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Consumption Smoothing, Commodity Markets, and Informal Transfers

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Abstract

How do low-income, rural households smooth consumption in the face of seasonal and stochastic variation in income when household access to formal financial services is limited? And how do consumption smoothing modes evolve in response to changes in transport infrastructure? We explore these questions by studying milk consumption smoothing for a panel of households from rural India. Household milk consumption is highly but incompletely smoothed relative to intertemporal variation in household milk production. Informal inter-household transfers provide only modest quasi-insurance. Mainly, households smooth consumption through milk market transactions. And as new roads reach villages, markets become even more important mechanisms for consumption smoothing, especially in high productivity seasons. These patterns underscore the central importance of product market participation for risk management in low-income rural communities.

Keywords: India, insurance, market participation, risk sharing, transactions costs

JEL codes: O12, D12, Q12

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1. Introduction

A large, longstanding body of economic theory and empirical evidence supports the hypothesis that people try to smooth consumption in the face of income that varies over time due to life cycle, seasonal and/or stochastic processes (Modigliani and Brumberg 1954; Friedman 1956; Hall 1978; Paxson 1992, 1993; Carroll 1997; Gourinchas and Parker 2002). Financial services – i.e., credit, insurance, and savings – are typically posited as the principal means by which people consumption smooth (Besley 1995; Deaton 1997). But low-income households routinely face liquidity constraints due to limited access to formal financial services and are therefore commonly found unable to fully smooth consumption (Zeldes 1989; Deaton 1991,1992). An extensive literature therefore explores alternative methods by which low-income households fill gaps in formal financial market access, such as through savings in the form of livestock, adjustments to labor supply, access to informal credit or insurance, etc. (Fafchamps 1992; Rosenzweig and Wolpin 1993; Alderman and Paxson 1994; Townsend 1994; Udry 1994; Fafchamps et al. 1998; Rose 2001; Fafchamps and Lund 2003; Dercon 2004; Attanasio et al. 2005; De Weerdt and Dercon 2006; Kazianga and Udry 2006; Fafchamps and Gubert 2007a,b; Fafchamps 2011; Ábrahám and Laczó 2018).

The literature has largely overlooked, however, the extent to which people use product market sales and purchases to smooth consumption.[1] The intuition behind product market transactions as a consumption smoothing mechanism is straightforward, indeed perhaps so straightforward as to have gone largely overlooked. Under perfect autarky, people only consume

[1] Barrett (2007) discusses how the 'displaced distortions' of financial market failures often manifest in product market transactions, for example the buy-low-sell-high phenomenon often observed in staple grains commodity markets (Stephens and Barrett 2011; Burke et al. 2019).

what they produce, thus consumption varies intertemporally with seasonal or stochastic variation in production, especially for non-storable goods. Deviations between consumption and production for purely autarkic households arise mainly due to informal transfers – gifts, loans, state-contingent insurance payments, etc. – among households. But as people leave autarky and engage in market-based exchange, they sell surpluses and purchase to fill shortfalls relative to optimal consumption levels, thereby smoothing out intertemporal variation in own production. The literature on agricultural household models and product market participation formalizes this intuition, clearly showing that market frictions destabilize consumption (Singh et al. 1986; Rosenzweig 1988; de Janvry et al. 1991; Zimmerman and Carter 2003; Barrett 2008). The agricultural household modeling and market participation literature, however, typically ignores the possibility of informal mutual insurance among households and largely abstracts away from intertemporal issues like consumption smoothing, just as the literature on informal insurance has assumed away consumption smoothing through commodity market transactions.

This paper links the consumption smoothing, informal insurance, and market participation literatures. We empirically explore how low-income, rural households jointly use product markets and informal, mutual insurance to smooth consumption and how exogenous changes to market access affect the extent and manner of households' consumption smoothing.

More precisely, we use monthly household panel data from rural India to study milk consumption smoothing in the face of seasonal and stochastic milk production. India is the world's largest milk producer and Indians consume considerably more milk than the global average, despite below-average income (USDA 2023). This reflects the unusual importance of regular milk consumption as a source of protein and key minerals – e.g., calcium, magnesium, potassium –

essential to good nutrition and health among vegetarians (Weaver 2009), who comprise more than a third of India's population (USDA 2023). Milk consumption smoothing is therefore essential from a food and nutrition security perspective. But milk production varies intertemporally because dairy animals' lactation cycle is highly sensitive to local weather conditions (Sirohi and Michaelowa 2007; Key and Sneeringer 2014). Moreover, milk production is typically correlated with crop production and off-farm income-earning opportunities in rural villages because weather and other shocks affect many sectors simultaneously (Birthal and Negi 2012; Perez-Mendez et al. 2019; Thornton and Herrero 2014). Furthermore, fluid milk is highly perishable, especially in hot tropical communities with little access to refrigeration; households cannot safely store it for more than several hours (Bachmann 1985; Rajendran and Mohanty 2004).[2] The non-storability of milk implies that rural households who lack reliable access to formal financial services must consumption smooth via some combination of sales and purchases through local markets and/or informal mutual insurance by way of informal transfers. This provides an excellent empirical setting to explore to what extent rural households depend on product markets versus non-market risk-sharing arrangements for consumption smoothing.

Households' relative dependence on market exchange versus informal transfers may evolve as transport infrastructure changes. Evidence from the literature suggests that high trade frictions and transaction costs can impede risk sharing (Fitzgerald 2012; Jack and Suri 2014). Better road infrastructure can make distant markets and relatives more accessible. Improved access might induce either an expanded mutual insurance network through more distant relatives whose

[2] Milk can be processed into products like butter, cheese, ghee or yogurt that are storable for somewhat longer periods. But such processing requires added inputs (especially of labor) and transformation from a liquid into a solid, obviating the health gains from fluid milk consumption in places where access to potable water remains limited. Milk can also be dried and stored as powder for really long periods, but doing so requires industrial-scale equipment far beyond the scale of individual households.

income streams are less strongly correlated with local villagers' (Rosenzweig and Stark 1989; Munshi and Rosenzweig 2016) or substitution away from reliance on informal transfers to smooth consumption as commodity market transactions become cheaper. It is unclear ex ante which effect will dominate. We use data on targeted, rule-based road construction and upgrading under the Pradhan Mantri Gram Sadak Yojana (PMGSY) program as a natural experiment to study how village-level exogenous variation in road connectivity influences households' consumption smoothing patterns via informal insurance relative to commodity market transactions.

In the remainder of the paper, we first describe the data and establish the considerable seasonality and stochasticity of milk production. We then develop an empirical approach that starts from the canonical social planner-based consumption risk sharing model (Townsend 1994) to test for within-community household risk-sharing in milk consumption. We then decompose observed consumption smoothing into the contributions of different channels: milk sales and purchases, as well as non-market inter-household transfers. We find that although Indian dairy-producing households do not achieve complete risk-sharing, on average, household milk consumption is insured from around 80 percent of the variation in household milk production. Far more consumption smoothing is achieved through milk purchases and sales in local product markets, not via informal transfers among households. Informal transfers play a role, but the quasi-insurance they provide is relatively modest. As one would expect based on household endowments, smaller farmers rely more on market purchases and larger, surplus-producing farmers rely more on sales to smooth milk consumption. Improved road access raises sales prices, lowers purchase prices, increases reliance on product markets for consumption smoothing, and reduces consumption smoothing via informal transfers, especially in winter for those with more livestock, suggesting that increased access to distant markets is more important than increased access to distant relatives.

There are two advantages of looking at village milk markets within the risk-sharing framework. First, the risk-sharing formulation essentially tests for complete markets. By comparing what we observe in the data with the social planners's optimum, we establish how far or close village milk markets are from that benchmark. Hence the literature testing the risk-sharing hypothesis on sub-components of consumption, even on individual commodities (De Weerdt and Dercon 2006; Bradford et al. 2022). Second, our data explicitly records consumption from transfers. A large social science literature documents interhousehold transfers of food within communities, ascribing these at least partly to risk-sharing motives (Fafchamps 2011). This paper also speaks to that literature.

2. Data and descriptive statistics

The primary data for this paper come from the Village Dynamics Studies in South Asia (VDSA) surveys. The VDSA surveys were conducted by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and focused on studying village economies in agroecologically and economically vulnerable regions of India (Walker and Ryan 1990). An uncommon feature of the VDSA surveys was that resident field investigators were permanently posted in selected villages and would visit households monthly to collect detailed data on various aspects of the household economy (Walker and Ryan 1990). These surveys have been used to study long-term productivity growth and the relationship between the scale of agricultural operations and farm productivity (Michler 2020; Foster and Rosenzweig 2022; Merfeld 2023).

The recent survey rounds cover 30 villages across three eastern states of Bihar, Jharkhand, and Orissa, and five states of Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, and Maharashtra in humid and semi-arid tropical regions (ICAR-ICRISAT 2010). Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, and Maharashtra represent low rainfall semi-arid tropical (SAT) regions practicing dryland agriculture. The Eastern states of Bihar, Jharkhand, and Orissa represent rainfall-dependent humid regions.

The VDSA villages and households were purposively sampled in four steps. Districts were selected in the first stage based on the major agroclimatic regions within SAT and Humid regions. Second, smaller administrative units called talukas within districts were selected based on weather, soil, and other variables. Finally, remote villages that didn't have access to infrastructure, government programs, and outside resources were selected. The sampled villages are mapped in Appendix Figure A1. Based on the village census, households in the villages were stratified based on operational land holdings and random household samples of equal size were then drawn from each stratum (Walker and Ryan 1990). Appendix Table A1 describes the sampling frame and household sample. The sampling method renders the VDSA surveys not representative of the sampled regions or states, as they were strategically chosen to reflect the most vulnerable rural population within the chosen regions. However, general trends in the VDSA surveys are consistent with overall trends at the all-India level (Michler 2020). Credit and insurance markets are underdeveloped in these villages; households largely rely on credit from informal sources borrowed at a very high interest rate of 60 to 120% per annum (Kumar et al. 2015).

The VDSA surveys collected detailed information at monthly frequency on household milk consumption – divided among home-produced, market-purchased, and transfers received from others – and on herd size and milk production and sales quantities by species – i.e., buffaloes, cows, goats, and sheep. The surveys record milk unit values in the consumption module and the price at which milk was sold in the production module. 52 percent of the total milk output comes from cows, 44 percent from buffaloes, and just 4 percent from small ruminants like sheep and goats. The monthly panel data we analyze include 1,314 households for a five-year period from 2010-11 to 2014-15. Our panel data are unbalanced, with, on average, a household observed for 47 out of the total 60 months. In terms of attrition, 34% of the households are observed for the entire period, and 44% of the households are observed for at least 59 months (See Appendix Figure A2 for the distribution of missing months per household.). Table Appendix A2 shows that the number of missing months per household is inversely correlated with baseline characteristics like consumption expenditure, operated land and the scale of production. This implies greater attrition for poorer households with less milk production. We test the robustness of our results to this non-random attrition from the panel.

To study how a reduction in trade costs influences consumption smoothing, we exploit variation in road construction and upgrades under the Pradhan Mantri Gram Sadak Yojana (PMGSY, the Prime Minister's Village Road Construction) scheme. The PMGSY was started in early 2000s to provide rural all-weather roads to unconnected villages across India. PMGSY roll-out followed a population-based rule (Asher and Novasad 2020; Garg et al. 2023). Villages with a household population greater than 1,000 were to be connected first, followed by villages with a population greater than 500, and only then villages with a population smaller than 500.[3] Data on rural road construction come from the Socioeconomic High-resolution Rural-Urban Geographic

[3] Studies show that the implementation broadly followed the population-based criteria (Asher and Novasad 2020; Shamdasani 2021).

(SHRUG) Dataset on India (Asher et al. 2021). SHRUG provides detailed information on the timing of rural road construction under the PMGSY. We use SHRUG to identify the year of PMGSY road completion for each of the 30 VDSA villages. The population-based targeted road construction under PMGSY provides exogenous variation in market access to the VDSA villages.

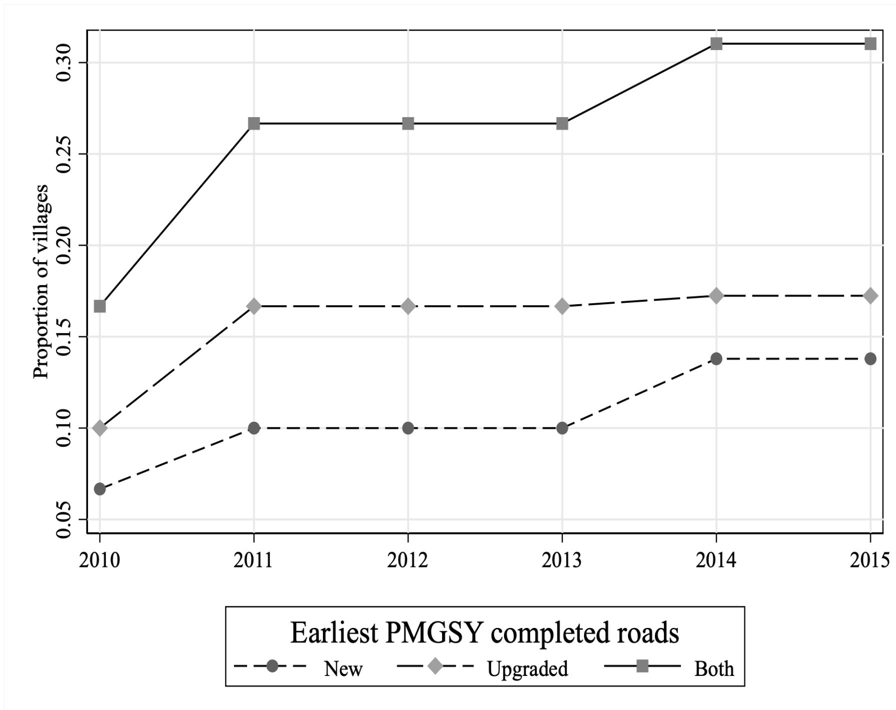

Figure 1: Variation in PMGSY road construction across VDSA villages over time.

