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The Economic and Social Impacts of Migration on Brand Expenditure: Evidence from Rural India

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Abstract

Households sending members to work away from home often receive information about lifestyles and consumption behaviors in those migration destinations (i.e., social remittances) along with economic remittances. We investigate the effect of having a migrant household member on household brand expenditures in rural India—a market characterized by substantial consumption of unbranded products. We collect and analyze household-level survey data from 434 households across 30 villages using an instrumental variable strategy. Economic remittances result in greater brand expenditure and this level is higher for poorer households. After controlling for economic remittances, the effect of migration on brand expenditures is more positive for households residing in more populous villages, with greater access to mobile phones, lower viewership of television media, and with less recently departed migrants. We demonstrate how marketing resource allocation across villages can be improved by incorporating migration data and provide insights for household targeting in the context of door-to-door selling in villages. Our results are robust to alternate, public policy-based instruments, and can be generalized to expenditure on private schools. Using additional survey data from 300 households in 62 new villages, we replicate our results by comparing within-households brand expenditures before and after the migration event.

Keywords: brands, migration, sending households, social remittances, television, mobile phone, rural, India, resource allocation, consumer socialization

In developing economies, as much as 60% of total consumer expenditure is allocated to unbranded products (Sheth, Sinha, and Shah 2016). A Credit Suisse Research Institute survey of 14,000 consumers from the largest developing economies finds that unbranded product consumption dominates in several categories; for instance, it constitutes 80% of total expenditure on apparel and jewelry (Kersley and Bhatti 2017). Rural consumers drive these statistics as they lack brand knowledge and brand access, and because they prefer to produce goods for their own consumption instead of buying them (Sheth 2011). In this paper, we study how rural consumers shift their expenditure towards branded consumption as a result of a prevalent phenomenon in rural communities: out-migration of household members to new and more urbanized areas.

Marketers are interested in understanding drivers of brand consumption among rural households. A major priority of brand marketers in developing markets is to persuade consumers to shift consumption away from widely available and relatively inexpensive unbranded products, towards branded products (Mishra 2013). Brand marketers cannot simply rely on the expectation that the share of unbranded products will organically decrease over time as incomes rise,[1] as there is evidence of an increasing share of *unbranded* products over time in categories like tea.[2] Marketers would benefit from proactively identifying and targeting households most amenable to consuming branded products. Despite the high prevalence of, and interest in, the consumption of unbranded products in developing markets, there is little academic research on its determinants.

We study the effect of sending a migrant to urban centers in search of better employment opportunities on the brand consumption of rural households. We focus on migration as a determinant of brand consumption for two reasons. First, rural out-migration is a major global

[1] Source: https://media-publications.bcg.com/india/Re-Imagining-FMCG-in-India.pdf
[2] Source: http://www.fao.org/docrep/meeting/019/AL289E.pdf

socioeconomic phenomenon. In India, where our study is set, there are an estimated 450 million internal migrants (De 2019). Second, economic migration is a unique shock to a rural household's consumption possibilities in that it combines monetary transfers to a household with exposure to novel lifestyles, aspirations, and consumption behaviors.

In light of this, we suggest that migration can affect brand expenditure through (at least) two distinct pathways. First, migrants who obtain better economic opportunities might send money or goods in kind to the sending household. "Economic remittances," or transfers from the migrant to the sending household in cash or kind, are a measure of the level of success of migration. They can increase the household's ability to pursue status-enhancing consumption. Concurrently, migration leads to the transmission of information on lifestyles, aspirations, and behaviors prevalent in new areas to migrant-sending households (Lindstrom and Muňoz-Franco 2005). This form of information diffusion, termed "social remittances" by Levitt (1998), can affect consumption patterns in sending communities (Solari 2019).

We examine several moderators of the economic and social impacts of migration on brand expenditure. These derive from the literatures of migration, consumer socialization, branding, and the role of technology in shaping outcomes of rural households. Considering the economic impact of migration, we estimate the extent to which economic remittances affect brand expenditure, and how this effect is moderated by the income of the migrant sending household. Considering the social impact of migration, we study how the sending household's ownership of mobile phones, viewing of television media, and recency of the migration event moderate the impact of migration on brand expenditure. We also estimate the moderating effect of village infrastructure, and residual migration effects (pertaining to migration costs, for example). To assess robustness, we explore whether these effects of migration extend to "branded" services (in particular, expenditure on private schools).

Designing an appropriate test of our predictions was a major challenge. Scanner panel data, or transaction records typical of developed markets, are not collected in developing markets. Brand expenditure levels are not available from publicly available household surveys conducted by government organizations.[3] In light of these challenges, in 2019, we partnered with Kantar India, a division of the Kantar Group, to collect survey data on expenditure from 403 households with and without migrant members, across 19 villages in India's most populous state. For causal inference, we use an instrumental variable approach within a regression framework. Our main instrument for the migrant-sending status of the focal household is the migrant-sending status of the two households in the same village, who are *least* proximate from the focal household. We replicate our findings using different data from 300 additional rural households that compares household expenditures before and after the migration event.

We find that economic remittances have a positive and significant impact on household consumption of branded products, and that the impact is greater for poorer households. Migration has a significantly greater impact for households that own mobile phones—devices which enable regular communication with the migrant and thus the transmission of social remittances. Furthermore, migration has a significantly smaller impact for households that own televisions (which serve as a substitute to social remittances for exposing households to brands) and for households that sent migrants more recently. Finally, migration has a significantly greater impact on households located in more populous villages where the retail infrastructure is better developed and branded products are available.

To the best of our knowledge, this is the first paper to investigate how migration affects brand consumption of migrant-sending households. Our work relates to recent research in marketing that has studied how consumption behavior changes with the economic situations of

[3] For experimental research, monetary incentives would have to be unfeasibly high to persuade members of some households to migrate, and even then, the assignment of the migration "treatment" would not be randomized.

consumers. This literature finds that during difficult economic times, consumers downgrade from national brands to cheaper private labels (Lamey et al. 2007), decrease expenditure on more publicly consumed products (Kamakura and Du 2012), and select less variety (Karlson et al. 2015). We contribute to this literature by studying the impact of migration, a novel source of economic and social change (Chandy and Narasimhan 2015), on brand expenditure, a novel aspect of consumption. We investigate poor consumers in a large market (rural India; population: 800 million) that has not been studied in the marketing literature.

Our study also contributes to a stream of research in development economics which investigates socioeconomic outcomes for migrant-sending households. 72% of the studies we review find positive effects of migration on income or expenditure of various types (e.g., Bryan, Chaudhury, and Mobarak 2014; Garlick et al. 2016); 28% find negative or null effects (e.g., Brown and Leeves 2007; Gibson et al. 2011; Mahapatro et al. 2017). These studies are summarized in Table 1. The mixed evidence suggests that migration outcomes are heterogeneous: it is not always immediately successful in improving economic livelihoods (Gibson et al. 2011). However, these individual studies have not closely analyzed potential dimensions of heterogeneity in migration impact. Our study therefore extends this research by explicitly investigating moderators of migration effects. To the best of our knowledge, we are also the first to consider both social and economic remittance effects of migration.

===== Insert Table 1 about here =====

Finally, our model and findings have practical implications for brand marketers allocating marketing resources in large developing economies, such as across the 650,000 villages of India. We demonstrate how marketers can use migration data to better allocate salesforce effort across villages of similar population, household income etc. We provide numerical estimates of the improvement in allocation performance as brand expenditure predictions become more accurate with the incorporation of migration data. Additionally, we consider the within-village resource allocation problem for door-to-door sales agents. We create a dashboard which estimates migration effects for 20 identifiable consumer segments in rural India. It illustrates substantial heterogeneity across households in their propensity to consume brands, implying that the 20 identifiable segments require differing levels of sales efforts if targeted.

Conceptual Framework and Hypotheses

We propose six hypotheses about the impact of migration on the brand expenditure of migrant sending households (henceforth "sending households"). Our outcomes of interest are the total household expenditure on branded products (brand expenditure) and the share of total household expenditure that goes to branded products (brand share). Increasing brand expenditure by households is a primary objective for brand managers as it directly corresponds to greater revenue for the firm. Moreover, an increase in brand share indicates shifted household *preferences* towards branded products, as it implies brand expenditure increases disproportionately more than total household expenditure.

The Impact of Economic Remittances

Economic remittances refer to transfers of money or products in kind from the migrant to the sending household. For many migrants in developing economies, sending substantial economic remittances is a central goal of their migration experience (Stark and Lucas 1988).

Do greater economic remittances result in greater brand expenditure and brand share by sending households? The literature documents several competing uses of economic remittances that either represent basic necessities or investments in the household's stock of human and physical capital: education of children (Yang 2008), health care (Mahapatro et al. 2017), housing (Adams and Cuecuecha 2010), modern farming technology (Mendola 2008), food and non-food expenditures (Bryan, Choudhary and Mobarak 2014), consumer durables (de Brauw and Rozelle 2008), and more capital-intensive forms of entrepreneurship (Yang 2008). Additionally, economic remittances could also be used for repayment of debt, savings for major life events, and for income diversification (Pan et al. 2020). In contrast to these uses of economic remittances, brand expenditure may be viewed as wasteful, especially when cheaper non-branded substitutes are widely available.

That said, in their study of the poorest households in the world, Banerjee and Duflo (2007) argue that these households spend a surprising amount on non-essentials. Although they do not measure brand expenditure, the authors document significant expenditure on weddings, religious festivals, and intoxicants which in part serve to enhance their social status in their community. In a similar way, households may spend economic remittances on branded products to leverage their status-enhancing effects, which are well-documented in developed markets (Leclerc, Hsee and Nunes 2005). Additionally, since brand consumption is less common in developing economies, it is perhaps even more likely to signal and enhance status than in developed markets. Consumers increase the share of their expenditure on status enhancing products during economic expansions (Kamakura and Du 2012). Conversely, during difficult economic times, consumers in the developed world are known to downgrade from national brands to cheaper private labels (Lamey et al. 2007). It follows that as the economic conditions of the household improves due to economic remittances, it may upgrade by spending more on brands. Furthermore, households who receive greater remittances might be able to afford those brands, which they could not afford otherwise. Higher income is associated with lower price sensitivity even in developing markets (Narayan, Rao and Sudhir 2015). These insights from the migration and marketing literatures suggest that brands (and their associated status signals) may become a spending priority for poor households when they receive economic remittances. Hence, we test the following hypothesis.

H_1: *Greater economic remittances by the migrant result in greater brand expenditure and brand share by sending households.*

Moderating effect of household income (excluding economic remittances). The status-enhancing benefit of brands might be less appealing to richer households who have greater access to other means of communicating status (Jaikumar and Sarin 2015), such as education, land ownership, and professional titles. Moreover, brands that have penetrated rural markets of developing economies are typically not luxury brands but "affordable" brands that have limited status signaling value to richer households in the village. Finally, poorer consumers are known to be more status conscious (Van Kempen 2007), which is another reason why they might spend more on brands for status enhancing benefits than richer consumers. Therefore, we expect a negative moderating effect of household income.[4] Formally,

H_2: *The positive effect of economic remittances on brand expenditure and brand share is weaker for households with higher income*.

The Impact of Social Remittances

We now consider how migration can affect the brand expenditure of sending households even after accounting for the impact of economic remittances. Research in economics on the consequences of migration has focused on economic remittances to sending households. Indeed, it is not uncommon for researchers to use the level of economic remittances as a summary measure of all consequences of migration (e.g., Mohanty, Dubey and Parida 2014). However, a more recent and emerging stream of research in sociology and other related disciplines, starting with Levitt (1998), has emphasized the social and cultural impact of migration through intangible transfers. *Social remittances*, or the flow of values, ideas, behaviors, practices between migrants and sending communities through proximate contacts or long-distance interactions, are less observable and quantifiable than economic remittances (Irina and Triandafyllidou 2017). Yet, these remittances can generate social, cultural, and

[4] Another reason for a negative moderating effect of income might be that rich households already consume as much branded products as they desire. However, the average monthly household income in the top quartile of our sample is Rs. 14,962 (US $204), which would put them in middle-income bracket nationally. Also, brand share is just 31% even in the top quartile, suggesting potential for growth.

behavioral changes in sending communities including changes in values and lifestyles (Suksomboon 2008).

For example, increased communication and bonding between Cubans living in Cuba and those who migrated to the U.S. led to "American-style consumerism" and conspicuous consumption in Cuba (Eckstein 2010). In an ethnographic study of female migrants in India, Mukherjee and Rayaprol (2019) find that social remittances effectively influence lifestyles in sending communities, partly because of the migrants' greater social status and knowledge. Importantly, social remittances encourage sending communities to adopt the behavior of migrants and others in the migrant destination. In our context, we expect that social remittances will positively influence sending households to consume brands. Beyond affordability, rural subsistence consumers face several constraints to purchasing novel products, such as low consumer/marketplace literacy and uncertainty around product quality. Social remittances from migrant family members could directly remove these constraints for branded products, in a similar way that messages from influencers on social media platforms and marketplace training programs help (Viswanathan et al. 2021; Zhang, Chintagunta, and Kalwani 2021)[5].

We note that social remittances can impact brand expenditure even without receipt of monetary remittances. This occurs when a part of household income (excluding monetary remittances) is used for increasing brand expenditure as household preferences towards branded products change. Therefore, to establish the presence and effect of social remittances, we present some theoretical determinants of social remittances and test if they indeed moderate the effect of sending a migrant member on brand expenditure, *after the effect of economic remittances is accounted for.*[6] We now lay out these moderating hypotheses in detail.

