

Mobility, Climate Shocks, and Demand for Information: Evidence from India

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Abstract

Weather shocks pose severe risks to agricultural communities in India. Information on how to mitigate their effects, however, can be difficult to access, as it spreads slowly through potentially sparse and distant social networks. Using novel cellphone mobility data merged with over 1.5 million calls to India’s national agricultural helpline, we document three patterns. First, mobility in rural India is severely constrained: over 75% of areas exhibit primarily local travel. Second, we examine how mobility and helpline calls correlate with climate shocks—heatwaves and extended droughts. While mobility increases during heatwaves, helpline calls decline. Third, this relationship varies systematically with baseline mobility levels: the negative association between climate shocks and calls is significantly weaker in low-mobility areas across multiple measures of geographic isolation. The heterogeneity is specific to agricultural information requests and concentrated during crop growing seasons.

The majority of India’s poverty is concentrated in rural areas, where agriculture is the dominant economic activity and therefore particularly vulnerable to climate change (World-Bank, 2012; Kala, 2023). An important mediator in how well and how quickly farmers learn climate-adaptive practices is how information spreads within their communities. However, information sharing in societies can be hampered by frictions such as social stigmas and preferences for homophily (Chandrasekhar, Golub, and Yang, 2019; Goffman, 1963; Golub and Jackson, 2009). A burgeoning literature has illuminated that *who* receives information may be instrumental for its widespread dissemination (Banerjee et al., 2019; Beaman et al., 2021). Still, social learning may depend on how farmers seek information and relief in times of distress.

In this project, we use NetMob’s origin-destination and population density data to create several measures that capture important facets of mobility and insularity. We combine this with daily call log data from India’s Kisan Call Center (KCC), one of the world’s largest agricultural extension programs, as well as daily precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and daily air temperature data from the ERA5 product of the European Centre for Medium-Range Weather Forecasts (ECMWF). We utilize this data to: **(1)** Document temporal and spatial patterns in mobility

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across India, and their relationship to other aspects of development; **(2)** Examine the relationship between climate shocks – such as consecutive hot or dry days¹ and farmers’ demand for information from KCC; and **(3)** Examine how mobility mediates the demand for and diffusion of information surrounding climate hazards.

1 Characterizing Mobility

First, we characterize the mobility pattern of India’s agricultural population. In Table 1, we explore differences in subdistrict characteristics and mobility between the full sample of Mission Antyodaya administrative data, made available through the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021), and rural subdistricts which sought information in a farmer helpline. These summary statistics illuminate the stark mobility deficit the rural poor face, not only in terms of total trips but in the length, duration, and speed of those trips, which may be attributable to their relative lack of access to transport and infrastructure (see: Table 3).

1.1 Patterns of Mobility

We first exploit India’s rapidly expanding cellular network coverage and cell phone penetration in the past decade to characterize the mobility patterns of rural agricultural communities. Cell phone penetration in rural India has expanded rapidly, enabling new measurement of mobility patterns using real-time data. While coverage is incomplete, we can characterize mobility for a large sample of rural communities. The closest analogue are time use surveys, but these can only determine average mobility patterns over a time period. Using the Spec-tus Origin-Destination (OD) data, we first attempt to characterize the mobility pattern of an on and off-season work week for an average farmer in rural India, and how their mobility might change throughout the season.

We begin by examining how people in India move and to where. Figure 1 plots the distribution of the number of daily outbound trips from a geohash, defined as a trip for which the start geohash is different than the end geohash. We observe that there is a large spread in the distribution – some places have well over 30 outbound trips per day. However, the majority of geohashes are the origin of relatively few (fewer than five) outbound trips per day. Zooming out, we illustrate in Figure 2 that over 75% of geohashes only contain trips that begin and end in the same area.

Having documented that mobility is overall quite low in India, we proceed to explore how trips and the length of those trips interact. In Figure 3, we plot the relationship between total trip count and the mean length of those trips for each geohash. The plot shows that when trip counts are high, trip lengths are also long. The bulk of the mass in the first quadrant shows that a large number of trips span several kilometers, suggesting these are

¹We define a “dry day” as a day with fewer than 2mm of precipitation, and a “hot day” as a day with a maximum temperature above a certain threshold, which we set flexibly at 30C, 35C, and 40C. Hogan and Schlenker (2024) documents that temperatures generally above 30C are harmful to several crop types; Zivin and Shrader (2016) documents that high temperatures, generally above 29C dramatically increases mortality.

likely trips across villages or towns rather than within communities. In other words, highly mobile places are characterized not just by the sheer number of trips but also by the relatively long distances those trips span.

1.1.1 Measures of Mobility

1. **Total Mobility Index:** calculated as the origin-destination population-weighted number of trips within and outside a geohash; the probability of a geohash only containing trips within itself; the distribution-ranked, population-weighted trips into a geohash (Inbound Popularity Rank) and out of a geohash (Outbound Popularity Rank); and an indicator for whether individuals in a geohash only move within their own geohash.
2. **Mobility Transition Matrix:** A row-stochastic transition matrix that normalizes trips by the row-sum of total outbound trips, to determine the probability that in the observation window a trip from unit i will end in unit j .
3. **Isolated Indicator:** Value equal to one if the geographic unit only has trips to itself during the entire observation period.
4. **Social Connectedness Mobility Index:** Based on Bailey et al. (2018), total number of trips between two locations i and j , divided by the product of their total trips.
5. **Within-farm trips:** We assume a log-normal distribution for trip length and gamma distribution for trip duration, in order to fully characterize the distribution given the mean and variance for each geographic unit. Errors are estimated based on implied parametric median and reported median. We assume a "within-farm" trip is of length and duration less than or equal to the 75th percentile of the distribution for fully agricultural geographic units, for that time period in the year.

1.2 Correlates of Mobility

One aspect of mobility that is of particular interest is its role in information diffusion and access to resources. Off-farm travel likely exposes farmers to different sources of information, whether they are directly seeking information or not. A natural example is a farmer visiting a local market as they source inputs for the upcoming season, a government office in order to apply to a subsidy or receive any form of aid, or simply visiting friends who, given well-documented social homophily in India, expose them to varied information. In other words, while we cannot determine the purpose of any given trip, their trips likely expose them to information that facilitates resource gathering.

We formally test for what aspects of infrastructure are most highly correlated with mobility in Table 2. Using data on village facilities from Mission Antyodaya, as accessed through the SHRUG, we run regressions of mobility on facilities, giving us correlational estimates. The results show that access to roads and public transport indeed corresponds with people moving more on a daily basis. In columns (2) and (3), we explore how infrastructure correlates with other descriptors of mobility, such as our Total Mobility Index, calculated as the origin and destination normalized number of trips take to, from, and within a geohash,

and the probability of self-transition, which expresses the likelihood that a given trip in a given geohash will end in the same geohash. We use the probability of self transition as a proxy for insularity. Between the two, our aim is to explore whether these aspects of infrastructure correlate with outside or insular movement. Public transport and all-weather roads are correlated with a lower probability of self-transition. In other words, it appears people with access to these facilities are more likely to travel significant distances from their own communities. Furthermore, geohashes with weekly markets have higher TMI, indicating more overall travel to, within, and from those places. This is consistent with markets serving as regional hubs for agricultural trade.

In Table 3, we regress mobility on each facility separately, adding in district fixed effects. Our outcome variable is the log of total trips. We find strong positive coefficients on most infrastructure variables: public transport, existence of all weather roads, existence of internal pucca roads, railway stations, and the existence of regular markets.

2 Farmer Helpline: Kisan Call Center (KCC)

To complement our agricultural mobility estimates with agricultural demand for information, we merge call logs of a nationwide, all-purpose farmer helpline. These Kisan Call Centers (KCC, literally farmer call center) aim to provide a single nationwide phone number that can answer farmer queries ranging from weather forecasts and access to government schemes, to crop and pest management. Each call is geo-located at the sub-district level, which we use as a key to merge onto the mobility data. For the relevant time period (2019-2020) this results in over 1.5 million individual calls, while the complete dataset spans from 2006-2024 and includes over 40 million calls.

Each call log provides rich details, including a rough transcript of the question raised by the farmer, the answer provided by the operator, as well as broad topic classification including the crop the farmer was inquiring about. This government service provides a direct measure of farmers' information-seeking behavior because KCC only provides information to farmers if they call in.

Our first observation is that the demand for information about crop management is strikingly seasonal and aligns exactly with the times of planting and harvest of each crop (see Figure 4). Notably, demand for crop management information is highest during the growing season rather than in preparation periods, suggesting that farmers do not call in preparation of the upcoming season but rather as concerns arise during it.

3 Climate Hazards, Movement, and Demand for Information

In this section we document how mobility and calls to KCC respond to climate shocks, and how those responses move in tandem. Recent work has explored how mobility can be a climate-adaptive action, as people can migrate to less shock-exposed areas (Lee et al., 2022). However, we have documented in previous sections that mobility is quite low among India's agricultural communities. In this case, relatively immobile rural households may respond

to climate hazards not through movement but through seeking information, calling KCC to understand what they can do to recover.