Note: Dates reflect village-level earliest date of road construction per SHRUG.

Figure 1 shows the proportion of villages connected or upgraded with PMGSY roads over the five-year period in our sample. Roughly 15 percent of the VDSA villages had roads upgraded or constructed under PMGSY before VDSA began in 2010. By 2015, this proportion had doubled to more than 30 percent. Overall, we observe a greater proportion of villages with upgraded roads than new roads. The changes in roads took place in two of the periods, from 2010-11 and from 2013-14, with no changes in PMGSY road construction in these villages between 2011 and 2013.

Table 1 presents the mean and standard deviation of key variables. In around half of the month-year observations, households report having a large dairy animal with an average herd size of one. Average monthly milk production was 12 liters per household member, two-thirds of which is sold in the market, on average. Almost all milk sales are local, i.e., within the village.

The National Institute of Nutrition (NIN) of India recommends 300 milliliters of milk consumption per adult per day, or 9 liters monthly per person. Average monthly milk consumption is just 5 liters per household member, about 55 percent of the NIN recommendations. Moreover, the reported milk consumption is less than the NIN's recommendations in 89 percent of household-month-year cases.[4] 57 percent of milk consumed is home-produced, the rest from market purchases and informal transfers. Milk consumption from other sources, mainly informal transfers, forms a very small part of the total milk consumption. These simple descriptive statistics provide the first indication that informal transfers may play less role in smoothing milk consumption than commodity market participation does.

Figure 2 presents the monthly averages of herd size, milk production, and yield per animal across all households in our sample. These averages are estimated marginal effects from regressions that control for household and year fixed effects. We observe some seasonal differences in average herd sizes, mostly statistically insignificant. Milk production, however, shows a strong seasonal pattern. The average milk production is the highest in winter but starts going down from April onwards and is lowest in the summer/monsoon months of July and August.

[4] Note that the averages presented in Table 1 only consider fluid milk consumption and do not account for other milk products consumed by the households, such as buttermilk, butter, or ghee. Non-inclusion of these milk products could explain why we observe a difference of around 1 liter per person between produced milk left after sales and home-produced milk consumed in Table 1. This can introduce measurement error in the dependent variable which can also be correlated with milk production. We explicitly account for the consumption of other milk-based products in estimation.

Panel (c) of the figure confirms that the seasonal pattern observed in milk production is almost entirely due to seasonal productivity shocks. Similar seasonal patterns in milk production and yields of large dairy animals for India are reported by Sirohi and Michaelowa (2007).

Table 1. Summary statistics

	(1)	(2)
Variables	Mean	SD
Dairy animal owning households	0.51	0.50
Herd size of large dairy animals (number)	0.92	1.30
Milk production (liter per person per month)	11.85	28.55
Milk sales (liter per person per month)	7.63	24.88
Milk consumption home-produced (liter per person per month)	2.83	4.88
Milk consumption purchased (liter per person per month)	2.05	2.90
Milk consumption informal transfers (liter per person per month)	0.08	0.65
Milk consumption total (liter per person per month)	4.96	4.53
Milk unit values/buy price (rupees per liter)	21.14	5.29
Milk sale price (rupees per liter)	19.60	5.31
Family members (number)	4.84	2.30
Consumption expenditure (rupees per person per month)	1736.40	4139.89
N	61420	

Note. N=25750 for milk sale price. Both milk unit values and sale prices are deflated by the monthly state-specific consumer price index for agricultural workers.

Figure 3 shows the seasonal patterns in milk consumption by source. Panel (a) displays a seasonal pattern in home-produced milk consumption similar to that of milk production (Figure 2). Panel (b) shows that market purchases follow an opposite seasonal pattern to home-produced milk, higher in summer than in winter. But higher milk purchases are not enough to offset the decline in milk production in the summer months as average total consumption falls in summer. Figures 2 and 3 indicate both strong seasonal and stochastic patterns in milk production and incomplete milk consumption smoothing for these households. The next section develops an empirical framework to test how households smooth milk consumption in the face of seasonal and stochastic variation in own milk production.

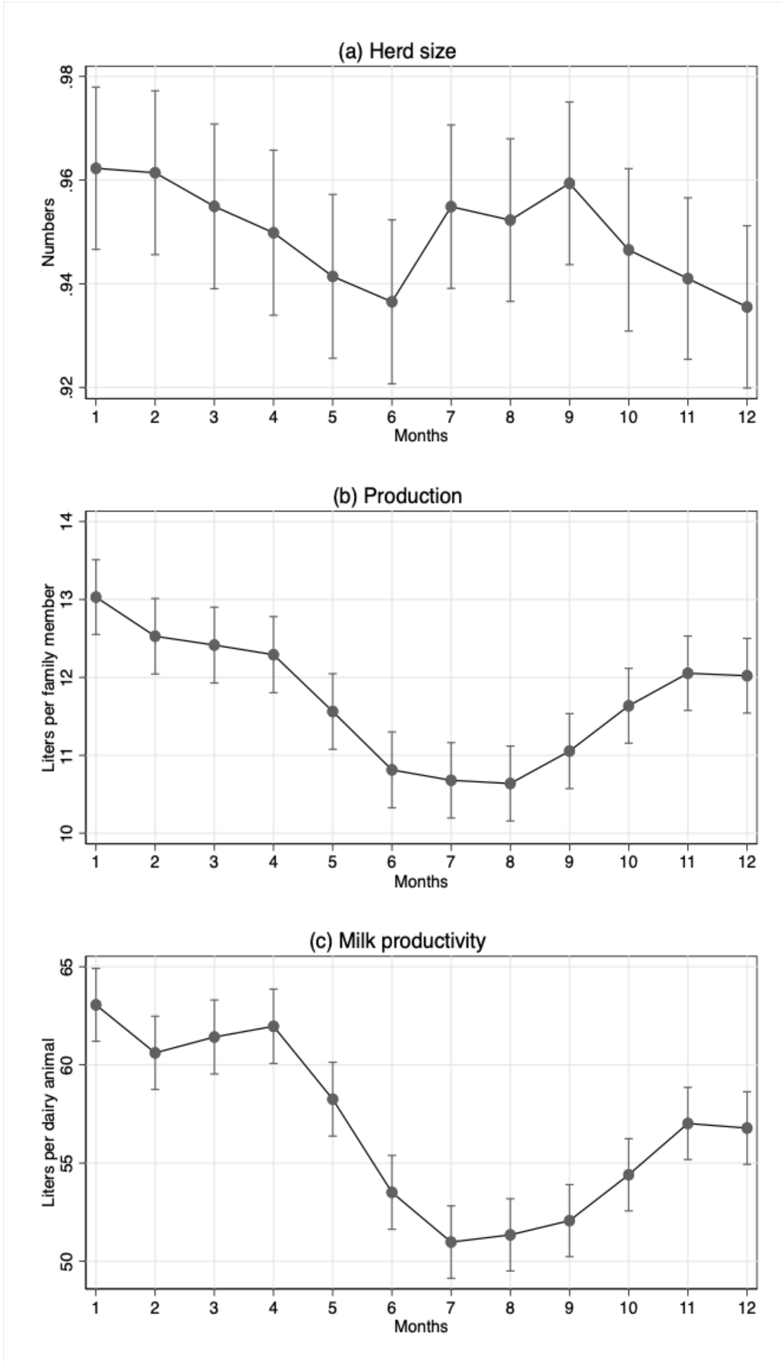

Figure 2. Seasonality in herd size, production and yield.

Notes: Herd size, production and milk productivity per dairy animal with 95% confidence intervals. Milk productivity is calculated as the total reported milk production divided by the total number of female cows and buffaloes. 96% of the reported milk production comes from cows and buffaloes. These averages are predicted from a regression controlling for household and year-fixed effects.

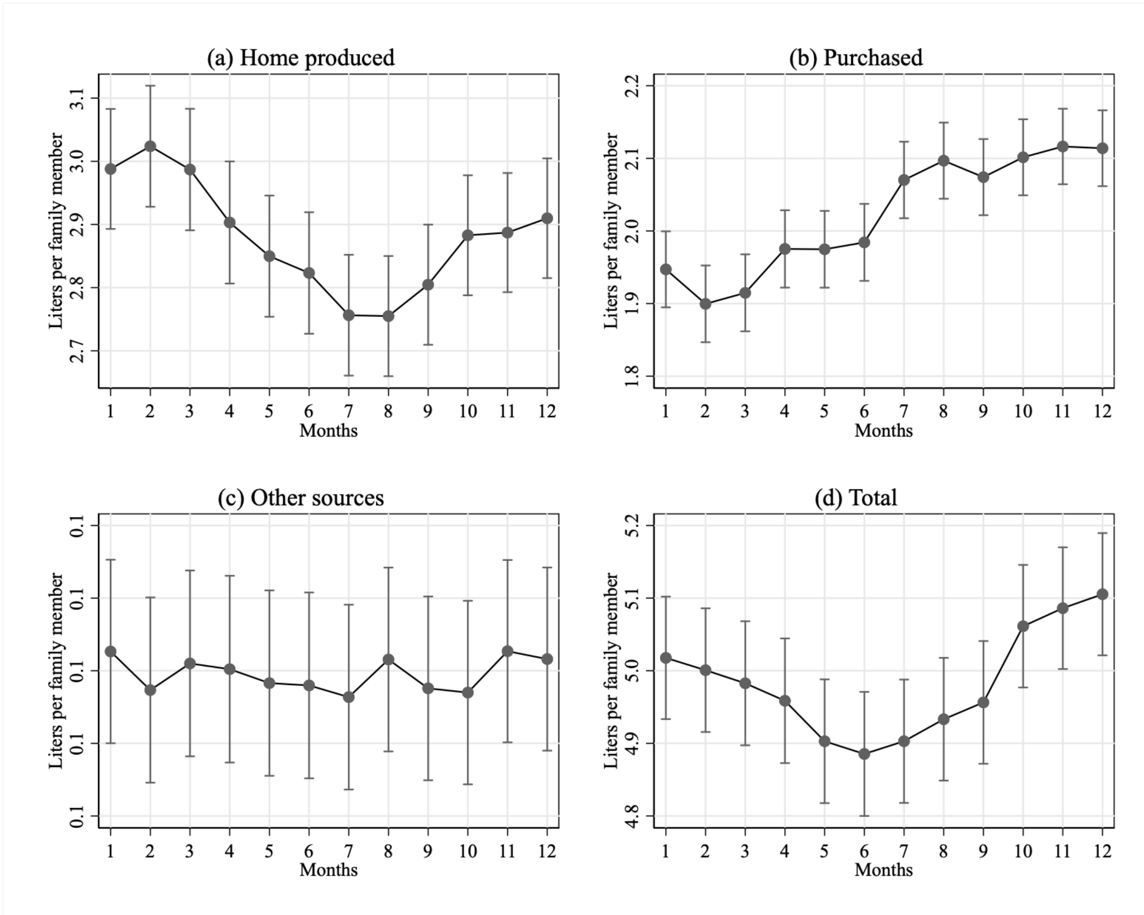

Figure 3. Seasonality in milk consumption by source.

Notes: Average milk consumption per family member with 95% confidence intervals. These averages are predicted from a regression controlling for household and year-fixed effects.

3. Empirical Framework

Our empirical strategy is to first follow the canonical approach to testing for household-level consumption smoothing via income pooling within a community, allowing for a community to be defined either geographically or socially, via caste membership. However, we seek to learn more than just *whether* households smooth consumption; we want to identify *how* they smooth consumption. We there extend the analysis to decompose consumption smoothing into different mechanisms algebraically and use that decomposition to establish to what extent households use market exchange versus informal (i.e., non-market) transfers to smooth milk consumption in the face of considerable seasonality and stochasticity in own production.