[5] It is possible that social remittances lead to lower brand expenditure. This could happen if migrants discourage family members from consuming brands, for instance, if migrants' own experiences with brands do not meet expectations.
[6] The economic impact of migration can also be conceptualized as the fraction of monetary remittances that is put towards brand expenditure.

Moderating effect of owning mobile phones. We first consider how a mobile phone may influence the transmission of social remittances. Nearly three-fourths of rural Indian households have a mobile phone (Raja 2019). With negligible demand for landline services, and lower mobile call tariffs than developed economies, mobile phones are the predominant technology for communication between sending rural households in developing economies and their migrants (Datta and Mishra 2011). We view the sending household's ownership of mobile phones as a key determinant of the social remittances they receive. Indeed, qualitative studies of migration in poor communities have characterized mobile phones as critical for regular transmission of social remittances between migrants and family members, relative to letters and family visits (Parrenas 2001; Mukherjee and Rayarpol 2019). In our context, sending households with mobile phones are likely to communicate more frequently with their migrants, thus increasing the likelihood and quantity of social remittances. Consequently, we propose the following.

H_3: *After controlling for economic remittances, the effect of migration on brand expenditure and brand share is stronger for sending households with mobile phones*.

Moderating effect of television media viewing. We now consider how media might moderate the effect of migration after controlling for economic remittances and income. We argue that TV viewership serves as a substitute for social remittances relating to brand consumption.

As a first step, we review the Indian TV media industry. 66% of households own a TV, with a majority of these households in rural areas. TV is the most favored advertising medium for the branded consumer packaged goods industry, with TV advertising accounting for an estimated 61% of industry ad spend[7]. The majority of rural Indian consumers watch TV at least once a week, usually with other family members or other members of the village community.

[7] Source: https://dentsu.in/uploads/digital_reports/DAN-e4m-Digital-Report-2020-Web-C3.pdf

Moreover, low data quality, speed, and high cost of access (in some states) make mobile phones the less preferred medium for viewing video content in rural India relative to TV (Gupta 2017), although this might change in the future as internet access becomes cheaper.

Research in developed markets has established the importance of TV as an important force shaping consumer behavior. TV viewing exposes viewers to images, accounts, and stories of life that are somewhat removed from viewers' daily experiences and social milieu. This increases consumers' aspiration for products, services, and lifestyles featured on TV (O'Guinn and Shrum 1997). TV viewing has been associated with greater material values such as increased happiness with purchasing more products and greater admiration of people who own expensive products (Shrum, Burroughs and Rindfleisch 2005). So, TV viewing affects not just the attitudes of consumers, but also their expenditure and consumption behavior. Closer to our context, Johnson (2001) finds that the influence of TV on rural Indian consumers is most noticeable in their commitment to modern consumerist lifestyles and their propensity to model behavior based on urban lifestyles (the phenomenon of "urban modeling"). "TV shows us what is good to buy," is a pertinent example of a consumer response from Johnson (2001).

Thus, households viewing more TV are more likely to be introduced to the offerings of more developed markets (e.g., urban Indian markets) such as brand names, advertising for brands, contexts for consuming brands, functional benefits of brands over unbranded versions, and the social status conferred by brands. When households are already familiar with brand consumption from their TV viewing, migrants may not perceive it as an interesting topic worth communicating about. Moreover, even if migrants do communicate about consumption practices at their destination, these practices may be less novel for TV viewing rural households. On the other hand, for a household who does not own a TV set and rarely watches TV, their migrant might be one of the few, if not only, credible source of information about consumption practices outside their village. Thus, TV viewing should negatively affect the quantity and efficacy of social remittances. Consequently, we expect the following.

H$_4$: *After controlling for economic remittances, the effect of migration on brand expenditure and brand share is stronger for sending households who view less TV media.*

Moderating effect of recency of migration. Next, we consider how the time elapsed since the migrant left the household (i.e., the recency of migration) moderates the effect of migration on brand expenditure. A migrant who has recently moved to a large city, is living out of his savings, and is unfamiliar with urban retailing formats (e.g., air-conditioned malls, supermarkets, hypermarkets, etc.) is less likely to have awareness about branded products than a migrant who has had sufficient time to explore the new market offerings of the city. Moreover, as time elapses, we also expect migrants to develop more favorable opinions of these new market offerings, as they are able to experience novel products for themselves and become acclimated to the consumption culture at their destinations. Consequently, we expect social remittances regarding branded products to be low at first, but to increase over time. Therefore, we propose the following:

H$_5$: *After controlling for economic remittances, the effect of migration on brand expenditure and brand share is stronger for households which have sent migrants less recently.*

Moderating effect of village retail infrastructure. Our moderators have thus far focused on demand-side influences. In addition, in villages where branded products are more available for purchase, households have greater opportunity to act upon social remittances and economic remittances. In lieu of direct measures of village retail infrastructure, which are not available to researchers, we proxy for it with village population. More populous villages are visited more frequently by the salesforce of brand manufacturer and are more likely to have distribution points for branded products (e.g., rural "stockists" and distributors in India) situated in close proximity. More populous villages also have a greater number of physical retail outlets. For example, in a village with 500 people, only a few small mom-and-pop stores might be financially viable. A village with 50,000 people is more likely to offer a wider variety of brands, across several product categories and different price points. This results in brands being more easily available in more populous villages.[8] Based on this discussion, we propose the following.

H$_6$: *The effect of migration on brand expenditure and brand share is stronger for sending households residing in villages with greater population.*

Our full conceptual framework is illustrated in Figure 1. Next, we present our data.

===== Insert Figure 1 about here =====

Study 1

Data and Sample

We collected data from 403 households from 19 villages in India's most populous state, Uttar Pradesh (2021 population of 235 million; 78% rural; per capita annual GDP of about $1,200; majority of households engaged in agriculture). As a comparison, Uttar Pradesh has approximately the same land area as the United Kingdom with 3 times its population. Along with Kantar, we identified 6 districts to ensure adequate geographical spread. Within each district, Kantar sampled 3-4 villages, such that: (i) there was substantial variation in the populations of the sampled villages (villages in our sample have populations ranging from 1,000 to 4,200) and (ii) the sampled villages were at different distances from the district headquarters, with at least one village in each district located greater than 50km (31miles) from the district headquarters.

[8] Brand-carrying retail outlets might make households more aware of brands, but might not persuade and convince households of their value in the same way a migrant who has sampled brands does, or the way TV advertisements do.

Following Indian census rules, a migrant was defined as someone who spends at least 3 months in a year away from home. In order to ensure sufficient variation in the time since the migrant left the village and to ensure adequate ability to compare sending households with a control group, we adopted a stratified sampling approach. We randomly sampled households from each of three strata: (i) *households with no migrant member* (n = 125); (ii) *more recent migrant sending households*, i.e. households with at least one migrant member who has left the village 3-12 months before the date of the survey (n = 146); and (iii) *less recent migrant sending households*, i.e. households with at least migrant member who has left the village over 12 months prior to the survey (n = 132). This led to a final sample size of 403 households. Details on how the stratified sampling approach was implemented are presented in Web appendix 1. Kantar field personnel administered the survey in a 4-week period starting November 1, 2019.

Each respondent provided information on the number of migrants in their household (if any), reason for migration of each migrant, duration since the migrant left the household (3-12 months or longer), and the average monthly amount of remittances received (if any) since his departure. Of all 278 sending households, 256 received remittances in cash or in kind in the past 12 months. All migrants migrated either "in search of employment" (n = 215) or to "take up employment which has already been secured" (n = 63).

In addition to migrating behavior and demographics, each respondent provided data on typical monthly household expenditures on different categories of food and non-food products. Crucially, each respondent also provided data on typical monthly household expenditures on brands (as opposed to unbranded variants) for these food and non-food categories. When asking about branded expenditure, we defined a brand as a "name, term, design, symbol, or any other feature that identifies one seller's good or service as distinct from those of other sellers," in accordance with the American Marketing Association's definition[9]. Expenditure on brands

[9] Source: https://www.ama.org/topics/branding/

included expenditure on store brands and private labels. For each village, Kantar field personnel confirmed that brands were available in all product categories, local brands had greater availability than national brands, and that unbranded products were always priced lower than branded products within a category. Details of the survey and the questionnaire appear in Web Appendix 1. To ensure validity of our expenditure measures, we tested whether respondents could distinguish between branded and unbranded versions of the same product, and surveyed retail stores frequented by a random sub-sample of respondents to confirm recall based expenditure measures. Further details of these and other verification steps appear in Web Appendix 2.

Additionally, for each household, Kantar field personnel identified the two households which lived at the least distance (i.e., which were physically closest) from the focal household, at the time of the survey. We use this to construct our main instrumental variable. Finally, we record the typical monthly household expenditure on their children's private school fees and government school fees.

Measures and Summary Statistics

As previously discussed, we employ two measures of brand consumption at the household level for our dependent variables: the stated monthly household expenditure on all branded products (brand expenditure) and the proportion of household expenditure on products that is spent on branded products (brand share). We also estimate the effect of migration on expenditure on unbranded products in order to assess the extent to which the migration effects we estimate are unique to brand expenditure. In other words, we aim to show that unbranded expenditure does not exhibit the same pattern of results.

$Migrant_i$ represents the migration status of household i (1 if it has a migrant member, 0 otherwise). This is the measure of migration status most commonly employed in the literature. Other measures are the monthly economic remittance received by the sending household (including the monetary value of remittances received in kind) $Econ\_Remit_i$, and the recency of migration $Recent_i$, defined as 0 if the migrant departed the sending household 3-12 months before the survey (i.e. more recent), and 1 if the migrant departed over 12 months prior (i.e. less recent). Data on the specific month when the migrant departed is not available to us. Recency of migration is a key moderator. Among other moderators, we measure viewership of TV media (TV_i) simply in terms of whether household i owns a TV (TV_i=1) or not (TV_i=0). This measure has the advantage of being at the household level. Other studies employ city or market specific measures of TV viewing. Data on the amount of TV content consumption are unavailable at the household level. Similarly, we construct the measure $Mobile_i$ which is defined as whether household i owns a mobile phone ($Mobile_i$=1) or not ($Mobile_i$=0). In addition, we control for household size, income, and the number of children in the household.

Key summary statistics appear in Table 2. On average, only 28% of product expenditure by a household is on brands, which leaves much scope for growth through efforts by marketers. Sending households receive an average of Rs. 1,475 (US $20) per month as economic remittances, which is roughly a fifth of their monthly income excluding remittances. Households which have more recently sent migrants spend less on branded products, and more on unbranded products, than households which have not sent a migrant. However, households which sent a migrant at least a year back spend more on branded products (both in absolute terms and in brand share) than households which have not sent a migrant. Other summary statistics and model-free evidence supporting our hypotheses appear in Web Appendix 3. Next, we discuss how we establish a causal link between migration and our measures of brand consumption, and separately identify the effects of economic and social remittances.

===== Insert Table 2 about here =====

Empirical Strategy and Identification

Our starting point for testing our hypotheses is the following OLS regression model (Equation 1) for each of the three dependent variables of interest (brand expenditure, brand share and unbranded expenditure).

$$y_i = \beta_0 + \beta_1 Migrant_i + \beta_2 HH\_Income_i + \beta_3 TV_i + \beta_4 Mobile_i + \beta_5 Migrant_i \; x \; Econ\_Remit_i + \beta_6 Migrant_i \; x \; Econ\_Remit_i \; x \; HH\_Income_i + \beta_7 Migrant_i \; x \; Mobile_i + \beta_8 Migrant_i \; x \; TV_i + \beta_9 Migrant_i \; x \; Recent_i + \beta_{10} Migrant_i \; x \; Village\_Pop_i + \beta_{11} Migrant_i \; x \; HH\_Income_i + \boldsymbol{x}_i'\gamma + \vartheta_v + \epsilon_i \qquad (1)$$

where $Migrant_i$ (1 if household i has sent a migrant, 0 otherwise) is our primary measure of migration status. The next 6 interaction terms correspond to our 6 hypotheses. Since economic remittances are not relevant for households not sending migrants, we interact economic remittances with the migration indicator. The coefficient of $Migrant_i \; x \; Econ\_Remit_i$ captures the main effect of economic remittances (H_1). For households not sending migrants, both $Migrant_i$ and $Migrant_i \; x \; Econ\_Remit_i$ are zero. For sending households who do not receive economic remittances, $Migrant_i \; x \; Econ\_Remit_i$ is zero but $Migrant_i$ is one. So, the effect of sending a non-remitting migrant is identified. To understand how monthly household income (HH_Income_i) moderates the effect of economic remittances (H_2), we interact $Migrant_i \; x \; Econ\_Remit_i$ with HH_Income_i. Having controlled for the effect of economic remittances, we now move on to H_3 to H_5 on social remittances. The coefficients of $Migrant_i \; x \; Mobile_i$, $Migrant_i \; x \; TV_i$, and $Migrant_i \; x \; Recent_i$, capture the moderating effects of ownership of mobile phones (H_3), access to TV media (H_4), and the recency of migration (H_5). Finally, to understand the effect of retail infrastructure of the village in which the household resides (H_6), we interact $Migrant_i$ with village population ($Village\_Pop_i$). Subsequently, we control for $Migrant_i \; x \; HH\_Income_i$ so that the effect of $Migrant_i \; x \; Econ\_Remit_i \; X \; HH\_Income_i$ is not confounded.