3.1 Response of Movements and Calls to Climate Hazards

First, we explore how mobility and demand for information (calls) respond to climate shocks independently through OLS regressions of total trips and total calls on rain and temperature shocks. We test responses to multiple definitions of these shocks, though we are consistent in how we define them temporally: heatwaves are always defined as three or more days for which the maximum daily temperature is above a certain threshold, and droughts are always defined as 15 or more days with fewer than 2mm of precipitation, taken as the average of the CHIRPS pixel values of daily precipitation across an administrative unit. We test different values of the temperature threshold for heatwaves – 30C, 35C, and 40C – as high temperatures may be harmful for different reasons. For example, 30C may be harmful for crops (Hogan and Schlenker, 2024) but not as much for people laboring outside. At 35C, the damage may scale up for crops and also for human health, and even further at 40C, where the ambient temperatures may be so extreme that even mild exposure could be dangerous for human health. We additionally test coefficients on consecutive days above (below) heat (rain) thresholds, as longer exposure may be more harmful and beget stronger adaptive actions.

In Table 5, we report our results on this exercise. The mobility response to heat shocks is always positive. While, at a geohash-5 level, we must remain agnostic as to what these movements mean, it is clear that trips increase by 21-23% in response to heatwaves, with the marginal additional day above a temperature threshold inducing additional trips at a rate of 0.2-1.3%, depending on the threshold. The mobility coefficients on droughts and consecutive dry days are negative, implying fewer trips in response to droughts. While we cannot disaggregate what specific actions are reflected in these fewer trips, it is possible that the adaptive actions that farmers take in response to droughts are different than those taken in response to heatwaves.

In columns (2) through (5), we examine how demand for information from KCC responds to these same climate shocks. Across the board, all significant coefficients are negative, particularly in response to shocks where the mobility response is quite high. This suggests that more mobile farmers are less likely to call the helpline on any given day. This negative correlation is consistent with different information-access patterns across areas with varying mobility levels, which we explore further in the following section.

3.2 Interaction of Information Provision and Mobility

Next, we explore the relationship between mobility and information seeking during climate shocks. Preliminary regression results on the relationship between mobility and information seeking are presented in Table 4. Every coefficient is negative, suggesting that calls increase when mobility is low. This pattern is evident as well in daily trip counts, as shown in Figure 6: individuals in places that have called to KCC are much less mobile than those in places that do not, suggesting that those who utilize KCC may not otherwise have the capacity to access other support networks.

Furthermore, mobility may be an important means of adapting to climate shocks. Individuals in places with high mobility may have better access to external support networks or may benefit from more intra-community social cohesion. In this case, KCC may prove critical for those unable to access network resources. In Table 5, we document that total trips unambiguously increase in response to high temperatures and heatwaves, though they decrease in response to droughts. The coefficients on calls to KCC are negative when statistically significant, thus calls drop when movement increases, and vice versa.

We explore this relationship more formally in Table 6, where we examine how our Total Mobility Index (TMI), which captures the population-weighted sum of total trips into and out of a place, interacts with the call response to climate shocks. Again, where statistically significant, the interaction coefficients are negative, suggesting KCC may provide a substitute for mobility as a response to climate shocks when mobility is low. These results are supported by results in Table 7, where we interact instead with the proportion of geohashes that only contain trips within itself – a measure of insularity. Additional results interacting with the probability of only taking trips within one’s own geohash (Table 8) and the distribution-ranked, population-weighted measures of inbound and outbound trips, bolster the narrative suggested in our aforementioned results.

Finally, we explore whether information-seeking patterns following climate shocks differ by mobility level. Information gained through KCC may spread more quickly in places that have high mobility, as people interact more and have more opportunities to share information. If this is the case, the rate of calling in response to climate shocks should revert to their normal levels more slowly in low mobility places as more individuals need to call in order for information to saturate. We therefore plot event studies of the call response to climate shocks in Figures 10 and 11, and we plot the event studies of the mobility-shock interactions in Figures 12, 13, 14, and 15. The event study patterns do not reveal consistent timing differences across mobility levels.

3.3 Conclusion

This paper documents the relationship between mobility and information access among India’s rural agricultural poor. We establish three key findings. First, mobility is severely constrained: over 75% of rural areas exhibit primarily local travel, with strong correlations to infrastructure deficits including roads, transport, and market access. Second, climate shocks – heatwaves and droughts – have opposite associations with mobility and helpline usage: mobility increases during heat stress while formal information-seeking through helplines declines. Third, this pattern varies systematically by baseline mobility: the negative association between shocks and calls is significantly weaker in low-mobility areas, suggesting heterogeneous information access strategies across communities. These patterns are consistent with mobility facilitating access to informal information networks that partially substitute for formal extension services. While we cannot definitively establish causal mechanisms with our correlational design, several features of the data strengthen an information-access interpretation. The heterogeneity is quantitatively large, robust across multiple mobility measures (though not all), driven specifically by agricultural information requests rather than general inquiries, and emerges during planting and growing seasons when information needs are acute.

Our findings have implications for agricultural extension policy. If geographically isolated farmers rely more heavily on formal services like helplines during climate stress, these services may be reaching particularly underserved populations. The mobility measures we construct could help policymakers identify areas where remote information services – helplines, SMS systems, radio programs – may be especially valuable relative to in-person extension.

More broadly, this work highlights how infrastructure constraints shape information-seeking behavior in developing countries. The combination of cellphone mobility data with administrative records from government services offers a scalable approach to identifying isolated communities and understanding their information access patterns. As climate shocks intensify and mobile phone penetration expands, such data may prove increasingly valuable for targeting information interventions in developing countries.

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Tables

Table 1: Mission Antyodaya Summary Statistics Comparison

Variable	Full Sample (5480 subdistricts)		KCC Sample (3895 subdistricts)	
	Mean	SD	Mean	SD
Has Public Transport	0.853	0.154	0.820	0.165
Connected to All-weather Road	0.850	0.140	0.810	0.147
Has Internal Pucca Road	0.527	0.237	0.515	0.219
Has Railway Station	0.068	0.091	0.052	0.075
Has Mandi	0.042	0.087	0.039	0.082
Has Regular Market	0.157	0.202	0.139	0.179
Has Weekly Haat	0.194	0.191	0.207	0.189
Total Population	296357.452	271548.473	258028.291	211690.667
Total Households	60635.351	46410.117	51929.920	36780.057
Has Bank	0.377	0.239	0.297	0.188
Has Broadband	0.579	0.264	0.490	0.253
Log(1 + Trips)	3.611	1.118	0.871	1.901
Log(1 + Trip Length)	8.397	1.352	1.914	3.759
Log(1 + Trip Duration)	4.887	0.930	1.140	2.315
Trip Speed	55.323	123.869	12.169	60.570

Table 2: Regressions: Mission Antyodaya Facilities, Total Trips, TMI, Prob. Self-Transition, and Total Calls

	(1) Log(1+Total Trips)	(2) Total Mobility Index	(3) Prob. Self-Transition	(4) Log(1+Total Calls)
Log(1+Total Pop.)	0.715*** (0.165)	-0.02136*** (0.00431)	-0.00847*** (0.00190)	0.213*** (0.0507)
Log(1+Total Farmers)	-0.564*** (0.116)	0.01126*** (0.00253)	0.00791*** (0.00144)	0.0694. (0.0346)
Public Transport	0.403 (0.310)	-0.02226 (0.01519)	-0.00581** (0.00191)	-0.166 (0.151)
All Weather Road	0.597** (0.215)	-0.02799. (0.01432)	-0.00947* (0.00389)	0.0775 (0.0940)
Internal Pucca Road	-0.148 (0.122)	-0.00340 (0.00641)	0.00237 (0.00204)	-0.127** (0.0449)
Railway Station	0.484 (0.344)	-0.07350*** (0.01147)	-0.00828 (0.00494)	-0.0969 (0.0947)
Mandi	0.995 (0.532)	0.00902 (0.03065)	-0.00444 (0.00974)	0.00934 (0.131)
Regular Market	0.361 (0.374)	0.01589 (0.01467)	-0.00632. (0.00334)	-0.0263 (0.0530)
Weekly Haat	-0.302 (0.210)	0.03296** (0.01107)	0.00332 (0.00284)	-0.0674 (0.0736)
Log(1 + No. of Self Help Groups)	-0.077 (0.075)	0.00536* (0.00220)	0.00095 (0.00077)	0.00306 (0.0212)
Observations	516,567	1,431,612	1,431,612	230,299
R^2	0.391	0.279	0.032	0.511
Within R^2	0.078	0.031	0.015	0.026

