

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

Journal of Marketing
 2021, Vol. 85(6) 63–82
 © American Marketing Association 2021
 Article reuse guidelines:
sagepub.com/journals-permissions
 DOI: 10.1177/00222429211021992
journals.sagepub.com/home/jmx



Vishal Narayan  and Shreya Kankanhalli

Abstract

Households that send members to work away from home often receive information about the lifestyles and consumption behaviors in those migration destinations (i.e., social remittances) along with money or goods (i.e., economic remittances). The authors 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. They 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 authors find that the effect of migration on brand expenditures is more positive for households in more populous villages, with greater access to mobile phones, lower viewership of television media, and less recently departed migrants. They 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. The results are robust to alternative, public policy–based instruments and can be generalized to expenditure on private schools. Using additional survey data from 300 households in 62 new villages, the authors replicate the results by comparing within-households brand expenditures before and after the migration event.

Keywords

brands, migration, consumer socialization, India, mobile phone, rural, social remittances, television

Online supplement: <https://doi.org/10.1177/00222429211021992>

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 article, we study how rural consumers shift their expenditure toward branded consumption as a result of a prevalent phenomenon in rural communities: out-migration of household members into 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 and toward 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 (Singhi, Jain, and Puri 2015), as there is evidence of an increasing share of unbranded products over time in categories such as tea (Food and Agriculture Organization of the United Nations 2010). 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

Vishal Narayan is Associate Professor of Marketing, NUS Business School, National University of Singapore, Singapore (email: bizvn@nus.edu.sg). Shreya Kankanhalli is Assistant Professor of Marketing, Smeal College of Business, Pennsylvania State University, USA (email: shreyak@psu.edu).

determinant of brand consumption for two reasons. First, rural out-migration is a major global 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 goods, 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 Muñoz-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.¹ 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 located farthest from the focal household. We replicate our findings using different data from 300 additional

rural households that compare 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 that 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 article 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 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 that investigates socioeconomic outcomes for migrant-sending households. Of the studies we review, 69% find positive effects of migration on income or expenditure of various types (e.g., Bryan, Chaudhury, and Mobarak 2014; Garlick, Leibbrandt, and Levinsohn 2016), and 31% find negative or null effects (e.g., Brown and Leves 2007; Gibson, McKenzie, and Stillman 2011; Mahapatro et al. 2017). These studies are summarized in Table 1. The mixed evidence suggests that migration outcomes are heterogeneous: migration is not always immediately successful in improving economic livelihoods (Gibson, McKenzie, and Stillman 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.

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 sales force effort across villages of similar population, household income, and so on. We provide numerical estimates of the improvement in allocation performance as brand expenditure predictions become more accurate with the

¹ 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.

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

| Reference | Data | Explanatory Variables | Dependent Variables | Main Effect | Moderating Effect of Household Income, Migration Recency, Technology Access, and Village Population | Instrument Variables |
|---|--|--|---|------------------------------|--|---|
| This research | 734 households across two studies, rural India | Having a migrant member and economic remittances | Brand expenditure Brand share | 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 | None studied | None (matching methods used) |
| Yang (2008) | 1,646 households, Philippines, panel | Economic remittances | Education expenditure Consumption | Positive | None studied | Exchange rate shocks in destination country |
| Bryan, Chaudhury, and Mobarak (2014) | 1,900 households, Bangladesh | Having a (seasonal) migrant member | Health expenditure Food expenditure Nonfood expenditure | Null Positive Positive | None studied | Random offer of financial incentive to migrate |
| Garlick, Leibbrandt, and Levinsohn (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 |

incorporation of migration data. In addition, we consider the within-village resource allocation problem for door-to-door sales agents. We create a dashboard that 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 (“sending households” hereinafter). 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 because it directly corresponds to greater revenue for the firm. Moreover, an increase in brand share indicates shifted household preferences toward branded products, as it implies that 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 represent either 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 Cuenca 2010), modern farming technology (Mendola 2008), food and nonfood expenditures (Bryan, Choudhary, and Mobarak 2014), consumer durables (De Brauw and Rozelle 2008), and more capital-intensive forms of entrepreneurship (Yang 2008). In addition, economic remittances could also be used for repayment of debt, savings for major life events, and income diversification (Pan et al. 2020). In contrast to these uses of economic remittances, brand expenditure may be viewed as wasteful, especially when cheaper nonbranded 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 nonessentials. Although the authors do not measure brand expenditure, they document significant expenditure on weddings, religious festivals, and intoxicants that serve in part 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). In addition, because 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 that 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 literature streams suggest that brands (and their associated status signals) may become a spending priority for poor households when they receive economic remittances. Thus, we test the following hypothesis:

H₁: 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 that 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.² Formally:

H₂: The positive effect of economic remittances on brand expenditure and brand share is weaker for households with higher income.

The Impact of Social Remittances

Next, we 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

² Another reason for a negative moderating effect of income might be that rich households already consume as many branded products as they desire. However, the average monthly household income in the top quartile of our sample is 14,962 Rs. (US\$204), which would put them in the middle-income bracket nationally. In addition, brand share is just 31% even in the top quartile, suggesting potential for growth.

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, and 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 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 United States led to “American-style consumerism” and conspicuous consumption in Cuba (Eckstein 2010, p. 1658). 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).³

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 toward 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.⁴ We lay out these moderating hypotheses in detail next.

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 (Mukherjee and Rayapol 2019; Parrenas 2001). 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:

H₃: 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 next 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. Sixty-six percent 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 (Dentsu Aegis Network 2020). 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. 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), though 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 consumers’ attitudes 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, p. 152).

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

³ 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.

