primarily driven by the migrant channel, or the migrant and export production channels.

The household-level results shine light on the relevance of large-scale policy spillovers. I find that households dependent on Indian rupees reduced their expenditure on non-food, infrequent items by 33.1% and 35.1% in 2017 and 2018 respectively. There is a sense that the government of India did not to anticipate the demonetization to impact Nepal as they are, to this day, reluctant to open official exchange facilities in neighboring countries. However, when two countries have strong economic ties like Nepal and India, my research suggests that consideration of neighboring economies should be incorporated in policy evaluation. Specifically, this study focuses on migrants as vectors for such spillovers. After witnessing the slow response of the Nepali government to repatriate migrant workers who lost their jobs and were housing insecure due to the pandemic, my hope is that this paper also guides home country policy decisions in response to shocks abroad.

[10] I could not find a dataset with demographic and geo-climatic controls at the VDC-level or a large household dataset that is representative at the VDC-level.

Another implication of this study is that informal credit is an important coping mechanism for non-metropolitan households facing income shocks. My results suggest that the reliance of households in my sample on informal credit in 2017 facilitated consumption smoothing of frequently purchased items. In countries with poor transport and banking infrastructure, unbanked populations facing wealth shocks would be best supported through local, community-based credit solutions.

Finally, I show that declines in non-food, infrequent expenditure are driven by households with above median asset holdings, which is in accordance with the literature on the impact of the policy in India. Households with above median asset holdings tend to have discretionary spending that they can reduce without large decreases in utility. Reductions in discretionary spending induced by foreign currency shocks, when sufficiently large and sustained, can potentially impact prices and wages in sectors that produce such items in the local economy. For below median asset households, my results suggest that they are reluctant to reduce spending in any category, as their income is largely spent on necessary goods. Such spending behavior is precarious, as frequent income shocks and consequent increases in informal borrowing can lead to informal credit constraints in the future. While informal credit systems are valuable, this evidence reiterates the need for institutional recognition of currency shocks as legitimate income shocks in closely tied economies and support for exposed economic agents.

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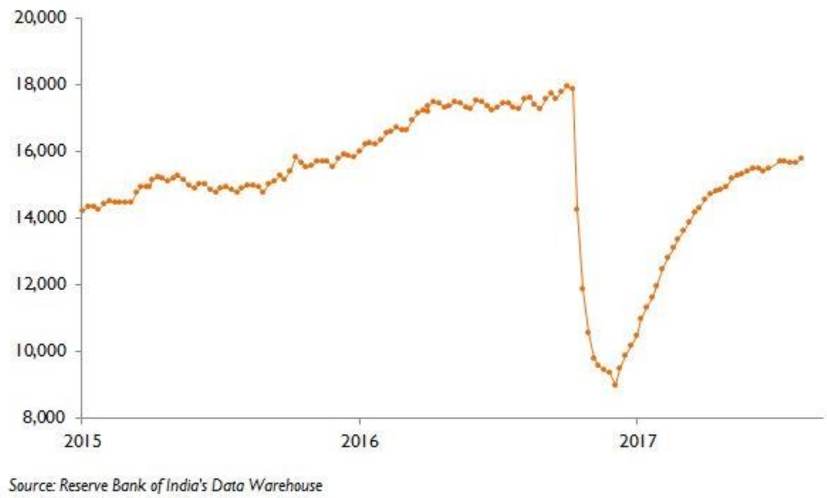
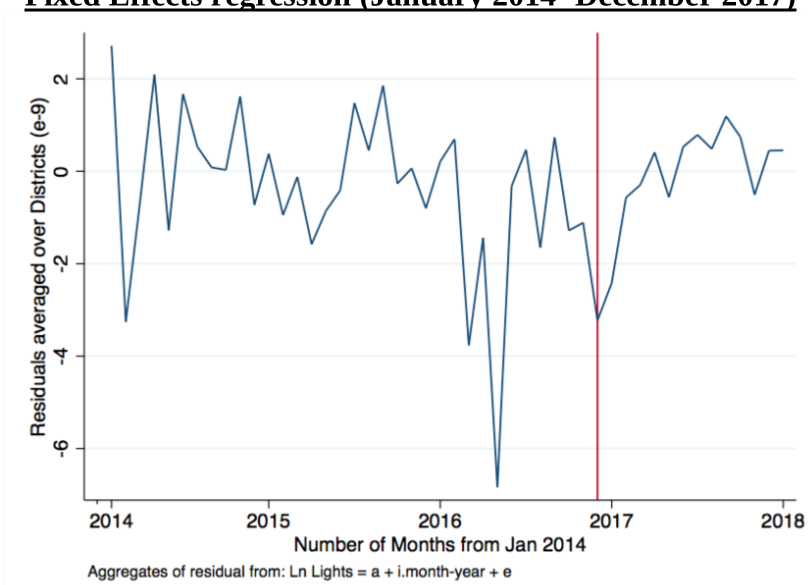
Tables & Figures

Figure 1: Currency-in-Circulation in India in Billion rupees, January 2015 – September 2017



Note: Currency-in-Circulation In India experienced a sharp drop in November 2016 and took over a year to return to pre-demonetization levels.