Table 3: Regressions: Mission Antyodaya Facilities and Total Trips

Dep. Var.: Log(1+Total Trips)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(1 + Total Pop.)	0.5683*** (0.0829)								
Log(1 + Total Farmers)		0.1837* (0.0777)							
Public Transport			0.7756** (0.2645)						
All Weather Road				0.8145*** (0.2227)					
Internal Pucca Road					0.0703 (0.1824)				
Railway Station						1.912*** (0.3924)			
Mandi							0.4980 (0.4258)		
Regular Market								0.8656** (0.3186)	
Weekly Haat									-0.5037. (0.2642)
Fixed-Effects:									
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	790,011	790,011	790,011	790,011	790,011	790,011	790,011	790,011	790,011
R^2	0.29588	0.28112	0.28037	0.28137	0.27849	0.28521	0.27883	0.28162	0.27984
Within R^2	0.02417	0.00371	0.00267	0.00405	0.000059	0.00938	0.00054	0.00440	0.00193

Table 4: Regression: Correlations Between Mobility and Calls to KCC

Dep. Variable: Total Calls	Regression Models			
	(1)	(2)	(3)	(4)
Log(1 + Total Trips)	-0.2552*** (0.0332)			
Log(1 + Total Length)		-0.1211*** (0.0090)		
Log(1 + Total Duration)			-0.2030*** (0.0175)	
Log(1 + Speed)				-0.2417*** (0.0162)
Fixed-Effects:				
Subdistrict FE	Yes	Yes	Yes	Yes
Observations	807,677	807,677	807,677	807,677
R^2	0.54261	0.54278	0.54274	0.54275
Within R^2	0.00063	0.00101	0.00092	0.00094

Table 5: Climatic Events, Trips, and Calls

	(1) Total Trips	(2) Total Calls	(3) Weather Calls	(4) Crop Mgmt. Calls	(5) Finance Calls
Any Shock	0.0592** (0.0174)	-0.0623 (0.0620)	-0.1232* (0.0496)	0.0337 (0.0894)	-0.0104 (0.0269)
Heatwave (30C)	0.2329*** (0.0161)	-0.0200 (0.0467)	-0.0211 (0.0243)	0.0177 (0.0769)	-0.0129 (0.0215)
Heatwave (35C)	0.2326*** (0.0121)	-0.1618*** (0.0438)	-0.1041* (0.0422)	-0.1384* (0.0604)	-0.0607* (0.0281)
Heatwave (40C)	0.2130*** (0.0121)	-0.2517*** (0.0474)	-0.2509*** (0.0462)	-0.1653* (0.0660)	-0.0566. (0.0297)
Consecutive Days Above 30C	0.0028*** (0.0002)	-0.0001 (0.0006)	0.0011* (0.0004)	-0.0008 (0.0009)	-0.0005. (0.0003)
Consecutive Days Above 35C	0.0046*** (0.0005)	-0.0041*** (0.0007)	-0.0019* (0.0007)	-0.0046*** (0.0011)	-0.0013. (0.0007)
Consecutive Days Above 40C	0.0132*** (0.0023)	-0.0146*** (0.0028)	-0.0110** (0.0032)	-0.0141*** (0.0019)	-0.0026 (0.0021)
Drought	-0.1054*** (0.0175)	-0.2182*** (0.0458)	-0.2213 (0.0681)	-0.1072** (0.0350)	0.0082 (0.0182)
Consecutive Days Precip. < 2mm	0.0003 (0.0005)	-0.0047*** (0.0007)	-0.0060*** (0.0011)	-0.0033*** (0.0005)	0.0005 (0.0004)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 6: Call Response to Climate Events Interacted with Total Mobility Index (TMI)

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0462 (0.0609)	-0.1136* (0.0540)	0.0500 (0.0863)	-0.0191 (0.0257)
Any Shock*TMI	-0.2489 (0.3213)	-0.1480 (0.2769)	-0.2518 (0.3596)	0.1338 (0.1541)
Heatwave (30C)	-0.0320 (0.0420)	-0.0362 (0.0217)	0.0139 (0.0725)	-0.0248 (0.0195)
Heatwave (30C)*TMI	0.1807 (0.2325)	0.2279 (0.2059)	0.0563 (0.2923)	0.1789 (0.1127)
Heatwave (35C)	-0.1509** (0.0422)	-0.0873. (0.0451)	-0.1237* (0.0561)	-0.0584. (0.0314)
Heatwave (35C)*TMI	-0.1549 (0.2477)	-0.2404 (0.2813)	-0.2096 (0.2426)	-0.0325 (0.1369)
Heatwave (40C)	-0.2442*** (0.0556)	-0.2525*** (0.0601)	-0.1321. (0.0712)	-0.0614 (0.0365)
Heatwave (40C)*TMI	-0.1003 (0.2238)	0.0218 (0.2626)	-0.4474 (0.3310)	0.0650 (0.1504)
Consec. Days > 30C	-0.0005 (0.0005)	0.0006 (0.0004)	-0.0008 (0.0008)	-0.0004* (0.0002)
Consec Days > 30C * TMI	0.0052 (0.0043)	0.0075. (0.0044)	0.0005 (0.0030)	-0.0003 (0.0013)
Consec. Days > 35C	-0.0038*** (0.0010)	-0.0018. (0.0010)	-0.0040** (0.0013)	-0.0009 (0.0006)
Consec. Days > 35C * TMI	-0.0036 (0.0068)	-0.0007 (0.0066)	-0.0073 (0.0053)	-0.0049 (0.0032)
Consec. Days > 40C	-0.0157*** (0.0028)	-0.0125** (0.0035)	-0.0133*** (0.0017)	-0.0029 (0.0024)
Consec. Days > 40C * TMI	0.0140 (0.0115)	0.0197 (0.0124)	-0.0105 (0.0187)	0.0036 (0.0060)
Drought	-0.1480** (0.0498)	-0.2356** (0.0740)	-0.0685. (0.0387)	0.0080 (0.0202)
Drought*TMI	-1.0425*** (0.1693)	-1.2284*** (0.2271)	-0.5736*** (0.1347)	0.0025 (0.0607)
Consec. Days Precip. < 2mm	-0.0039*** (0.0007)	-0.0051*** (0.0012)	-0.0030*** (0.0006)	0.0007 (0.0004)
Consec. Days Precip. < 2mm*TMI	-0.0112*** (0.0027)	-0.0133*** (0.0035)	-0.0041. (0.0022)	-0.0017. (0.0010)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 7: Call Response to Climate Events Interacted with Proportion of Geohashes in Sub-district Traveling Only Within Own Geohash

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0999 (0.0624)	-0.1412. (0.0697)	-0.0245 (0.0867)	-0.0203 (0.0377)
Any Shock*Prop. Within	0.0447 (0.0424)	0.0214 (0.0496)	0.0690 (0.0523)	0.0117 (0.0254)
Heatwave (30C)	-0.0531 (0.0412)	-0.0175 (0.0290)	-0.0459 (0.0704)	-0.0218 (0.0303)
Heatwave (30C)*Prop. Within	0.0396 (0.0293)	-0.0044 (0.0292)	0.0761. (0.0374)	0.0106 (0.0241)
Heatwave (35C)	-0.1839*** (0.0436)	-0.0754. (0.0409)	-0.1901* (0.0705)	-0.0689. (0.0378)
Heatwave (35C)*Prop. Within	0.0263 (0.0240)	-0.0340 (0.0288)	0.0613. (0.0355)	0.0098 (0.0185)
Heatwave (40C)	-0.2137*** (0.0523)	-0.1603** (0.0525)	-0.1757. (0.1023)	-0.0714. (0.0414)
Heatwave (40C)*Prop. Within	-0.0447 (0.0334)	-0.1065** (0.0360)	0.0123 (0.0684)	0.0174 (0.0239)
Consec. Days > 30C	-0.0007 (0.0004)	0.0006. (0.0003)	-0.0017* (0.0007)	-0.0001 (0.0002)
Consec Days > 30C * Prop. Within	0.0006 (0.0005)	0.0006 (0.0006)	0.0010* (0.0005)	-0.0004 (0.0003)
Consec. Days > 35C	-0.0039*** (0.0010)	-0.0008 (0.0008)	-0.0053*** (0.0013)	-0.0011 (0.0007)
Consec. Days > 35C * Prop. Within	-0.0002 (0.0007)	-0.0012. (0.0007)	0.0009 (0.0009)	-0.0002 (0.0005)
Consec. Days > 40C	-0.0120*** (0.0031)	-0.0060* (0.0028)	-0.0155*** (0.0036)	-0.0017 (0.0033)
Consec. Days > 40C * Prop. Within	-0.0031 (0.0024)	-0.0059* (0.0028)	0.0016 (0.0042)	-0.0011 (0.0017)
Drought	-0.1445* (0.0601)	-0.2428** (0.0843)	-0.0641 (0.0514)	0.0104 (0.0261)
Drought*Prop. Within	-0.0882. (0.0482)	-0.0903 (0.0552)	-0.0515 (0.0401)	-0.0026 (0.0137)
Consec. Days Precip. < 2mm	-0.0040*** (0.0008)	-0.0055*** (0.0011)	-0.0035** (0.0011)	0.0010* (0.0004)
Consec. Days Precip. < 2mm*Prop. Within	-0.0008 (0.0010)	-0.0006 (0.0008)	0.0002 (0.0009)	-0.0005* (0.0002)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 8: Call Response to Climate Events Interacted with Probability of Self Transition