The control variables in our model (captured by the vector $\boldsymbol{x}_i$) include $Size_i$, the number of household members excluding the migrant, and $Child_i$, a dummy variable measuring whether the household has any children. Larger households might be more price sensitive and spend less on branded products or spend on bulk packs which are less likely to be branded. For the same household size, a household with children might spend less on brands since brands targeted specifically at children may be less commonly available in developing rural markets. We also control for the main effects of access to TV media, access to mobile phones, and household income. We expect all of these variables to positively affect brand expenditure and brand share. Finally, to control for factors which might affect brand expenditure across villages (e.g., variations in distribution intensity), we include village-specific fixed effects, ϑ_v. We estimate this OLS regression model separately for all three dependent variables. OLS regression models offer better in-sample predictive power for our data than tobit models or OLS regression models of the logarithms of each dependent variable. Substantive results remain unchanged across specifications.

Causal identification of migration effects. A key threat to identifying causal effects of migration on brand expenditure is the non-random selection by households into sending migrants, which potentially could relate to their brand preferences. Bronnenberg, Dubé and Gentzkow (2012) assume that migration status and the determinants of brand preferences (of the migrant) are orthogonal. They show that migrants from a state in the US and non-migrants in that state are quite similar in terms of observed characteristics. However, there could be unobserved factors which systematically affect both migration propensity and brand preferences of the sending household. For example, fluctuating household debt levels could co-determine migration propensity and brand expenditures. These time-varying unobserved factors are not dealt with through controls for household income and could lead to biased parameter estimates. To deal with this endogeneity issue, we adopt a two-staged least squares modeling approach (Germann, Ebbes, and Grewal 2015) with a household-level instrument (IV_i). We specify the following first stage equation for migration propensity.

$$Migrant_i = \alpha_0 + \alpha_1 IV_i + \alpha_2 Size_i + \alpha_3 Child_i + \alpha_4 HH\_Income_i + \alpha_5 TV_i + \alpha_6 Mobile_i + \delta_i \quad (2)$$

To be valid, the instrument should satisfy criteria of exclusion and relevance. Exclusion implies that IV_i is uncorrelated with the error term of the main equation (ϵ_i), and that E($IV_i \; x \; \epsilon_i$) = 0. Relevance implies that the instrument is sufficiently highly correlated with the endogenous variable, i.e $\alpha_1 \neq 0$. Although the migration literature has frequently used village- or district-specific instruments (e.g., rainfall levels in the village, share of urban population in the district, distance of the village from the nearest town), we prefer household-level instruments since they are more likely to predict household-specific migration behavior and thus not suffer from weak instrument bias. As mentioned, we are able to identify the two households in our survey which are closest, in terms of physical distance, to the focal household. We label these households "neighbors" even though they do not usually reside in the contiguous dwelling. Borrowing from the literature which utilizes network information on peers to construct instruments (e.g., Sunder, Kim and Yorkston 2019), we exploit this network information to create exclusion restrictions. Our main instrument is the migrant-sending status of distant households who are *not* neighbors of the focal household; rather, these distant households are their neighbors' neighbors, or further along in the network. The intuition behind our instrument strategy is that sending behavior of distant households is correlated with the sending propensity of the focal household, but not with the error term associated with the brand expenditure equation of the focal household.

===== Insert Figure 2 about here =====

We identify those two households from the *same* village as the focal household, who are *least* proximate from the focal household. In other words, we select "IV households" by maximizing the degrees of separation from the focal household. We illustrate this using a hypothetical example of a 5-household village in Figure 2. Households E and F are least proximate from the focal household A and serve as "IV households" for that household. We define IV_i as 0 if neither "IV household" has a migrant, 1 if only one "IV household" has at least one migrant, and 2 if both "IV households" have at least one migrant.

Conceptually, our instrument is relevant because migration decisions across households in the same village are likely correlated due to unobserved destination-specific or village-specific factors (e.g., the construction of a bridge 100 miles away might encourage migration from the village). Households' migration decisions are affected by the sending behavior of other households in the village (Hiwatari 2016). Migration by others in the village reduces migration risks through the diffusion of destination specific information about employment opportunities.

Our instrument satisfies the exclusion restriction because the propensity for a distant household to send a migrant is unlikely to be correlated with the error term in equation 1, especially after controlling for income, TV ownership and mobile phone ownership. One possibility is that the focal household observes another household first send a migrant, and then observes this household increase its brand consumption. After that, the focal household could increase its own brand consumption due to social effects in brand consumption. This might violate the exclusion restriction since migrant-sending behavior of the neighbor is correlated with brand expenditure of the focal household. However, this phenomenon seems far less plausible for households which have several degrees of separation between them than for immediate neighbors. Therefore, we expect sending behavior of "IV households" to be uncorrelated with the error term associated with the brand expenditure of the focal household. Empirical evidence on the relevance and validity of our instrument appears in Web Appendix 4. Equation 2 represents a linear probability model. In Web Appendix 5, we show robustness to the assumption of linearity. Later in the paper, we discuss the robustness of our results to an alternate instrument.

On identifying effects of social remittances from migration. Our study takes a first step at quantifying the effect of social remittances from migration on a household level outcome. Prior quantitative research on the impact of migration has instead focused solely on economic remittances, in the absence of direct measures of the quantity and content of communications between household members. Meanwhile, studies of social remittances have typically recorded and qualitatively interpreted conversations between the migrant and the sending households, but not the estimated impact of such remittances econometrically. In order to do so, we use direct measures of economic remittances and theoretical determinants of the quantity and efficacy of social remittances. In equation (1), we measure the impact of economic remittances as the coefficient of the interaction of having a migrant household member and the amount of monetary remittances received. After controlling for this economic impact, the residual effect of having a migrant member should, at least in part, be the social remittance-based impact. We decompose this residual effect into the theoretical determinants of the quantity and efficacy of social remittances. As previously discussed, these are: i) the sending household's ownership of mobile phones; ii) viewership of television media; and iii) the recency of the migration event. By estimating equation (1), we test if these determinants indeed moderate the effect of sending a migrant member on brand expenditure, after the effect of economic remittances is accounted for. Next, we describe the estimation results.

===== Insert Table 3 about here =====

Results

We present results of models with three dependent variables (brand share, expenditure on branded products, and expenditure on unbranded products). In Table 4, we present four models for brand share (with and without moderators; with and without instrumenting), and one model each for the two other dependent variables (with moderators and with instrumenting). Columns (1) and (2) show the OLS estimates for brand share, first without the moderator variables in equation (1), and then with the moderator variables. Column (3) then presents the full model for brand share with moderators, with our instrumental variable strategy for identifying causal migration effects. Finally, Columns (4) through (6) show IV estimation results for the full model with other dependent variables. Subsequent to presenting the results in Table 4, we discuss the robustness of this research to the realm of services.

===== Insert Table 4 about here =====

We find positive interaction effects of migration status and economic remittances on brand share in support of H_1 (β = .150, SE = .031, $p < .01$), and on brand expenditure. However, this increase in brand share due to economic remittances is lower for households with greater income as the interaction effect of migration status, remittances, and income is negative. This suggests stronger remittance effects for poorer households, in line with H_2 (β = -.007, SE = .003, $p < .05$).

Next, we discuss migration effects due to the transmission of social remittances. We find positive interaction effects of migration status and mobile phone ownership on both brand share and brand expenditure. This suggests that sending households exchange brand related information with migrants using mobile phones, and consequently increase brand consumption. This leads to a greater effect of migration (after controlling for economic remittances) on households with mobile ownership, as per H_3 (β =.481, SE = .240, $p < .05$). Our estimates of the effects of TV viewership are in the opposite direction, in accordance with H_4. We find negative interaction effects of migration status and TV ownership, on both brand share (β = -.298, SE = .106, $p < .01$) and brand expenditure. This provides evidence consistent with the notion that communication from migrants about brands might be less novel for consumers who have already been exposed to similar messages on TV. For other households, communication with their migrants might be one of the few sources of credible information about consumption practices outside their village. The opposing moderating effects of TV ownership versus mobile ownership, suggest that these interaction terms are not simply capturing the effect of unobserved household tastes for branded products (e.g. their willingness to experiment with new products, or taste for status-enhancing products), as these variables would be correlated to mobile and TV ownership in the same way.

The effect of sending a migrant on the brand share of the sending household is greater if the migrant has left the village at least a year back than if the migrant has recently migrated as we theorized in H_5 ($\beta = .192$, SE = .036, $p < .01$). This is consistent with greater social remittances in the long term. We also find, in support of H_6, that after controlling for remittances, migration effects are greater in more populous villages ($\beta = .046$, SE = .021, $p < .05$). More populous villages are closer to urban markets in terms of retail infrastructure, thus providing sending household a greater opportunity to emulate the lifestyle of their urban counterparts by consuming more brands.

The effects of control variables are also informative. TV ownership is associated with greater brand expenditure and brand share, providing novel evidence of the effectiveness of TV as a tool that shapes consumer behavior in a developing economy. Somewhat surprisingly, mobile phone ownership is associated with lower expenditure on branded products (and greater expenditure on unbranded products). To the extent that mobile phones connote social status in developing economies, it is possible that mobile phones serve as substitutes for other branded products, and that households spend less on other branded goods to purchase a mobile phone.

Marginal Effects of Migration on the Brand Share of the Sending Household

Based on the following equation, we use the data and parameter estimates from the 2SLS model to compute household specific estimates of the marginal overall effect of migration among migrant sending households on brand share.

$$Marg_{i,migrant\_sending} = \beta_1 + \beta_5 Econ\_Remit_i + \beta_6 Econ\_Remit_i \ x \ HH\_Income_i + \beta_7 Mobile_i + \beta_8 TV_i + \beta_9 Recent_i + \beta_{10} Village\_Pop_i + \beta_{11} HH\_Income_i \quad (3)$$

Consistent with the migration literature, which shows both positive and negative migration effects (Table 1), we find a high level of heterogeneity in marginal effects across households, with the minimum, mean, and maximum marginal effects being -.989, -.015 and .982 respectively (histograms of household specific estimates appear in Web Appendix 6). This suggests that marketers should expect large positive effects of migration only on specific segments of migrant sending households. Based on our parameter estimates, these are households which receive greater economic remittances, live in more populous villages, and own mobile phones. The minimum, mean, and maximum marginal effects for households who receive greater than mean levels of economic remittances, own a mobile phone, and reside in villages with above-mean population are -.143, .330 and .982 respectively. Migration produces strong positive effects on the brand share of such households.

Next, we compute the marginal effect of economic remittances, by estimating the effect of receiving one thousand rupees of economic remittances on the brand shares of households. This is given by $\beta_5 + \beta_6 HH\_Income_i$. The minimum, mean, and maximum marginal effects of economic remittances across all households which receive remittances are -.025, .079 and .147 respectively, with smaller marginal effects for households with greater income. The marginal effect on brand share at the mean value of monthly household income is .085 (SE = .015, t = 5.484), and this increase of 8.5 percentage points is significantly different from zero at the 1% level.

Finally, we compute the marginal effect of social remittances on brand share as $\beta_7 Mobile_i + \beta_8 TV_i + \beta_9 Recent_i$. As discussed earlier, the ownership of mobile phones and TV, and the recency of migration serve as reasonable proxies across which we expect social remittances to vary. Since all three measures are binary, the marginal effect takes 8 levels, with the minimum, mean, and maximum marginal being -.298, .359 and .673 respectively. The marginal effect of social remittances on brand share at the mean values of the three variables is .313 (SE = .047, *t* = 6.716), which is again significantly different from zero at the 1% level. To compare the social remittance effect with the economic remittance effect, we take the ratio of the economic remittance effect and the social remittance effect, i.e. $\beta_5 + \beta_6 HH\_Income_i)/(\beta_7 Mobile_i + \beta_8 TV_i + \beta_9 Recent_i)$. At mean values of these variables, this ratio is 0.224, suggesting that the economic remittance effects are weaker than social remittance effects in our data. However, we caution against conclusive interpretations of relative magnitudes as $\beta_7 Mobile_i + \beta_8 TV_i + \beta_9 Recent_i$ is only our best proxy measure of the social remittance effect rather than a precise and complete measure. Direct measures of social remittances would enable more robust estimates of this ratio.

Robustness Checks

Robustness to expenditure on branded services. Our conceptual framework is based on how economic and social remittances from migration alter sending households' preferences and ability to afford brands. So far, we have provided evidence showing how sending migrants leads to increased brand share and brand expenditure of goods. We estimate the effect of migration on monthly household expenses for children's private schooling, a type of "branded" service. As mentioned, we collected data on households' monthly expenditures, on their children's private and government school fees. Details of our measures, specification, and results appear in Web Appendix 7. We find strong evidence supporting our hypotheses.

Robustness to an alternate instrument. We leverage varying participation by households in a rural employment program to construct an alternative instrument for migration. In 2005, the Indian government passed the Mahatma Gandhi Employment Guarantee Act, aimed at enhancing rural income by providing at least 100 days of wage-based employment in a year, to every household whose adult members volunteer for manual work. As one of the largest employment generation schemes globally, this scheme has been rolled out to all rural districts in India[10]. One of the objectives of this scheme is to curb outmigration of workers from rural to urban areas by ensuring greater local employment opportunities (Das 2011). Indeed, participation in this scheme has been found to negatively impact migration from villages, especially short-term migration (Imbert and Papp 2020). In our survey, we ask each household the number of days of employment received in the past one year under this scheme. Consistent with previous research, we find a negative correlation (-.28; $p < .01$) between the number of days of employment received by household i, and $Migrant_i$. So this serves as a relevant instrument.