(a) Risk sharing test

Let the per member milk consumption and production of household *i* in village *v,* month *m* and year *t* be denoted by C_{ivmt} and Y_{ivmt}, respectively. A standard empirical test of the optimal risk-sharing hypothesis, following Townsend (1994), is

$$c_{ivmt} = \tau_{vmt} + \beta y_{ivmt} + \varepsilon_{ivmt} \qquad (1)$$

where $c_{ivmt} = \Delta \ln(C_{ivmt})$ and $y_{ivmt} = \Delta \ln(Y_{ivmt})$ denote seasonally differenced log milk consumption and production, respectively, and τ_{vmt} are the village specific time fixed effects that control for village level aggregate shocks,[5] and ε_{ivmt} is a mean zero, iid error term. Under complete risk-sharing, conditional on village-level aggregate shocks captured by village-time fixed effects, $\beta = 0$. Household consumption is uncorrelated with household production and simply tracks its reference group reflected in the village-time fixed effects, indicating maximal feasible consumption smoothing.

The village might not be the appropriate social structure for risk sharing. Informal risk sharing networks commonly form endogenously based on trust, kinship networks, migrant status, and affiliations to particular social groups within a village (Fafchamps 1992; Fafchamps and Lund

[5] See Appendix section (a) for the theoretical foundations of the optimal risk sharing test. Note that because we estimate (1) in seasonal first differences, the Pareto weights associated with each household in the structural problem specified in the Appendix drop out.

2003; De Weerdt and Dercon 2006; Kinnan and Townsend 2012). Some households may be poorly integrated socially within the village and thus may get left out of social insurance networks (Vanderpuye-Orgle and Barrett 2009). In the context of India, caste identity is an important factor influencing social network formation (Vanneman et al. 2006; Desai and Dubey 2011; Munshi and Rosenzweig 2016; Munshi 2019; Debnath and Jain 2020). Caste affiliation may impede the exchange of food across households belonging to different castes within communities (Marriott 2017; Raheja 1988; Béteille 2012; Munshi 2019). Caste affiliations might therefore be a more relevant grouping for testing risk sharing and social insurance (Munshi and Rosenzweig 2016; Mazzocco and Saini 2012).

If caste is the relevant social structure for risk sharing, the Pareto optimal allocation rule should equate individual consumption with aggregate resources of the caste based sub-populations rather than that of the entire village. Therefore, the appropriate risk sharing test specification is

$$c_{icvmt} = \tau_{cvmt} + \beta y_{icvmt} + \varepsilon_{icvmt} \qquad (2)$$

in which we replace village-time fixed effects of (1) with narrower caste-village-time fixed effects. In the empirical results reported in the next section, we test for risk sharing using both village and caste-level definitions of the relevant community. It makes little qualitative difference to inference about consumption smoothing and risk pooling, although goodness of fit tests suggest the village-based definitions fit the data somewhat better than caste-based ones do.

(b) Preference shocks and measurement error

Given that our data are monthly, it is important to differentiate changes in household consumption due to production fluctuations from seasonal changes in milk consumption. Seasonal preference changes could also exist, however, as omitted variables in our baseline specification that might confound if correlated with production shocks. If preferences vary seasonally – as when people value consuming liquids more during hotter periods – then the Pareto optimal consumption allocation will depend on both village level-aggregate shocks and household-level seasonal preferences (Chiappori et al. 2014).[6] The monthly panel data allow us to control for household-specific preference shocks. Consider the following version of the test in equation (1):

$$c_{ivmt} = a_{it} + m_{im} + \tau_{vmt} + \beta y_{ivmt} + \varepsilon_{ivmt} \qquad (3)$$

where a_{it} and m_{im} denote household-specific year and month fixed effects, respectively. Household specific year fixed effects allow us to control for annual preference shocks and household specific month fixed effects control for inter-household differences in seasonal preference changes (see Appendix section (b) for details.).

A concern with the estimation of equations (1)-(3) is that self-reported milk consumption and production include measurement errors. Assuming that mismeasured values of consumption and production are defined as $C_{ivmt} = C^*_{ivmt}\theta_i^C u_{it}^C v_{im}^C$ and $Y_{ivmt} = Y^*_{ivmt}\theta_i^Y u_{it}^Y v_{im}^Y$, with household-specific (θ_i), household year specific (u_{it}) and household month specific (v_{im}) error components, Appendix section (b) shows that the fixed effects in equation (3) can also control for such errors.

This leaves the possibility of household-year-month specific measurement errors in production. Moreover, household-year-month specific preference shocks might be correlated with milk production. In both cases, the β estimate will be biased. Lagged variables have often been

[6] See Appendix section (b) Equation B3 for the first order condition with preference shocks.

used as instruments to correct the bias in risk-sharing parameter estimates due to measurement errors and omitted preference shocks (Dubois 2000). In our case, assuming that measurement errors in milk production are uncorrelated with measurement errors in the number of dairy animals, we can use lagged values of changes in the herd size of dairy animals as instruments. Note that changes in herd sizes might also have some measurement error but likely be much less than in self-reported milk production. Moreover, herd size data and milk production data are collected in different modules within the livestock module of the VDSA survey, further minimizing the likelihood of correlated measurement errors in the two estimates. In using the lagged changes in herd sizes as instruments, we also assume that herd size changes in the prior month are uncorrelated with contemporaneous preference shocks.

(c) Multiple commodities with non-separability

The canonical risk-sharing framework assumes one composite commodity. Since we test for risk sharing in a specific commodity, fluid milk, we must consider the possibility of substitution across different commodities and how that might impact consumption smoothing in a single commodity.

Building on the standard model, consider the social planner's problem in a two-commodity world. Suppose each household has now a preference over two goods given by a homothetic utility function $U_i = U(C_{ivs}^Y, C_{ivs}^X)$ where $C_{ivs}^Y$and C_{ivs}^X are the amount of milk and all other non-milk goods consumed in state s. The utility function is non-separable in the two commodities. As before, the optimal risk-sharing benchmark can be obtained by solving the social planner's allocation problem, maximizing a weighted sum of expected utilities: $\sum_{i=1}^{N} \lambda_i \sum_{s=1}^{S} \pi_s \, U(C_{ivs}^Y, C_{ivs}^X)$, subject to the aggregate village level resource constraints $\sum_{i=1}^{N} C_{ivs}^Y = \sum_{i=1}^{N} Y_{ivs} = W_{vs}^Y$ and $\sum_{i=1}^{N} C_{ivs}^X =$

$\sum_{i=1}^{N} X_{ivs} = W_{vs}^{X}$ for the two commodities.[7] As discussed in Townsend (1994), such optimization will lead to two first-order conditions, and non-separability will imply equalization of the marginal utility of both commodities at the optimum. Therefore, aggregate endowments of both commodities will determine individual consumption allocations (Mace 1991; Cochrane 1991; Townsend 1994). This yields a variant of equation (1):

$$c_{ivmt} = \sum_{j=1}^{J} \gamma_j \mu_{jvmt} + \beta y_{ivmt} + \varepsilon_{ivmt} \qquad (4)$$

Where there are J commodities (including milk) in household's utility function and μ_{jvmt} denotes the village level aggregate shock and the associated parameter γ_j for j^{th} commodity consumed by the household. Equation (4) allows for non-separability in the utility function by explicitly controlling for village level aggregate shocks of different commodities. The parameters in Equation (4) can be heterogenous based on households having different risk preferences (Kurosaki 2001; Schulhofer-Wohl 2011). Under that scenario, the risk sharing test can be written as

$$c_{ivmt} = \sum_{j=1}^{J} \gamma_{ij} \mu_{jvmt} + \beta y_{ivmt} + \varepsilon_{ivmt} \qquad (5)$$

where now the parameters (γ_{ij}) on commodity specific aggregate shocks are heterogenous across households. Assuming a random coefficient structure, Pesaran (2006) shows that a panel data regression in Equation (5) can be estimated using the following specification

$$c_{ivmt} = \alpha_i + \beta_i y_{ivmt} + \eta_i \bar{y}_{vmt} + \sigma_i \bar{c}_{vmt} + \varepsilon_{ivmt} \qquad (6)$$

[7] We skip the subscript *m* for month here without loss of generality.

Equation (6) is estimated by running a time series regression for each household with $\bar{y}_{vmt}$ and $\bar{c}_{vmt}$ as controls.[8] This is known as the Common Correlated Effects Mean Group (CCEMG) estimator and remains consistent under slope homogeneity and for any fixed number of unobserved common factors (Pesaran 2006; Eberhardt et al. 2013; Fuleky et al. 2018). Note that equation (6) also allows for household-specific heterogeneity in the risk sharing parameter. Such heterogeneity may arise if complete risk sharing is rejected and the degree to which households can smooth consumption varies across households. The CCEMG estimator provides a consistent estimate of the mean of the parameter distribution.

(d) Consumption smoothing channels

Tests for optimal risk sharing do not identify the different channels through which households smooth consumption. We follow the methodology proposed by Asdrubali et al. (1996) and Asdurbali et al. (2020) to quantify the contribution of different channels to a household's consumption smoothing. Consider the following identity:

$$C_{ivmt} \equiv Y_{ivmt} + P_{ivmt} - S_{ivmt} + O_{ivmt} \qquad (7)$$

where C_{ivmt} is milk consumption, Y_{ivmt} is milk production, P_{ivmt} represents milk purchases, S_{ivmt} the quantity of milk sold, and O_{ivmt} is the milk consumed from other sources, mainly transfers of milk among households. We define two additional measures, $Y^P_{ivmt} = Y_{ivmt} + P_{ivmt}$, the sum of milk produced and milk purchased from the market, i.e., gross household-level milk availability, and $Y^S_{ivmt} = Y_{ivmt} + P_{ivmt} - S_{ivmt}$, which is net household-level milk availability, i.e., milk production and market purchases net of milk sales. All quantities are expressed in per household

[8] For a village v with N households, $\bar{y}_{vmt}$ and $\bar{c}_{vmt}$ are $\bar{c}_{vmt} = \sum_{i=1}^{N} \Delta \ln(C_{ivmt})/N$ and $\bar{y}_{vmt} = \sum_{i=1}^{N} \Delta \ln(Y_{ivmt})/N$.

member terms. Given these measures, household i's per person milk production can be expressed as:

$$Y_{ivmt} = \frac{Y_{ivmt}}{Y_{ivmt}^{P}} \times \frac{Y_{ivmt}^{P}}{Y_{ivmt}^{S}} \times \frac{Y_{ivmt}^{S}}{C_{ivmt}} \times C_{ivmt} \qquad (8)$$

With some algebraic manipulation (see Appendix section (c) for details), equation (8) can be expressed as the following identity:

$$\beta = 1 - \beta^{P} - \beta^{S} - \beta^{O} \qquad (9)$$

where the β on the lefthand side of equation (9) is the risk sharing coefficient from equation (1). Equation (9) expresses β as the residual after consumption smoothing achieved via purchases and sales of milk indicated by β^{P} and β^{S}, respectively, while β^{O} captures consumption smoothing achieved via informal transfers among households.

Given this structure, the null hypothesis of autarky or no consumption smoothing implies $\beta = 1$. If $\beta < 1$, then the estimate $(1 - \beta)$ can be interpreted as the degree of risk-sharing within the village (Asdurbali et al. 1996; Jalan and Ravallion 1999; Asdurbali et al. 2020). The β's on the RHS of equation (9) can be estimated as coefficients from the following system of equations:

$$y_{ivmt} - y_{ivmt}^{P} = \tau_{vmt}^{P} + \beta^{P} y_{ivmt} + \varepsilon_{ivmt}^{P} \qquad (10)$$

$$y_{ivmt}^{P} - y_{ivmt}^{S} = \tau_{vmt}^{S} + \beta^{S} y_{ivmt} + \varepsilon_{ivmt}^{S} \qquad (11)$$

$$y_{ivmt}^{S} - c_{ivmt} = \tau_{vmt}^{O} + \beta^{O} y_{ivmt} + \varepsilon_{ivmt}^{O} \qquad (12)$$

The parameters in this system of equations are assumed to be homogenous but can vary across households. For example, a household with a larger scale of production will more likely sell than purchase milk for home consumption. This implies that the channels through which larger farmers with surpluses and smaller farmers with deficits smooth consumption may differ.

(e) Trade costs, seasonality, scale of production and prices

The transactions costs of participating in milk markets may vary over time and among villages. Reduced trade costs due to better road infrastructure may thereby change households' incentives and interact with milk production and seasonality in complex ways. Whether improved connectivity with communities outside one's village boosts informal insurance via extended, caste-based social networks or consumption smoothing through market participation is an empirical question that we can easily accommodate in our empirical structure. Consider the following characterization of the parameters in the system of equations (10)-(12):

$$\beta^k = \delta + \theta^H HS_i + \theta^R ROAD_{vt} + \theta^W WINTER_m + \gamma^{HR} HS_i \times ROAD_{vt} + \gamma^{HW} HS_i \times WINTER_m + \gamma^{HRW} HS_i \times ROAD_{vt} \times WINTER_m \qquad (13)$$

where $k = \{P, S, O\}$, HS denotes the household's average dairy herd size over the entire survey period as an indicator of its scale of production, $ROAD$ is a dummy variable that captures village-level variation in road construction or upgradation under the PMGSY, and $WINTER$ is a dummy variable that takes values 1 for October, November, December, January, February, and March, reflecting seasonality in production.