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0582 (0.0652)	-0.1191* (0.0510)	0.0409 (0.0925)	-0.0103 (0.0261)
Any Shock*Pr(Self Transition)	0.3605 (0.4307)	0.3544 (0.4792)	0.6271 (0.4133)	0.0088 (0.2307)
Heatwave (30C)	-0.0153 (0.0497)	-0.0186 (0.0265)	0.0261 (0.0800)	-0.0130 (0.0207)
Heatwave (30C)*Pr(Self Transition)	0.4122 (0.3225)	0.2248 (0.2979)	0.7359. (0.4097)	-0.0064 (0.1767)
Heatwave (35C)	-0.1617** (0.0459)	-0.1053* (0.0439)	-0.1323* (0.0625)	-0.0662* (0.0273)
Heatwave (35C)*Pr(Self Transition)	0.0071 (0.3502)	-0.1152 (0.3009)	0.5771 (0.3932)	-0.5215. (0.2556)
Heatwave (40C)	-0.2582*** (0.0488)	-0.2587*** (0.0457)	-0.1627* (0.0663)	-0.0634* (0.0274)
Heatwave (40C)*Pr(Self Transition)	-0.6912. (0.3842)	-0.8259 (0.5775)	0.2662 (0.5179)	-0.7199. (0.4139)
Consec. Days > 30C	-0.0001 (0.0007)	0.0012* (0.0005)	-0.0007 (0.0009)	-0.0005. (0.0003)
Consec Days > 30C * Pr(Self Transition)	0.0065 (0.0048)	0.0087. (0.0051)	0.0078 (0.0050)	-0.0047. (0.0026)
Consec. Days > 35C	-0.0041*** (0.0007)	-0.0020* (0.0008)	-0.0045*** (0.0012)	-0.0014* (0.0006)
Consec. Days > 35C * Pr(Self Transition)	-0.0072 (0.0062)	-0.0072 (0.0053)	0.0042 (0.0097)	-0.0154* (0.0056)
Consec. Days > 40C	-0.0155*** (0.0029)	-0.0119** (0.0035)	-0.0143*** (0.0021)	-0.0033 (0.0020)
Consec. Days > 40C * Pr(Self Transition)	-0.0806** (0.0281)	-0.0726 (0.0497)	-0.0120 (0.0267)	-0.0628*** (0.0138)
Drought	-0.2302*** (0.0481)	-0.3310*** (0.0668)	-0.1146** (0.0361)	0.0077 (0.0180)
Drought*Pr(Self Transition)	-1.0402* (0.4071)	-1.0954* (0.4172)	-0.6470* (0.2947)	-0.0395 (0.1337)
Consec. Days Precip. < 2mm	-0.0049*** (0.0007)	-0.0062*** (0.0012)	-0.0034*** (0.0005)	0.0005 (0.0004)
Consec. Days Precip. < 2mm*Pr(Self Transition)	-0.0202* (0.0091)	-0.0195** (0.0067)	-0.0070 (0.0049)	-0.0064* (0.0031)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 9: Call Response to Climate Events Interacted with Inbound Popularity Rank

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.211*** (0.071)	-0.186* (0.074)	-0.233* (0.106)	-0.006 (0.047)
Any Shock*PopRankIn	0.000025* (0.000012)	0.000011 (0.000007)	0.000045* (0.000018)	-0.000001 (0.000005)
Heatwave (30C)	-0.101* (0.051)	-0.025 (0.036)	-0.181* (0.088)	-0.009 (0.029)
Heatwave (30C)*PopRankIn	0.000014 (0.000009)	0.000001 (0.000004)	0.000034* (0.000015)	-0.000001 (0.000003)
Heatwave (35C)	-0.283*** (0.068)	-0.163 (0.086)	-0.301** (0.097)	-0.063 (0.059)
Heatwave (35C)*PopRankIn	0.000021* (0.000009)	0.000010 (0.000010)	0.000028* (0.000012)	0.0000005 (0.000006)
Heatwave (40C)	-0.422*** (0.077)	-0.370*** (0.095)	-0.381*** (0.102)	-0.048 (0.058)
Heatwave (40C)*PopRankIn	0.000030* (0.000011)	0.000021 (0.000013)	0.000038** (0.000012)	-0.000001 (0.000006)
Consec. Days > 30C	-0.001 (0.0009)	0.001 (0.0006)	-0.003* (0.0014)	-0.001 (0.0004)
Consec Days > 30C * PopRankIn	0.0000002 (0.0000002)	0.0000001 (0.0000001)	0.0000004 (0.0000002)	0.00000002 (0.00000004)
Consec. Days > 35C	-0.005*** (0.0008)	-0.002** (0.0006)	-0.007*** (0.0014)	-0.001 (0.001)
Consec. Days > 35C * PopRankIn	0.0000002 (0.0000001)	0.0000001 (0.0000001)	0.0000005* (0.0000002)	-0.00000006 (0.0000001)
Consec. Days > 40C	-0.015*** (0.004)	-0.011** (0.003)	-0.019*** (0.002)	-0.001 (0.003)
Consec. Days > 40C * PopRankIn	0.0000001 (0.0000004)	-0.0000001 (0.0000005)	0.000001 (0.0000005)	-0.0000004 (0.0000002)
Drought	-0.325** (0.094)	-0.423** (0.133)	-0.194* (0.074)	0.037 (0.039)
Drought*PopRankIn	0.000018 (0.00001)	0.000018 (0.000013)	0.000015 (0.000009)	-0.000005 (0.000004)
Consec. Days Precip. < 2mm	-0.006*** (0.001)	-0.007*** (0.001)	-0.004*** (0.001)	0.001* (0.0004)
Consec. Days Precip. < 2mm*PopRankIn	0.0000002 (0.0000001)	0.0000002 (0.0000001)	0.0000001 (0.0000001)	-0.00000008 (0.00000005)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 10: Call Response to Climate Events Interacted with Outbound Popularity Rank

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.210*** (0.070)	-0.185* (0.073)	-0.231* (0.104)	-0.007 (0.046)
Any Shock*PopRankOut	0.000025* (0.000012)	0.000010 (0.000007)	0.000044* (0.000018)	-0.000001 (0.000005)
Heatwave (30C)	-0.100* (0.050)	-0.025 (0.036)	-0.179 (0.087)	-0.009 (0.029)
Heatwave (30C)*PopRankOut	0.000014 (0.000009)	0.000001 (0.000004)	0.000034* (0.000015)	-0.000001 (0.000003)
Heatwave (35C)	-0.282*** (0.068)	-0.163 (0.086)	-0.301** (0.096)	-0.063 (0.059)
Heatwave (35C)*PopRankOut	0.000021* (0.000009)	0.000010 (0.000010)	0.000028* (0.000012)	0.000001 (0.000006)
Heatwave (40C)	-0.422*** (0.077)	-0.370*** (0.095)	-0.381*** (0.101)	-0.049 (0.058)
Heatwave (40C)*PopRankOut	0.000030* (0.000011)	0.000021 (0.000013)	0.000038** (0.000012)	-0.000001 (0.000006)
Consec. Days > 30C	-0.001 (0.0009)	0.001 (0.001)	-0.003* (0.001)	-0.001 (0.0004)
Consec Days > 30C * PopRankOut	0.0000002 (0.0000002)	0.0000001 (0.0000001)	0.0000004 (0.0000002)	0.0000002 (0.0000004)
Consec. Days > 35C	-0.005*** (0.0008)	-0.002*** (0.001)	-0.007*** (0.001)	-0.001 (0.001)
Consec. Days > 35C * PopRankOut	0.0000002 (0.0000001)	0.0000001 (0.0000001)	0.0000005* (0.0000002)	-0.00000006 (0.0000001)
Consec. Days > 40C	-0.015*** (0.004)	-0.011** (0.003)	-0.019*** (0.002)	-0.001 (0.003)
Consec. Days > 40C * PopRankOut	0.0000001 (0.0000004)	-0.0000001 (0.000001)	0.000001 (0.000001)	-0.0000004 (0.0000002)
Drought	-0.324** (0.093)	-0.422** (0.132)	-0.194* (0.073)	0.036 (0.038)
Drought*PopRankOut	0.000018 (0.00001)	0.000018 (0.000013)	0.000015 (0.000008)	-0.000005 (0.000004)
Consec. Days Precip. < 2mm	-0.006*** (0.001)	-0.007*** (0.001)	-0.004*** (0.001)	0.001* (0.0004)
Consec. Days Precip. < 2mm*PopRankOut	0.0000002 (0.0000001)	0.0000002 (0.0000001)	0.0000001 (0.0000001)	-0.00000008 (0.00000005)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Figures