In terms of the exclusion restriction, this scheme is targeted at relatively poorer sections of rural society and pays minimum wages. Thus, income from this scheme is perhaps more likely to be used for fulfilling basic necessities than for buying expensive brands. Another possibility of how this scheme might affect brand expenditure is if brand marketers allocate resources across villages based on the implementation of this scheme (e.g. a marketer could make a brand available only in those villages where this scheme has been implemented for at least 3 years). Village-level fixed effects control for that possibility. Importantly, since we control for household income from all sources, we account for potential increase in brand expenditure (and brand share) due to increased income from this scheme. Indeed, the coefficient of this instrument, when employed as an additional covariate in equation 1, is not significant (M = 0.11, SE = 0.38), suggesting that this instrument satisfies the exclusion restriction. We estimate the 2SLS model with this instrument for each of the three dependent variables. Results (Table 5) are quite similar to those obtained with the first instrument, and show that our results are robust to the choice of instruments. First stage regression estimates appear in Table 3.

===== Insert Table 5 here =====

[10] Source: https://nrega.nic.in/netnrega/home.aspx

Robustness of estimates of social remittance effects. We provide a robustness check to support our assertion that social remittances from migration influence brand expenditure. Specifically, we consider a subset of households which should, in theory, receive a negligible amount of social remittances. We then demonstrate that for this subset of households, our moderation hypotheses specific to social remittances do not hold while our moderation hypothesis specific to economic remittances do. Details appear in Web Appendix 8. In addition to these robustness checks, we replicate our results through a new study that relies on within-household differences in brand expenditure to identify migration effects.

Study 2

Identification of migration effects in the first study relied on differences in brand expenditure *across* households of different migration status. Our objective in this study is to identify migration effects based on *within*-household differences. This helps us to rule out the possibility of our results being affected by unobservable differences between sending and non-sending households. For this purpose, we survey 300 migrant-sending households and collect two observations from each household: before migration and after migration. The former observation is collected as retrospective recall of pre-migration baselines. Identification then relies on within-household differences in brand expenditure following the migration event. Two observations per household enable us to control for unobserved household-specific characteristics.

In this survey, Kantar sampled three states (Bihar, Jharkhand, and Uttar Pradesh) which are known to have high rates of rural-urban migration. They have a combined population approximately equal to that of the United States. Kantar then sampled 6 districts within each state, and 3-4 villages within each district, leading to a total of 62 villages. There were no overlaps with the villages sampled in the first study. Kantar maintains an active database of mobile phone numbers and names of heads of thousands of households across rural India. For each sampled village, Kantar field personnel randomly selected several respondents from this database and conducted telephonic surveys in August 2020. This study is confined to households sending economic migrants. Kantar ensured that at least 4 sending households were surveyed from each village, leading to a total sample of 300 households. Offline surveys were not feasible due to the COVID-19 pandemic. Given the high penetration of mobile phones in rural India and low penetration of Internet enabled devices, telephonic surveys are widely regarded as being more representative than online surveys.

For cost considerations and potential respondent fatigue, we followed Kantar's recommendation to restrict the survey to 10 minutes per respondent. For this reason, we focused solely on testing our six hypotheses, with a simple before-after research design. In addition to collecting data on all moderators in Equation 1 (household income, village population, TV ownership, recency of migration, monthly remittances), and controls (household size and whether the household has children), Kantar first asked respondents to recall household expenditure on branded and on unbranded products in January 2020 (the last month unaffected by the COVID-19 pandemic). Next, Kantar asked respondents to recall household expenditure on branded and unbranded products in a typical month *prior* to the date when the migrant left their household. Finally, Kantar collected data on the time when the migrant left the household, the household size before the migration event, and the household income in a typical month prior to migration. Since all households in this survey own a mobile phone, we do not estimate the effect of mobile phone ownership.

Consistent with the empirical strategy for the first study, we specify the following random effects regression model, for each of the three dependent variables.

$$y_{is} = \beta_0 + \beta_1 Post_{is} + \beta_2 HH\_Income_i + \beta_3 TV_i + \beta_4 Post_{is}\, x\, Econ\_Remit_i + \beta_5 Post_{is}$$

$$x\, Econ\_Remit_i\, x\, HH\_Income_{is} + \beta_6 Post_{is}\, x\, TV_i + \beta_7 Post_{is}\, x\, Recent_i + \beta_8 Post_{is}\, x\, Village\_Pop_i + \beta_9 Village\_Pop_i + \boldsymbol{x}'_{is}\gamma + \alpha_i + \vartheta_d + \epsilon_{is} \qquad (4)$$

where $Post_{is}$ (1 if observation *s* for household *i* is post migration, 0 otherwise) is the treatment indicator (before or after). The coefficient of $Post_{is}\ x\ Econ\_Remit_i$ captures the main effect of economic remittances (H_1). The coefficients of $Post_{is}\ x\ TV_i$, $Post_{is}\ x\ Village\_Pop_i$ and $Post_{is}\ x\ Recent_i$, capture the moderating effects of TV ownership, village retail infrastructure and recency of migration, after controlling for remittances. Given the small number of households per village, we replace village fixed effects with district fixed effects ϑ_d and control for village population. In another specification, we included fixed effects for the month and year when the migrant left the village. None of these fixed effects were statistically significant, alleviating concerns about time-varying unobservables which might affect brand expenditures. Household specific random effects ($\alpha_i \sim N(0,\sigma^2)$) control for unobserved household characteristics. Summary statistics appear in Web Appendix 9.

Parameter estimates of models of brand share, brand expenditure and expenditure on unbranded products appear in Table 6. Consistent with the first study, we find positive moderating effects of remittances, village retail infrastructure (proxied by population), and less recent migration on brand expenditure and brand share. We find a negative effect of TV ownership. The 3-way interaction between the treatment indicator, remittances, and income is not significant, perhaps because of the small sample size of this study, but in the hypothesized direction. In summary, we find strong evidence supporting our hypotheses using data collected in from different villages, and relying on intra-household variations for identification.

===== Insert Table 6 here =====

Discussion and Implications

Our research offers several actionable insights for brand managers interested in the allocation of marketing resources across villages in India and for household-level targeting decisions within villages. We also offer insights to managers and policymakers interested in increasing adoption of brand services, such as private school education, in rural settings.

Implications for Brand Marketers

Allocation of marketing resources to villages. Allocation of resources across 650,000 villages is not easy, especially given the historically low levels of brand consumption and lack of knowledge about what might increase it. Our conversations with several marketing managers who focus on rural Indian markets confirmed that resource allocation is usually based on village population and household income; both statistics are available at the village level from census reports. Collection of migration data is seen as costly and time consuming, with no clear benefits prior to our research. We now estimate the improvement in the effectiveness of resource allocation if marketers collect and incorporate migration data into their resource allocation process.

Consider a common resource allocation task where a marketing manager has a limited salesforce and is trying to decide the number of "salesforce visit days" to allocate to each village in a geographical market for the purpose of demand generation, improving in-store visibility of branded products, taking orders from retailers, etc. For this purpose, she estimates the monthly expenditure on branded products in each village, and allocates one "salesforce visit day" per month for every 200,000 rupees of brand expenditure. Table 7 shows the allocation of salesforce days for a market of 9 such randomly selected villages in our data. In column 4, we compute the "optimal" allocation based on the actual household level brand expenditure from our study (multiplied by the village population, and then divided by 200,000). However, this data is not available to marketers, so they need to predict it.

===== Insert Table 7 here =====

Next, we predict household level brand expenditure using Equation 1, based on the following "baseline" data from our study that is not related to migration. We note that this "baseline" data closely resembles the data a typical marketing manager might have. We estimate our model using baseline data from households in the remaining 10 villages (i.e. those not in the set of 9 villages mentioned above), and then make out-of-sample predictions of brand expenditure for all households in the 9 villages (see Table 9). Based on these estimates, we report village-level salesforce day allocations under the same allocation policy. Next, we repeat this exercise, except we predict brand expenditure using *both the baseline data and our migration data* (i.e. all variables in Equation 1). We again make out-of-sample predictions for 9 villages, and report village-level salesforce day allocations based on the "baseline and migration" data.

We find that the mean absolute deviation in the number of salesforce days allocated per village under the "optimal" allocation and allocation based on "baseline" data is 16.2 days. On the other hand, the mean absolute deviation in the number of salesforce days allocated per village under the "optimal" allocation and allocation based on "baseline and migration" data is 5.4 days. This represents an improvement (i.e., decrease) in MAD of 66%. In other words, using migration data for predicting brand expenditure leads to better resource allocation, even when primary data on household descriptors other than household income (such as TV ownership) is available. Further details appear in Web Appendix 10. The purpose of this analysis is illustrative as brand managers are more likely to base resource allocations on predicted expenditure on their own brand, as opposed to branded expenditure of all products. However, it underlines the opportunity for major improvements in resource allocation with simple migration descriptors.

Although the benefits of employing migration data are clear, the costs of collecting such data at the household level can be high. Yet, there are several reasons why this might be a worthy marketing investment. First, given the high correlation in migration choices within a village (due to supply side factors) and within a household over time, a one-time survey of migration choices can be used to predict migration status over a long horizon. Second, data on migration status is available at the district level from census reports. This can serve as a starting point for identifying the villages to be surveyed. Third, given the high penetration of mobile phones in rural India, telephonic surveys are a cheaper alternative to door-to-door surveys.

Intra-village targeting of households. In recent years, business models of female entrepreneurs selling branded products door-to-door to rural households have received increased attention from marketing practitioners and development researchers (Dolan 2012). Increasing the effectiveness of such entrepreneurs is useful not just to meet business objectives but also to alleviate poverty (Dolan and Scott 2009). Our results suggest that when selling to households within a village with similar income levels, these entrepreneurs can be more successful if they target households who have sent migrants in the distant past and own a TV. In informal conversations with rural residents, we found that this information about other households is easy to gather and is often publicly known within the village. It is also less sensitive to gather than information on household income.

To illustrate the differences in brand expenditure across households within a village, we present a dashboard (see Table 8) of predicted monthly brand expenditure for a representative village for 20 segments of households. These segments differ in their migrant sending characteristics, remittance receiving characteristics, mobile phone ownership, and TV ownership. Although some of these predictions are based on small sample sizes, our dashboard demonstrates large differences in brand consumption across segments. This suggests different rationales and approaches to targeting different segments of households: for example, segments containing households who recently sent migrants may be less attractive for targeting in the short-term but critical for long-term brand education and loyalty cultivation.

Given the low education levels of rural sales entrepreneurs, brand managers can create such selling aids similar to Table 8 to guide them in terms of which households to focus their time on, for the highest sales effectiveness.

===== Insert Table 8 here =====

As migrant-sending households which receive more remittances spend more on brands, one way to target such households could be to advertise and promote brands through well-established remittance channels such as public banks, informal banks, credit co-operatives, and microcredit institutions. Information on such channels can be readily obtained from village elders and migrant-sending households.

Implications for Education Marketers and Policy Makers.

While we only study the impact of migration on adoption of private schooling (a branded service) as a robustness check, the societal importance of improving education quality drives us to discuss some unique implications of our results for education marketers and policy makers. Beyond investing in villages with high income levels, managers of rural private schools should consider investing in areas with high incidence of long-term migration (i.e. migrants who have left the village over a year back) and high levels of remittance receipts. This could mean opening more schools in such areas, and/or allocating more teaching and monetary resources to existing schools in such areas. Policy makers could do better by targeting education subsidies at households not sending migrants, or those who have recently sent migrants. Much of the economic migration from rural India is short-term (Imbert and Papp 2020). Such households are much less likely to send their children to private schools. Less recent migrants are more likely to be female, older, of upper castes, and with more education (Kumar and Viswanathan 2012). We are unaware of targeting decisions in any industry in rural India which systematically consider the heterogeneity in types of migration.

Implications for Theory

Migration effects on the behavior of the sending household have typically been studied using the cost-benefit framework, wherein economic remittances constitute the major benefits. We extend this framework on the benefits side, to jointly study the effects of both economic remittances and social remittances. We find that social remittance effects on brand share are large, statistically significant, and comparable to economic remittance effects. This underlines the importance of adopting a broader framework for understanding migration as a shock that combines monetary benefits with changes in household behaviour through exposure to different products, brands, lifestyles, and values of the migrant destination.

Our research also has implications for the theory of consumer socialization. TV viewing increases consumers' aspiration for products, services, and lifestyles featured on TV. Our finding of a negative moderating effect of TV ownership on brand expenditure suggests that migration and TV viewing might be competing channels for consumer socialization in developing markets. Future research analyzing specific content of conversations with migrants and TV programs could help us better understand complementarities and substitutions across these two channels. Furthermore, the positive role of mobile phone ownership in enhancing migration effects suggests that consumer socialization might accelerate as the cost of mobile phone ownership decreases. On the other hand, it is possible that with increasing use of mobile phones to view online content, social remittances from migrants will not remain sufficiently novel to alter consumption of the sending household. Finally, our finding that migration effects are stronger in more populous villages suggests that a comprehensive framework of studying migration effects should consider the retail environment of the sending household and the role of marketers' decisions in shaping that environment.

Conclusion

This research is the first attempt to study how migration affects brand expenditure. In focusing on this key outcome for marketers, we contribute to scholarship on migration by econometrically identifying effects of *both* economic and social remittances. Additionally, we generate insights for marketing academics and practitioners on how preferences for branded products develop among the poorest consumers in the world, and how information on their migration can be leveraged by firms to make better targeting decisions.

As such, our findings are neither comprehensive nor without limitations. Collecting high-quality data from rural markets is costly and time consuming. Consequently, we restricted our data collection efforts to two surveys across three states in India. Future research should assess the robustness of our findings across different rural communities, both within and outside India. Additionally, exploring how migration affects household expenditure at a category level can lead to more specific insights at a product-market level. The impact of internal migration on the attitudes of the migrant-sending households towards status enhancing opportunities can also be explored. Remittance effects on brand expenditure could partly be driven by lowering of financial liability levels of the sending household; income controls might not fully capture that. From a measurement standpoint, we employ a binary measure of recency of migration. A continuous measure might aid identification of potentially non-linear effects of recency. Our research illustrates that migration without economic remittances can still have significant impact on the consumption behavior of sending households through social remittances. Measuring social remittances directly in these communities remains challenging, presenting opportunities for future studies. Finally, given the paucity of research on migration without economic remittances, future studies can explore whether this type of migration influences poverty and inequality in sending communities.