⁴ The economic impact of migration can also be conceptualized as the fraction of monetary remittances that is put toward brand expenditure.

brands, contexts for consuming brands, functional benefits of brands over unbranded versions, and the social status conferred by brands. On the one hand, 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 that does not own a TV set and rarely watches TV, their migrant might be one of the few, if not only, credible sources of information about consumption practices outside their village. Thus, TV viewing should negatively affect the quantity and efficacy of social remittances. Consequently, we propose the following:

H₄: After controlling for economic remittances, the effect of migration on brand expenditure and brand share is stronger for sending households that 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 their savings, and is unfamiliar with urban retailing formats (e.g., air-conditioned malls, supermarkets, hypermarkets) 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:

H₅: After controlling for economic remittances, the effect of migration on brand expenditure and brand share is stronger for households that 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 on social and economic remittances. In lieu of direct measures of village retail infrastructure, which are not available to researchers, we proxy for these with village population. More populous villages are visited more frequently by the sales force of the 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.⁵ Drawing on this discussion, we propose the following:

H₆: The effect of migration on brand expenditure and brand share is stronger for sending households in more populous villages.

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

Study I

Data and Sample

We collected data from 403 households from 19 villages in India’s most populous state, Uttar Pradesh (population of 235 million in 2021; 78% rural; per capita annual gross domestic product 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 three times its population. Along with Kantar, we identified six districts to ensure adequate geographical spread. Within each district, Kantar sampled three to four villages, such that (1) 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 (2) the sampled villages were at different distances from the district headquarters, with at least one village in each district located greater than 50 km (31 miles) from the district headquarters.

Following Indian census rules, a migrant was defined as someone who spends at least three months a year away from home. 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: (1) households with no migrant member ($n = 125$), (2) more recent migrant-sending households (i.e., households with at least one migrant member who left the village 3–12 months before the date of the survey [$n = 146$]), and (3) less recent migrant-sending households (i.e., households with at least one migrant member who left the village over 12 months prior to the survey [$n = 132$]). This led to a final sample size of 403 households. Web Appendix 1 provides details on how we implemented the stratified sampling approach. Kantar field personnel administered the survey in a four-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 the migrant’s departure. Of all 278 sending households, 256 received remittances in cash or in kind in the past 12 months. All migrants migrated

⁵ 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.

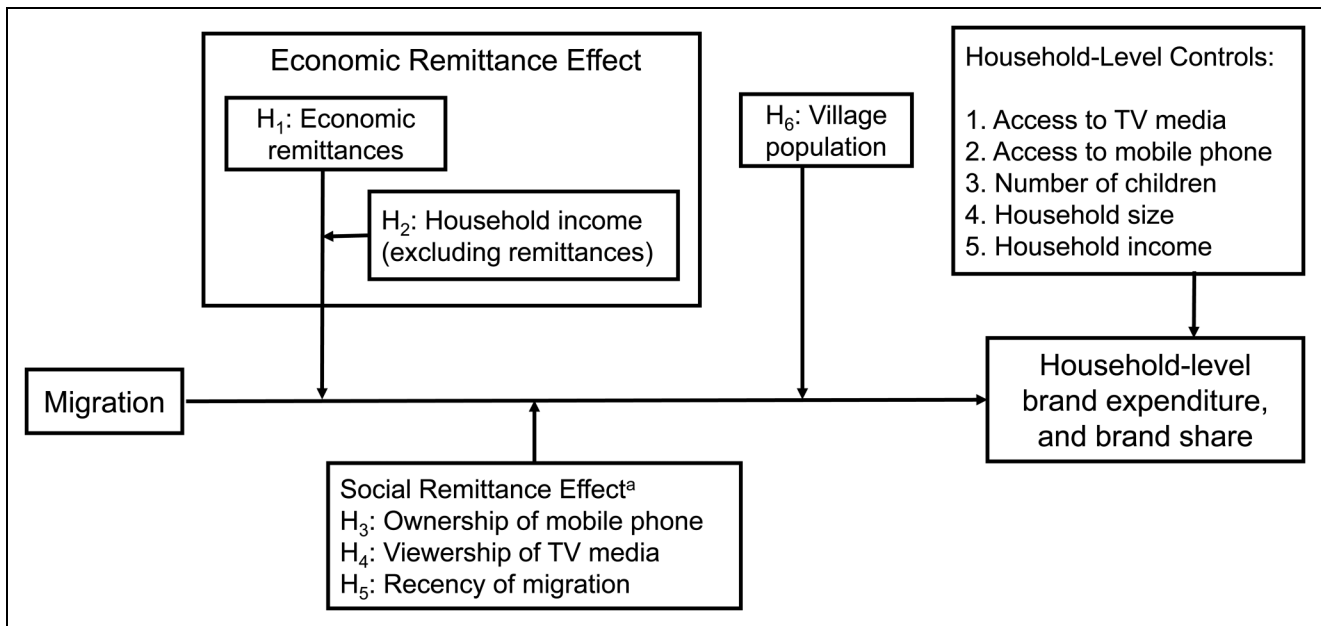


Figure 1. Impact of migration on brand expenditure and brand share of migrant-sending households.

^aThe sum of the interaction effects of migration with ownership of TV, ownership of mobile phone, and the recency of migration is identified as the social remittance effect.

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 nonfood products. Crucially, each respondent also provided data on typical monthly household expenditures on brands (as opposed to unbranded variants) for these food and nonfood 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 (<https://www.ama.org/topics/branding/>). Expenditure on brands 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 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 the 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 subsample of respondents to confirm recall-based expenditure measures. Further details of these and other verification steps appear in Web Appendix 2.

In addition, for each household, Kantar field personnel identified the two households that lived at the shortest distance (i.e., 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 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,

Table 2. Summary Statistics of Each Stratified Sample of Study I.

| Variable | Households Not Sending Migrant | | Households Sending More Recent Migrant | | Households Sending Less Recent Migrant | | All Households | |
|---|--------------------------------|-------|--|-------|--|-------|--------------------|-------|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Monthly expenditure on branded products (Rs.) | 1,406 | 2,631 | 1,165 | 1,779 | 3,662 | 6,960 | 2,058 | 4,509 |
| Monthly expenditure on unbranded products (Rs.) | 3,190 | 2,232 | 4,180 | 2,187 | 3,078 | 1,917 | 3,512 | 2,172 |
| Brand Share | .24 | .26 | .19 | .21 | .40 | .31 | .28 | .28 |
| Econ_Remit _i | N.A. | N.A. | 1,365 | 1,595 | 1,597 | 1,786 | 1,475 ^a | 1,689 |
| 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 | 8,504 | 3,468 | 10,092 | 3,775 | 10,542 | 4,923 | 9,747 | 4,181 |
| TV _i | .70 | .46 | .58 | .49 | .53 | .50 | .60 | .49 |
| Mobile _i | .87 | .34 | .91 | .29 | .89 | .31 | .89 | .31 |
| Village_Pop _i | 2,532 | 970 | 2,517 | 980 | 2,558 | 927 | 2,535 | 958 |
| Number of Households | 125 | | 146 | | 132 | | 403 | |

^aBased on 278 households that sent a migrant.