To capture the changes in incentives due to reduced trade costs, we study the prices at which households buy and sell milk. The VDSA survey consumption module records the unit values of milk consumed and the production module records the prevailing price at which milk sold. We use these monthly prices to test whether seasonal production and access to new roads affect purchase and sales prices.

Both the buy and sell price are conditional on households' market participation decisions, therefore they are endogenous to both observable and unobservable characteristics of the household, including preferences, quality and type of milk, transactions volume and timing, etc. (Deaton 1988; Barrett 2008). Consider the following empirical model for milk price differentials:

$$\begin{aligned}\ln\left(P_{ivmt}^{buy}\right) - \ln\left(P_{ivmt}^{sell}\right) &= \alpha_i + m_{vm} + \tau_{vt} + \delta^{HR} HS_i \times ROAD_{vt} + \delta^{HW} HS_i \times WINTER_m \\ &+ \delta^{RW} ROAD_{vt} \times WINTER_m + \delta^{HRW} HS_i \times ROAD_{vt} \times WINTER_m \\ &+ \varepsilon_{ivmt} \qquad (14)\end{aligned}$$

where the dependent variable is the price band (de Janvry et al. 1991, Barrett 2008), the difference between the log of unit values for buying and selling milk for household *i* in village *v* in month *m* at year *t*. We include household fixed effects to control for time-invariant factors that would influence the price differential, like the household's distance from local market. We also include village-specific month fixed effects to control for village-level seasonality in milk production, herd composition, trader presence, etc. Finally, village-year fixed effects account for interannual (e.g., weather) shocks and policy changes that can influence the price differential. We estimate equation (14) individually with buying and selling prices as well as the price differential.

Note that the sales (purchase) price of milk is observed conditional on milk being sold (bought), and the decision to sell (buy) milk itself is a function of trade costs. The differential is therefore only be observed for the subsample of farmers who both sell and buy milk within the same period. To test the robustness of our results to missing buy and sell price differential, we estimate Equation (14) on a balanced panel of households reporting both buy and sell price for all 60 months of the survey.

(f) Storage, financial transactions and anticipatory shocks

Although fluid milk storage may be infeasible to smooth milk consumption, other commodities rural households produce and consume are storable. A priori, it is unclear how storage of other commodities would influence consumption smoothing of a non-storable commodity like milk. One can check this by conditioning on the household's stocks of other important food commodities in our regressions (or changes in stockholding in first differences regressions).

We also empirically test the sensitivity of our consumption smoothing estimates to financial and asset transactions like borrowing, lending, savings, investments and asset sales. Anticipated production shocks – e.g., a household that knows it will lose household labor to marriage, migration or schooling in the coming season – may also lead to future production shocks influencing current consumption. We therefore also test the importance of future and past production shocks on current milk consumption.

4. Estimation results

(a) Risk-sharing, caste-based social structure, and preference shocks

Table 2 presents the estimates from the risk-sharing regressions. Column 1 presents estimates from regressions with household fixed effects. In columns 2 and 3, we include year and month fixed effects to control for aggregate shocks and seasonality. In column 4 we introduce village-year fixed effects to control for village-specific aggregate shocks and village-month fixed effects to control for village-specific seasonality. In column 5, we relax the assumption that aggregate year shocks and seasonality are independent and introduce village-month-year fixed effects. Column 6 presents the seasonal differences-based test and is our preferred empirical specification. Specification 7 substitutes a caste-based definition of the risk-pooling group for the village-based one. Finally, to rule out the possibility that household specific-preference shocks generate spurious correlation between consumption and production, we include household year and month fixed effects in the last specification (column 8).

The complete risk-sharing hypothesis is clearly rejected for these households as we observe a positive and statistically significant association between household-level consumption and production in all these specifications. Indeed, we cannot reject the null that the β coefficient estimates are all the same, roughly 0.20, implying that only about 20 percent of variation in household milk output translates into variation in consumption, indicating considerable, albeit statistically significantly incomplete milk consumption smoothing and risk sharing within the community, whether defined by geography or caste.

Table 2. Tests of risk-sharing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: log milk consumption per person							
						Seasonally differenced		
y_{ivmt}	0.211***	0.215***	0.215***	0.203***	0.201***			
	(0.024)	(0.026)	(0.026)	(0.025)	(0.026)			
$\Delta\, y_{ivmt}$						0.200***	0.196***	0.202***
						(0.027)	(0.029)	(0.035)
Family members	-0.099***	-0.099***	-0.099***	-0.097***	-0.097***			
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)			
Log MPCE	0.216***	0.207***	0.209***	0.205***	0.210***			
	(0.027)	(0.028)	(0.028)	(0.024)	(0.024)			
Δ Family members						-0.101***	-0.103***	-0.120***
						(0.008)	(0.008)	(0.008)
Δ Log MPCE						0.207***	0.201***	0.153***
						(0.033)	(0.024)	(0.022)
Household FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Month FE	No	No	Yes	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Village×Month FE	No	No	No	Yes	No	No	No	No
Village×Year FE	No	No	No	Yes	No	No	No	No
Household×Month FE	No	No	No	No	No	No	No	Yes
Household×Year FE	No	No	No	No	No	No	No	Yes
Village×Month×Year	No	No	No	No	Yes	No	No	Yes
Caste×Village×Month×Year	No	No	No	No	No	No	Yes	No
N	61,420	61,420	61,420	61,420	61,420	45,578	45,180	43,965
R^2	0.74	0.75	0.75	0.78	0.80	0.23	0.42	0.645
F	191.46	162.31	160.31	172.73	171.81	176.82	144.96	227.48

Notes: y_{ivmt} and $\Delta\, y_{ivmt}$ denote log per person household milk production in its seasonal difference respectively. The dependent variable in the last specification is seasonally differenced log milk consumption per person. MPCE denotes the monthly per person value of consumption expenditure. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Aggregate shocks to other commodities and risk sharing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: seasonally differenced log milk consumption per person							CCEMG
$\Delta\, y_{ivmt}$	0.194***	0.192***	0.193***	0.192***	0.192***	0.191***	0.224***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.069)
Village average Δ log milk expenditure per member	0.702***	0.710***	0.729***	0.731***	0.731***	0.729***	
	(0.047)	(0.056)	(0.054)	(0.053)	(0.055)	(0.054)	
Village average Δ log cereals expenditure per member		-0.059	-0.019	-0.011	-0.013	-0.009	
		(0.072)	(0.070)	(0.070)	(0.070)	(0.068)	
Village average Δ log pulses expenditure per member		-0.033	-0.030	-0.021	-0.025	-0.034	
		(0.040)	(0.039)	(0.040)	(0.037)	(0.036)	
Village average Δ log vegetables expenditure per member			-0.065***	-0.063***	-0.058**	-0.056**	
			(0.023)	(0.022)	(0.022)	(0.022)	
Village average Δ log fruits expenditure fruits per member			-0.016	-0.013	-0.010	-0.009	
			(0.011)	(0.012)	(0.012)	(0.012)	
Village average Δ log meat eggs & fish expenditure per member				-0.020**	-0.017*	-0.016*	
				(0.009)	(0.009)	(0.009)	
Village average Δ log oils expenditure per member				-0.017	-0.016	-0.008	
				(0.030)	(0.029)	(0.029)	
Village average Δ log sugar expenditure per member				-0.023	-0.019	-0.017	
				(0.045)	(0.046)	(0.045)	
Village average Δ log beverages expenditure per member					-0.002	-0.001	
					(0.014)	(0.014)	
Village average Δ log processed foods expenditure per member					-0.012	-0.006	
					(0.014)	(0.014)	
Village average Δ log other foods expenditure per member					-0.014	-0.009	
					(0.026)	(0.028)	
Village average Δ log non food expenditure per member						-0.043*	
						(0.023)	

Notes: N=44,759 household-month observations. All regressions include the change in household size and change in log per member value of consumption as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. CCEMG denotes estimates from the Common Correlated Effects Mean Group Estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

(b) Multiple commodities

As discussed in section 3, relaxing the composite good assumption and separability in the utility function means that aggregate shocks of all commodities in a household's utility function could determine optimal milk consumption. Although village- or caste-specific time fixed effects would control for all aggregate shocks, including to other commodities, it is still useful to check whether village consumption of other food commodities correlates with the household's milk consumption.

Table 3 presents the estimates of risk-sharing tests, including village-level aggregate consumption expenditures of other commodity groups consumed by households in our data. Note that, though we consider the physical quantity of milk consumption and production, the aggregate shocks to other commodities are in value terms for two reasons. First, we have to aggregate commodities that are not in standardized units. Second, using expenditures also implies that we can account for commodity price-based variation as well as volumetric variation.

Specifications 1 to 6 in Table 3 yield estimates of β quite comparable to our estimates in Table 2. In general, village-level expenditure on vegetables and meat, fish, and eggs, and non-food items show a negative and statistically significant correlation with milk consumption. The last specification in the table presents the estimates from the CCEMG estimator, which accounts for the possibility that the coefficients on the aggregate shocks are heterogeneous across households, as might occur if risk preferences vary across households (Schulhofer-Wohl 2011). Allowing for heterogeneity in the aggregate shocks, however, does not seem to influence our estimates much (Table 3 specification 7). Roughly 20 percent of variation in household milk production passes through to its milk consumption.

(c) Decomposing consumption smoothing channels

The results thus far are fairly representative of many prior studies of risk sharing and consumption smoothing, finding that there exists considerable consumption smoothing but that risk sharing within villages is incomplete (e.g., Townsend 1994; Vanderpuye-Orgle and Barrett 2009). But what mechanisms do households use to smooth consumption? That question remains underexplored, especially the possibility that households lacking good access to financial services rely primarily on commodity markets, rather than informal transfers mediated by familial and social networks, to smooth consumption in the face of time-varying production.

Table 4 presents the β estimates from Equations (10) to (12) estimated as a system with standard errors clustered at the village level.[9] The estimates in columns 1 to 4 represent consumption smoothing achieved from milk purchases, sales, and other sources (mainly inter-household transfers), respectively. The estimate in the last column is residual and is the same as the one reported in column 6 of Table 2, again indicating that, on average, household milk consumption is insured against around 80 percent of variation in household milk production ($1 - \beta = 0.80$).

Looking at columns 1 and 2 of the table, we observe that two-thirds of the variation in milk production are smoothed by the purchase and sales of milk. Market purchases account for almost half of the consumption smoothing achieved in these villages, followed by milk sales which account for another 36 percent of the total consumption smoothing, although we cannot reject the

[9] The adding up constraint in Equation (9) is satisfied automatically due identity (7) and the linear system of equations in (1) and (10)-(12). These equations are estimates as a system using the conditional mixed processes (CMP) suite of commands in STATA.

null that commodity market purchases and sales are equally important to consumption smoothing. In total, market sales and purchases account for 83 percent of the total consumption smoothing by these households. Informal transfers account for less than 17 percent of the total consumption smoothing, significantly less than either market purchases or sales – much less both – despite the disproportionate attention they receive in the literature.

Table 4. Consumption smoothing channels

	(1)	(2)	(3)	(4)
Proportion of production shocks smoothed out by	Purchases	Sales	Transfers	Residual
	β^P	β^S	β^O	β
	0.380***	0.287***	0.133***	0.200***
	(0.022)	(0.046)	(0.038)	(0.027)
1. $H^0: 1-\beta=0$	0.800***			
	(0.027)			
2. $H^0: \beta^P-\beta^S=0$	0.093			
	(0.057)			
3. $H^0: \beta^P-\beta^O=0$	0.248***			
	(0.048)			
4. $H^0: \beta^S-\beta^O=0$	0.155**			
	(0.076)			
5. $H^0: \beta^P+\beta^S-\beta^O=0$	0.535***			
	(0.077)			

Notes: N=45,578 household-month observations. All regressions include the change in household size and change in log consumption per member as control variables. Figures in parentheses report standard errors clustered at the village level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

To check whether the omitted consumption of other milk products biases estimates, we include changes in per-person consumption of buttermilk, butter, ghee, and other milk-based products consumed by households as covariates. Appendix Table A3 shows that our estimates are robust to the inclusion of these covariates. We also test whether our estimates are robust to other types of measurement errors as mentioned in section 3(b). Table A4 in the appendix presents the instrumental variables estimates of the risk-sharing coefficients where the instruments are lagged herd sizes. These estimates are comparable to the estimates in Table 4.

(d) Seasonality, scale of production, new roads and prices

Before we move on to analyzing how the scale of production and new roads interact with the different channels of consumption smoothing, we see how incentives in the form of the prices at which milk is bought and sold are influenced by reduced trade costs in the form of access to new roads.