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Table 1: A Review of the Literature on the Effect of Migration on Sending Households

Reference	Data	Explanatory Variable(s)	Dependent Variable(s)	Main Effect	Moderating effect of household income, migration recency, technology access, and village population	Instrument Variable(s)
This research	734 households across two studies, rural India	Having a migrant member **and** economic remittances	Brand expenditure Brand Share	Positive Positive	Lower positive effect on households with more income, more recent migration, and mobile phone access Greater positive effect of TV access, village population	Migration status of least proximate household in village social network
Adams (1998)	469 households, Pakistan	Economic remittances	Asset value	Null	None studied	None (Panel methods used)
Adams, Cuecuecha, and Page (2008)	800 households, Ghana	Economic remittances	Poverty rates	Negative	None studied	None (Selection model used)
Esquivel & Huerta-Pineda (2007)	17,167 households, Mexico	Economic remittances	Poverty rates	Negative	None studied	None (Matching methods used)
Mahapatro et al. (2017)	125,000 households, India	Economic remittances	Health expenditure Education expenditure Food Expenditure	Positive Positive Negative	None studied	None (Matching methods used)
Yang (2008)	1646 households, Philippines, panel	Economic remittances	Education expenditure Consumption	Positive Null	None studied	Exchange rate shocks in destination country
Bryan, Chaudhury and Mobarak (2014)	1900 households, Bangladesh,	Having a (seasonal) migrant member	Health expenditure Food expenditure Non-food Expenditure	Positive Positive Positive	None studied	Random offer of financial incentive to migrate
Garlick et al. (2016)	22,255 households, South Africa	Having a migrant member	Household income	Positive	None studied	None (Matching methods used)
Gibson, McKenzie and Stillman (2011)	118 households, Tonga	Having a migrant member	Household income	Negative	None studied	Lottery for permission to migrate
Mergo (2016)	500 households, Ethiopia	Having a migrant member	Consumption	Positive	None studied	Lottery for permission to migrate
Morten (2019)	438 households, India	Having a (seasonal) migrant member	Household income Consumption	Positive Null	None studied	None

Table 2: Summary Statistics of Each Stratified Sample of Study 1

	Households not sending migrant		Households sending more recent migrant		Households sending less recent migrant		All households	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Monthly Expenditure on Branded Products (Rs.)	1406	2631	1165	1779	3662	6960	2058	4509
Monthly Expenditure on Unbranded Products (Rs.)	3190	2232	4180	2187	3078	1917	3512	2172
Brand Share	0.24	0.26	0.19	0.21	0.40	0.31	0.28	0.28
$Econ\_Remit_i$	NA	NA	1365	1595	1597	1786	1475*	1689
$Size_i$	4.96	2.23	5.82	2.47	5.63	2.41	5.49	2.40
$Child_i$	1.79	1.41	1.98	1.40	1.77	1.43	1.85	1.42
HH_Income_i	8504	3468	10092	3775	10542	4923	9747	4181
TV_i	0.70	0.46	0.58	0.49	0.53	0.50	0.60	0.49
$Mobile_i$	0.87	0.34	0.91	0.29	0.89	0.31	0.89	0.31
$Village\_Pop_i$	2532	970	2517	980	2558	927	2535	958
Number of Households	125		146		132		403	

Notes:
* based on 278 households which sent a migrant
$Village\_Pop_i$: the population (in thousands) of the village in which the household resides;
HH_Income_i is the monthly household income in thousands of rupees;

Table 3: First Stage Regression of Migration Status on Instrument and Household Characteristics

	Model 1	Model 2
Instrument	Migration status of distant households	Number of days of employment from employment scheme
Coefficient of Instrument	0.408*** (0.044)	-0.258*** (0.041)
$Size_i$	0.002 (0.016)	0.023* (0.017)
$Child_i$	-0.028 (0.026)	-0.039 (0.027)
HH_Income_i	0.011* (0.006)	0.014** (0.006)
TV_i	-0.099* (0.055)	-0.089 (0.059)
$Mobile_i$	0.072 (0.070)	0.054 (0.074)
R^2	0.25	0.17
F-stat	5.35***	3.23**
R^2 *(without instrument)*	0.08	0.08
F-stat (without instrument)	1.51*	1.51*
Anderson-Rubin statistic for test of weak instrument	28.06***	12.37***
Cragg-Donald Wald F Statistic for test of weak instrument	28.13***	11.90***

Notes:
$*p < 0.1$; $**p < 0.05$; $***p < 0.01$
$Village\_Pop_i$ refers to the population (in thousands) of the village in which the focal household resides; HH_Income_i is in thousands of rupees; All models incorporate village specific fixed effects, and are based on Equation 2. The instrument in Model 1 is the migrant-sending status of the two households in the same village, who are *least* proximate from the focal household. The instrument in Model 2 is the number of days of employment received by the sending household, in the past year, in a rural employment scheme.

Table 4: Effects of Migration on Brand Share, Expenditure on Branded Products, and Expenditure on Unbranded Products (with network based instrument)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Dependent Variable	Brand Share	Brand Share	Brand Share	Brand Share	Exp. on Branded Products	Exp. on Unbranded Products
$Migrant_i$	0.279**	0.078	0.281***	-1.901**	-32,103**	13,794**
	(0.056)	(0.101)	(0.061)	(0.739)	(14154)	(5432)
HH_Income_i	0.007**	0.010*	-0.000	-0.027*	-422.0	396.8***
	(0.004)	(0.006)	(0.004)	(0.014)	(275.5)	(105.7)
TV_i	0.098***	0.141***	-0.005	0.271***	5,302***	-574.6
	(0.028)	(0.046)	(0.032)	(0.097)	(1866)	(716.0)
$Mobile_i$	0.028	0.087	-0.046	-0.308**	-5,604**	3,172***
	(0.045)	(0.065)	(0.040)	(0.148)	(2833)	(1087)
$Migrant_i$ x $Econ\_Remit_i$ (H_1)	NA	0.083***	NA	0.150***	2,478***	-979.2**
		(0.019)		(0.031)	(781.2)	(299.8)
$Migrant_i$ x $Econ\_Remit_i$ x HH_Income_i (H_2)	NA	-0.002**	NA	-0.007**	-127.1**	61.49**
		(0.001)		(0.003)	(63.13)	(24.22)
$Migrant_i$ x $Mobile_i$ (H_3)	NA	0.134*	NA	0.481**	7,689*	-4,515.8**
		(0.082)		(0.240)	(4604)	(1766.8)
$Migrant_i$ x TV_i (H_4)	NA	-0.106*	NA	-0.298***	-4,083**	932.7
		(0.054)		(0.106)	(2023)	(776.2)
$Migrant_i$ x $Recent_i$ (H_5)	NA	0.189***	NA	0.192***	2,763***	-1129.7***
		(0.028)		(0.036)	(705.9)	(270.9)
$Migrant_i$ x $Village\_Pop_i$ (H_6)	NA	0.045**	NA	0.238**	4,546**	-1,426.0**
		(0.015)		(0.098)	(1874)	(719.1)
$Migrant_i$ x HH_Income_i	NA	0.010*	NA	0.046*	765.4*	-420.0**
		(0.006)		(0.021)	(408.7)	(156.8)
$Size_i$	0.002	-0.010	-0.020**	0.001	184.2	112.3
	(0.009)	(0.008)	(0.000)	(0.011)	(215.5)	(82.7)
$Child_i$	-0.036***	-0.003	0.020	0.003	12.98	-236.1**
	(0.014)	(0.012)	(0.015)	(0.017)	(323.7)	(124.2)
R^2	0.060	0.308	0.282	0.552	0.250	0.783
Instrument for Migration	NO	NO	YES	YES	YES	YES

Notes:
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$*; $Migrant_i$ is 1 if the household has a migrant member, 0 otherwise; $Econ\_Remit_i$: mean remittances received by the household per month, in thousand rupees; $Village\_Pop_i$: the population (in thousands) of the village in which the household resides; HH_Income_i is in thousands of rupees; All models incorporate village specific fixed effects; $Recent_i$: 1 if migrant left household over 1 year ago, 0 otherwise; the dependent variable is brand share for Models 1-4, expenditure on branded products for Model 5 and expenditure on unbranded products for Model 6; in any model, variables corresponding to cells marked "NA" were not included in the model. The instrument in all models is the migrant-sending status of the two households in the same village, who are *least* proximate from the focal household.

Table 5: Effects of Migration on Brand Share, Expenditure on Branded Products, and Expenditure on Unbranded products (with instrument based on employment policy)

	Model 1	**Model 2**	**Model 3**
Dependent Variable	Brand Share	Exp. on Branded Products	Exp. on Unbranded Products
Migrant$_i$	-1.713***	-32,105**	10,510**
	(0.645)	(12927)	(4518)
HH_Income$_i$	-0.023*	-420.5	340.7***
	(0.013)	(257.2)	(89.9)
TV$_i$	0.251***	5,292***	-219.9
	(0.087)	(1758)	(614.5)
Mobile$_i$	-0.275**	-5,588**	2,560***
	(0.013)	(2647)	(925.3)
Migrant$_i$ x Econ_Remit$_i$ (H_1)	0.141***	2,474***	-815.7**
	(0.037)	(733.0)	(256.2)
Migrant$_i$ x Econ_Remit$_i$ x HH_Income$_i$ (H_2)	-0.006**	-126.8**	50.44**
	(0.003)	(60.04)	(20.98)
Migrant$_i$ x Mobile$_i$ (H_3)	0.423**	7,689*	-3,517**
	(0.212)	(4256)	(1487)
Migrant$_i$ x TV$_i$ (H_4)	-0.276***	-4,072**	549.0
	(0.095)	(1906)	(666.3)
Migrant$_i$ x Recent$_i$ (H_5)	0.188***	2,760***	-1049.9***
	(0.034)	(691)	(241.6)
Migrant$_i$ x Village_Pop$_i$ (H_6)	0.214**	4,535**	-1004.5*
	(0.086)	(1722)	(601.7)
Migrant$_i$ x HH_Income$_i$	0.041**	763.0**	-330.8**
	(0.019)	(377.5)	(131.9)
Size$_i$	-0.001	183.8	134.2*
	(0.010)	(211.8)	(74.0)
Child$_i$	0.004	13.36	-253.2**
	(0.011)	(322.0)	(112.5)
R^2	0.592	0.393	0.821
Instrument for Migration	YES	YES	YES

Notes:
$p < 0.1$; $**p < 0.05$; $***p < 0.01$; *Migrant$_i$* is 1 if the household has a migrant member, 0 otherwise; *Econ_Remit$_i$*: mean remittances received by the household per month, in thousand rupees; *Village_Pop$_i$*: the population (in thousands) of the village in which the household resides; *HH_Income$_i$* is in thousands of rupees; All models incorporate village specific fixed effects; *Recent$_i$* : 1 if migrant left household over 1 year ago, 0 otherwise; all three models have the same covariates; the dependent variable for each model appears in the first row; the instrument in all models is the number of days of employment received by the sending household, in the past year, in a rural employment scheme.

Table 6: Effects of Migration on Brand Share, Expenditure on Branded Products, and Expenditure on Unbranded products (identification using within-household differences)

Dependent Variable	Brand Share (Model 1)	Exp. on Branded Products (Model 2)	Exp. on Unbranded Products (Model 3)
$Post_i$	0.008	-1233.0	283.3**
	(0.014)	(805.9)	(103.8)
HH_Income_i	-1.94 X 10^{-7}	0.032	0.006
	(8.10 X 10^{-7})	(0.039)	(0.006)
TV_i	0.037*	646.8	975.5**
	(0.020)	(586.3)	(337.2)
$Post_i$ x $Econ\_Remit_i$ (H_1)	2.57 X 10^{-6}***	0.12***	0.002
	(0.33 X 10^{-6})	(0.02)	(0.002)
$Post_i$ x $Econ\_Remit_i$ x HH_Income_{is} (H_2)	-3.15 X 10^{-8}	-0.002	0.000
	(2.81 X 10^{-8})	(0.002)	(0.002)
$Post_i$ x TV_i (H_4)	-0.113***	-3,891.9***	10.4
	(0.009)	(555.4)	(56.7)
$Post_i$ x $Recent_i$ (H_5)	0.058***	1733.0**	64.3
	(0.012)	(618.1)	(78.2)
$Post_i$ x $Village\_Pop_i$ (H_6)	0.009***	4886.3***	23.5**
	(0.002)	(114.7)	(11.7)
$Size_i$	-0.001	179.1**	370.0***
	(0.003)	(85.1)	(55.5)
$Child_i$	0.011	701.8	-184.2
	(0.027)	(689.8)	(455.3)
$Village\_Pop_i$	-0.004	-95.9	-37.0
	(0.004)	(126.9)	(74.8)
R^2	0.352	0.392	0.392

Notes:
$p < 0.1$; $**p < 0.05$; $***p < 0.01$; *$Post_i$* is 1 if observation pertains to post migration period, 0 otherwise; *$Econ\_Remit_i$* refers to mean remittances received by the household per month, in thousand rupees; *$Village\_Pop_i$* refers to the population (in thousands) of the village in which the focal household resides; *HH_Income_i* is in thousands of rupees; *$Recent_i$*: 1 if migrant left HH over 1 year ago, 0 otherwise; All models incorporate district specific fixed effects, and household specific random effects; Brand share is the dependent variable for Model 1; expenditure on branded products is the dependent variable for Model 2; expenditure on unbranded products is the dependent variable for Model 3.