Notes: 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; N.A. = not applicable.

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 1,475 Rs. (US\$20) per month as economic remittances, which is roughly a fifth of their monthly income excluding remittances. Households that have sent migrants more recently spend less on branded products, and more on unbranded products, than households that have not sent a migrant. However, households that sent a migrant at least a year back spend more on branded products (both in absolute terms and in brand share) than households that 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.

Empirical Strategy and Identification

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

$$\begin{aligned}
 y_i = & \beta_0 + \beta_1 \text{Migrant}_i + \beta_2 \text{HH.Income}_i + \beta_3 \text{TV}_i + \beta_4 \text{Mobile}_i \\
 & + \beta_5 \text{Migrant}_i \times \text{Econ.Remit}_i + \beta_6 \text{Migrant}_i \\
 & \times \text{Econ.Remit}_i \times \text{HH.Income}_i + \beta_7 \text{Migrant}_i \\
 & \times \text{Mobile}_i + \beta_8 \text{Migrant}_i \times \text{TV}_i + \beta_9 \text{Migrant}_i \times \text{Recent}_i \\
 & + \beta_{10} \text{Migrant}_i \times \text{Village.Pop}_i + \beta_{11} \text{Migrant}_i \\
 & \times \text{HH.Income}_i + \mathbf{x}_i' \gamma + \delta_v + \epsilon_i,
 \end{aligned}$$

(1)

where Migrant_i (1 if household i has sent a migrant, 0 otherwise) is our primary measure of migration status. The next six interaction terms correspond to our six hypotheses. Because economic remittances are not relevant for households not sending migrants, we interact economic remittances with the migration indicator. The coefficient of $\text{Migrant}_i \times \text{Econ.Remit}_i$ captures the main effect of economic remittances (H_1). For households that have not sent migrants, both Migrant_i and $\text{Migrant}_i \times \text{Econ.Remit}_i$ are 0. For sending households that do not receive economic remittances, $\text{Migrant}_i \times \text{Econ.Remit}_i$ is 0 but Migrant_i is 1. So, the effect of sending a nonremitting migrant is identified. To understand how monthly household income (HH.Income_i) moderates the effect of economic remittances (H_2), we interact $\text{Migrant}_i \times \text{Econ.Remit}_i$ with HH.Income_i . Having controlled for the effect of economic remittances, we move on to social remittances (H_3 – H_5). The coefficients of $\text{Migrant}_i \times \text{Mobile}_i$, $\text{Migrant}_i \times \text{TV}_i$, and $\text{Migrant}_i \times \text{Recent}_i$ 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 $\text{Migrant}_i \times \text{HH.Income}_i$ so that the effect of $\text{Migrant}_i \times \text{Econ.Remit}_i \times \text{HH.Income}_i$ is not confounded.

The control variables in our model (captured by the vector \mathbf{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 because 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 that 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 nonrandom 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 U.S. state and nonmigrants in that state are quite similar in terms of observed characteristics. However, there could be unobserved factors that systematically affect both migration propensity and brand preferences of the sending household. For example, fluctuating household debt levels could codetermine migration propensity and brand expenditures. These time-varying unobserved factors are not addressed through controls for household income and could lead to biased parameter estimates. To deal with this endogeneity issue, we adopt a two-stage 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.

$$\text{Migrant}_i = \alpha_0 + \alpha_1 IV_i + \alpha_2 \text{Size}_i + \alpha_3 \text{Child}_i + \alpha_4 \text{HH_Income}_i + \alpha_5 \text{TV}_i + \alpha_6 \text{Mobile}_i + \delta_i. \quad (2)$$

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 $E(IV_i \times \epsilon_i) = 0$. 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 because they are more likely to predict household-specific migration behavior and thus not suffer from weak instrument bias. As previously mentioned, we are able to identify the two households in our survey that 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 that 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 that are *not* neighbors of

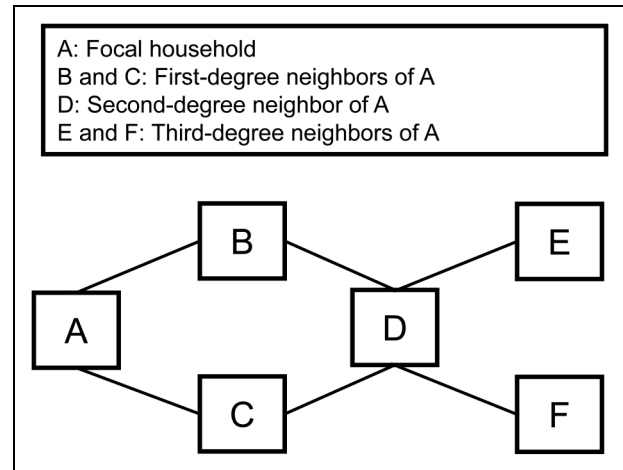


Figure 2. Illustration of identification of least proximate households from focal household.

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.

We identify those two households from the same village as the focal household, that are *farthest* 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 five-household village in Figure 2. Households E and F are farthest 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 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 because migrant-sending behavior of the neighbor is correlated with brand expenditure of the focal household. However, this phenomenon seems far less plausible

for households that have several degrees of separation between them than for immediate neighbors. Therefore, we expect sending behavior of “TV 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. Subsequently, we discuss the robustness of our results to an alternative 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. 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 (1) the sending household’s ownership of mobile phones, (2) the sending household’s viewership of television media, and (3) the recency of the migration event. By estimating Equation 1, we test whether 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.