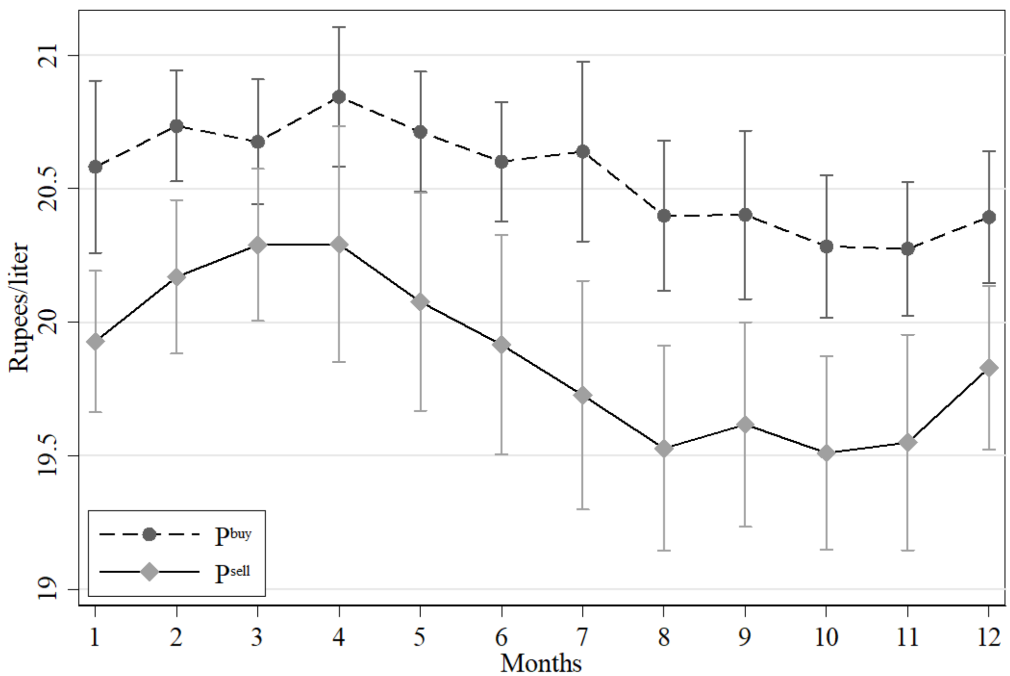

Figure 4. Monthly average milk buy and sell price for dairy animal owning households.

Note: Figure presents seasonality in real milk prices deflated by monthly state-specific consumer price index for agricultural workers. Averages are predicted from a regression controlling for household fixed effects, with 95% confidence intervals.

Figure 4 shows the seasonal price gap between monthly average commodity buy and sell prices conditional on household and fixed effects. This clearly shows both the significant seasonal variation in milk prices as well as the consistent gap of 3-5 percent between buy and sell prices.

Table 5. Scale of production, roads, seasonality and prices

	(1)	(2)	(3)	(4)	(5)	(6)
				Households with		
	$\ln(P^{buy})$	$\ln(P^{sell})$	$\ln(P^{buy}) - \ln(P^{sell})$	$\ln(P^{buy}) - \ln(P^{sell})$ for at least		
			Overall sample	36 months	48 months	60 months
(a) With all roads						
$HS \times WINTER$	-0.002	-0.001	-0.000	-0.001	-0.002	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
$HS \times ROAD$	-0.012**	0.015***	-0.001	-0.012	-0.018**	-0.029***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.002)
$ROAD \times WINTER$	-0.016*	-0.029***	0.017***	0.027***	0.018**	0.017*
	(0.009)	(0.005)	(0.006)	(0.005)	(0.009)	(0.008)
$HS \times ROAD \times WINTER$	0.002	0.003	0.001	-0.000	-0.000	0.005
	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
(b) With new roads						
$HS \times WINTER$	-0.002	-0.000	-0.000	-0.001	-0.002	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$HS \times NROAD$	-0.017**	0.020***	-0.008**	-0.020***	-0.026***	-0.023***
	(0.007)	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)
$NROAD \times WINTER$	-0.018	-0.034***	0.010	0.020*	0.010	0.044***
	(0.023)	(0.005)	(0.015)	(0.010)	(0.014)	(0.005)
$HS \times NROAD \times WINTER$	0.006	0.004*	0.005	0.003	0.002	-0.007***
	(0.015)	(0.002)	(0.008)	(0.005)	(0.006)	(0.002)
N	40442	25339	25339	18562	12431	2700

Notes: All regressions include household fixed effects, village month fixed effects and village year fixed effects. Control variables include log household size, log value of total consumption per member and herd size. HS is the household average herd size over the entire period. ROAD captures rural road construction or upgrades under the PMGSY. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October through March. Figures in parentheses are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 presents the estimates of Equation (14) for milk purchase unit values, sales price and the price differential. These regressions also include the log of total consumption value per person, log household size and herd size as controls. On average, roads lead to a reduction in the price at which farmers with larger herds purchase milk and an increase in the price at which they sell milk. We also observe some seasonal variation in the effect of new roads on sale prices. In column 3 panel (b), we observe that new roads lead to a narrower price band between buy and sell prices for milk-producing households. To see the sensitivity of these estimates to missing buy and sell price differential, we present estimates by sequentially removing households with 24 and 12 months of missing price differential in columns 4 and 5. Finally in column 6, we present estimates from a balanced panel of households where the price differential is observed for all 60 months of the survey. These estimates are consistent with the estimates in column 3 for the overall sample.

(e) Seasonality, scale of production, roads, and consumption smoothing

How does consumption smoothing via different channels vary with the household scale of dairy production and with road access? Table 6 shows that households with larger average herd sizes rely more on sales for consumption smoothing than purchases. This is intuitive as larger dairy farmers experience more periods of surplus milk production than do those with smaller herds. In winter – the highest milk productivity season – larger dairy farmers divert some seasonal surplus milk to informal transfers and reduce purchases. This is evident in the positive and statistically significant triple interaction between production shocks, average herd size, and the winter dummy (Table 6 specifications 1 and 3). We also find some evidence that improvement in road access leads to greater consumption smoothing via milk sales among households with larger herds.

Table 6. Scale of production, roads, seasonality and channels of risk-sharing

	(1)	(2)	(3)	(4)
	β^P	β^S	β^O	β
$\Delta\, y_{ivmt}$	0.491***	0.209***	0.099**	0.201***
	(0.036)	(0.058)	(0.042)	(0.037)
$\Delta\, y_{ivmt} \times HS$	-0.064***	0.046***	0.029	-0.011
	(0.012)	(0.017)	(0.021)	(0.010)
$\Delta\, y_{ivmt} \times ROAD$	-0.039	0.042	-0.061	0.058
	(0.055)	(0.083)	(0.057)	(0.066)
$\Delta\, y_{ivmt} \times WINTER$	0.004	0.005	-0.017	0.008
	(0.010)	(0.014)	(0.013)	(0.015)
$\Delta\, y_{ivmt} \times HS \times ROAD$	-0.026	0.033*	0.015	-0.023
	(0.022)	(0.019)	(0.028)	(0.015)
$\Delta\, y_{ivmt} \times HS \times WINTER$	-0.015**	-0.007	0.026**	-0.004
	(0.007)	(0.011)	(0.012)	(0.008)
$\Delta\, y_{ivmt} \times HS \times ROAD \times WINTER$	0.001	-0.013	-0.016	0.028
	(0.013)	(0.018)	(0.011)	(0.029)

Notes: N=45,578 household-month observations. All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household milk production. HS is the average household herd size over the entire period. ROAD captures rural road construction or upgrades under the PMGSY. WINTER is a dummy variable that takes values 1 for October through March. Figures in parentheses are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We do not observe strong effects of reduced trade costs due to PMGSY roads in Table 6. This could be because we combine road upgrades with new road construction into one variable. To see whether new roads have a stronger effect on consumption smoothing patterns, in Table 7 we present the estimates considering only new roads constructed under PMGSY. We indeed find that new roads reduce a household's consumption exposure to variation in milk production by 5.1 percentage points relative to a base of 22.5 percent, although that estimate is not statistically significant at conventional levels. The introduction of a new road eliminates the seasonal winter increase in consumption smoothing via informal transfers among households with larger herds (Table 7 specification 3).[10]

[10] These findings are robust to inclusion of interactions with upgraded roads.

Table 7. Scale of production, new roads, seasonality and channels of risk-sharing

	(1)	(2)	(3)	(4)
	β^P	β^S	β^O	β
$\Delta\, y_{ivmt}$	0.477***	0.210***	0.088**	0.225***
	(0.033)	(0.055)	(0.038)	(0.039)
$\Delta\, y_{ivmt} \times HS$	-0.063***	0.052***	0.028	-0.018*
	(0.010)	(0.015)	(0.018)	(0.010)
$\Delta\, y_{ivmt} \times NROAD$	0.039	0.058	-0.045	-0.051
	(0.041)	(0.065)	(0.058)	(0.042)
$\Delta\, y_{ivmt} \times WINTER$	0.003	0.006	-0.016	0.007
	(0.010)	(0.014)	(0.012)	(0.014)
$\Delta\, y_{ivmt} \times HS \times NROAD$	-0.065***	0.028*	0.042	-0.005
	(0.015)	(0.017)	(0.027)	(0.022)
$\Delta\, y_{ivmt} \times HS \times WINTER$	-0.014**	-0.008	0.025**	-0.003
	(0.006)	(0.010)	(0.010)	(0.007)
$\Delta\, y_{ivmt} \times HS \times NROAD \times WINTER$	-0.009	-0.013	-0.029***	0.051
	(0.020)	(0.031)	(0.010)	(0.051)

Notes: N=45,578 household-month observations. All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October through March. Figures in parentheses are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Although road construction under the PMGSY was targeted based on the baseline village population, new roads could have crowded in other complementary infrastructure in these villages or coincided with other development interventions or policy changes in the VDSA villages. If this is true, then the Table 7 results might arise from other, correlated village-level changes. Appendix Tables A5 and A6 show that the findings in Table 7 are robust to controlling for other unobserved village-level trends potentially correlated with road construction.

(f) Seasonality, scale of production, new roads, dairy processing capacity and complementary infrastructure

The VDSA states vary in the structure of their dairy value chains. For example, Gujarat and Karnataka have a high presence of dairy cooperatives. In comparison, Maharashtra has a higher private processor presence. The Eastern states of Bihar, Jharkhand and Odisha have less developed milk value chains, with most of the milk sales made to the informal sector.

We therefore also explore whether the scale of production, seasonality, and access to new roads have different implications for consumption smoothing via sales to formal and informal channels (Appendix Table A7). We define formal channels as sales to cooperatives and private processors. Informal channels include sales to local agents, shops, and fellow farmers. 78 percent of the total milk sales are made to formal sources and only 22 percent are made to informal sources. Appendix Table A7 shows that new roads enhance the contribution of sales to formal channels in consumption smoothing, especially for farmers with a larger scale of production. This seems to happen at the cost of lower consumption smoothing from milk sales to informal channels.

Although these differences in milk value chains are structural and are observed at the baseline, the construction of new roads could be correlated with the expansion of dairy processing capacity in these states. Village-level data on milk processing plants for the survey period are unavailable, but state-level data on the number of milk processing plants is available from the Annual Survey of Industries. We use these data to test whether village-level road construction correlates with state-level milk processing capacity changes. Appendix Table A8 shows that milk processing capacity is uncorrelated with road expansion under the PMGSY. New roads may attract other complementary infrastructure, including formal banking institutions. While the VDSA villages were remote to begin with, our results for PMGSY roads can also be driven by greater availability of credit through newer banking infrastructure. Appendix Table A9 however shows that village level roads under the PMGSY are uncorrelated with the expansion of banking infrastructure in these villages.

(g) Storage, financial transactions and risk sharing

Although fluid milk is not storable, rural households do maintain stocks of other storable food commodities with the objective of intertemporal consumption smoothing through consumption or sale of stored product.[11] If in periods of adverse milk production shocks households use pre-existing stocks of other food items to smooth their total food consumption, then milk consumption may show extra sensitivity to production shocks (Ábrahám and Laczó 2018). Changes in stocks would then be omitted variables in our prior specifications. We find no evidence, however, that changes in stocks of other commodities influence the estimated risk-sharing parameter (Appendix Table A10). Changes in stocks of cereals and pulses are uncorrelated with milk consumption.[12]

Rural households also rely on savings and dis-savings, sale and purchase of assets, and credit for consumption smoothing. Such transactions can also be used to smooth a single component of food consumption and, although clearly endogenous, might be included as covariates in the risk-sharing regression. Appendix Table A11 presents the resulting regression estimates, which show that the magnitude and statistical significance of the risk-sharing parameter estimate hardly change with the inclusion of different financial transactions undertaken by VDSA households during the survey period (Appendix Table A11).

[11] Households also maintain stocks of foodgrains as agricultural inputs, e.g., as seeds or animal feed.

[12] This is likewise true if we include changes in the value of total stocks, which included food grains, seeds, animal feed, and other commodities (Appendix Table A10 Specification 3).

One final concern with the estimates of the risk-sharing parameter is that we only capture the instantaneous correlation between consumption and production. Future shocks to milk production may influence current milk consumption if such shocks are anticipated by the households. Likewise, past shocks may also influence current consumption if they have persistent effects, e.g., on preferences or social networks. While the canonical risk-sharing model rules out lagged and lead effects of idiosyncratic production shocks, a failure of complete risk-sharing opens up such a possibility. Appendix Figure A3 presents the estimates of 12 months lagged and lead effects of production shocks on current milk consumption. The instantaneous production shock shows the highest correlation with current milk consumption; all other estimates are close to zero.