Table 7: Improving Salesforce Allocation by Incorporating Migration Information

Village	Population (L)	HH level Brand Exp.* (from study) (M)	Optimal salesforce days (N)	Predicted Brand Exp. (B1)*	Salesforce days based on B1 (O)	Predicted Brand Exp. (B2)*	Salesforce days based on B2 (P)
				Data: Baseline	Data: Baseline	Data: Baseline and Migration	Data: Baseline and Migration
A	2,000	1,743	13	1,128	8	1,035	8
B	2,500	3,940	36	2,025	18	3,267	30
C	4,000	348	5	2,043	30	996	15
D	1,500	2,028	11	1,273	7	640	3
E	1,000	633	2	174	1	299	1
F	1,300	3,474	16	1,328	6	1,800	9
G	3,000	4,972	54	2,638	29	5,031	55
H	3,500	4,949	63	2,012	26	4,997	64
I	4,000	198	3	1,674	24	883	13

Notes:
Exp: expenditure; HH: household; * per household in rupees; All salesforce days pertain to monthly allocations; Village names have not been shared to protect the privacy of respondents; optimal salesforce days (N) for a village are the village level brand expenditure (based on population and HH level brand expenditure) divided by 50,000. The prediction of brand expenditure using baseline data (B1) is based on income, TV ownership, phone ownership, population, HH size, and number of children in the HH. Salesforce allocation based on baseline data (O) is given by (B1 X village population / 5.49 X 50,000), rounded to the nearest integer. Next, to quantify the value of migration data, we predict household level brand expenditure using both the baseline data, and our migration data (i.e. all variables in Equation 1). Salesforce allocation based on this "baseline and migration" data (P) is given by (B2 X village population / 5.49 X 50,000), rounded to the nearest integer. Mean absolute deviation (MAD) with "baseline data" (the mean of the absolute difference between the salesforce days allocated to a village based on baseline data, and optimal salesforce days allocated to that village) is 16.2 days. MAD with "baseline and migration data" is 5.4 days. This represents an improvement (i.e. decrease) in MAD of 66% due to usage of migration data in the allocation of salesforce days. Further details appear in Web Appendix 10.

Table 8: Sales Guides Predicting Brand Expenditure using Migration Information

Migration type	Remittance type	TV Ownership		Mobile Phone Ownership	
		Yes	No	Yes	No
No Migration	NA	2449	1020	1487	848
Migrant left 3-12 months back	High	1073	2612	1805	2076
Migrant left 3-12 months back	Low	605	503	564	549
Migrant left over a year back	High	7744	3108	6018	9037
Migrant left over a year back	Low	2530	1008	1337	3900

Notes:
Each cell contains the predicted brand expenditure for households in that cell. For example, for all households which receive “low” remittances, have a migrant who left over a year back, and own a TV, the predicted brand expenditure is Rs. 2,530. High remittance: exceeding median value of Rs. 917 per month.

Figure 1: Impact of Migration on Brand Expenditure and Brand Share of Migrant Sending Households

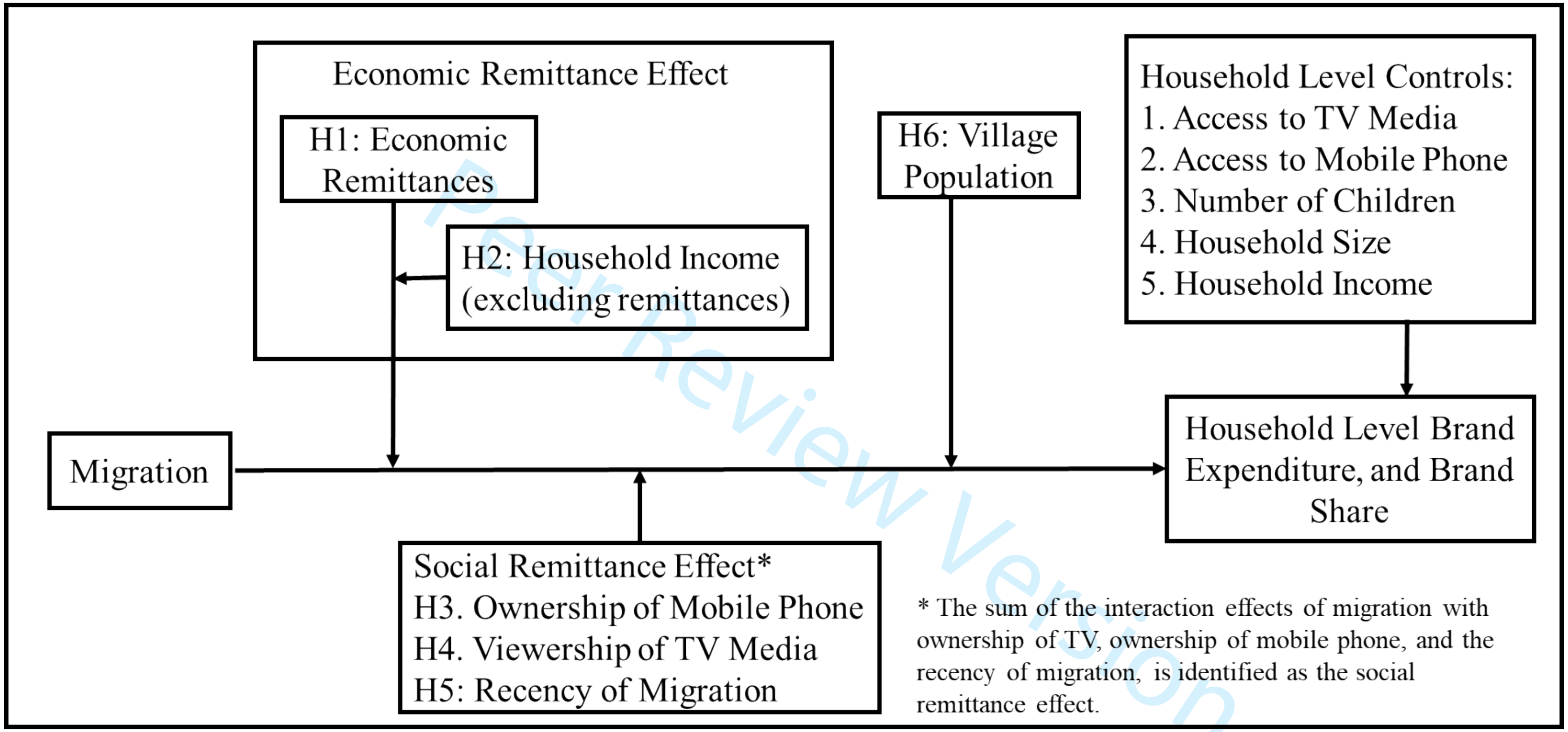
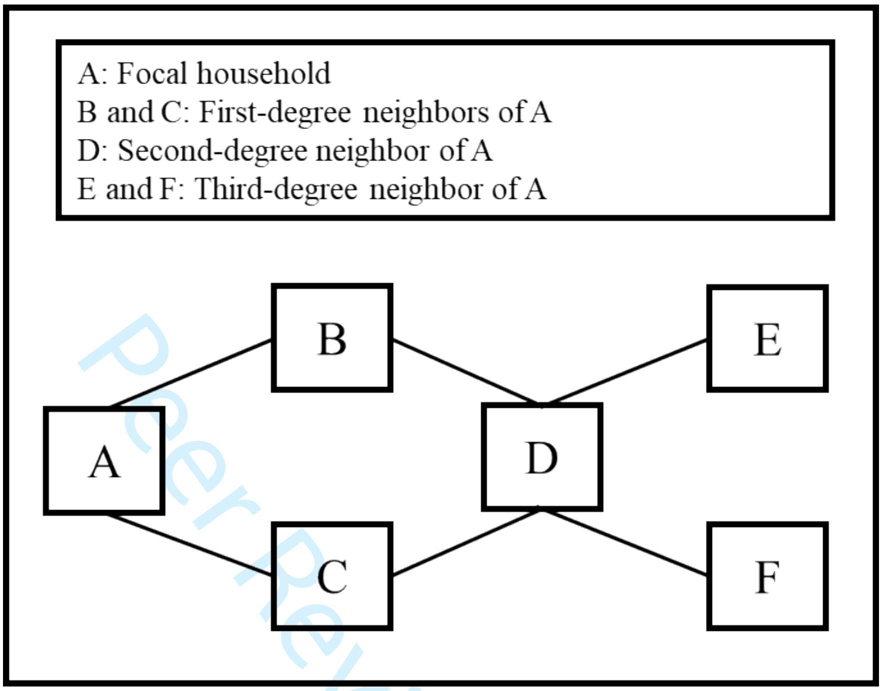


Figure 2: Illustration of Identification of Least Proximate Households from Focal Household



The Economic and Social Impacts of Migration on Brand Expenditure:
Evidence from Rural India

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Web Appendices: Table of Contents

Web Appendix 1: Further Details of the First Study

1. In each village, Kantar field personnel first enumerated all households (irrespective of their income levels) and classified each household into one of the three strata: : (i) households with no migrant member; (ii) more recent migrant sending households, i.e. households with at least one migrant member who has left the village 3-12 months before the date of the survey; and (iii) less recent migrant sending households, i.e. households with at least migrant member who has left the village over 12 months prior to the survey. Kantar field personnel then randomly selected 18 to 24 households per village across the three strata (approximately in the ratio 1:1:1). Random sampling ensured that households of all income levels were represented
2. We designed the questionnaire with inputs from Kantar senior managers and field personnel, borrowing specific items from the National Sample Survey, a periodic survey of Indian households conducted by the National Sample Survey Office (NSSO) of the Government of India. This survey has been used in migration studies (Mohanty et al., 2014), but does not record brand expenditure.
3. In our sample, 27 households sent two migrants each. Other households sent one migrant or no migrant at all. Classification of the household in terms of recency of migration (more recent or less recent) is based on the behavior of the migrant who first migrated. Classification based on the behavior of all migrants in the household does not affect our results.
4. Responses to the questions “Did the migrant migrate due to a natural disaster (drought, flood, tsunami, etc.)?” and “Did the migrant migrate due to social or political problems (riots, terrorism, political refugee, bad law and order, etc.)?” were all zero. We conclude that shock-related migration is not prevalent in our data.
5. Kantar also confirmed that each village had at least one store selling branded and unbranded foods, and at least one store selling branded and unbranded products for non-food categories (e.g. apparel, appliances, etc.)
6. Other than the date and time of the interview, data on the following types of variables were collected from each respondent: village specific variables, household (HH) specific demographic variables, HH specific variables about expenditure, HH specific variables about migration behavior, and a HH specific variable about neighbors. Details appear below.

Village specific variables

1. Name of village.
2. Distance from the village to the district headquarter (in km).
3. Whether the village has the following amenities (yes or no): railway station, police station, bus stop, marketplace, post office, paved road and electricity.

In addition, data on the following variables were collected from government sources: the village population, the gender ratio (number of females per thousand males) of the village, and the literacy level (proportion of the population that can read and write).

Demographic variables (HH specific)

1. District of residence (pick one of Bahraich, Gorakhpur, Jaunpur, Lalitpur, Meerut, and Sant Kabir Nagar).
2. Name of village of residence.
3. Whether the respondent is the Chief Wage Earner (CWE), defined as the person who contributes maximum to the monthly HH expenditure.
4. Education level of CWE (whether the CWE is illiterate, is educated up to primary school, up to middle school, up to high school, some college but not graduate, graduate or post graduate).
5. Occupation level of CWE (whether the CWE is an unskilled worker, skilled worker, petty trader, shop owner, businessman, self-employed professional, clerk/salesman, supervisor, junior officer/executive, senior officer/executive, housewife, student, retired, unemployed).

6. Whether the house in which the respondent lives is *pucca* (walls and roof made of cement and bricks), *kuccha* (walls and roof not made of cement and bricks), or *semi-pucca* (either walls or roof are made of cement).
7. Whether the house in which the respondent live is owned or rented.
8. Whether the HH owns each of the following assets: land, building or other constructions, livestock or poultry, agricultural machinery, non-farm machinery, transportation devices, and consumer durables including TV and mobile phone (both smartphone and other mobile phone). Only ownership was recorded. The monetary value of each asset was not recorded.
9. Whether the household belongs to any one of the following groups: Scheduled Castes, Scheduled Tribes or Other Backward Caste.
10. Whether the HH possesses a ration card (yes/no). A ration card provides access to subsidized foods in India.
11. Age of each HH member in years (members under 18 years of age were classified as children)
12. Employment received by all HH members under the Mahatma Gandhi Employment Guarantee Act, in terms of number of days in the past.

Expenditure variables (HH specific)

1. HH expenditure on the following FOOD categories in the 30 days preceding the date of the survey (in Rs.): Cereals & cereal products (includes muri, chira, maida, suji, noodles, bread (bakery), barley, cereal substitutes, etc.); Pulses & pulse products (includes soyabean, gram products, besan, sattu, etc.); Milk and milk products (includes milk condensed/powder, baby food, ghee, butter, ice- cream, etc.); Edible oil and Vanaspati; Vegetables, fruits and nuts; Egg, fish and meat; Sugar, salt and spices; Non-alcoholic beverages (e.g. tea, coffee, fruit juice); Processed food such as biscuits, cake, pickles, sauce, cooked meals; Tobacco and alcoholic beverages. Category definitions follow household expenditure surveys conducted by the NSSO of the Government of India.