Figure 2: Aggregated Residuals of Ln Night Time Light intensity from month-year Fixed Effects regression (January 2014- December 2017)



Notes: Trends incorporate month-year fixed effects to decrease month to month variation in the data. Residuals averaged over districts for country level. The red line represents November 2016, i.e. when demonetization was announced (35th month from January 2014).

Table 1: Summary Statistics for District data

Variable	N	Mean	Std dev	Min	Max
Migrant to India Share, 2011 (in %)	52	1.045	0.950	0	4.081
Demographic controls, 2011:					
Districts near border with India	19				
Literacy rate	52	0.608	0.096	0.420	0.805
Rural population (proportion of total)	52	0.868	0.157	0.356	1
Proportion in agricultural work	52	0.303	0.091	0.040	0.468
Log of Population	52	12.618	0.928	8.785	14.371
Geo-climatic controls, 2011:					
Rainfall (in mm)	52	1,888.92	630.68	764.50	3,921.40
Area (in km^2)	52	1,640.74	710.29	122.81	3,642.00

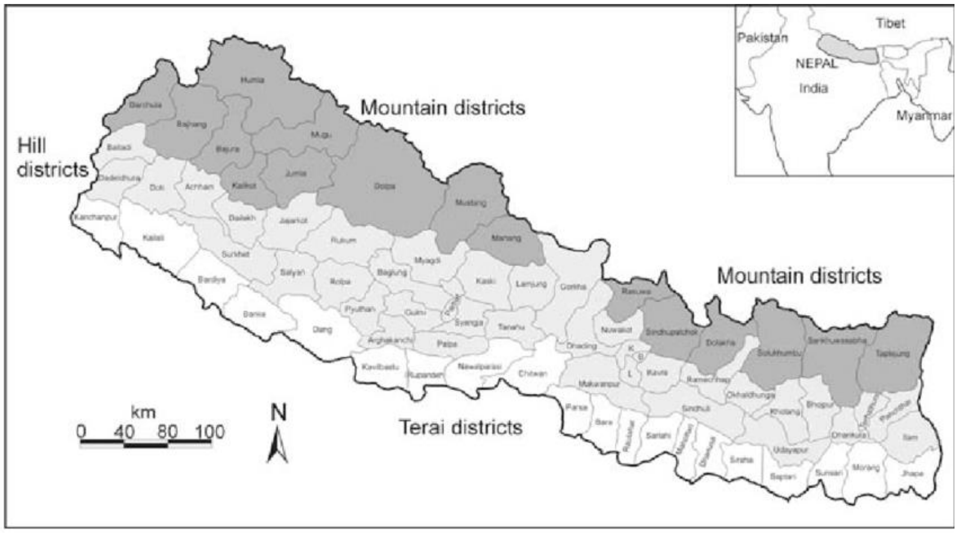
Notes: Districts in the Himalayan region (or Mountain region; refer to figure 3) and districts not represented in the Nepal DHS 2011 have been omitted from the analyses, leading to 52 out of 75 districts being included in my district level analysis.

Table 2: Summary Statistics for Household data

Variable	N	Mean	Std dev	Min	Max
Ln per capita HH Expenditure on:					
Food (past 7 days)					
2016	2,202	5.514	0.647	1.609	7.624
2017-2018	4,430	5.491	0.638	2.100	7.713
Non-food, frequent (past 7 days)					
2016	2,053	3.512	1.213	0.693	7.787
2017-2018	4,270	4.038	1.071	0.916	9.280
Non-food, infrequent (past year)					
2016	2,201	8.228	1.204	0.461	14.845
2017-2018	4,430	8.413	1.353	0.366	16.173
Ln Borrowing:					
Formal (Past year)					
2016	2,202	0.626	2.568	0	15.068
2017-2018	4,430	0.356	1.996	0	15.202
Informal (Past year)					
2016	2,202	3.754	5.190	0	15.456
2017-2018	4,430	2.800	4.827	0	15.687
Households with Migrant income from India (2016)	146				
Household Controls (2016):					
No. of HH members	2,202	5.209	1.972	1	17
No. of migrants to India per HH	2,202	0.483	0.970	0	11
Household Income	2,202	21,227.6	31,185.14	416.667	101,000
Migrant Income from India	2,202	1,094.96	5,810.684	0	180,208.3
Assets	2,202	40,509.27	117,762.9	0	630,000
Asset HHI	2,202	0.792	0.341	0	1
Time to nearest daily market (hours)	2,202	1.188	7.235	0	216.050

Note: Sample excludes households in the Himalayan region (or Mountain region; refer to figure 3) of Nepal. Income, Expenditure and Borrowing data are measured in Nepali Rupees. Borrowing data refers to new borrowing in the last year, and is log transformed after adding 1.