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 and 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 4–6 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.

We find positive interaction effects of migration status and economic remittances on brand share, in support of H₁ ($\beta = .150$, $SE = .031$, $p < .01$), 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 H₂ ($\beta = -.007$, $SE = .003$, $p < .05$).

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, per H₃ ($\beta = .481$, $SE = .240$, $p < .05$). Our estimates of the effects of TV viewership are in the opposite direction, in accordance with H₄. We find negative interaction effects of migration status and TV ownership, on both brand share ($\beta = -.298$, $SE = .106$, $p < .01$) 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 left the village at least a year before than if the migrant migrated recently, as we theorized in H₅ ($\beta = .192$, $SE = .036$, $p < .01$). This is consistent with greater social remittances in the long term. We also find, in support of H₆, 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 its 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 they 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 two-stage least squares model to compute household specific estimates of the marginal overall effect of migration among migrant-sending households on brand share.

$$\begin{aligned} \text{Marg}_{i,\text{migrant_sending}} = & \beta_1 + \beta_5 \text{Econ_Remit}_i + \beta_6 \text{Econ_Remit}_i \\ & \times \text{HH_Income}_i + \beta_7 \text{Mobile}_i + \beta_8 \text{TV}_i \quad (3) \\ & + \beta_9 \text{Recent}_i + \beta_{10} \text{Village_Pop}_i \\ & + \beta_{11} \text{HH_Income}_i. \end{aligned}$$

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. In line with our parameter estimates, these are households that receive greater economic remittances, live in more populous villages, and own mobile phones. The minimum, mean, and maximum marginal effects for households that 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 1,000 Rs. of economic remittances on the brand shares of households. This is given by $\beta_5 + \beta_6 \text{HH_Income}_i$. The minimum, mean, and maximum marginal effects of economic remittances across all households that 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 $.085$ ($\text{SE} = .015$, $t = 5.484$), 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 $\beta_7 \text{Mobile}_i + \beta_8 \text{TV}_i + \beta_9 \text{Recent}_i$. As discussed previously, the ownership of mobile phones and TV and the recency of migration serve as reasonable proxies across which we expect social remittances to vary. Because all three measures are binary, the marginal effect takes eight 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 $.313$ ($\text{SE} = .047$, $t = 6.716$), 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., $\beta_5 + \beta_6 \text{HH_Income}_i / (\beta_7 \text{Mobile}_i + \beta_8 \text{TV}_i + \beta_9 \text{Recent}_i)$. At mean values of these variables, this ratio is $.224$, suggesting

that the economic remittance effects are weaker than social remittance effects in our data. However, we caution against conclusive interpretations of relative magnitudes because $\beta_7 \text{Mobile}_i + \beta_8 \text{TV}_i + \beta_9 \text{Recent}_i$ is only our best proxy measure of the social remittance effect rather than a precise and complete measure. Direct measures of social remittances would allow for 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 previously, 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.⁶ 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 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 . Therefore, 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 three years). Village-level fixed effects control for that possibility.

⁶ See <https://orcid.org/0000-0001-7230-3084>.

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

| Instrument | Model 1 | Model 2 |
|---|--|---|
| | Migration status of distant households | Number of days of employment from employment scheme |
| Coefficient of instrument | .408*** (.044) | -.258*** (.041) |
| Size _i | .002 (.016) | .023* (.017) |
| Child _i | -.028 (.026) | -.039 (.027) |
| HH_Income _i | .011* (.006) | .014** (.006) |
| TV _i | -.099* (.055) | -.089 (.059) |
| Mobile _i | .072 (.070) | .054 (.074) |
| R ² | .25 | .17 |
| F-statistic | 5.35*** | 3.23** |
| R ² (without instrument) | .08 | .08 |
| F-statistic (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*** |

* $p < .1$.** $p < .05$.*** $p < .01$.

Notes: 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 located farthest 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.

Importantly, because 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 ($M = .11$, $SE = .38$), suggesting that this instrument satisfies the exclusion restriction. We estimate the two-stage least squares 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.

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 that 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, whereas our moderation hypotheses 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 rule out the possibility of our results being affected by unobservable differences between sending and nonsending 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 premigration 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) that 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 six districts within each state, and three to four 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 telephone 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, telephone 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 ten

Table 4. Effects of Migration on Brand Share, Expenditure on Branded Products, and Expenditure on Unbranded Products (with Network-Based Instrument).

| Dependent variable | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|-----------------|----|----------------|----|----------------|-----|-----------------|-----|--------------------------|-----|----------------------------|-----|
| | Brand share | | Brand share | | Brand share | | Brand share | | Exp. on branded products | | Exp. on unbranded products | |
| Migrant _i | .279** (.056) | | .078 (.101) | | .281*** (.061) | | -1.901** (.739) | | -32,103** (14,154) | | 13,794** (5432) | |
| HH_Income _i | .007** (.004) | | .010* (.006) | | -.000 (.004) | | -.027* (.014) | | -422.0 (275.5) | | 396.8*** (105.7) | |
| TV _i | .098*** (.028) | | .141*** (.046) | | -.005 (.032) | | .271*** (.097) | | 5,302*** (1866) | | -574.6 (716.0) | |
| Mobile _i | .028 (.045) | | .087 (.065) | | -.046 (.040) | | -.308** (.148) | | -5,604** (2,833) | | 3,172*** (1,087) | |
| Migrant _i × Econ_Rem _i ; (H ₁) | N.A. | | .083*** (.019) | | N.A. | | .150*** (.031) | | 2,478*** (781.2) | | -979.2** (299.8) | |
| Migrant _i × Econ_Rem _i × HH_Income _i ; (H ₂) | N.A. | | -.002** (.001) | | N.A. | | -.007** (.003) | | -127.1** (63.13) | | 61.49** (24.22) | |
| Migrant _i × Mobile _i ; (H ₃) | N.A. | | .134* (.082) | | N.A. | | .481** (.240) | | 7,689* (4,604) | | -4,515.8** (1,766.8) | |
| Migrant _i × TV _i ; (H ₄) | N.A. | | -.106* (.054) | | N.A. | | -.298*** (.106) | | -4,083** (2,023) | | 932.7 (776.2) | |
| Migrant _i × Recent _i ; (H ₅) | N.A. | | .189*** (.028) | | N.A. | | .192*** (.036) | | 2,763*** (705.9) | | -1,129.7*** (270.9) | |
| Migrant _i × Village_Pop _i ; (H ₆) | N.A. | | .045** (.015) | | N.A. | | .238** (.098) | | 4,546** (1,874) | | -1,426.0** (719.1) | |
| Migrant _i × HH_Income _i | N.A. | | .010* (.006) | | N.A. | | .046* (.021) | | 765.4* (408.7) | | -420.0** (156.8) | |
| Size _i | .002 (.009) | | -.010 (.008) | | -.020** (.000) | | .001 (.011) | | 184.2 (215.5) | | 112.3 (82.7) | |
| Child _i | -.036*** (.014) | | -.003 (.012) | | .020 (.015) | | .003 (.017) | | 12.98 (323.7) | | -236.1** (124.2) | |
| R ² | .060 | No | .308 | No | .282 | Yes | .552 | Yes | .250 | Yes | .783 | Yes |
| Instrument for migration | | No | | No | | Yes | | Yes | | Yes | | Yes |