2. HH expenditure on the following NON-FOOD categories in the 30 days preceding the date of the survey (in Rs.): Fuel and light, Toiletries, Cosmetics, Clothing and Footwear, Bedding, Other persona and home care items (including spectacles, torch, umbrella, lighter, electric bulb, tube light, glassware, bucket, agarbatti, insecticide), Furniture and Fixtures, Crockery and utensils and cooking appliances, Household appliances (refrigerator, sewing machine, washing machine), TV and Video Recorder, Jewellery and Ornaments, Personal transport equipment (includes bicycle, scooter, car, tyres and tubes, etc.), Watch and PC and Telephones (including mobile and smartphone), Other durable goods. Category definitions follow household expenditure surveys conducted by the NSSO of the Government of India.

3. Household expenditure on branded products for each of the categories listed in (1) and (2), in the 30 days preceding the date of the survey (in Rs.) These definitions follow household expenditure surveys conducted by the NSSO of the Government of India.

4. Household expenditure on tuition for both private and public schools and colleges in the 30 days preceding the date of the survey (in Rs.)

Migration variables (HH specific)

1. Whether any member of the household has migrated out any time in the past 365 days, and spent at least 3 months in that period away from home (yes/no). A binary classification of the recency of migration in common. The Organization for Economic Co-operation and Development (OECD), a major intergovernmental organization comprising 35 countries, defines “short-term” migration as that lasting between 3 and 12 months (i.e., since the migrant left the village), and “long term migration” as that lasting more than 12 months. So all migrants in our study for which $Recent_i = 1$, are “long term” migrants as per the OECD definition.

2. Reason for migration of each member who has migrated. These could be one of the following: in search of employment, or to take up employment which has already been secured, or others.

3. Whether each migrant migrated due to a natural disaster (drought, flood, tsunami, etc.)

4. Whether each migrant migrated due to social or political problems (riots, terrorism, political refugee, bad law and order, etc.)
5. Whether it has been 3-12 months since the migrant has left the village ($Recent_i$=0), or longer ($Recent_i$=1).
6. Average monthly amount of money remitted by each migrant member in Rs.
7. Average monthly market value of goods remitted by each migrant member in Rs.
8. Level of literacy and education of each migrant member. This could be one of the following: illiterate, literate without formal schooling, literate with formal schooling, diploma/certificate course, graduate or post graduate.

Neighbor variable (HH specific)

For each household Kantar field personnel identified the two households in the sample, which lived at the least distance (i.e. which were physically closest) from the focal household, at the time of the survey.

Web Appendix 2: Features to Ensure Greater Internal Validity of the First Study

First, to test whether respondents understood the differences between branded and unbranded products, we asked each respondent whether each of 9 products were branded or not. All 403 respondents were able to correctly identify each product as being branded or unbranded[1]. Second, before being asked to mention expenditure on branded and unbranded products on various categories, respondents were shown pictures of branded and unbranded products of such categories (see Figure below as an example of pictures of unbranded foods and branded foods). Third, we measured household expenditure in two different ways, both of which lead to the same estimate of expenditure for all respondents. We first asked respondents their monthly income, expenditure and savings. Later in the survey, we asked for category level monthly expenditures on various branded and unbranded products and services. The sum of category level expenditures is the same as the total monthly expenditure reported earlier, for all respondents. Finally, we make use of the fact that most households buy branded food and grocery products from a small number of stores (usually 1 or 2) in the village. For 20 households (about 5% of our sample), we verified the reported expenditure on branded food and grocery products with handwritten receipts from stores, or from records obtained from the stores (not all households obtain receipts). We did not find any systematic differences between self-reported expenditure and receipts/records thus obtained[2].

Figure W1: Pictures of Unbranded Foods and Branded Foods

Unbranded Foods	Branded Foods
	

[1] For this question, the unbranded products were tomatoes from a vegetable hawker, a bar of green colored soap, a fridge put together by the local engineer, and a necklace bought from the village fare (“mela”). The branded products were Bata shoes, the State Bank of India, Nalli sarees, Britannia biscuits and Samsung smartphones.

[2] Receipts and records were obtained for brand expenditure for a 7-day period preceding the date of the survey. These estimates were multiplied with 4.28, and then compared with 30-day self-reported brand expenditures.

Web Appendix 3: Additional Summary Statistics of the First Study

The matrix of pairwise correlation coefficients appears in Table W1. Economic remittances have a greater correlation with brand expenditure than with expenditure on unbranded products, resulting in a positive correlation between remittance and brand share. Finally, migrant sending households spend more on branded products (as a proportion of their income and remittances receipts) in the 10 most populous villages in our data than in the remaining 9 villages. This proportion is 0.24 (SD = 0.66) per household for those residing in the top 10 villages, and 0.16 (SD = 0.17) for others. Brand expenditure (as a proportion of income) does not differ as much among households not sending migrants. Households living in the top 10 villages and not sending migrants spend 17% (SD = 0.31) of their income on branded products. Housing living in less populous villages and not sending migrants, spend 14% (SD = 0.18) of their income on branded products. This suggests that the population of a village might moderate the effect of sending a migrant, on the brand expenditure of its resident households.

Table W1: Pairwise Correlation Coefficients Between All Variables in the Model

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Expenditure on Branded Products	1											
2	Expenditure on Unbranded Products	-0.23*	1										
3	Brand Share	0.65*	-0.48*	1									
4	Migration ($Migrant_i$)	0.10	0.10*	0.09	1								
5	Less Recent Migration ($Recent_i$)	0.25*	-0.14*	0.32*	0.47*	1							
6	Economic Remittance Receipt ($Econ\_Remit_i$)	0.35*	-0.00	0.43*	0.44*	0.26*	1						
7	Household Size ($Size_i$)	0.04	0.21*	-0.04	0.15*	0.04	0.03	1					
8	Number of Children ($Child_i$)	-0.05	0.02	-0.15*	0.03	-0.04	-0.22*	0.71*	1				
9	Monthly Household Income (HH_Income_i)	0.11*	0.31*	0.09	0.20*	0.13	0.09	0.38*	0.23*	1			
10	Access to TV (TV_i)	0.23*	-0.03	0.19*	0.14*	0.10*	0.17*	0.10	-0.04	0.06	1		
11	Access to Mobile Phone ($Mobile_i$)	-0.07	0.11*	0.00	0.05	0.00	0.07	0.17*	0.11*	0.10	0.13*	1	
12	Village Population ($Village\_Pop_i$)	0.03	0.02	-0.16*	0.00	0.02	0.01	0.04	-0.05	-0.02	-0.02	-0.01	1

Notes:
*$p < 0.05$
All expenditures, income and remittances are monthly household level figures in Indian rupees
Migration: 1 if HH sent migrant, 0 otherwise
Less Recent Migration: 1 if migrant left HH over 1 year ago, 0 otherwise
Access to TV: 1 if HH owns TV, 0 otherwise
Access to mobile phone: 1 if anyone in the HH owns a mobile phone, 0 otherwise
Paired correlations between remit and other variables are computed based on 278 observations for which migration is 1. Correlations between all other variables are based on 403 observations.

Web Appendix 4: Relevance and Validity of the Instrumental Variable

We present empirical evidence on the relevance and validity of our instrument. The mean degrees of separation between the focal household and the "IV households" is 2.91. A household's neighbor is separated from it by 1 degree; a neighbor's neighbor is separated by 2 degrees, etc. 34% of households have neighbor's neighbors as "IV households"; the remaining majority of households have "IV households" which are even more separated. The correlation between Mig_i and IV_i is 0.37 ($p < 0.01$), suggesting relevance. As evidence of satisfying the exclusion restrictions, the correlations between IV_i and the three dependent variables are all statistically insignificant. The correlation of IV_i with brand share is 0.06 ($p > 0.1$), that with brand expenditure is 0.12 ($p > 0.1$) and that with expenditure on unbranded products is 0.11 ($p > 0.1$). First stage regression results appear in Table 3. As expected, in Model 1, the coefficient of the instrument is positive and significant ($p < 0.01$). The Cragg-Donald Wald F-Statistic for the test of weak instrument and the Anderson-Rubin statistic for the test of weak instrument are 28.13 and 28.06 respectively. These far exceed the threshold value of 10 suggested by Stock, Wright and Yogo (pp. 522, 2002), rejecting the null hypothesis that the instrument is weak. The R^2-statistic of the first stage equation without the instrument (i.e. assuming $\alpha_1 = 0$) is 0.08. Inclusion of the instrument leads to an R^2-statistic of 0.25, a major increase. In summary, our instrument is relevant, strong, and satisfies exclusion restrictions. To test whether the interaction terms in equation 1 are endogenous, we conducted the Wu-Hausman test and the Durbin-Wu-Hausman test for each interaction term. The null hypothesis that the variable is exogenous, could not be rejected for any interaction term ($p > 0.1$). For these tests, the instrument for the interaction between Mig_i and another variable, is the interaction of IV_i and that other variable.

Finally, for some focal households, the number of "IV households" which are at the maximum level of separation from the focal household, exceeds 2. We then randomly selected 2 "IV households" from all possible "IV households". Replacing our instrument by the "mean number of migrant sent by all IV households" does not change our substantive results.

Reference

Stock, James H., Jonathan H. Wright, and Motohiro Yogo (2002), "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business Economics and Statistics*, 4, 518-529.

Web Appendix 5. Robustness to linear probability model for the first stage.

We test the robustness of our results to the fact that we model migration status ($Migrant_i$, a binary variable) as a linear regression model in the first stage (equation 2). In order to produce fitted values (of $Migrant_i$) which are uncorrelated with the residuals of the second stage equation, it is important for the first stage model to be linear. We conduct the following commonly employed robustness analysis (e.g., Kanuri and Andrews 2019, Jindal 2020). First we specify a probit model of migration status as follows:

$$Migrant_i^* = \alpha_0 + \alpha_1 IV_i + \alpha_2 Size_i + \alpha_3 Child_i + \alpha_4 MHI_i + \alpha_5 TV_i + \alpha_6 Mob_i + \delta_i$$

where $Migrant_i^*$ is a latent variable such that $Migrant_i$ = 1 if $Migrant_i^*$ > 0; $Migrant_i$= 0 otherwise; and δ_i ~ N(0, 1). We then derive the inverse Mills ratio, which is the ratio of the probability density function to the cumulative distribution function of the predicted probabilities, obtained from this probit model. Finally, we re-estimate the stage 2 regression models of brand share (equation 1 of the paper), expenditure on branded products and expenditure on unbranded products - with the inverse Mills ratio as an additional control variable in each regression. Parameter estimates are quite similar to those reported earlier, and the coefficient of the inverse Mills ratio is not statistically significant in any model.

Table W2: First Stage Probit Model of Migration Status on Instrument and Household Characteristics

Covariates	Coefficient Estimate
Instrument (Migration status of distant households)	0.020*** (0.003)
$Size_i$	0.138*** (0.051)
$Child_i$	-0.267*** (0.080)
HH_Income_i	0.055** (0.023)
TV_i	-0.719*** (0.162)
$Mobile_i$	0.171 (0.245)
Pseudo R^2	0.19

**P>|z| < 0.1; ** P>|z| < 0.05; *** P>|z| < 0.01*

Table W3: Second Stage Regression Model of Brand Share, Expenditure on Branded Products, and Expenditure on Unbranded Products, with Inverse Mills Ratio

Dependent Variable	Brand Share	Exp. on Branded Products	Exp. on Unbranded Products
Inverse Mills Ratio	-9.4×10^{-6} (63.5×10^{-6})	-1.31 (1.23)	-0.14 (0.46)
Migrant$_i$	-1.912** (0.770)	-33,641** (14957)	13,629** (5616)
HH_Income$_i$	-0.027* (0.015)	-449.2 (290.0)	393.9*** (108.5)
TV$_i$	0.272*** (0.100)	5,454*** (1943)	-558.2 (729.6)
Mobile$_i$	-0.310** (0.152)	-5,856** (2960)	3,145*** (1111)
Migrant$_i$ x Econ_Remit$_i$ (H_1)	0.151*** (0.042)	2,569*** (823)	-959** (309)
Migrant$_i$ x Econ_Remit$_i$ x HH_Income$_i$ (H_2)	-0.007** (0.003)	-135.9** (66.8)	60.5** (25.1)
Migrant$_i$ x Mobile$_i$ (H_3)	0.484* (0.248)	8,104* (4822)	-4,471** (1810)
Migrant$_i$ x TV$_i$ (H_4)	-0.299*** (0.107)	-4,141** (2073)	926.4 (778.4)
Migrant$_i$ x Recent$_i$ (H_5)	0.192*** (0.037)	2,760*** (717)	-1130*** (269)
Migrant$_i$ x Village_Pop$_i$ (H_6)	0.239** (0.102)	4,761** (1983)	-1,403* (744)
Migrant$_i$ x HH_Income$_i$	0.047** (0.022)	820.5* (435.2)	-414** (163)
Size$_i$	0.001 (0.012)	242 (233)	118.5 (87.7)
Child$_i$	0.002 (0.017)	-60.15 (341.5)	-244.0* (128.2)
R^2	0.550	0.278	0.786

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; *Migrant$_i$* is 1 if the household has a migrant member, 0 otherwise; *Econ_Remit$_i$*: mean remittances received by the household per month, in thousand rupees; *Village_Pop$_i$*: the population (in thousands) of the village in which the household resides; *HH_Income$_i$* is in thousands of rupees; All models incorporate village specific fixed effects; *Recent$_i$* : 1 if migrant left household over 1 year ago, 0 otherwise;

References

Kanuri, Vamsi K., and Michelle Andrews (2019), “The Unintended Consequence of Price-Based Service Recovery Incentives,” *Journal of Marketing*, 83(5), 57-77.