Figure 3: Map of Nepal with districts and geographcal divisions



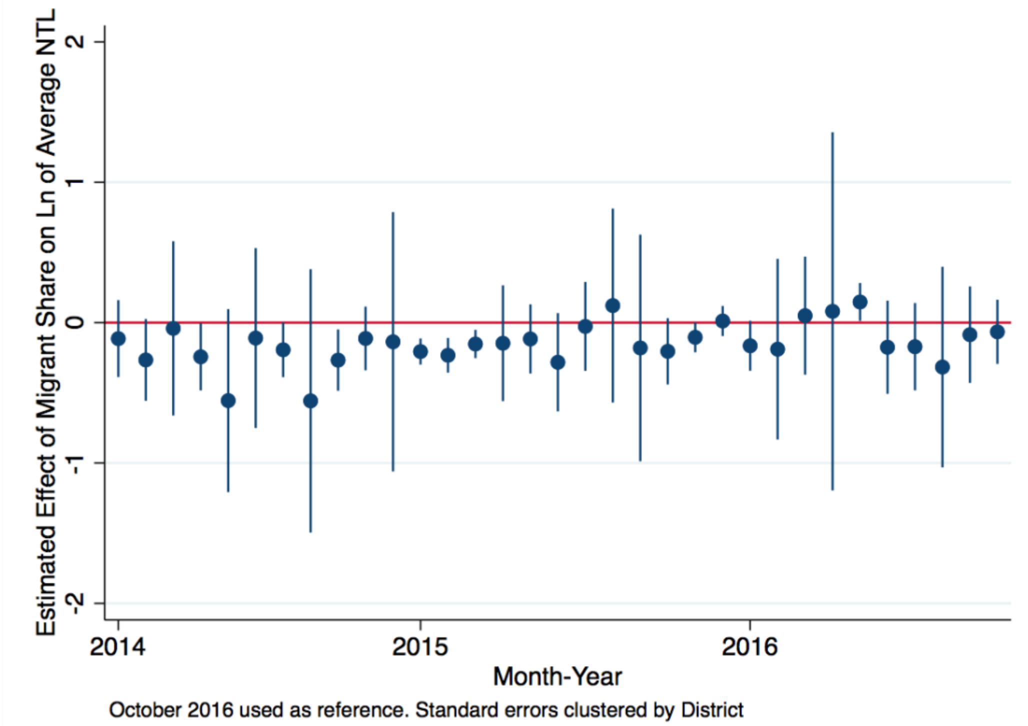
Notes: Districts in the Mountain region (dark grey) have been omitted from the analyses. The majority of these districts border China and have low migrant to India share.

Table 3: Results from Test for Differential Linear Trends in NTL Intensity Growth by District in the Pre-Demonetization Period

Outcome: Log of Monthly Average of Night-time Light intensity (Jan 2014-Oct 2016)				
	(1)	(2)	(3)	(4)
$Trend_{my}$ x $share_{d,s}$	0.000737	0.00102	0.00111	0.00108
	(0.00104)	(0.00109)	(0.00123)	(0.00126)
District FE	Y	Y	Y	Y
Development Region-Month-Year FE.	Y	Y	Y	Y
Ln Population (2011) x $Trend_{my}$	N	Y	Y	Y
District controls x $Trend_{my}$	N	N	Y	Y
Geo-climatic controls x $Trend_{my}$	N	N	N	Y
N	1,768	1,768	1,768	1,768
R^2	0.850	0.850	0.850	0.850
adj. R^2	0.829	0.829	0.829	0.828

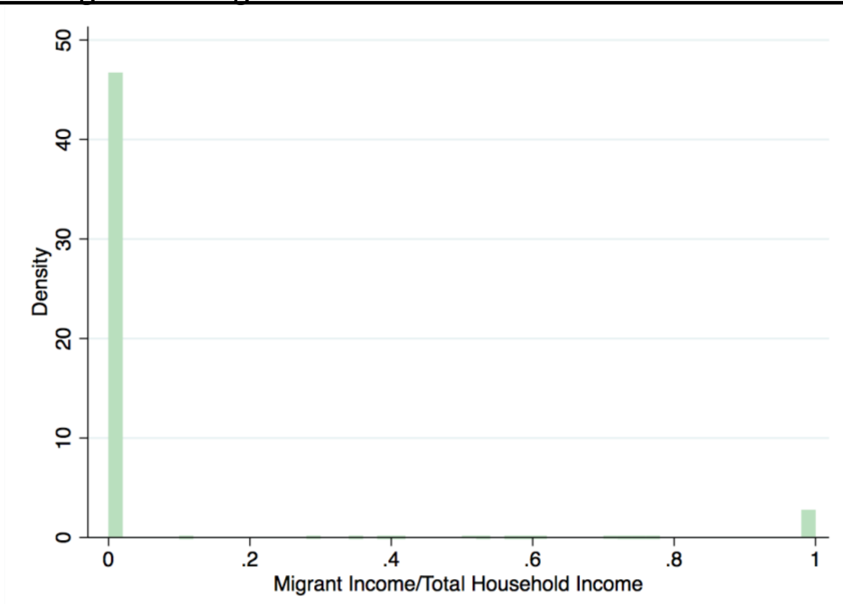
Notes: An observation is district-month-year. Table reports estimates from the differential linear trend model (equation 2). Panel sample is restricted to the pre-demonetization period (January 2014–October 2016). $share_{d,s}$ is the proportion of population of district *d* in development region *s* who are migrants to India. $Trend_{my}$ is a variable that equals to 1 for observation in January 2014, 2 for February 2014, and so on. The baseline specification includes district and development region-month-year effects, and further time-invariant controls are interacted with the trend variable and included in each successive column as indicated. District controls include: rural population as a proportion, proportion of working-aged individuals working in agriculture, literacy rate, and an indicator for whether the district is located on the border with India. Geo-climatic controls include: rainfall (2011) and area of district**.** Standard errors in parentheses, clustered by district. * p<0.1, ** p<0.05, *** p<0.01.