Figure 1: Distribution of Outbound Trips

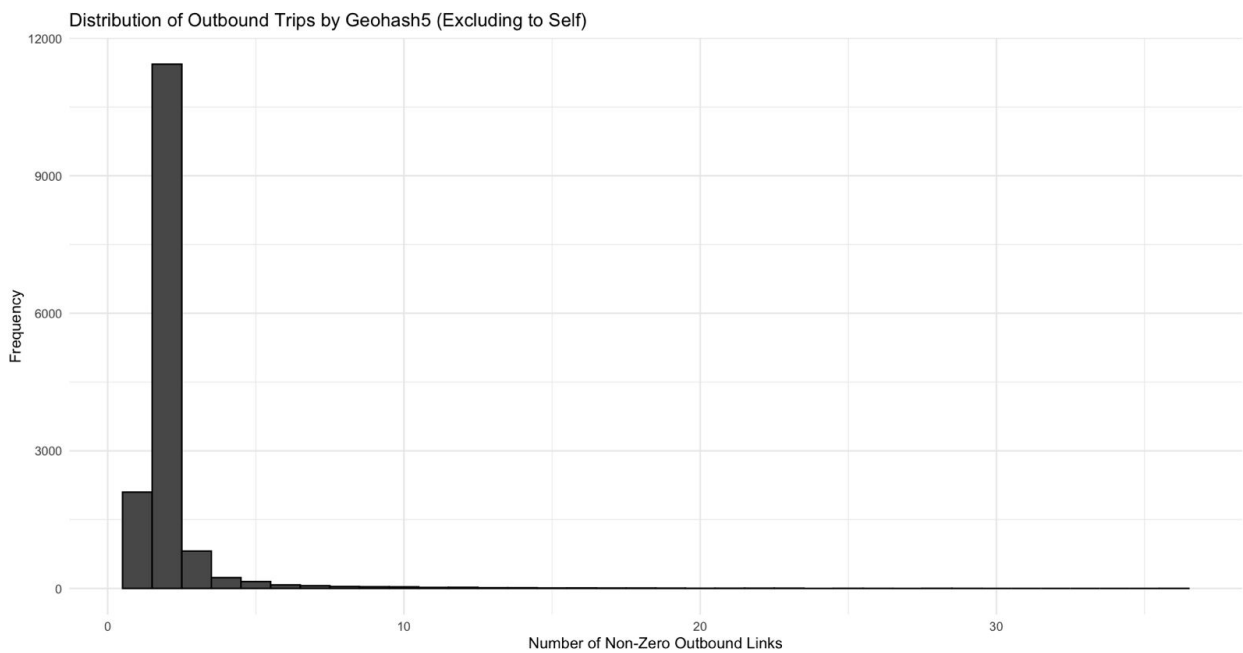


Figure 2: Insularity of Geohash Travel

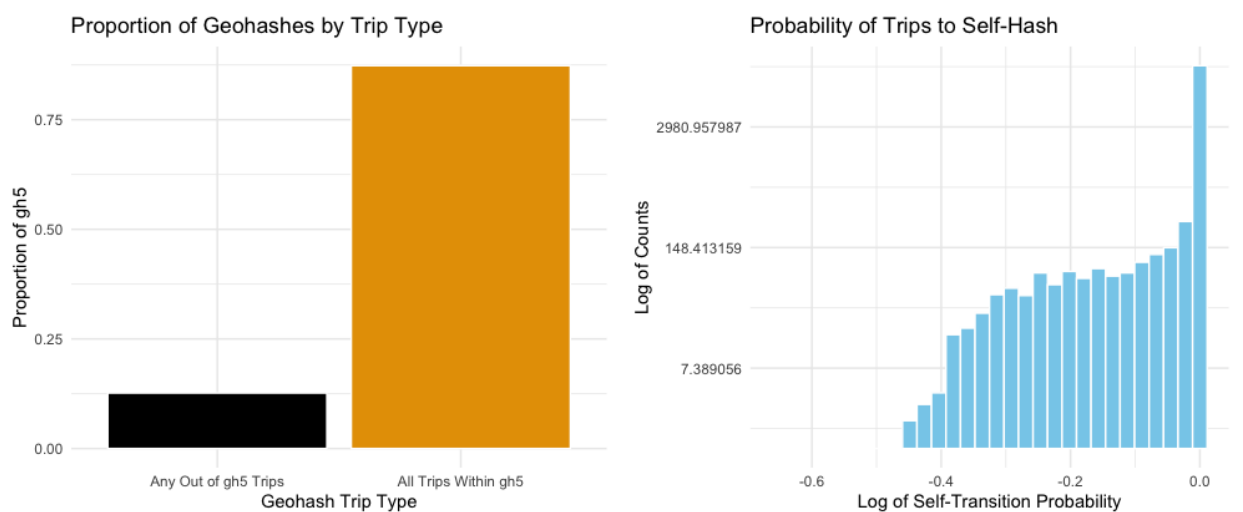


Figure 3: Relationship Between Number of Trips and Mean Trip Distance (m)