*p < .1.

**p < .05.

***p < .01.

Notes: Migrant_i is 1 if the household has a migrant member, 0 otherwise; Econ_Rem_i = mean remittances received by the household per month, in thousands of rupees; Village_Pop_i = the population (in thousands) of the village in which the household resides; HH_Income_i is in thousands of rupees; N.A. = not applicable. All models incorporate village-specific fixed effects. Recent_i = 1 if migrant left household over one year ago and 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 "N.A." were not included in the model. The instrument in all models is the migrant-sending status of the two households in the same village that are farthest 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).

| Dependent variable | Model 1 | Model 2 | Model 3 |
|---|---------------------|--------------------------|----------------------------|
| | Brand share | Exp. on branded products | Exp. on unbranded products |
| Migrant _i | -1.713*** (.645) | -32,105** (12,927) | 10,510** (4,518) |
| HH_Income _i | -.023* (.013) | -420.5 (257.2) | 340.7*** (89.9) |
| TV _i | .251*** (.087) | 5,292*** (1,758) | -219.9 (614.5) |
| Mobile _i | -.275** (.013) | -5,588** (2,647) | 2,560*** (925.3) |
| Migrant _i × Econ_Rem _i (H ₁) | .141*** (.037) | 2,474*** (733.0) | -815.7** (256.2) |
| Migrant _i × Econ_Rem _i × HH_Income _i (H ₂) | -.006** (.003) | -126.8** (60.04) | 50.44** (20.98) |
| Migrant _i × Mobile _i (H ₃) | .423** (.212) | 7,689* (4,256) | -3,517** (1,487) |
| Migrant _i × TV _i (H ₄) | -.276*** (.095) | -4,072** (1,906) | 549.0 (666.3) |
| Migrant _i × Recent _i (H ₅) | .188*** (.034) | 2,760*** (691) | -1,049.9*** (241.6) |
| Migrant _i × Village_Pop _i (H ₆) | .214** (.086) | 4,535** (1,722) | -1,004.5* (601.7) |
| Migrant _i × HH_Income _i | .041** (.019) | 763.0** (377.5) | -330.8** (131.9) |
| Size _i | -.001 (.010) | 183.8 (211.8) | 134.2* (74.0) |
| Child _i | .004 (.011) | 13.36 (322.0) | -253.2** (112.5) |
| R ² | .592 | .393 | .821 |
| Instrument for migration | Yes | Yes | Yes |

p* < .1.*p* < .05.****p* < .01.

Notes: Migrant_i is 1 if the household has a migrant member, 0 otherwise; Econ_Rem_i = mean remittances received by the household per month, in thousands of rupees; Village_Pop_i = the population

(in thousands) of the village in which the household resides; HH_Income_i = in thousands of rupees. All models incorporate village-specific fixed effects. Recent_i = 1 if migrant left household over one year ago and 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.

minutes per respondent. For this reason, we focused solely on testing our six hypotheses, with a simple before-and-after research design. In addition to collecting data on all moderators in Equation 1 (household income, village population, TV ownership, recency of migration, and monthly remittances) and controls (household size and whether the household has children), Kantar first asked respondents to recall household expenditure on branded and 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. Because 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.

$$\begin{aligned}
 y_{is} = & \beta_0 + \beta_1 \text{Post}_{is} + \beta_2 \text{HH.Income}_{i} + \beta_3 \text{TV}_{i} + \beta_4 \text{Post}_{is} \\
 & \times \text{Econ.Rem}_{i} + \beta_5 \text{Post}_{is} \times \text{Econ.Rem}_{i} \\
 & \times \text{HH.Income}_{is} + \beta_6 \text{Post}_{is} \times \text{TV}_{i} + \beta_7 \text{Post}_{is} \times \text{Recent}_{i} \quad (4) \\
 & + \beta_8 \text{Post}_{is} \times \text{Village.Pop}_{i} + \beta_9 \text{Village.Pop}_{i} \\
 & + \mathbf{x}_{is}'\gamma + \alpha_i + \theta_d + \epsilon_{is},
 \end{aligned}$$

where Post_{is} (1 if observation *s* for household *i* is post migration and 0 otherwise) is the treatment indicator (before or