(h) Non-random attrition and consumption smoothing

Appendix Table A2 shows that attrition from the panel is non-random and is inversely correlated with the households' wealth status and scale of production. This is also reconfirmed when we estimate a logit model for time varying attrition from the panel (Appendix Table A12). Poorer households are more likely to be missing observations than wealthier households. We observe some seasonality in attrition with the likelihood of missing observations being higher in the first half of the year but do not find any significant annual trend. We use inverse probability weighting (IPW) to adjust our estimates for this non-random attrition. Appendix Figure A4 presents the density of the estimated attrition probability by the attrition indicator. Appendix Table A13 presents the IPW estimates for consumption smoothing channels which are comparable to our original estimates. Appendix Table A14 presents estimates for the balanced panel of households observed in all 60 months of the survey. These estimates are again comparable to our original estimates.

While our main estimates seem robust to attrition, it could still be that attrition is correlated with road expansion, and our results with respect to the PMGSY are driven by selective attrition rather than road expansion. We however do not find strong evidence of that (Appendix Table A15). Finally, Appendix Tables A16 and A17 present the IPW and balanced panel estimates of the role of reduced trade costs on consumption smoothing channels. These estimates leave the key message unchanged.

5. Conclusions

In this paper, we study fluid milk consumption smoothing in rural India, uncovering the different channels through which rural households insulate fluid milk consumption from intertemporal fluctuations in their own milk production. We do that within the conventional empirical testing framework of the complete risk-sharing hypothesis, demonstrating a method to decompose the contribution to consumption smoothing of different channels.

We consistently reject the complete consumption smoothing and risk-sharing hypothesis; but we observe a high degree of consumption insurance. Households manage to quasi-insure against roughly 80 percent of milk output variation. Commodity market transactions – milk sales and purchases – are the dominant channel through which this high degree of insurance is achieved, three times (and statistically significantly) more important than informal transfers for consumption smoothing. We also observe seasonal differences in our estimates. Given the greater supply of fluid milk in the winter season, we find that larger surplus-producing households rely more on milk sales and informal transfers for consumption smoothing in the winter months.

Further, we find that improved road infrastructure reduces commodity market trade frictions – as manifest in buy-sell price margins – and reduces the role of informal transfers without any impact on overall consumption smoothing. As rural villages become better integrated into the broader national and global economy, markets – not transfers among increasingly accessible distant relations and friends – increasingly take up the role of insulating consumption from production shocks. This finding has special relevance if future changes in climate make local weather more unpredictable and household level agricultural production more volatile. Commodity markets may offer a crucial medium through which poorer households can insulate consumption from increasing production volatility. While considerable attention has been paid to the role of financial inclusion and informal insurance networks to cushioning rural households against risk, we must not overlook the central role that product markets play in facilitating risk management and consumption smoothing.

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Appendix

(a) Canonical risk sharing model

For illustrative purposes, we start with the canonical risk-sharing framework, per Townsend (1994) and the literature that builds on that seminal paper. We later discuss variants that relax some of the assumptions in this basic framework. Consider *N* agents living within a village. Each agent *i* in village *v* has a stochastic endowment of a commodity Y_{ivs}, the realization of which is based on different but finite states of the world, *s*. Each state occurs with an exogenous probability π_s with $\sum_{s=1}^{S} \pi_s = 1$. Each agent i has a continuous, monotonically increasing, concave, and twice differentiable utility function $U_i = U(C_{ivs})$, where C_{ivs} is the amount consumed of the good in state s. Each agent's expected utility is thus $\sum_{s=1}^{S} \pi_s \, U(C_{ivs})$.

The optimal risk-sharing benchmark can be obtained by solving the social planner's allocation problem for this economy. The social planner maximizes a weighted sum of expected utilities: $\sum_{i=1}^{N} \lambda_i \sum_{s=1}^{S} \pi_s \, U(C_{ivs})$, where λ_i are the Pareto weights, subject to the aggregate village level resource constraint $\sum_{i=1}^{N} C_{ivs} = \sum_{i=1}^{N} Y_{ivs} = W_{vs}$. The first-order condition for an agent i is

$$\lambda_i \pi_s U'(C_{ivs}) = \mu_{vs} \qquad \text{(A1)}$$

where μ_{vs} is the Lagrange multiplier on the aggregate resource constraint. The first-order condition implies that each agent's marginal utility will only depend on the village level aggregate resources and will be independent of individual endowments. Assuming a CRRA utility function, $\frac{C^{1-\gamma}}{1-\gamma}$, Equation (A1) can then be expressed as

$$\ln(C_{ivs}) = \frac{1}{\gamma} \ln \lambda_i - \frac{1}{\gamma} \ln\left(\frac{\mu_{vs}}{\pi_s}\right) \qquad \text{(A2)}$$

where γ is the coefficient of relative risk aversion. The absence of any other variable including household income/endowment on the RHS of Equation (A2) forms the basis for the Townsend (1994) test of full insurance.

(b) Risk sharing test with preference shocks and measurement error

Assume that the utility function in (A1) is given as

$$U(C_{ivmt}) = b_{imt}\frac{C_{ivmt}^{1-\gamma}}{1-\gamma} \qquad \text{(B1)}$$

where *C* denotes consumption for household *i* in village *v* for month *m* and year *t*. b_{imt} are preference shocks. The first-order condition can be written as

$$C_{ivmt} = \left(\frac{1}{\lambda_i}\right)^{-\frac{1}{\gamma}}\left(\frac{1}{b_{imt}}\right)^{-\frac{1}{\gamma}}\left(\frac{\mu_{vmt}}{\pi_{mt}}\right)^{-\frac{1}{\gamma}} \qquad \text{(B2)}$$

Based on the first order condition in Equation (B2), consider the following version of the risk-sharing test

$$C_{ivmt} = \lambda_i^{\frac{1}{\gamma}} b_{imt}^{\frac{1}{\gamma}}\left(\frac{\mu_{vmt}}{\pi_{mt}}\right)^{-\frac{1}{\gamma}} Y_{ivmt}^{\beta} \qquad \text{(B3)}$$

where we have added production as multiplicative to the RHS of the first-order condition. For complete risk sharing, $\beta = 0$. Assume preference shocks to have the following multiplicative form

$$b_{imt} = \sigma_i \phi_{it} \omega_{im} \qquad \text{(B4)}$$

where b_{imt} has a household specific component (σ_i), household year specific trends (ϕ_{it}) and seasonal preference changes (ω_{im}). Moreover, consumption and production are measured with errors in the following manner.

$$C_{ivmt} = C^*_{ivmt}\theta^C_i u^C_{it} v^C_{im} \qquad \text{(B5)}$$

$$Y_{ivmt} = Y^*_{ivmt}\theta^Y_i u^Y_{it} v^Y_{im} \qquad \text{(B6)}$$

Equations B5 and B6 model the measurement errors as multiplicative, with both variables having a household-specific error (θ_i), a household-year-specific error (u_{it}), and a household-month-specific error (v_{im}) in measurement. Substituting B4, B5 and B6 in B3, we get

$$C^*_{ivmt}\theta^C_i u^C_{it} v^C_{im} = \lambda_i^{\frac{1}{\gamma}}(\sigma_i\phi_{it}\omega_{im})^{\frac{1}{\gamma}}\left(\frac{\mu_{vmt}}{\pi_{mt}}\right)^{-\frac{1}{\gamma}}(Y^*_{ivmt}\theta^Y_i u^Y_{it} v^Y_{im})^{\beta} \qquad \text{(B7)}$$

Taking logs on both sides and simplifying, we get

$$\ln(C^*_{ivmt}) = \alpha_i + b_{it} + \vartheta_{im} + t_{vmt} + \beta\ln(Y^*_{ivmt}) + \varepsilon_{ivmt} \qquad \text{(B8)}$$

with the $\alpha_i = \frac{1}{\gamma}\ln\lambda_i + \frac{1}{\gamma}\ln\sigma_i + \beta\ln\theta^Y_i - \ln\theta^C_i$, $b_{it} = \frac{1}{\gamma}\ln\phi_{it} + \beta\ln u^Y_{it} - \ln u^C_{it}$, $\vartheta_{im} = \frac{1}{\gamma}\ln\omega_{im} + \beta\ln v^Y_{im} - \ln v^C_{im}$ and $t_{vmt} = -\frac{1}{\gamma}\ln\left(\frac{\mu_{vmt}}{\pi_{mt}}\right)$.

(c) Production variance decomposition

To decompose production variance, we take logs and seasonal first difference of equation (8) on both sides to get

$$\Delta \mathrm{Ln}(Y_{ivmt}) = \Delta \mathrm{Ln}(Y_{ivmt}) - \Delta \mathrm{Ln}(Y_{ivmt}^{P}) + \Delta \mathrm{Ln}(Y_{ivmt}^{P}) - \Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right) + \Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right) - \Delta \mathrm{Ln}(C_{ivmt}) + \Delta \mathrm{Ln}(C_{ivmt}) \qquad \text{(C1)}$$

Multiplying by $\Delta \mathrm{Ln}(Y_{ivmt})$ on both sides and taking expectations we get

$$\begin{aligned} \mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right) &= \mathrm{Cov}\left(\Delta \mathrm{Ln}(Y_{ivmt}) - \Delta \mathrm{Ln}(Y_{ivmt}^{P}), \Delta \mathrm{Ln}(Y_{ivmt})\right) \\ &+ \mathrm{Cov}\left(\Delta \mathrm{Ln}(Y_{ivmt}^{P}) - \Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right), \Delta \mathrm{Ln}(Y_{ivmt})\right) \\ &+ \mathrm{Cov}\left(\Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right) - \Delta \mathrm{Ln}(C_{ivmt}), \Delta \mathrm{Ln}(Y_{ivmt})\right) \\ &+ \mathrm{Cov}\left(\Delta \mathrm{Ln}(C_{ivmt}), \Delta \mathrm{Ln}(Y_{ivmt})\right) \qquad \text{(C2)} \end{aligned}$$

Then dividing by $\mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right)$ on both sides we get

$$\begin{aligned} 1 &= \frac{\mathrm{Cov}\left(\Delta \mathrm{Ln}(Y_{ivmt}) - \Delta \mathrm{Ln}(Y_{ivmt}^{P}), \Delta \mathrm{Ln}(Y_{ivmt})\right)}{\mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right)} \\ &+ \frac{\mathrm{Cov}\left(\Delta \mathrm{Ln}(Y_{ivmt}^{P}) - \Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right), \Delta \mathrm{Ln}(Y_{ivmt})\right)}{\mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right)} \\ &+ \frac{\mathrm{Cov}\left(\Delta \mathrm{Ln}\left(Y_{ivmt}^{S}\right) - \Delta \mathrm{Ln}(C_{ivmt}), \Delta \mathrm{Ln}(Y_{ivmt})\right)}{\mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right)} \\ &+ \frac{\mathrm{Cov}\left(\Delta \mathrm{Ln}(C_{ivmt}), \Delta \mathrm{Ln}(Y_{ivmt})\right)}{\mathrm{Var}\left(\Delta \mathrm{Ln}(Y_{ivmt})\right)} \qquad \text{(C3)} \end{aligned}$$

or

$$1 = \frac{\mathrm{Cov}(y_{ivmt} - y_{ivmt}^{P}, y_{ivmt})}{y_{ivmt}} + \frac{\mathrm{Cov}\left(y_{ivmt}^{P} - y_{ivmt}^{S}, y_{ivmt}\right)}{y_{ivmt}} + \frac{\mathrm{Cov}\left(y_{ivmt}^{S} - c_{ivmt}, y_{ivmt}\right)}{y_{ivmt}} + \frac{\mathrm{Cov}(c_{ivmt}, y_{ivmt})}{y_{ivmt}} \qquad \text{(C4)}$$

where the lowercase variables denote log seasonal first differences. Note that these terms are regression coefficients and can be written concisely as:

$$1 = \beta^{P} + \beta^{S} + \beta^{O} + \beta \qquad \text{(C5)}$$

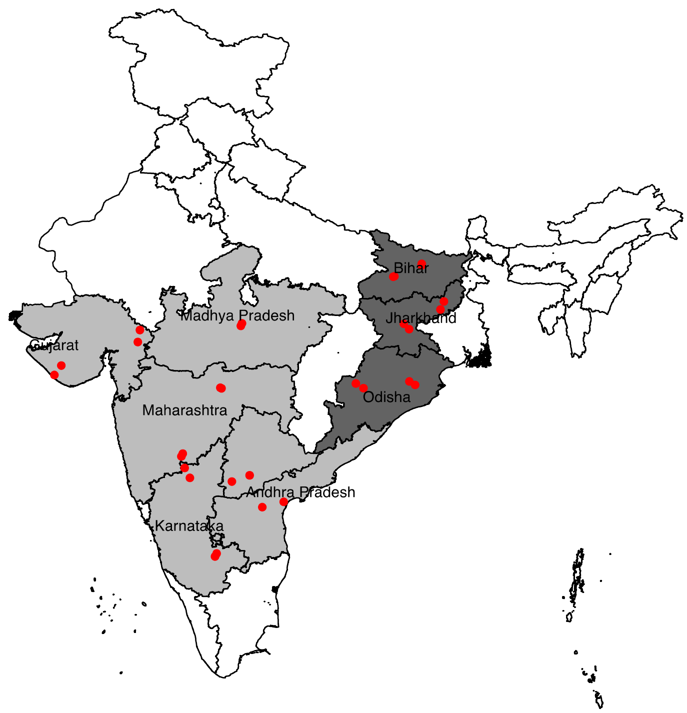

Figure A1. Locations of 30 sampled villages across 8 states of India

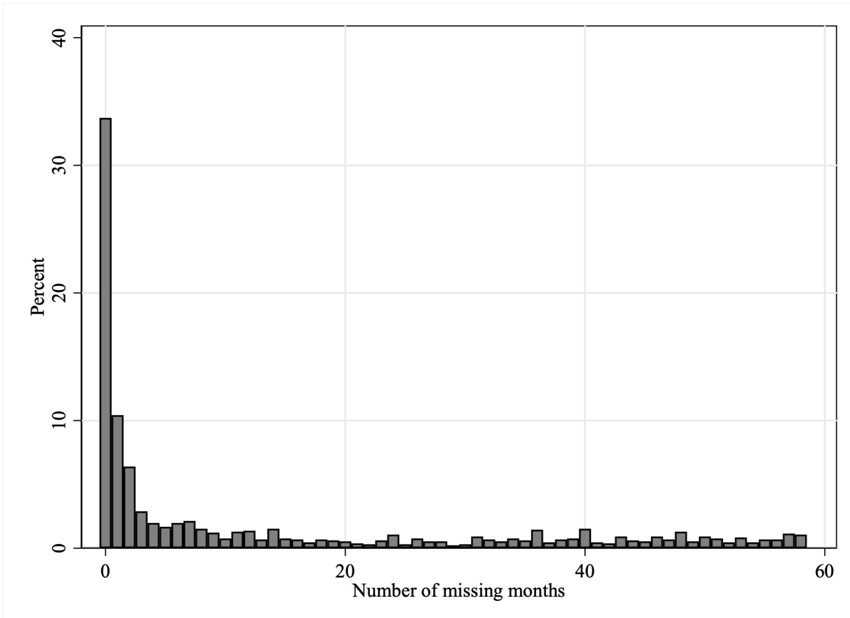

Figure A2. Distribution of missing months per household

Note: The distribution of the number of missing months per sample household (maximum duration is 60 months).

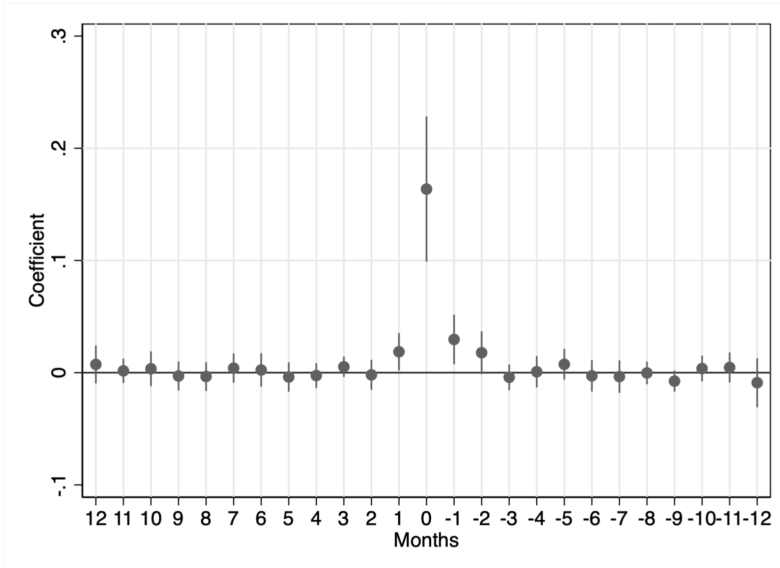

Figure A3. Lead and lagged milk production and risk sharing.

Note: The figure plots the estimated coefficients of 12-month lead and lagged log differenced milk production per person with 95% confidence intervals.

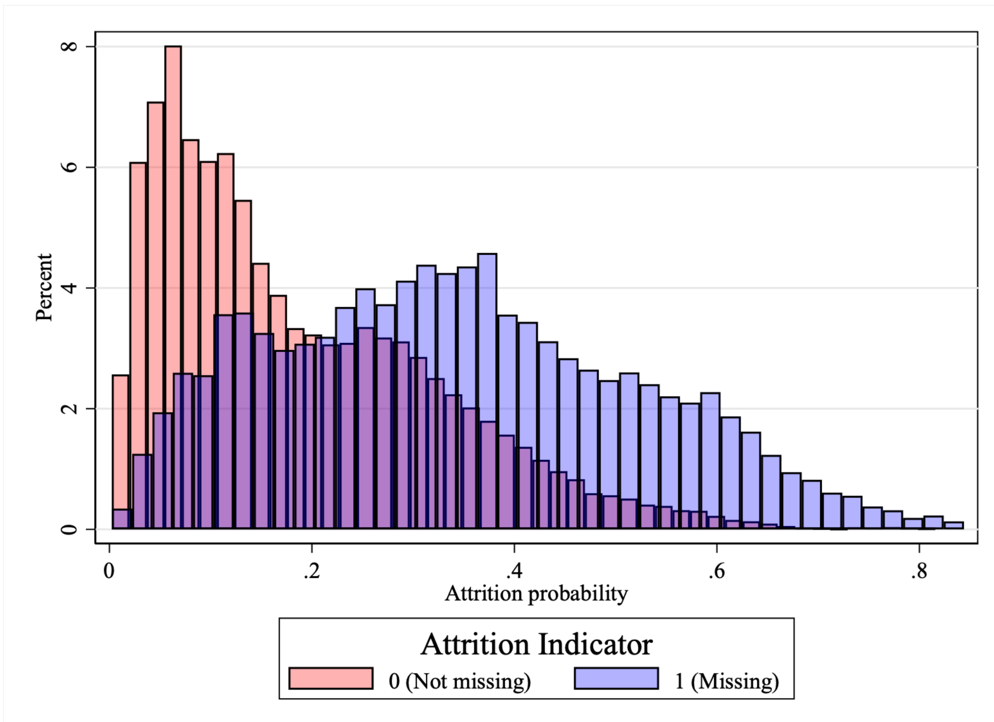

Figure A4. Estimated attrition probability

Note: The figure plots the predicted probabilities from a logit model for attrition from sample based on observed household characteristics and month and year fixed effects.

Table A1. VDSA sampling frame

Region	State	District	Village	Households in the village	Sample
Semi Arid Tropics	Andhra Pradesh	Mahbubnagar	Aurepalle	984	70
	Andhra Pradesh	Mahbubnagar	Dokur	545	50
	Andhra Pradesh	Prakasam	JC Agraharam	382	40
	Andhra Pradesh	Prakasam	Pamidipadu	1214	40
	Maharashtra	Akola	Kanzara	319	62
	Maharashtra	Akola	Kinkhed	189	52
	Maharashtra	Solapur	Kalman	660	61
	Maharashtra	Solapur	Shirapur	546	89
	Karnataka	Bijapur	Kapanimbargi	320	40
	Karnataka	Bijapur	Markabbinahalli	392	40
	Karnataka	Tumkur	Belladamadugu	276	40
	Karnataka	Tumkur	Tharati	401	40
	Gujarat	Junagadh	Karamdi Chingariya	240	40
	Gujarat	Junagadh	Makhiyala	789	40
	Gujarat	Panchmahal	Babrol	750	40
	Gujarat	Panchmahal	Chatha	289	40
	Madhya Pradesh	Raisen	Papda	164	40
	Madhya Pradesh	Raisen	Rampura Kalan	359	40
Eastern	Bihar	Patna	Arap	1166	40
	Bihar	Patna	Baghakole	503	40
	Bihar	Darbhanga	Inai	590	40
	Bihar	Darbhanga	Susari	644	40
	Jharkhand	Dumka	Dumariya	202	40
	Jharkhand	Dumka	Durgapur	126	40
	Jharkhand	Ranchi	Dubaliya	211	40
	Jharkhand	Ranchi	Hesapiri	96	40
	Orissa	Bolangir	Ainlatunga	307	40
	Orissa	Bolangir	Bilaikani	171	40
	Orissa	Dhenkanal	Sogar	428	40
	Orissa	Dhenkanal	Chandrasekharpur	302	40

Note: The table provides details regarding the number of households in the village and the number of households surveyed within each village under the VDSA project.
Source: https://web.archive.org/web/20220522133130/http://vdsa.icrisat.ac.in/vdsa-desgImplementation.aspx

Table A2. Correlation between baseline household characteristics and number of missing months of total milk consumption per household

Household characteristics	Correlation	p-values
Dairy animal ownership	-0.185	0.000
Herd size of large dairy animals (number)	-0.137	0.006
Milk consumption total (liter per person per month)	-0.120	0.000
Milk production (liter per person per month)	-0.176	0.000
Milk sales (liter per person per month)	-0.167	0.000
Family members (number)	-0.058	0.045
Consumption expenditure (rupees per person per month)	-0.145	0.000
Operated land (hectares)	-0.167	0.000

Note: Household characteristics are averages for the baseline year of 2010-2011.

Table A3. Channels of risk-sharing with other controls

	(1)	(2)	(3)	(4)
Proportion of production shocks smoothed out by	Purchases	Sales	Transfers	Residual
$\Delta\ y_{ivmt}$	0.377***	0.293***	0.131***	0.198***
	(0.022)	(0.044)	(0.038)	(0.027)
Δ Log cons. of other milk products per person	-0.009	-0.119	0.446**	-0.318*
	(0.105)	(0.139)	(0.216)	(0.179)
Δ Log cons. of ghee per person	-0.477**	0.113	0.119	0.246
	(0.205)	(0.110)	(0.176)	(0.187)
Δ Log cons. of yoghurt per person	0.112**	-0.250***	0.052	0.087*
	(0.052)	(0.054)	(0.052)	(0.047)
N	45578			

Notes: All regressions include the change in household size and change in log consumption per member as control variables. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4. Instrumented channels of risk-sharing

	(1)	(2)	(3)	(4)	(5)
	$\Delta\, y_{ivmt}$	β^P	β^S	β^O	β
	First stage		Instrumental variable regressions		
Δ Dairy animals	0.527***				
	(0.074)				
$\Delta\, y_{ivmt}$		0.337***	0.397***	0.085***	0.175***
		(0.036)	(0.057)	(0.032)	(0.030)
N			44759		
Δ Dairy animals (lag 1)	0.468***				
	(0.070)				
$\Delta\, y_{ivmt}$		0.340***	0.418***	0.071**	0.167***
		(0.038)	(0.055)	(0.035)	(0.032)
N			41975		
Δ Dairy animals (lag 2)	0.410***				
	(0.064)				
$\Delta\, y_{ivmt}$		0.338***	0.432***	0.064*	0.162***
		(0.042)	(0.056)	(0.036)	(0.038)
N			40593		
Δ Dairy animals (lag 3)	0.356***				
	(0.055)				
$\Delta\, y_{ivmt}$		0.337***	0.415***	0.080**	0.162***
		(0.045)	(0.057)	(0.040)	(0.044)
N			39435		
Δ Dairy animals (lag 4)	0.297***				
	(0.045)				
$\Delta\, y_{ivmt}$		0.339***	0.407***	0.085*	0.161***
		(0.049)	(0.059)	(0.044)	(0.053)
N			38345		

Notes: All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. Column 1 presents the first stage regression results. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Scale of production, new roads, seasonality and consumption smoothing via milk purchases

	(1)	(2)	(3)	(4)	(5)
$\Delta\ y_{ivmt}$	0.479***	0.480***	0.479***	0.480***	0.483***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
$\Delta\ y_{ivmt} \times HS$	-0.061***	-0.061***	-0.061***	-0.061***	-0.059***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$\Delta\ y_{ivmt} \times NROAD$	0.039	0.037	0.038	0.036	0.061
	(0.056)	(0.060)	(0.056)	(0.059)	(0.052)
$\Delta\ y_{ivmt} \times WINTER$	0.002	0.002	0.003	0.003	0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta\ y_{ivmt} \times HS \times NROAD$	-0.067**	-0.068**	-0.066**	-0.068**	-0.063**
	(0.020)	(0.022)	(0.021)	(0.023)	(0.025)
$\Delta\ y_{ivmt} \times HS \times WINTER$	-0.014**	-0.013**	-0.014**	-0.013**	-0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
$\Delta\ y_{ivmt} \times HS \times NROAD \times WINTER$	-0.009	-0.010	-0.009	-0.010	-0.012
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Village FE	Yes	No	Yes	No	Yes
Household FE	No	Yes	No	Yes	No
Month FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Village × Month FE	No	No	No	No	Yes
Village × Year FE	No	No	No	No	Yes
N	45578	45544	45578	45544	45541