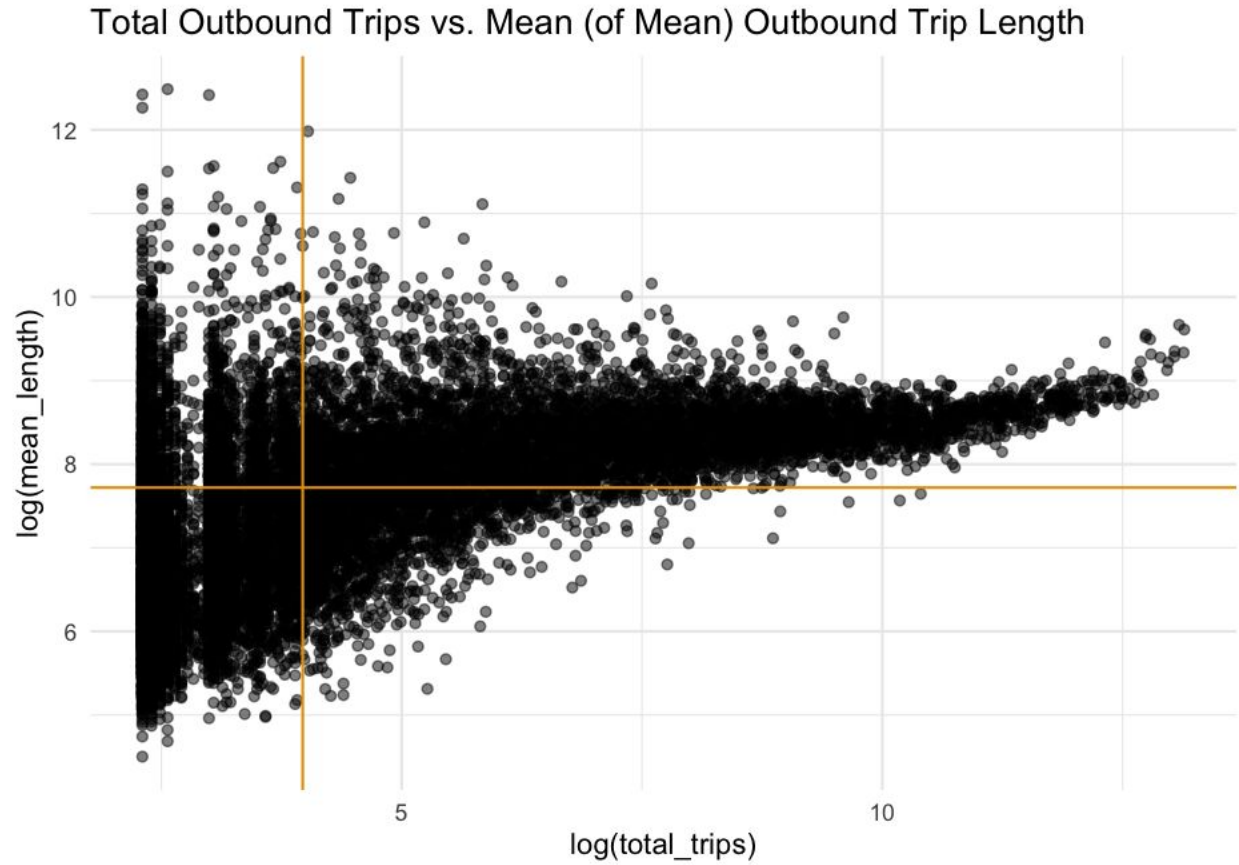


Figure 4: Seasonality of Calls for Top Crops Over Time

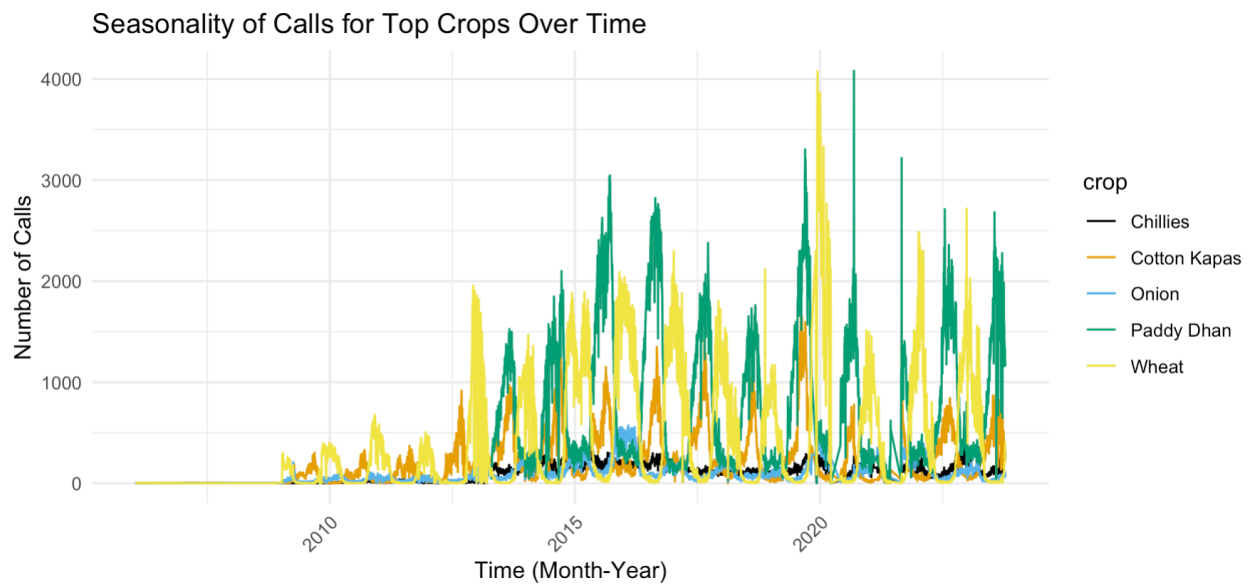


Figure 5: Evolution of Calls and Trips in Basmat in 2019

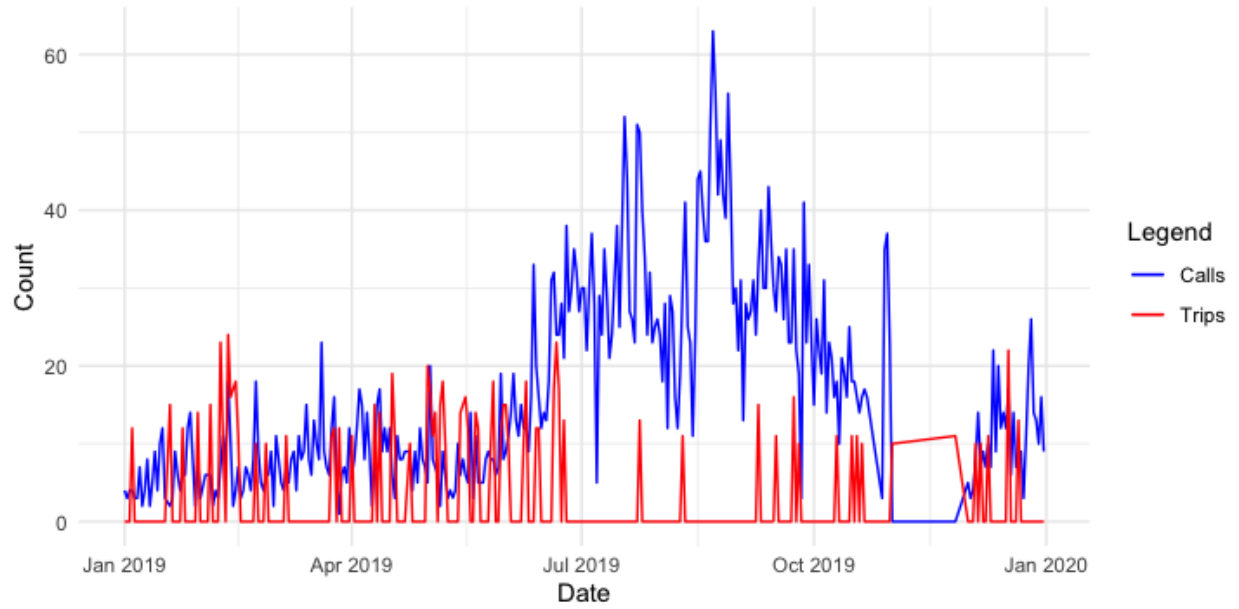


Figure 6: Daily Total Trips by Group

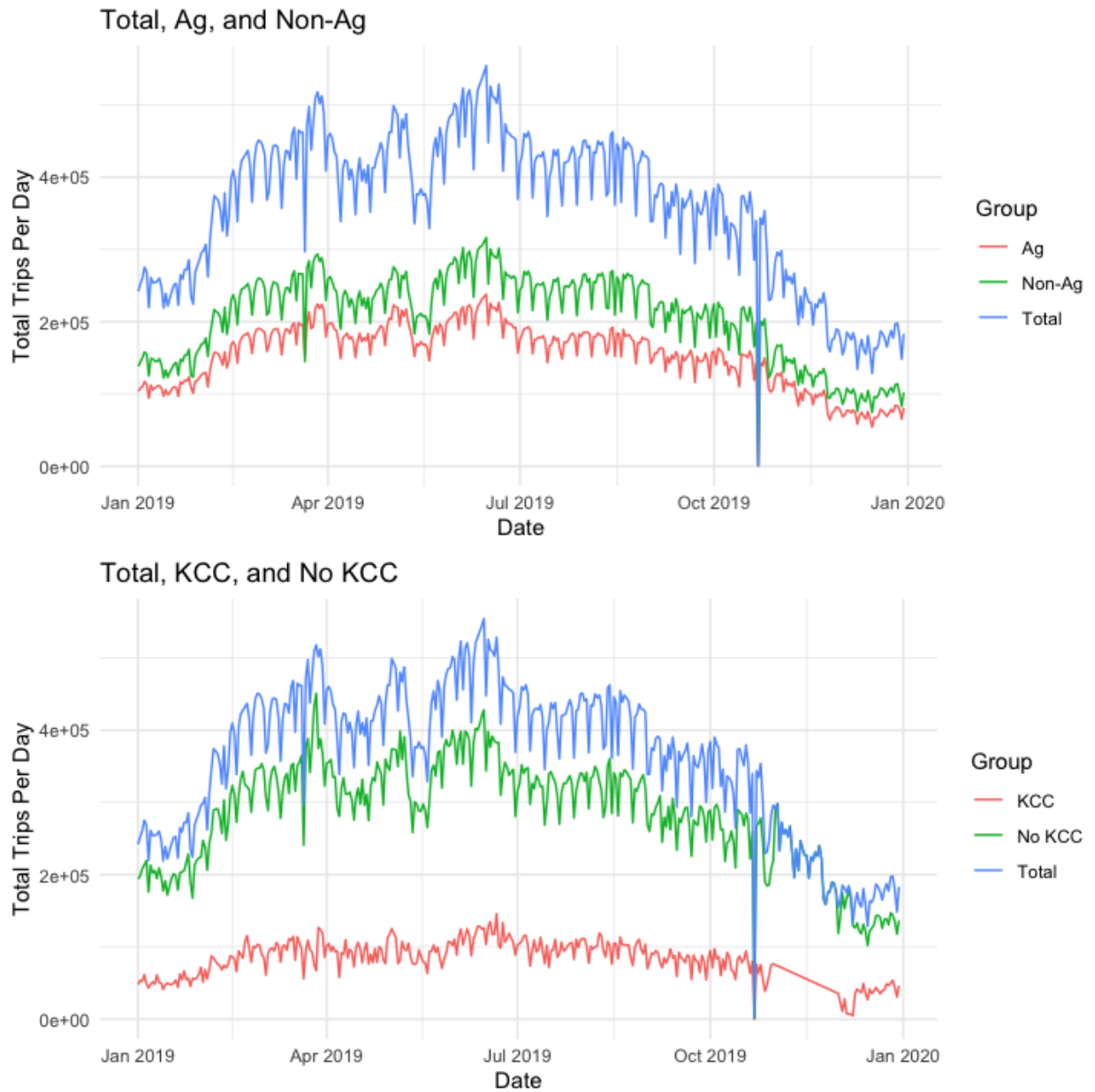


Figure 7: Daily Total Trips by Group in June



Figure 8: Spatial Distribution of Total Mobility Index and Calls to KCC