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>i</i>} | .008 (.014) | -1,233.0 (805.9) | 283.3** (103.8) |
| HH_Income _{<i>i</i>} | -1.94×10^{-7} (8.10×10^{-7}) | .032 (.039) | .006 (.006) |
| TV _{<i>i</i>} | .037* (.020) | 646.8 (586.3) | 975.5** (337.2) |
| Post _{<i>i</i>} × Econ_Rem _{<i>i</i>} (H ₁) | 2.57×10^{-6} *** ($.33 \times 10^{-6}$) | .12*** (.02) | .002 (.002) |
| Post _{<i>i</i>} × Econ_Rem _{<i>i</i>} × HH_Income _{<i>i</i>} (H ₂) | -3.15×10^{-8} (2.81×10^{-8}) | -.002 (.002) | .000 (.002) |
| Post _{<i>i</i>} × TV _{<i>i</i>} (H ₄) | -.113*** (.009) | -3,891.9*** (555.4) | 10.4 (56.7) |
| Post _{<i>i</i>} × Recent _{<i>i</i>} (H ₅) | .058*** (.012) | 1,733.0** (618.1) | 64.3 (78.2) |
| Post _{<i>i</i>} × Village_Pop _{<i>i</i>} (H ₆) | .009*** (.002) | 4,886.3*** (114.7) | 23.5** (11.7) |
| Size _{<i>i</i>} | -.001 (.003) | 179.1** (85.1) | 370.0*** (55.5) |
| Child _{<i>i</i>} | .011 (.027) | 701.8 (689.8) | -184.2 (455.3) |
| Village_Pop _{<i>i</i>} | -.004 (.004) | -95.9 (126.9) | -37.0 (74.8) |
| R ² | .352 | .392 | .392 |

p* < .1.*p* < .05.****p* < .01.

Notes: Post_{*i*} is 1 if observation pertains to post migration period and 0 otherwise; Econ_Rem_{*i*} = mean remittances received by the household per month, in thousands of rupees; Village_Pop_{*i*} = 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 one year ago and 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, and expenditure on unbranded products is the dependent variable for Model 3.

after). The coefficient of Post_{*i*} × Econ_Rem_{*i*} captures the main effect of economic remittances (H₁). The coefficients of Post_{*i*} × TV_{*i*}, Post_{*i*} × Village_Pop_{*i*}, and Post_{*i*} × Recent_{*i*} capture the moderating effects of TV ownership, village retail infrastructure, and recency of migration, respectively, 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 that 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 three-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 intrahousehold variations for identification.

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 policy makers 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

Table 7. Improving Sales Force Allocation by Incorporating Migration Information.

| Village | Population (L) | Household-Level Brand Exp. ^a (from Study) (M) | Optimal Sales Force Days (N) | Predicted Brand Exp. ^a (B1) | Sales Force Days Based on B1 (O) | Predicted Brand Exp. ^a (B2) | Sales Force 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 |

^aPer household, in rupees.

Notes: All sales force days pertain to monthly allocations; village names have not been shared to protect the privacy of respondents; optimal sales force days (N) for a village are the village-level brand expenditure (based on population and household-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, household size, and number of children in the household. Sales force allocation based on baseline data (O) is given by $(B1 \times \text{village population} / 5.49 \times 50,000)$, 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). Sales force allocation based on this “baseline and migration” data (P) is given by $(B2 \times \text{village population} / 5.49 \times 50,000)$, rounded to the nearest integer. Mean absolute data (MAD) with “baseline data” (the mean of the absolute difference between the sales force days allocated to a village based on baseline data and optimal sales force 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 sales force days. Further details appear in Web Appendix 10.

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 in which a marketing manager has a limited sales force and is trying to decide the number of “sales force 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, and so on. For this purpose, the manager estimates the monthly expenditure on branded products in each village and allocates one sales force visit day per month for every 200,000 Rs. of brand expenditure. Table 7 shows the allocation of sales force days for a market of nine 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, these data are not available to marketers, so they need to predict it.

Next, we predict household-level brand expenditure using Equation 1, based on the following “baseline” data from our study that are not related to migration. We note that these

“baseline” data closely resemble the data a typical marketing manager might have. We estimate our model using baseline data from households in the remaining ten villages (i.e., those not in the aforementioned set of nine villages) and then make out-of-sample predictions of brand expenditure for all households in the nine villages (see Table 7). Drawing on these estimates, we report village-level sales force 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 nine villages and report village-level sales force day allocations using the “baseline and migration” data.

We find that the MAD in the number of sales force days allocated per village under the “optimal” allocation and allocation based on “baseline” data is 16.2 days. In contrast, the MAD in the number of sales force 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 (e.g., TV ownership) are 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 are 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, telephone surveys are a cheaper alternative to door-to-door surveys.

Intravillage 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 that 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 that 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.

As migrant-sending households that 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 cooperatives, 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,

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 | N.A. | 2,449 | 1,020 | 1,487 | 848 |
| Migrant left 3–12 months ago | High | 1,073 | 2,612 | 1,805 | 2,076 |
| | Low | 605 | 503 | 564 | 549 |
| Migrant left over a year ago | High | 7,744 | 3,108 | 6,018 | 9,037 |
| | Low | 2,530 | 1,008 | 1,337 | 3,900 |

Notes: N.A. = not applicable. Each cell contains the predicted brand expenditure for households in that cell. For example, for all households that receive “low” remittances, have a migrant who left over a year previous, and own a TV, the predicted brand expenditure is 2,530 Rs. High remittance exceeds the median value of 917 Rs. per month.

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 ago) 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 that 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 that 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 behavior 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’ aspirations 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. However, 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. In addition, 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. In addition, 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 toward status-enhancing opportunities could 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 in identification of potentially nonlinear 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 could explore whether this type of migration influences poverty and inequality in sending communities.

Acknowledgments

The authors thank Vrinda Kadiyali, Aradhna Krishna, Dinesh Puranam, and seminar participants at the Cambridge Judge School of Business, the University of Technology Sydney, and the 2019 Marketing Science Conference in Italy for useful comments and suggestions. Finally, the authors thank field personnel of Kantar India for their painstaking efforts for high-quality data collection from rural India.

Associate Editor

Hari Sridhar


Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The first author acknowledges generous financial support by the National University of Singapore.