Figure 4: Event Figure, Migrant to India share by District (Jan 2014 – Oct 2016)



Notes: Figure plots the estimates and the 95% confidence intervals from the pre-trends event-study model (equation 3) at the district-level. Migrant share refers to the proportion of the population of a district who are migrants to India prior to the demonetization (2011). October 2016 is omitted as the reference month. Standard errors are clustered by district.

Figure 5: Histogram of Migrant Income as a Fraction of Total Household Income



Notes: Sample includes households in 2016**.** Migrant income refers to income earned by household members in India specifically. Although there is non-zero density for values between 0 and 1, majority of the density lies close to these extreme values.

Table 4: Results from Test for Differential Time Trends Household Per Capita Expenditure Growth in the Pre-Demonetization Period

	Outcomes: log of per capita Expenditure (in Nepali Rs.) on		
	food items	*non-food items, frequent*	*non-food items, infrequent*
	(1)	(2)	(3)
$Year_{1996,y}$ x $dep_{i,d}$	-0.294	0.811	0.640
	(0.282)	(0.476)	(0.636)
$Year_{2004,y}$ x $dep_{i,d}$	0.0326	-0.210	-0.741
	(0.282)	(0.476)	(0.636)
District FEs	Y	Y	Y
Household Controls	Y	Y	Y
N	1,102	1,095	1,081
R^2	0.534	0.342	0.328
adj. R^2	0.486	0.272	0.257

Notes: An observation is household-year. Table reports estimates from the main pre-trends check model at the household-level (equation 7), with per capita food, non-food frequent and non-food, infrequent expenditures as the outcomes. The sample covers households in non-Himalayan districts in Nepal (refer to: figure 3) prior to the demonetization in 1996, 2004 and 2011. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $Year_{1996,y}$ and $Year_{2004,y}$ are indicators that equal to 1 for observations in 1996 and 2004, respectively. Household controls include: number of household members, number of migrants to India, assets, asset HHI and time to nearest bank. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Results from Test for Differential Time Trends in Household Borrowing Growth in the Pre-Demonetization Period

	Outcome: Log of amount borrowed (in Nepali Rs.) through:		
	Overall	*Informal channels*	*Formal channels*
	(1)	(2)	(3)
$Year_{1996,y}$ x $dep_{i,d}$	-2.298	0.129	-2.527
	(1.878)	(1.282)	(1.781)
$Year_{2004,y}$ x $dep_{i,d}$	0.639	1.350	-0.713
	(1.878)	(1.282)	(1.781)
District FEs	Y	Y	Y
Household Controls	Y	Y	Y
N	1,102	1,102	1,102
R^2	0.176	0.501	0.265
adj. R^2	0.090	0.449	0.189

Notes: An observation is household-year. Estimates are from the main pre-trends check model at the household-level (equation 7), with the natural log of borrowing as the outcome. The sample covers households in non-Himalayan districts in Nepal (refer to: figure 3) prior to the demonetization in 1996, 2004 and 2011. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $Year_{1996,y}$ and $Year_{2004,y}$ are indicators that equal to 1 for observations in 1996 and 2004, respectively. Household controls include: number of household members, number of migrants to India, assets, asset HHI and time to nearest bank. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Results from District Level Regression, Log of Night-Time Light Intensity vs. Migrant to India Share and Time

	Outcome: Ln Night-Time light intensity by district and month			
	(1)	(2)	(3)	(4)
$share_{d,s}$ x $I_{during,my}$	0.113***	0.0768**	0.0195	0.00203
	(0.0351)	(0.0339)	(0.0233)	(0.0202)
$share_{d,s}$ x $I_{post,my}$	-0.0645*	-0.0353	-0.0235	-0.0159
	(0.0333)	(0.0329)	(0.0217)	(0.0203)
Districts FEs	Y	Y	Y	Y
Development Region Month-year *FEs*	Y	Y	Y	Y
Ln Population (2011) x $I_{During,my}$ & $I_{Post,my}$	N	Y	Y	Y
District Controls x $I_{During,my}$ & $I_{Post,my}$	N	N	Y	Y
Geo-climatic Controls x $I_{During,my}$ & $I_{Post,my}$	N	N	N	Y
N	2,496	2,496	2,496	2,496
R^2	0.868	0.871	0.877	0.878
adj. R^2	0.851	0.854	0.860	0.861