Jindal, Niket (2020), “The Impact of Advertising and R&D on Bankruptcy Survival: A Double-Edged Sword,” *Journal of Marketing*, 84(5).

Web Appendix 6: Marginal Effects of Migration on the Brand Share of the Sending Household

Figure W6.1: Marginal Effects of Migration on Brand Share of Sending Households

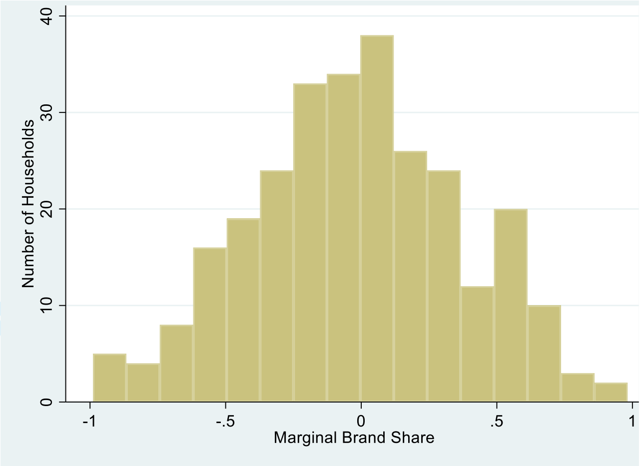


Figure W6.2: Marginal Effects of Economic Remittances on Brand Share of Households Which Receive Economic Remittances

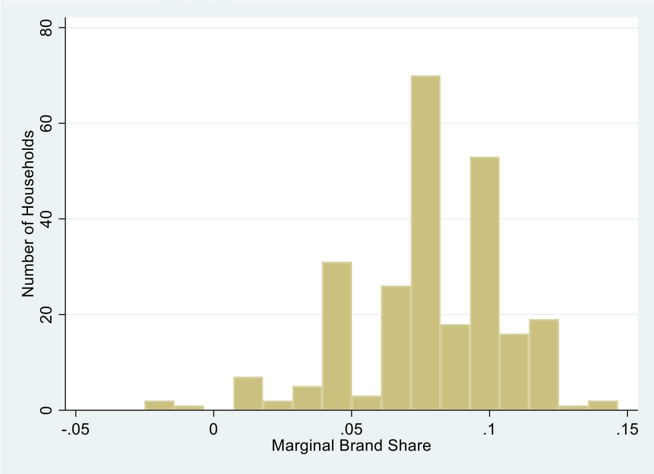
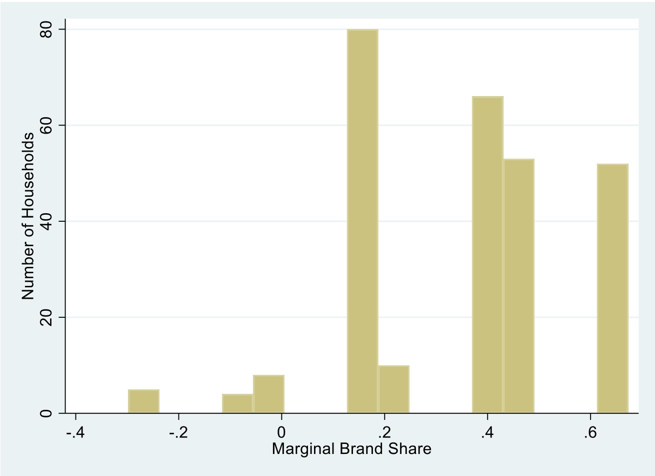


Figure W6.3: Marginal Effects of Social Remittances on Brand Share of Households Which Receive Social Remittances



Web Appendix 7: Effect of Migration on Branded Service Expenditure

We provide details on the data and specification underlying the robustness analysis on branded services (private schooling).

Migrant-sending households spend more on private school fees (*M* = Rs. 169, *SD* = 249) than other households do (*M* = Rs. 127, *SD* = 254)[3]. Although private schools are known to offer better educational outcomes than government schools in rural India, only 30% of enrollment is in private schools. To assess the effect of migration on private school expenditure, we take into account the left censoring of private school expenditure data (49% of observations are zero). Accordingly, we estimate a Type 1 Tobit model[4] with IVs, wherein private school expenditure $PvtSchoolExp_i$ is determined a normally distributed latent variable $PvtSchoolExp_i^*$ such that $PvtSchoolExp_i = PvtSchoolExp_i^*$ if $PvtSchoolExp_i^* > 0$; else $PvtSchoolExp_i = 0$. The expenditure equation specified below is identical to equation 1 but with a latent dependent variable.

$$PvtSchoolExp_i^* = \beta_0 + \beta_1 Migrant_i + \beta_2 HH\_Income_i + \beta_3 TV_i + \beta_4 Mobile_i + \beta_5 Migrant_i \; x \; Econ\_Remit_i + \beta_6 Migrant_i \; x \; Econ\_Remit_i \; X \; HH\_Income_i + \beta_7 Migrant_i \; x \; Mobile_i + \beta_8 Migrant_i \; x \; TV_i + \beta_9 Migrant_i \; x \; Recent_i + \beta_{10} Migrant_i \; x \; Village\_Pop_i + \beta_{11} Migrant_i \; x \; HH\_Income_i + \boldsymbol{x}_i'\gamma + \vartheta_v + \epsilon_i$$

The first stage equation for instrumenting migration status is the same as Equation 2. Next we present the results from this analysis. Parameter estimates provide evidence supporting our hypotheses. Greater remittances result in greater expenditure on private schools supporting H_1 (β = 155.22, SE = 62.41, $p < .05$), with a smaller increase for higher income households consistent with H_2 (β = -13.83, SE = 5.26, $p < .05$). After controlling for remittances, we find greater private school expenditure for sending households which do not own a TV supporting H_4 (β = -273.8, SE = 163.1, $p < .1$) and which sent a migrant at least a year back in support of H_5 (β = 430.99, SE = 57.20, $p < .01$). Although estimates of moderating effects of mobile phone ownership and village retail infrastructure (proxied by population) are not statistically significant, these estimates are directionally consistent with our hypotheses. To the extent that private school education is of higher quality than education in government run schools in India, these results point to the welfare-enhancing effects of migration.

[3] For government school fees, for migrant-sending households, *M* = Rs. 13, *SD* = 48; for other households, *M* = Rs. 8, *SD* = 28. Fees for such schooling are quite low due to subsidies, and are therefore not our focus.

[4] Replacing the Tobit model for private school expenditure with OLS regression does not change our results. There is no left censoring in brand expenditure data; all observations exceed zero.

Web Appendix 8: Robustness of estimates of social remittance effects

We provide a robustness check to support our assertion that social remittances from migration influence brand expenditure. In lieu of direct measures of social remittances (e.g., content of conversations between migrant and sending household members, frequency of electronic communication, frequency of offline communication etc.), we assume that households without access to a mobile phone receive (almost) no social remittances regarding brand consumption. Given the low usage of landline phones in rural India and the infrequency of travel between villages and migrant destinations, it is reasonable to assume that mobile phones are the primary communication mode between the migrant and the sending household. We estimate the nested model below, using only data from households which do not own a mobile phone. This model is the same as the main 2SLS model specified in the paper, except that we drop the two variables related to access to mobile phones ($Mobile_i$ and $Migrant_i\ x\ Mobile_i$).

Estimates of this model appear in the table on the next page. The main effect of migration after controlling for economic remittances, the interaction effects of migration with TV ownership and with village population are not significant; suggesting an absence of social remittance effects among households with no mobile phones. As expected, the hypotheses of the positive effect of economic remittances, and the negative moderating effect of household income continue to be supported. Although we find a significant effect of the recency of migration (i.e. less recent migration has a more positive effect), the magnitude of this effect is smaller than that in the model estimated on all households. This analysis provides greater validity to our empirical strategy of identifying social remittance effects.

Table W4: Second Stage Regression Model of Brand Share, and Expenditure on Branded Products, on Households which do not own a mobile phone

Dependent Variable	Brand Share	Exp. on Branded Products
Migrant$_i$	0.72 (0.57)	9905 (12703)
HH_Income$_i$	0.128** (0.040)	2992*** (878)
TV$_i$	0.084 (0.141)	5097*** (3130)
Migrant$_i$ x Econ_Remit$_i$ (H$_1$)	0.25*** (0.07)	15183*** (1533)
Migrant$_i$ x Econ_Remit$_i$ x HH_Income$_i$ (H$_2$)	-0.022*** (0.006)	-1002*** (130)
Migrant$_i$ x TV$_i$ (H$_4$)	-0.00 (0.19)	-5172 (4185)
Migrant$_i$ x Recent$_i$ (H$_5$)	0.15** (0.06)	4,142*** (1440)
Migrant$_i$ x Village_Pop$_i$ (H$_6$)	-0.10 (0.12)	-1922 (2757)
Migrant$_i$ x HH_Income$_i$	-0.100** (0.044)	1851* (981)
Size$_i$	-0.039 (0.023)	-363 (508)
Child$_i$	0.022 (0.029)	719 (650)
R^2	0.84	0.90

Notes: **p < 0.1; **p < 0.05; ***p < 0.01;* Remittance refer to mean remittances received by the household per month, in thousand rupees. Population refers to the population (in thousands) of the village in which the focal household resides. All models incorporate village specific fixed effects. Recency: 1 if migrant left the household over 1 year ago, 0 otherwise.

Web Appendix 9: Brand Expenditure Before Migration, in a Short Term After Migration, in the Long Term After Migration: Summary Statistics of Study 2

	Before Sending Migrant		After Sending Migrant 3-12 Months Back		After Sending Migrant Over 12 Months Back	
Number of Households (HH)	300		53		247	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Monthly Expenditure on Branded Products in rupees	3104	2474	2562	2008	5541	7477
Monthly Expenditure on Unbranded Products in rupees	4733	2934	4072	2241	5151	3105
Brand Share	0.39	0.16	0.38	0.14	0.45	0.18
Annual Remittance Receipt in Rupees	NA	NA	12481	5119	19519	23381
Household Size ($Size_i$)	7.48	2.71	6.20	2.14	6.54	2.82
Monthly Household Income in Rupees (HH_Income_i)	8005	5047	12481	5119	10542	13380
Whether the household has children (1 if yes, 0 otherwise; $Child_i$)			0.87	0.34	0.88	0.32
Access to TV (1 if HH owns TV, 0 otherwise; TV_i)			0.60	0.49	0.62	0.48
Village population ($Village\_Pop_i$)			3467	2422	3398	2344

Note: number of children, TV ownership and village population for the time prior to migration were not recorded in this study.

Web Appendix 10: Improving Salesforce Allocation by Incorporating Migration Information

Salesforce allocation in our context refers to the number of salesforce days allocated to work in a village for a specific month. Salesforce is a costly resource because of salary expenses, travel and boarding expenses of the salespeople which typically travel from cities to villages, and because of lack of availability of trained salespeople willing to work in less hospitable and inaccessible rural areas. We assume that the number of salesforce days allocated to a village in a month is based solely on the predicted demand of branded products in that village for that month. For every Rs. 50,000 of predicted brand expenditure per month, 1 salesforce day is allocated for that month. Specifically, for a given village in a given month:

Number of allocated salesperson days = predicted expenditure on all branded products (in rupees) / 50,000 (E1)

For example, if the estimated monthly brand expenditure across a village is Rs. 200,000, a salesperson would spend 4 days in the village that month. We first compute salesforce allocation under the "optimal" policy. This is the situation wherein the manager can perfectly predict brand expenditure; i.e. predicted brand expenditure = actual brand expenditure as reported by households in our study. For a specific village, we report mean household expenditure from our study in column M of Table 7. Next assuming 5.49 members per household (based on our study), we extrapolate the village level brand expenditure as follows:

Village level brand expenditure (actual) = Household expenditure X village population / 5.49 (E2)

Based on equations E1 and E2, the optimal salesforce allocation (in days) for a village is the actual village level brand expenditure (from E2) divided by 50,000. We round this number to the nearest integer and report this in column N of Table 7.

Next we compute household level expenditure using "baseline data", i.e. monthly household income, TV ownership, mobile phone ownership, village population, size of the household, and the number of children in the household. We first estimate our model using baseline data from households in the remaining 10 villages (i.e. those not in the set of 9 villages mentioned above), and make out-of-sample predictions of household level brand expenditure in the 9 villages. This appears as column B1 of Table 7. Salesforce allocation based on this baseline data is given by (B1 X village population / 5.49 X 50,000), rounded to the nearest integer. We report this in column O of Table 7.

Next, to quantify the value of migration data, we predict household level brand expenditure using both the baseline data, and our migration data (i.e. all variables in Equation 1). Again we make out-of-sample predictions for 9 villages (column B2), and report village-level salesforce day allocations based on the "baseline and migration" data. Salesforce allocation based on this "baseline and migration" data is given by (B2 X village population / 5.49 X 50,000), rounded to the nearest integer. We report this in column P of Table 7.

Now, we compare salesforce allocation under the "optimal" policy when brand expenditure can be predicted with perfect accuracy (column N), salesforce allocation under the "baseline data" policy (column O), and salesforce allocation under the "baseline + migration data" policy. Mean absolute deviation (MAD) with "baseline data" is the mean (across villages) of the absolute difference between the salesforce days allocated to a village based on baseline data, and optimal salesforce days allocated to that village. We find that MAD with baseline data is 16.2 days. Mean absolute deviation (MAD) with "baseline and migration data" is the mean (across villages) of the absolute difference between the salesforce days allocated to a village based on baseline data, and optimal salesforce days allocated to that village. We find that MAD with baseline data is 5.4 days. This represents an improvement (i.e. decrease) in MAD of 66% due to usage of migration data in the allocation of salesforce days.