ORCID iD

Vishal Narayan  <https://orcid.org/0000-0001-7230-3084>

References

- Adams, Richard H. Jr. (1998), "Remittances, Investment, and Rural Asset Accumulation in Pakistan," *Economic Development and Cultural Change*, 47 (1), 155–73.
- Adams, Richard H. Jr. and Alfredo Cuecuecha (2010), "Remittances, Household Expenditure and Investment in Guatemala," *World Development*, 38 (11), 1626–41.
- Adams, Richard H. Jr., Alfredo Cuecuecha, and John Page (2008), "The Impact of Remittances on Poverty and Inequality in Ghana," Policy Research Working Paper No. 4732, World Bank.
- Banerjee, Abhijit V. and Esther Duflo (2007), "The Economic Lives of the Poor," *Journal of Economic Perspectives*, 21 (1), 141–68.
- Bronnenberg, Bart J., Jean-Pierre Dubé, and Matthew Gentzkow (2012), "The Evolution of Brand Preferences: Evidence from Consumer Migration," *American Economic Review*, 102 (6), 2472–2508.
- Brown, Richard P.C. and Gareth Leeves (2007), *Impacts of International Migration and Remittances on Source Country Household Incomes in Small Island States: Fiji and Tonga*. Brisbane, Australia: University of Queensland.
- Bryan, Gharad, Shyamal Chowdhury, and Ahmed M. Mobarak (2014), "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 82 (5), 1671–1748.
- Chandy, Rajesh and Narasimhan Om (2015), "Millions of Opportunities: An Agenda for Research in Emerging Markets," *Customer Needs and Solutions*, 2 (4), 251–63.
- Das, Pallav (2011), "MGNREGA and Rural-Urban Migration in India," *Journal of Research in Commerce and Management*, 2 (2), 43–47.

- Datta, Amrita and Sunil Kumar Mishra (2011), "Glimpses of Women's Lives in Rural Bihar: Impact of Male Migration," *Indian Journal of Labour Economics*, 54 (3), 457–77.
- De, Supriyo (2019), "Internal Migration in India Grows, But Inter-State Movements Remain Low," *World Bank Blogs* (December 18), <https://blogs.worldbank.org/peoplemove/internal-migration-india-grows-inter-state-movements-remain-low>.
- De Brauw, Alan and Scott Rozelle (2008), "Migration and Household Investment in Rural China," *China Economic Review*, 19 (2), 320–35.
- Dentsu Aegis Network (2020), "Digital Advertising in India 2020," research report (accessed August 17, 2021), https://dentsu.in/uploads/digital_reports/DAN-e4m-Digital-Report-2020-Web-C3.pdf.
- Dolan, Catherine (2012), "The New Face of Development: The 'Bottom of the Pyramid' Entrepreneurs," *Anthropology Today*, 28 (4), 3–7.
- Dolan, Catherine and Linda Scott (2009), "Lipstick Evangelism: Avon Trading Circles and Gender Empowerment in South Africa," *Gender and Development*, 17 (2), 203–18.
- Eckstein, Susan (2010), "Immigration, Remittances, and Transnational Social Capital Formation: A Cuban Case Study," *Ethnic and Racial Studies*, 33 (9), 1648–67.
- Esquivel, Gerardo and A. Huerta-Pineda (2007), "Remittances and Poverty in Mexico: A Propensity Score Matching Approach," *Integration and Trade Journal*, 27 (11), 45–57.
- Food and Agriculture Organization of the United Nations (2010), "Committee on Commodity Problems: Intergovernmental Group on Tea, 19th Session," (May), <http://www.fao.org/3/AL289E/AL289E.pdf>.
- Garlick, Julia, Murray Leibbrandt, and James Levinsohn (2016), "Individual Migration and Household Incomes," National Bureau of Economic Research, No. w22326.
- Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!" *Journal of Marketing*, 79 (3), 1–22.
- Gibson, John, David McKenzie, and Steven Stillman (2011), "The Impacts of International Migration on Remaining Household Members: Omnibus Results from a Migration Lottery Program," *Review of Economics and Statistics*, 93 (4), 1297–1318.
- Gupta, Soumya (2017), "Television Still the Best Way to Reach Rural Consumers: IMRB," *LiveMint* (September 2), <https://www.livemint.com/Consumer/xLQzroqNCCBvBrIVfbbmAO/Television-still-the-best-way-to-reach-rural-consumers-IMRB.html>.
- Hiwatri, Masato (2016), "Social Networks and Migration Decisions: The Influence of Peer Effects in Rural Households in Central Asia," *Journal of Comparative Economics*, 44 (4), 1115–31.
- Imbert, Clement and John Papp (2020), "Short-Term Migration, Rural Public Works, and Urban Labor Markets: Evidence from India," *Journal of the European Economic Association*, 18 (2), 927–63.
- Irina, Isaakyan and Anna Triandafyllidou (2017), "Sending So Much More Than Money: Exploring Social Remittances and Transnational Mobility," *Ethnic and Racial Studies*, 40 (15), 2787–2805.
- Jaikumar, Saravana and Ankur Sarin (2015), "Conspicuous Consumption and Income Inequality in an Emerging Economy: Evidence from India," *Marketing Letters*, 26 (3), 279–92.
- Johnson, Kirk (2001), "Media and Social Change: The Modernizing Influences of Television in Rural India," *Media, Culture & Society*, 23 (2), 147–69.
- Kamakura, Wagner A. and Du Rex Yuxing (2012), "How Economic Contractions and Expansions Affect Expenditure Patterns," *Journal of Consumer Research*, 39 (2), 229–47.
- Karlson, Kurt A., Jared Wolfe, Simon J. Blanchard, Joel C. Huber, and Dan Ariely (2015), "The Budget Contraction Effect: How Contracting Budgets Lead to Less Varied Choice," *Journal of Marketing Research*, 52 (3), 337–48.
- Kersley, Richard and Maria Bhatti (2017), "The Credit Suisse EM Consumer Survey 2017: China and India's New Consumption Recovery," Credit Suisse (March), <https://www.credit-suisse.com/media/assets/corporate/docs/about-us/research/publications/emerging-consumer-survey-2017.pdf>.
- Kumar, K.S. Kavi and Brinda Viswanathan (2012), "Weather Variability and Agriculture-Implications for Long- and Short-Term Migration in India," Working paper 220, Centre for Development Economics, Delhi School of Economics.
- Lamey, Lien, Barbara Deleersnyder, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2007), "How Business Cycles Contribute to Private Label Success: Evidence from the United States and Europe," *Journal of Marketing*, 71 (1), 1–15.
- Leclerc, France, Christopher K. Hsee, and Joseph C. Nunes (2005), "Narrow Focusing: Why the Relative Position of a Good in Its Category Matters More than It Should," *Marketing Science*, 24 (2), 194–205.
- Levitt, Peggy (1998), "Social Remittances: Migration Driven Local-Level Forms of Cultural Diffusion," *International Migration Review*, 32 (4), 926–48.
- Lindstrom, David P. and Elisa Muñoz-Franco (2005), "Migration and the Diffusion of Modern Contraceptive Knowledge and Use in Rural Guatemala," *Studies in Family Planning*, 36 (4), 277–88.
- Mahapatro, Sandhya, Ajay Bailey, K.S. James, and Inge Hutter (2017), "Remittances and Household Expenditures in India and Selected States," *Migration and Development*, 6 (1), 83–101.
- Mendola, Mariapia (2008), "Migration and Technological Change in Rural Households: Complements or Substitutes?" *Journal of Development Economics*, 85 (1/2), 150–75.
- Mergo, Teferi (2016), "The Effects of International Migration on Migrant-Source Households: Evidence from Ethiopian Diversity-Visa Lottery Migrants," *World Development*, 84, 69–81.
- Mishra, Digbijay (2013), "Demand for Unbranded Products on a Rise: Survey," *Business Standard* (February 12), http://www.business-standard.com/article/companies/demand-for-unbranded-products-on-a-rise-survey-113021200886_1.html.
- Mohanty, Sanjay K., Manisha Dubey, and Jajati K. Parida (2014), "Economic Well-Being and Spending Behavior of Households in India: Does Remittances Matter?" *Migration and Development*, 3 (1), 38–53.
- Morten, Melanie (2019), "Temporary Migration and Endogenous Risk Sharing in Village India," *Journal of Political Economy*, 127 (1), 1–46.
- Mukherjee, Anushyama and Aparna Rayaprol (2019), "Women Migrants and Social Remittances: The Case of Barkas in