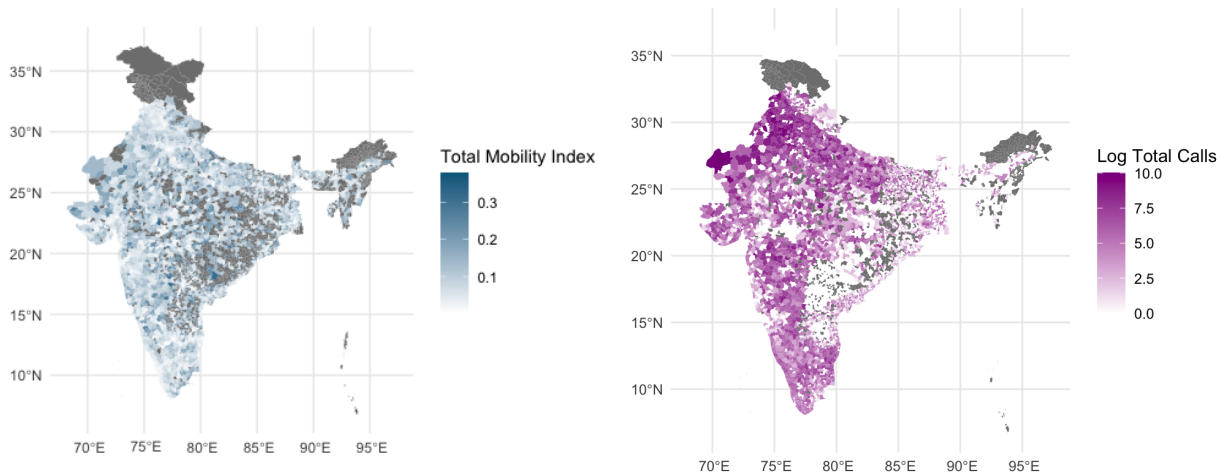


Figure 9: Spatial Distribution of Hot and Dry Days

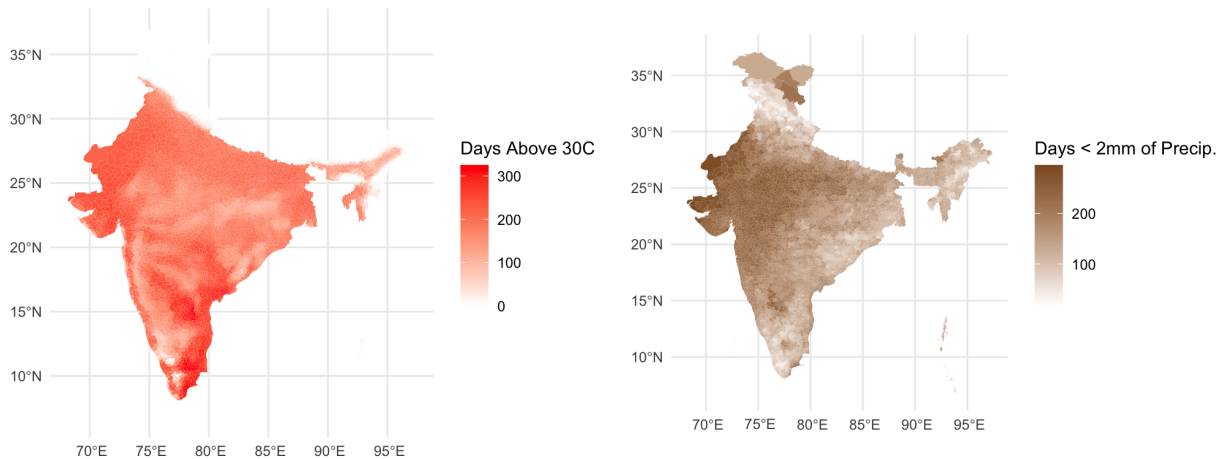


Figure 10: Call Volume Response to Consecutive Hot Days, by Threshold

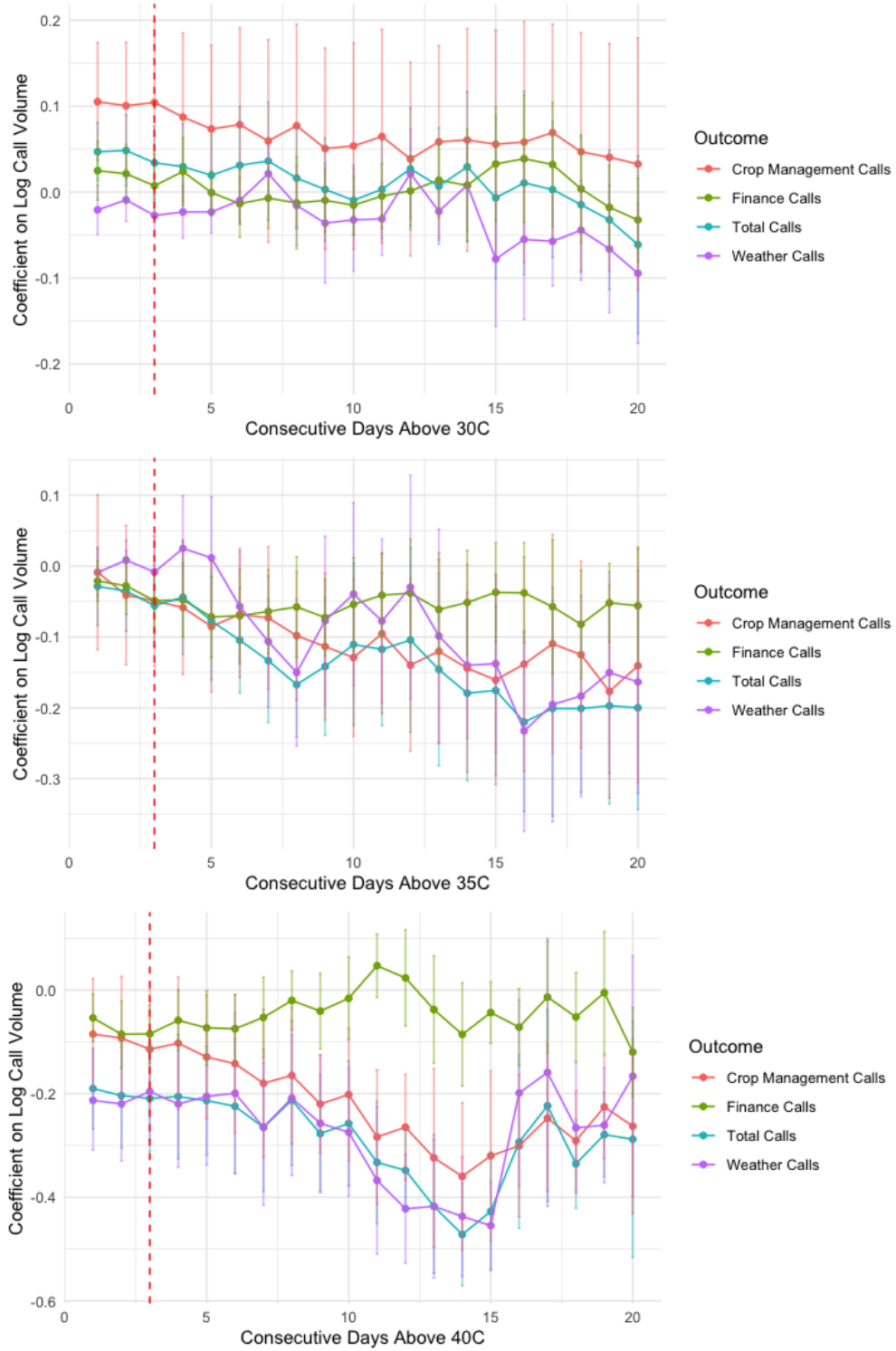


Figure 11: Call Volume Response to Consecutive Dry Days

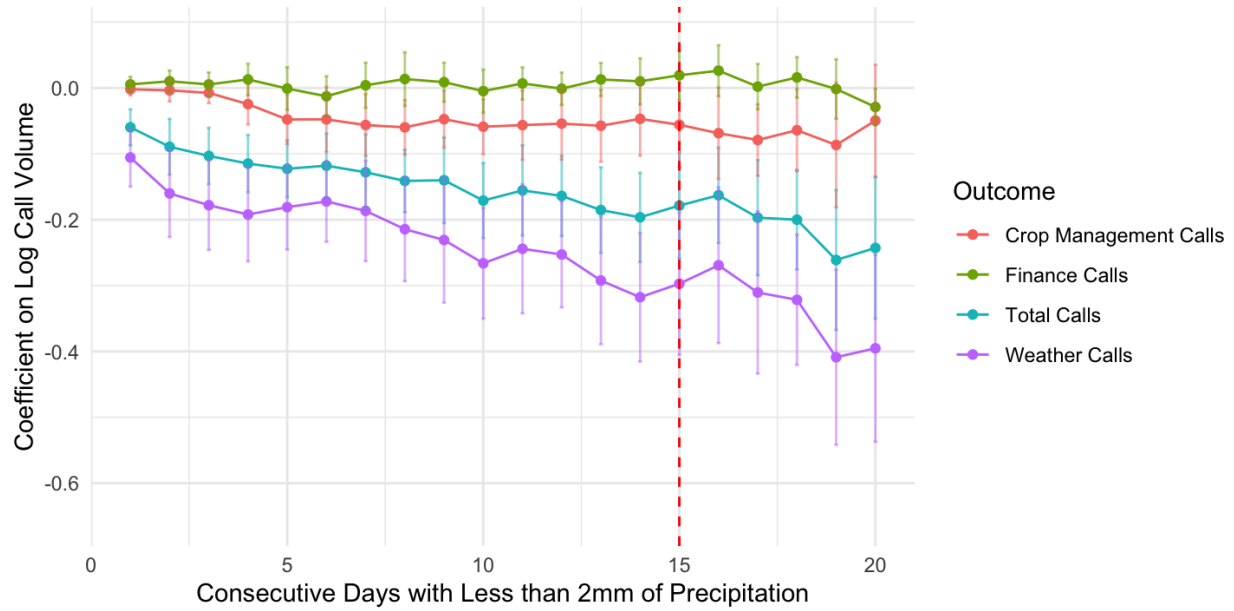


Figure 12: Call Volume Response to Consecutive Days Above 40C by TMI Quintile