Notes: An observation is district-month-year. Table reports estimates from the main district level DD model (equation 1). $share_{d,s}$ is the proportion of population of district *d* in development region *s* who are migrants to India prior to the demonetization (2011). $I_{During,my}$ is an indicator that equals to 1 for observation in November 2016–March 2017 and $I_{Post,\ my}$ equals to 1 for observation in April 2017–December 2017. The baseline specification includes district and development region-month-year effects, and further time-invariant controls are interacted with the during and post indicators and included in each successive column as indicated in the table. District controls (2011) include: rural population as a proportion, proportion of working-aged individuals working in agriculture, literacy rate, and an indicator for whether the district is located on the border with India. Geo-climatic controls (2011) include: rainfall and area of district**.** Standard errors in parentheses, clustered by district. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Results from Household Level Regression on Per Capita Expenditure Growth

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $dep_{i,d}$	0.159	0.174*	0.162	0.157	-0.334**	-0.331**
	(0.0992)	(0.101)	(0.238)	(0.237)	(0.151)	(0.150)
$I_{2018,y}$ x $dep_{i,d}$	0.0668	0.0769	0.376	0.371	-0.351***	-0.351***
	(0.0741)	(0.0755)	(0.278)	(0.279)	(0.127)	(0.127)
District FEs	Y	Y	Y	Y	Y	Y
Household Controls	N	Y	N	Y	N	Y
N	6,632	6,632	6,632	6,632	6,631	6,631
R^2	0.139	0.301	0.116	0.182	0.185	0.275
adj. R^2	0.133	0.287	0.110	0.166	0.179	0.261

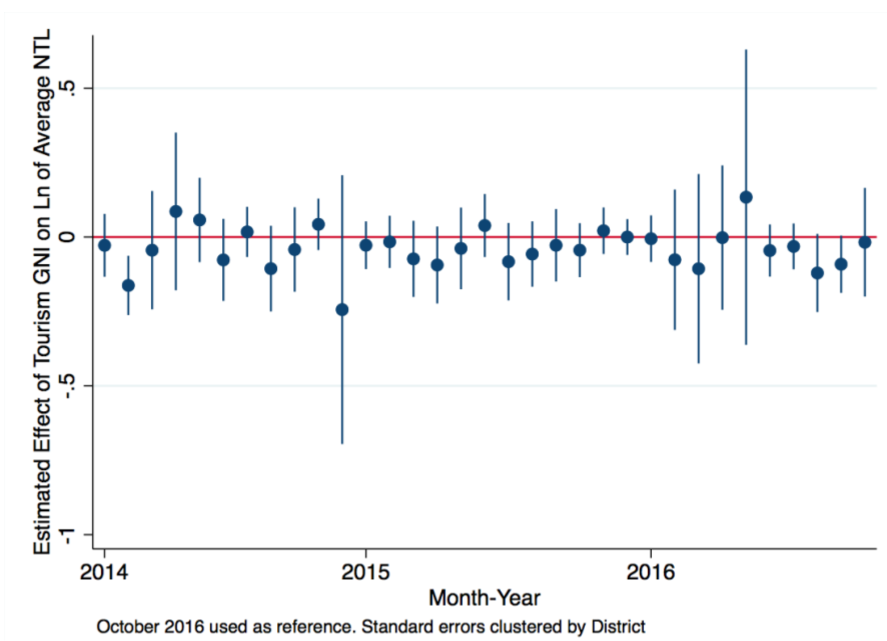
Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of expenditure per capita as the outcome. dep_i is an indicator that is equal to 1 if household i in district d has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI and time to nearest market. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.0

Table 8: Results from Household Level Regression on Borrowing Growth

	Outcomes: Log of Borrowing (in Nepali Rs.)					
	Overall		*through formal channels*		*through informal channels*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $dep_{i,d.}$	1.032*	1.036*	0.00518	0.00649	1.055*	1.058*
	(0.600)	(0.598)	(0.392)	(0.396)	(0.577)	(0.575)
$I_{2018,y}$ x $dep_{i,d}$	-0.525	-0.524	-0.0202	-0.0202	-0.525	-0.525
	(0.594)	(0.592)	(0.302)	(0.304)	(0.571)	(0.569)
District FEs	Y	Y	Y	Y	Y	Y
Household Controls	N	Y	N	Y	N	Y
N	6,632	6,632	6,632	6,632	6,632	6,632
R^2	0.100	0.117	0.014	0.031	0.104	0.120
adj. $R^{2.}$	0.094	0.099	0.007	0.012	0.098	0.103

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of borrowing as the outcome. $dep_{i,d}$ is an indicator that is equal to 1 if household i in district d has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI and time to nearest bank. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Figure 6: Event Figure, Tourism GNI by district (Jan 2014 – Oct 2016)



Notes: Figure plots the estimates and the 95% confidence intervals from the pre-trends event-study model (equation 3) at the district-level, with tourism GNI as the source of variation. Tourism GNI refers to the World Bank's estimates for GNI by district earned through hotels and "tourist quality" restaurants in 2014. October 2016 is omitted as the reference month. Standard errors are clustered by district.