Notes: All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\ y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October, November, December, January, February, and March. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Scale of production, new roads, seasonality and consumption smoothing via informal transfers

	(1)	(2)	(3)	(4)	(5)
$\Delta\, y_{ivmt}$	0.080*	0.078	0.080*	0.078	0.076*
	(0.043)	(0.045)	(0.043)	(0.045)	(0.041)
$\Delta\, y_{ivmt} \times HS$	0.019	0.019	0.018	0.019	0.018
	(0.022)	(0.023)	(0.022)	(0.023)	(0.020)
$\Delta\, y_{ivmt} \times NROAD$	-0.050	-0.038	-0.051	-0.039	-0.087*
	(0.051)	(0.050)	(0.050)	(0.050)	(0.044)
$\Delta\, y_{ivmt} \times WINTER$	-0.015	-0.016	-0.015	-0.016	-0.017
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
$\Delta\, y_{ivmt} \times HS \times NROAD$	0.047*	0.043	0.048*	0.044	0.038
	(0.025)	(0.027)	(0.025)	(0.027)	(0.024)
$\Delta\, y_{ivmt} \times HS \times WINTER$	0.026*	0.028*	0.026*	0.028*	0.025
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)
$\Delta\, y_{ivmt} \times HS \times NROAD \times WINTER$	-0.023**	-0.024**	-0.022**	-0.023**	-0.022**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)
Village FE	Yes	No	Yes	No	Yes
Household FE	No	Yes	No	Yes	No
Month FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Village × Month FE	No	No	No	No	Yes
Village × Year FE	No	No	No	No	Yes
N	44797	44763	44797	44763	44760

Notes: All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October, November, December, January, February, and March. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7. Scale of production, new roads and consumption smoothing via sales to formal and informal channels

	(1)	(2)
	Consumption smoothing via sales to	
	Formal channels	Informal channels
$\Delta\, y_{ivmt}$	0.168***	0.047
	(0.049)	(0.045)
$\Delta\, y_{ivmt} \times HS$	0.020	0.027*
	(0.012)	(0.015)
$\Delta\, y_{ivmt} \times NROAD$	0.125*	-0.036
	(0.069)	(0.046)
$\Delta\, y_{ivmt} \times WINTER$	-0.005	0.016
	(0.011)	(0.010)
$\Delta\, y_{ivmt} \times HS \times NROAD$	0.054**	-0.028*
	(0.022)	(0.016)
$\Delta\, y_{ivmt} \times HS \times WINTER$	0.007	-0.015*
	(0.007)	(0.008)
$\Delta\, y_{ivmt} \times HS \times NROAD \times WINTER$	0.012	0.009
	(0.009)	(0.007)
N	45154	44677
Sales (%)	78.35	21.65

Notes: Formal channels include sales to cooperatives and private processors. Informal channels include sales to local agents, shops, and fellow farmers. All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October, November, December, January, February, and March. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8. New roads and state-level dairy processing capacity

	(1)	(2)	(3)
	Log dairy plants (both cooperative and private)	Log material consumed by dairy plants in rupees lacs	Log inputs consumed by dairy plants in rupees lacs
$UROAD$	-0.003	-0.006	0.001
	(0.008)	(0.011)	(0.011)
$NROAD$	-0.009	0.006	0.012
	(0.013)	(0.022)	(0.022)
N		295	

Notes: All regressions include state fixed effects and time dummies. UROAD, and NROAD capture either village road upgradation or new rural road construction under the PMGSY respectively. Figures in parenthesis are standard errors robust to the intra-state correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A9. New roads and new bank branches in VDSA villages

	(1)	(2)
$UROAD$	-0.038	
	(0.028)	
$NROAD$		-0.054
		(0.039)
N	173	

Notes: The dependent variable is a dummy which equals 1 if a new bank branch came up in a VDSA village in a particular year and is 1 thereafter. Data on bank branches at the village level comes from the SHRUG database. All regressions include village fixed effects and time dummies. UROAD, and NROAD capture either village road upgradation or new rural road construction under the PMGSY respectively. Figures in parenthesis are standard errors robust to the intra-state correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A10. Change in stocks of other commodities and risk-sharing

	(1)	(2)	(3)
Dependent variable: seasonally differenced log milk consumption per person			
$\Delta\ y_{ivmt}$	0.200***	0.200***	0.200***
	(0.027)	(0.027)	(0.027)
Δ Log cereal stocks quantity per member	0.006	0.009	
	(0.008)	(0.008)	
Δ Log pulses stocks quantity per member		-0.014	
		(0.009)	
Δ Log value of total stocks per member			0.006
			(0.008)
N		45578	

Notes: All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\ y_{ivmt}$ denotes seasonally differenced log per person household production of milk. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A11. Savings, asset sales, other financial transactions and risk-sharing

	(1)	(2)	(3)	(4)	(5)
Dependent variable: seasonally differenced log milk consumption per person					
$\Delta\ y_{ivmt}$	0.200***	0.200***	0.200***	0.200***	0.200***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Δ Log savings per member	-0.004				
	(0.004)				
Δ Log withdrawal per person	-0.003				
	(0.003)				
Δ Log durables purchased per member		-0.008**			
		(0.004)			
Δ Log durables sold per member		-0.002			
		(0.005)			
Δ Log loans taken per person			-0.004**		
			(0.002)		
Δ Log loans given per person			0.001		
			(0.002)		
Δ Log gifts received per person				-0.000	
				(0.002)	
Δ Log gifts given per person				0.004	
				(0.003)	
Δ Log land purchased per person					0.006
					(0.004)
Δ Log land sold per person					-0.015
					(0.009)
N			44779		

Notes: All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\ y_{ivmt}$ denotes seasonally differenced log per person household production of milk. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A12. Determinants of attrition

	(1)
Ln(Number of dairy animals)	1.047***
	(0.381)
Ln(Milk production per member)	-0.622***
	(0.159)
Ln(Number of household members)	-1.069***
	(0.292)
Ln(Monthly consumption expenditure per member)	-1.355***
	(0.268)
Ln(Operated land)	-0.458**
	(0.219)
Social group: Other Backward Caste	-0.594*
	(0.355)
Social group: Others	0.446
	(0.295)
Social group: Scheduled Caste	-0.090
	(0.306)
Social group: Scheduled Tribe	0.523
	(0.660)
2.month	0.095**
	(0.039)
3.month	0.147*
	(0.076)
4.month	0.164**
	(0.071)
5.month	0.106*
	(0.063)
6.month	0.180**
	(0.070)
7.month	0.044
	(0.080)
8.month	-0.010
	(0.079)
9.month	-0.031
	(0.066)
10.month	-0.051
	(0.068)
11.month	-0.151
	(0.113)
12.month	-0.123
	(0.110)
2011.year	0.047
	(0.105)
2012.year	-0.022

	(0.134)
2013.year	0.026
	(0.142)
2014.year	-0.028
	(0.167)
2015.year	-0.188
	(0.196)
N	78840

Notes: The dependent variable is a dummy variable, which is 1 if the total milk consumption is missing for the household and 0 otherwise. Household characteristics like herd size, consumption expenditure, milk production, number of household members and operated land are averages for the entire period. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A13. Channels of risk-sharing estimates adjusted for attrition from panel

	(1)	(2)	(3)	(4)
Proportion of production shocks smoothed out by	Purchases	Sales	Transfers	Residual
	β^P	β^S	β^O	β
	0.394***	0.277***	0.117***	0.212***
	(0.022)	(0.047)	(0.033)	(0.029)
$H^0: 1-\beta=0$	0.788***			
	(0.029)			
$H^0: \beta^P-\beta^S=0$	0.117*			
	(0.060)			
$H^0: \beta^P-\beta^O=0$	0.277***			
	(0.040)			
$H^0: \beta^S-\beta^O=0$	0.161**			
	(0.072)			
$H^0: \beta^P+\beta^S-\beta^O=0$	0.554***			
	(0.069)			
N	44757			

Notes: Regressions are adjusted for attrition by inverse probability weighting. All regressions include household size and value of consumption as control variables. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A14. Channels of risk-sharing: balanced panel

	(1)	(2)	(3)	(4)
Proportion of production shocks smoothed out by	Purchases	Sales	Transfers	Residual
	β^P	β^S	β^O	β
	0.399***	0.355***	0.060***	0.186***
	(0.035)	(0.049)	(0.022)	(0.038)
1. $H^0: 1-\beta=0$	0.814***			
	(0.038)			
2. $H^0: \beta^P-\beta^S=0$	0.043			
	(0.078)			
3. $H^0: \beta^P-\beta^O=0$	0.339***			
	(0.041)			
4. $H^0: \beta^S-\beta^O=0$	0.296***			
	(0.055)			
N	25104			

Notes: Estimates from a subsample of households with total milk consumption data for all 60 months. All regressions include the change in household size and change in log per member value of consumption as control variables. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A15. Roads, herd size, seasonality and attrition

	(1)	(2)
Dependent variable: =1 if total milk consumption missing for a month, 0 otherwise		
$UROAD$	-0.030	
	(0.063)	
$WINTER$	-0.005	-0.008
	(0.005)	(0.006)
$UROAD \times WINTER$	-0.023	
	(0.023)	
$HS \times UROAD$	0.075	
	(0.073)	
$HS \times WINTER$	-0.005*	-0.003
	(0.002)	(0.002)
$HS \times UROAD \times WINTER$	0.007	
	(0.005)	
$NROAD$		0.058
		(0.042)
$NROAD \times WINTER$		-0.018
		(0.016)
$HS \times NROAD$		-0.029*
		(0.015)
$HS \times NROAD \times WINTER$		-0.001
		(0.009)
N	78840	

Notes: The dependent variable is a dummy variable, which is 1 if the total milk consumption is missing for the household and 0 otherwise. UROAD, and NROAD capture either village road upgradation or new rural road construction under the PMGSY respectively. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A16. Scale of production, new roads, seasonality and channels of risk-sharing adjusted for attrition

	β^P	β^S	β^O	β
$\Delta\, y_{ivmt}$	0.484***	0.204***	0.078**	0.235***
	(0.033)	(0.056)	(0.035)	(0.042)
$\Delta\, y_{ivmt} \times HS$	-0.057***	0.048***	0.023	-0.013
	(0.010)	(0.016)	(0.018)	(0.010)
$\Delta\, y_{ivmt} \times NROAD$	0.037	0.065	-0.040	-0.062
	(0.040)	(0.066)	(0.056)	(0.044)
$\Delta\, y_{ivmt} \times WINTER$	0.002	0.009	-0.016	0.005
	(0.010)	(0.013)	(0.012)	(0.014)
$\Delta\, y_{ivmt} \times HS \times NROAD$	-0.068***	0.031*	0.048	-0.010
	(0.017)	(0.017)	(0.031)	(0.020)
$\Delta\, y_{ivmt} \times HS \times WINTER$	-0.015**	-0.009	0.028***	-0.004
	(0.006)	(0.009)	(0.010)	(0.008)
$\Delta\, y_{ivmt} \times HS \times NROAD \times WINTER$	-0.011	-0.018	-0.032***	0.060
	(0.020)	(0.034)	(0.009)	(0.056)
N		44757		

Notes: Regressions are adjusted for attrition by inverse probability weighting. All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October through March. Figures in parentheses are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A17. Scale of production, new roads, seasonality and channels of risk-sharing: balanced panel

	(1)	(2)	(3)	(4)
	β^P	β^S	β^O	β
$\Delta\, y_{ivmt}$	0.482***	0.271***	0.056**	0.191***
	(0.049)	(0.055)	(0.028)	(0.050)
$\Delta\, y_{ivmt} \times HS$	-0.054***	0.060***	0.001	-0.006
	(0.013)	(0.012)	(0.012)	(0.011)
$\Delta\, y_{ivmt} \times NROAD$	0.065	0.123**	-0.105***	-0.083
	(0.047)	(0.054)	(0.027)	(0.053)
$\Delta\, y_{ivmt} \times WINTER$	0.006	-0.015	-0.002	0.010
	(0.012)	(0.018)	(0.017)	(0.014)
$\Delta\, y_{ivmt} \times HS \times NROAD$	-0.088***	-0.011	0.070***	0.028**
	(0.012)	(0.013)	(0.012)	(0.013)
$\Delta\, y_{ivmt} \times HS \times WINTER$	-0.018**	0.010	0.008	0.001
	(0.009)	(0.010)	(0.010)	(0.007)
$\Delta\, y_{ivmt} \times HS \times NROAD \times WINTER$	0.011**	0.001	-0.015***	0.002
	(0.005)	(0.005)	(0.005)	(0.004)
N	25104			

Notes: Estimates from a subsample of households with total milk consumption data for all 60 months. All regressions include the change in household size and change in log consumption per member as control variables. $\Delta\, y_{ivmt}$ denotes seasonally differenced log per person household production of milk. HS is the average herd size of a farm household during the entire period. NROAD captures new rural road construction under the PMGSY. WINTER is a dummy variable that takes values 1 for October, November, December, January, February, and March. Figures in parenthesis are standard errors robust to the intra-village correlation of residuals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.