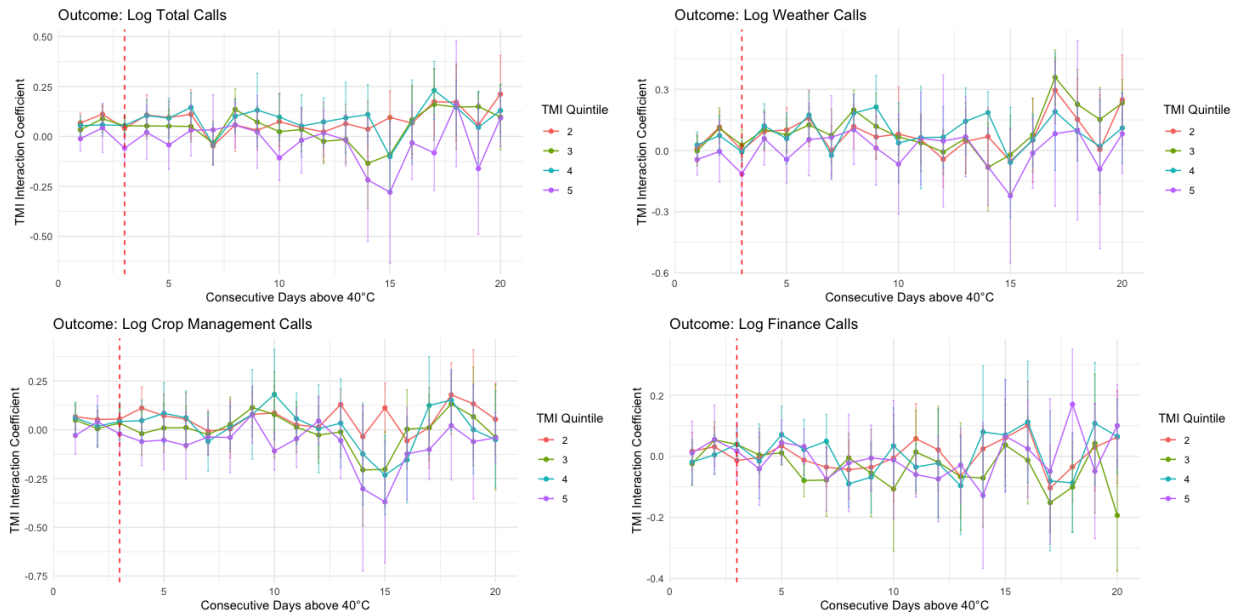


Figure 13: Call Volume Response to Consecutive Dry Days by TMI Quintile

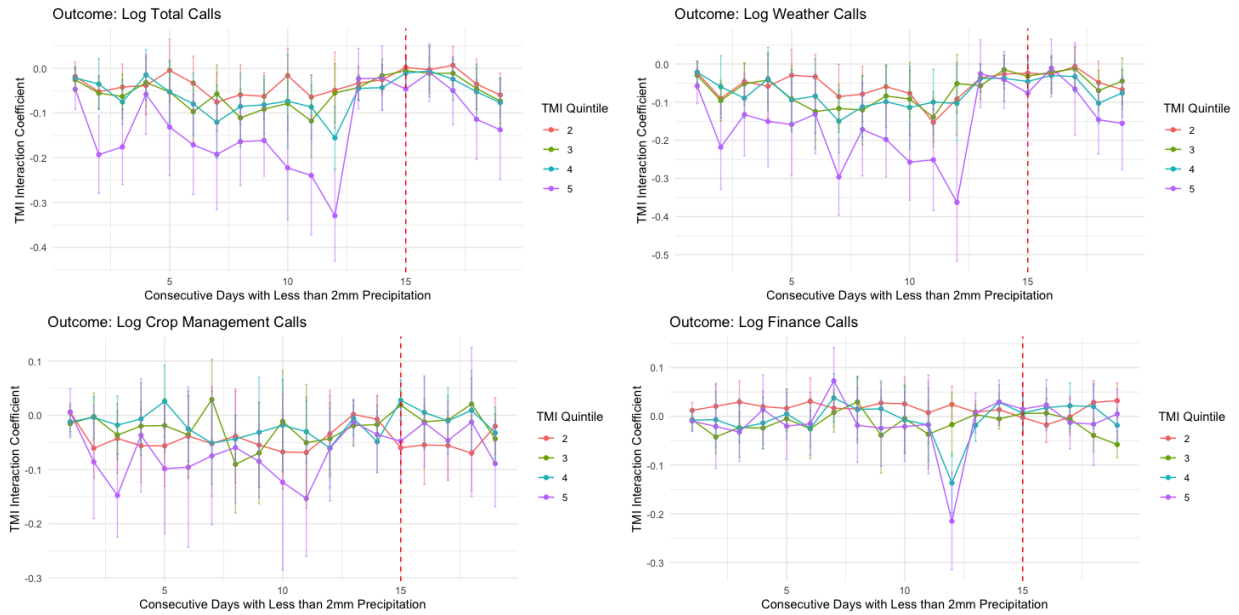


Figure 14: Call Volume Response to Consecutive Days Above 40C by Pr(Self Transition) Quintile

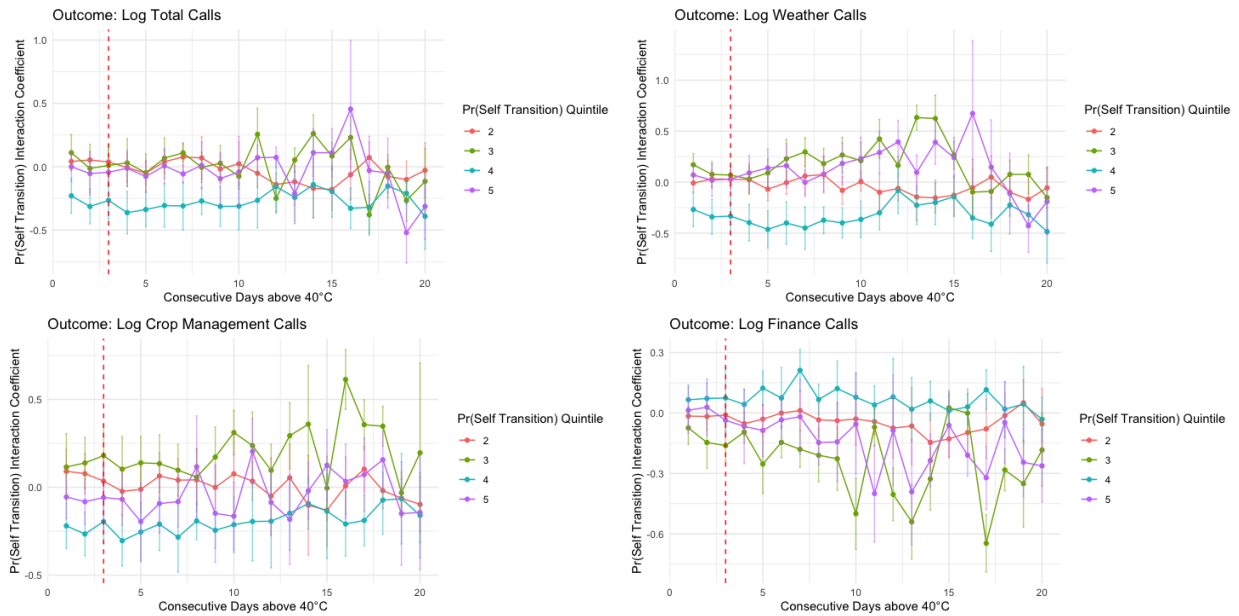


Figure 15: Call Volume Response to Consecutive Dry Days by Pr(Self Transition) Quintile