Table 9: Results from District Level Regression, Night-Time Light Intensity Growth vs. Tourism GNI and Time

	Outcome: Ln of Night-Time Light Intensity by district			
	(1)	(2)	(3)	(4)
$TourGNI_{d,s} \times I_{During,my}$	0.139***	0.134***	0.106***	0.0649
	(0.0242)	(0.0261)	(0.0392)	(0.0435)
$TourGNI_{d,s} \times I_{Post,my}$	-0.134***	-0.128***	-0.0252	-0.00600
	(0.0108)	(0.0135)	(0.0192)	(0.0221)
Districts FEs	Y	Y	Y	Y
Development region-Month-year FEs	Y	Y	Y	Y
Ln Population (2011) x $I_{During,my}$ & $I_{Post,my}$	N	Y	Y	Y
District Controls x $I_{During,my}$ & $I_{Post,my}$	N	N	Y	Y
Geo-climatic Controls x $I_{During,my}$ & $I_{Post,my}$	N	N	N	Y
N	3,168	3,168	3,168	3,168
R^2	0.857	0.857	0.860	0.860
adj. R^2	0.842	0.842	0.845	0.845

Notes: An observation is district-month-year. Table reports estimates from the main district level DD model (equation 1), with tourism GNI as the source of variation. Tourism GNI refers to the World Bank's estimates for GNI by district earned through hotels and "tourist quality" restaurants in 2014. $I_{During,my}$ is an indicator that equals to 1 for observation in November 2016–March 2017 and $I_{Post,my}$ equals to 1 for observation in April 2017–December 2017. The baseline specification includes district and development region-month-year effects, and further time-invariant controls are interacted with the during and post indicators and included in each successive column as indicated in the table. District controls (2011) include: rural population as a proportion, proportion of working-aged individuals working in agriculture, literacy rate, and an indicator for whether the district is located on the border with India. Geo-climatic controls (2011) include: rainfall and area of district**.** Standard errors in parentheses, clustered by district. * p<0.1, ** p<0.05, *** p<0.01.

Table 10: Results from Household Level Regression on Per Capita Expenditure Growth by Above/Below Median Asset Holdings

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$dep_{i,d}$ x $I_{2017,y}$	-0.183	-0.160	-0.698*	-0.711*	-1.082***	-1.067**
	(0.130)	(0.127)	(0.376)	(0.372)	(0.302)	(0.301)
$dep_{i,d}$ x $I_{2017,y}$ x $low\_asset_{i,d}$	0.458**	0.443*	1.092***	1.123***	0.867***	0.862**
	(0.222)	(0.228)	(0.367)	(0.367)	(0.321)	(0.324)
$dep_{i,d}$ x $I_{2018,y}$	-0.0717	-0.0699	-0.111	-0.124	-0.648**	-0.646**
	(0.0994)	(0.100)	(0.301)	(0.302)	(0.262)	(0.264)
$dep_{i,d}$ x $I_{2018,y}$ x $low\_asset_{i,d}$	0.178	0.177	0.562*	0.567*	0.302	0.299
	(0.115)	(0.116)	(0.292)	(0.303)	(0.411)	(0.413)
District FEs	Y	Y	Y	Y	Y	Y
Household Controls	N	Y	N	Y	N	Y
N	5,754	5,754	5,481	5,481	5,754	5,754
R^2	0.147	0.317	0.160	0.236	0.211	0.285
adj. R^2	0.139	0.300	0.152	0.217	0.204	0.268

Notes: An observation is household-year. Table reports estimates from the household DDD model (equation 8), with the natural log of expenditure per capita as the outcome. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. $Low\_asset_{i,d}$ is an indicator that equals to 1 if household *i* in district *d* is below the median asset holding in my 2016 sample. The households with above median assets are used as reference. Assets include the total value of all reported financial and physical assets. Household controls include: number of household members, number of migrants to India, time to nearest market, household head education and ethnicity fixed effects. Although the sample size of this analysis is lower than that of the main analysis on per capita expenditures (stemming from the use of asset quartiles as a source of variation), the results of the main analysis generally hold for this reduced sample as well (Table A3 in appendix). Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: F-Test Results for Joint Significance of Estimated Effects on Expenditures

Expenditure Category:	*Year* t	β_t	β_j	$\beta_t + \beta_j$	*F-statistic*
Food	2017	-0.160	0.443	0.283	3.00*
	2018	-0.0699	0.177	0.107	1.03
Non-food, frequent items	2017	-0.711	1.123	0.412	1.82
	2018	-0.124	0.567	0.443	1.89
Non-food, in frequent items	2017	-1.07	0.861	-0.206	1.41
	2018	-0.646	0.299	-0.347	2.33

Notes: Estimates used for these tests are presented in columns (2), (4) and (6) of Table 10. β_t is the marginal effect for a household dependent on Indian rupees with above median asset holdings (reference group) in Year *t*. β_j is the marginal effect of being dependent on Indian rupees and with below median asset holdings with reference to households with the above median asset holdings. The relevant joint null hypothesis is given by H_0: $\beta_t + \beta_j = 0$. The test statistic follows an F-distribution with 1, 41 degrees of freedom. * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Results from Household Level Regression on Number of Household Members