- Hyderabad," *Review of Women's Studies, Economic & Political Weekly*, 54 (17), 62–68.
- Narayan, Vishal, Vithala R. Rao, and K. Sudhir (2015), "Early Adoption of Modern Grocery Retail in an Emerging Market: Evidence from India," *Marketing Science*, 34 (6), 825–42.
- O'Guinn, Thomas C. and L.J. Shrum (1997), "The Role of Television in the Construction of Consumer Reality," *Journal of Consumer Research*, 23 (4), 278–94.
- Pan, Zehan, Xu Wei, Guixin Wang, Sen Li, and Chuankai Yang (2020), "Will Remittances Suppress or Increase Household Income in the Migrant-Sending Areas? Modeling the Effects of Remittances in Rural China," *China Economic Review*, 61, 101452.
- Parrenas, Rhacel S. (2001), "Mothering from a Distance: Emotions, Gender and Intergenerational Relations in Filipino Transnational Families," *Feminist Studies*, 27 (2), 361–90.
- Raja, Vidya (2019), "Tring Tring! NEARLY Three-Fourths of Rural India Has a Mobile Connection Now," *The Better India* (January 24), <https://www.thebetterindia.com/170458/india-mobile-connectivity-handset-rural-growth/>.
- Sheth, Jagdish N. (2011), "Impact of Emerging Markets on Marketing: Rethinking Existing Perspectives and Practices," *Journal of Marketing*, 75 (4), 166–82.
- Sheth, Jagdish. N. Mona Sinha and Reshma Shah (2016), *Breakout Strategies for Emerging Markets: Business and Marketing Tactics for Achieving Growth*. London: Pearson Education.
- Shrum, L.J., James E. Burroughs, and Aric Rindfleisch (2005), "Television's Cultivation of Material Values," *Journal of Consumer Research*, 32 (3), 473–79.
- Singhi, Abheek, Nimisha Jain, and Namit Puri (2015), "CII National FMCG Summit: 2015: Re-Imagining FMCG in India," research report (December), The Boston Consulting Group, <https://media-publications.bcg.com/india/Re-Imagining-FMCG-in-India.pdf>.
- Solari, Cinzia D. (2019), "Transnational Moral Economies: The Value of Monetary and Social Remittances in Transnational Families," *Current Sociology*, 67 (5), 760–77.
- Stark, Oded and Robert E. Lucas (1988), "Migration, Remittances, and the Family," *Economic Development and Cultural Change*, 36 (3), 465–81.
- Suksomboon, Panitee (2008), "Remittances and 'Social Remittances': Their Impact on Livelihoods of Thai Women in the Netherlands and Non-Migrants in Thailand," *Gender, Technology and Development*, 12 (3), 461–82.
- Sunder, Sarang, Kihyun Hannah Kim, and Eric A. Yorkston (2019), "What Drives Herding Behavior in Online Ratings? The Role of Rater Experience, Product Portfolio, and Diverging Opinions," *Journal of Marketing*, 83 (6), 93–112.
- Van Kempen, Luuk (2007), "Status Consumption and Ethnicity in Bolivia: Evidence from Durables Ownership," *International Journal of Consumer Studies*, 31 (1), 76–89.
- Viswanathan, Madhubalan, Nita Umashankar, Arun Sreekumar, and Ashley Goreczny (2021), "Marketplace Literacy as a Pathway to a Better World: Evidence from Field Experiments in Low-Access Subsistence Marketplaces," *Journal of Marketing*, 85 (3), 113–29.
- Yang, Dean (2008), "International Migration, Remittances and Household Investment: Evidence from Philippine Migrants' Exchange Rate Shocks," *Economic Journal*, 118 (528), 591–630.
- Zhang, Wanqing, Pradeep Chintagunta, and Manohar Kalwani (2021), "Social-Media, Influencers, and Adoption of an Eco-Friendly Product: Field Experiment Evidence from Rural China," *Journal of Marketing*, 85 (3), 10–27.