	Outcomes: Number of Household members			
	living in Dwelling		*migrants to India*	
	(1)	(2)	(3)	(4)
$I_{2017,y}$ x $dep_{i,d}$	0.00800	0.00709	-0.000966	-0.00146
	(0.0129)	(0.0128)	(0.00533)	(0.00496)
$I_{2018,y}$ x $dep_{i,d}$	0.00193	0.000802	0.000995	0.000884
	(0.00159)	(0.00121)	(0.000774)	(0.000769)
District FEs	Y	Y	Y	Y
HH Controls	N	Y	N	Y
N	6,632	6,632	6,632	6,632
R^2	0.100	0.160	0.094	0.139
adj. R^2	0.093	0.144	0.087	0.123

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), number of household members living in dwelling (columns (1) and (2)) and the number of household members who are migrants to India (columns (3) and (4)). $dep_{i,d}$ is an indicator that is equal to 1 if household i in district d has a migrant worker earning income in India prior to the demonetization (2016). I_{2017} is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest bank, household head education and ethnicity fixed effects. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table 13: Results from Household Level Regression on Unit Price of Food Items

	Outcome: Unit price of							
	Rice	*Rice*	*Lentils*	*Lentils*	*Sugar*	*Sugar*	*Onions*	*Onions*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_{2017} x $dep_{i,ds}$	0.202	0.312	0.424	1.862	-0.447	-0.693	-3.798	-4.346
	(1.380)	(1.438)	(3.280)	(3.272)	(2.044)	(2.080)	(6.847)	(8.569)
District FEs	Y	Y	Y	Y	Y	Y	Y	Y
HH controls	N	Y	N	Y	N	Y	N	Y
N	3,420	3,420	2,812	2,812	3,721	3,721	3,295	3,295
R^2	0.106	0.131	0.392	0.452	0.279	0.306	0.010	0.029
adj. R^2	0.094	0.102	0.382	0.430	0.270	0.284	-0.004	-0.007

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with prices of staple foods (rice, lentils, sugar and onions) as the outcomes. dep_i is an indicator that is equal to 1 if household *i* has a migrant worker earning income in India prior to the demonetization (2016). I_{2017} is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest bank, household head education and ethnicity fixed effects. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Appendix

Table A1: Results from Household Level Regression on Per Capita Expenditure Growth with Continuous Dependency Variable

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $ln(dep_{i,d})$	0.0399**	0.0398**	0.0311	0.0310	-0.0707**	-0.0715**
	(0.0190)	(0.0186)	(0.318)	(0.310)	(0.0354)	(0.0342)
$I_{2018,y}$ x $ln(dep_{i,d})$	0.0173	0.0172	0.0827***	0.0827***	-0.0773***	-0.0777***
	(0.0161)	(0.0152)	(0.0298)	(0.0288)	(0.0266)	(0.0259)
District FEs	Y	Y	Y	Y	Y	Y
HH Controls	N	Y	N	Y	N	Y
N	6,632	6,632	6,632	6,632	6,631	6,631
R^2	0.109	0.243	0.107	0.181	0.152	0.242
adj. R^2	0.103	0.228	0.101	0.164	0.146	0.227

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of per capita expenditures as the outcome. In this analysis, dep_i is migrant income from India as a fraction of total income for household *i* in district *d* prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest market, household head education and ethnicity fixed effects. This table is in comparison to Table 7, which uses an indicator variable for household dependence. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Results from Household Level Regression on Borrowing Growth with Continuous Dependency Variable

	Outcomes: Log of Borrowing (in Nepali Rs.)					
	Overall		*through formal channels*		*through informal channels*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $ln(dep_{i,d})$	0.241	0.241*	0.00605	0.00643	0.241*	0.242*
	(0.139)	(0.138)	(0.0523)	(0.0525)	(0.138)	(0.136)
$I_{2018,y}$ x $ln(dep_{i,d})$	-0.117	-0.117	0.000221	0.000239	-0.122	-0.122
	(0.118)	(0.118)	(0.0517)	(0.0518)	(0.117)	(0.117)
District FEs	Y	Y	Y	Y	Y	Y
HH Controls	N	Y	N	Y	N.	Y
N	6,632	6,632	6,632	6,632	6,632	6,632
R^2	0.100	0.117	0.014	0.030	0.104	0.120
adj. $R^{2.}$	0.094	0.099	0.007	0.012	0.098	0.103

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of borrowing as the outcome. In this analysis, $dep_{i,d}$ is equal to migrant income from India as a fraction of total income for household i in district d prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest bank, household head education and ethnicity fixed effects. This table is in comparison to Table 8, which uses an indicator variable for household dependence. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table A3: Results from Household Level Regression on Per Capita Expenditure Growth on Sample after Omitting Missing Asset Values

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $dep_{i,d}$	0.148	0.161	0.108	0.0963	-0.499***	-0.488***
	(0.102)	(0.0985)	(0.173)	(0.173)	(0.189)	(0.190)
$I_{2018,y}$ x $dep_{i,d}$	0.0508	0.0522	0.314	0.307	-0.433***	-0.432***
	(0.0875)	(0.0865)	(0.165)	(0.166)	(0.144)	(0.145)
District FEs	Y	Y	Y	Y	Y	Y
HH Controls	N	Y	N	Y	N	Y
N	5,754	5,754	5,481	5,481	5,754	5,754
R^2	0.141	0.315	0.127	0.190	0.184	0.280
adj. R^2	0.134	0.299	0.119	0.172	0.178	0.263

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of expenditure per capita as the outcome. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest market, household head education and ethnicity fixed effects. This table is in comparison to Table 7, which uses fixed effects to impute missing asset values and, consequently, has a larger sample size. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Results from Household Level Regression on Per Capita Expenditure Growth on Sample after Omitting Missing Asset Values

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $dep_{i,d}$	0.148	0.161	0.108	0.0963	-0.499***	-0.488***
	(0.102)	(0.0985)	(0.173)	(0.173)	(0.189)	(0.190)
$I_{2018,y}$ x $dep_{i,d}$	0.0508	0.0522	0.314	0.307	-0.433***	-0.432***
	(0.0875)	(0.0865)	(0.165)	(0.166)	(0.144)	(0.145)
District FEs	Y	Y	Y	Y	Y	Y
Household Controls	N	Y	N	Y	N	Y
N	5,754	5,754	5,481	5,481	5,754	5,754
R^2	0.141	0.315	0.127	0.190	0.184	0.280
adj. R^2	0.134	0.299	0.119	0.172	0.178	0.263

Notes: An observation is household-year. Table reports estimates from the main household DD model (equation 6), with the natural log of expenditure per capita as the outcome. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. Household controls include: number of household members, number of migrants to India, assets, asset HHI, time to nearest market, household head education and ethnicity fixed effects.. This table is in comparison to Table 7, which uses fixed effects to impute missing asset values and, consequently, has a larger sample size. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.

Table A5: Results from Household Level Regression on Per Capita Expenditure Growth by Asset Quartiles

	Outcomes: Log of per capita Expenditure (in Nepali Rs.) on:					
	food items		*frequent, non-food items*		*infrequent, non-food items*	
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{2017,y}$ x $dep_{i,d.}$	-0.443	-0.310	-0.870	-0.716	-1.536*	-1.265
	(0.284)	(0.264)	(0.596)	(0.594)	(0.828)	(-0.831)
$I_{2018,y}$ x $dep_{i,d}$	-0.270	-0.190	-0.323	-0.213	-1.153*	-0.916
	(0.237)	(0.233)	(0.819)	(0.814)	(0.611)	(0.606)
$I_{2017,y}$ x $dep_{i,d}$ x $AQ_{i,j}$, for:						
j = 1	0.766*	0.620	1.523***	1.282**	1.230	0.808
	(0.412)	(0.410)	(0.552)	(0.547)	(0.987)	(0.996)
j = 2	0.758**	0.598*	1.472***	1.311***	2.027**	1.707*
	(0.356)	(0.346)	(0.451)	(0.438)	(0.939)	(0.946)
j = 3	0.317	0.181	-0.0535	-0.234	0.461	0.229
	(0.295)	(0.268)	(0.651)	(0.644)	(0.946)	(0.945)
$I_{2018,y}$ x $dep_{i,d}$ x $AQ_{i,j}$, for:						
j = 1	0.469**	0.367	1.261	1.062	1.223*	0.826
	(0.225)	(0.219)	(0.808)	(0.816)	(0.620)	(0.616)
j = 2	0.335	0.225	0.625	0.504	0.653	0.357
	(0.321)	(0.317)	(0.554)	(0.549)	(0.601)	(0.599)
j = 3	0.230	0.141	0.00765	-0.115	0.498	0.294
	(0.227)	(0.225)	(0.842)	(0.836)	(0.785)	(0.778)
District FEs	Y	Y	Y	Y	Y	Y
Household Controls	N	Y	N	Y	N	Y
N	5,754	5,754	5,481	5,481	5,754	5,754
R^2	0.147	0.317	0.153	0.206	0.219	0.293
adj. R^2	0.138	0.300	0.143	0.185	0.211	0.275

Notes: An observation is household-year. Table reports estimates from the household DDD model (equation 8, with asset quartile indicators), with the natural log of expenditure per capita as the outcome. $dep_{i,d}$ is an indicator that is equal to 1 if household *i* in district *d* has a migrant worker earning income in India prior to the demonetization (2016). $I_{2017,y}$ is an indicator that equals to 1 for observations in 2017 and $I_{2018,y}$ equals to 1 for observations in 2018. $AQ_{i,j}$ is an indicator that equals to 1 if household *i* is in asset quartile *j* in my 2016 sample. The 4th asset quartile is used as a reference. Assets include the total value of all reported financial and physical assets. Household controls include: number of household members, number of migrants to India, time to nearest market, household head education and ethnicity fixed effects. This table is in comparison to Table 10. Standard errors clustered by district. * p<0.10, ** p<0.05, *** p<0.01.