Munich Personal RePEc Archive

Identity Politics, Partisan Sentiment and Household Spending

Ghosh, Arkadev and Mitra, Aruni and Mukherji, Ronit

Duke University, The University of Manchester, Ashoka University

28 May 2025

Online at https://mpra.ub.uni-muenchen.de/128843/
MPRA Paper No. 128843, posted 15 May 2026 15:47 UTC

Identity Politics, Partisan Sentiment and Household Spending*

Arkadev Ghosh† Aruni Mitra‡ Ronit Mukherji§

November 14, 2025

Abstract

We examine how political shifts affect household economic sentiment and spending in identity-polarized settings. Using panel data on over 178,000 Indian households, we find that sentiment about personal finances—and, to a lesser extent, the national economy—predicts expenditure, even after accounting for income changes. Using close state elections, we show that Muslims become markedly more pessimistic than Hindus about national economic conditions following victories by the Hindu-nationalist party, but exhibit relatively smaller differences in personal financial sentiment, and no detectable divergence in expenditure. A Bayesian learning framework explains the insulation of consumption from politically induced sentiment shocks through the limited transmission of macro-beliefs to individual behavior in high-volatility environments.

Keywords: sentiment, consumption, close elections, identity politics
JEL Codes: C36, D72, D83, E7, E20

*For comments and suggestions, we thank James Banks, Piotr Denderski, David Green, Anubhav Jha, Matt Lowe, Abhiroop Mukhopadhyay, Gareth Nellis, Sanjay R. Singh, seminar participants at the universities of Padova, Leicester and Manchester, and participants at the Household Finance and Human Capital Workshop at King's College London. We thank Jingjing Zhang and Hailun Chen for their excellent research assistance. This research uses proprietary data maintained by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE) and made available to Ronit Mukherji through the Centre for Economic Data and Analysis (CEDA) at Ashoka University. Ronit Mukherji also acknowledges the Trivedi Centre for Political Data (TCPD) at Ashoka University for providing access to data from the Election Commission of India. Aruni Mitra acknowledges funding from the Manchester-Ashoka University Seed-corn Fund, administered by the Faculty of Humanities at the University of Manchester, to support collaborative research projects. We received no other grant from public, commercial, or not-for-profit funding agencies. We alone are responsible for all errors and interpretations.

†Duke University. Email: arkadev.ghosh@duke.edu (*Corresponding Author*).
‡The University of Manchester. Email: aruni.mitra@manchester.ac.uk.
§Ashoka University. Email: ronit.mukherji@ashoka.edu.in.

1 Introduction

Many political systems around the world are shaped by enduring identity cleavages—along ethnic, caste, or religious lines—and are often characterized by clientelistic links between parties and voters (Anderson, Francois and Kotwal, 2015). In such settings, household economic behavior, including consumption decisions, can be influenced both by shifts in identity-based sentiment around elections and politically targeted changes in access to state resources (see, for example, Aneja and Ritadhi (2022)). At the same time, however, high income volatility and limited access to formal risk-smoothing mechanisms can make households cautious, leading them to compartmentalize their beliefs and respond only selectively to political developments. These dynamics remain poorly understood, despite being central to how political change shapes economic behavior in large parts of the developing world.

In this paper, we examine how shifts in political power towards groups with majoritarian or anti-minority rhetoric shape households' economic outcomes in India—the world's largest multiparty democracy. Specifically, we examine how close election victories by the Hindu-majoritarian Bharatiya Janata Party (BJP) affect the income, expenditure, and economic sentiment of the two most populous religious groups, namely, Hindus and Muslims. Beyond the impact of political change on household consumption through politically motivated changes in income, we also examine how partisan beliefs about households' own future financial condition and the national economy influence spending. Understanding these patterns is important because identity politics may shape socioeconomic inequality through its divergent influence on household beliefs and behavior.

We use novel data from a large panel of Indian households—the Consumer Pyramids Household Survey (CPHS)—and exploit district-level quasi-random variation in the share of close state assembly elections won by the BJP to identify causal effects.[1] State assembly elections are held at the constituency level, but the smallest administrative unit for which we observe household location is the district (which is a collection of constituencies). Therefore, we use the BJP's *strike rate* in close elections among all constituencies within a district as an instrument for its total seat share in that district.[2] We estimate household-level regressions of economic outcomes on district-level BJP seat share, instrumented using its strike rate in close elections, and interact it with household religious identity to capture differential effects on Hindu and Muslim households. A key feature of our design is that we leverage religious identity—specifically the well-documented tendency of Muslim voters in India to oppose the BJP—as a pre-determined and largely immutable marker of political align-

[1] The BJP was in power at the federal level throughout our sample period. Since Indian states wield considerable fiscal power, BJP victories in state assembly elections during this period can be more directly tied to changes in household economic sentiment.

[2] In other words, our instrument is the proportion of close elections won by the BJP in a district. This strategy exploits the fact that once an election is sufficiently close, the outcome is effectively random—driven by exogenous factors such as weather shocks, turnout fluctuations, or small idiosyncratic events beyond parties' control. As a result, the BJP's win rate in close elections provides exogenous variation in its overall performance at the district level. Similar close-election instruments have been widely used in the literature (see, for example, Clots-Figueras (2011), Bhalotra and Clots-Figueras (2014), and Aneja and Ritadhi (2022)).

ment.[3] Hindus, by contrast, are not similarly consolidated for or against the BJP, owing to significant caste, regional, and other internal cleavages. Using religious identity, rather than self-reported partisanship, separates households more cleanly along political lines: it provides a stable marker of alignment that is not itself shaped by short-term economic conditions or expectations about electoral outcomes, thereby strengthening the causal interpretation of our results.

We find that Muslim households in districts with a higher share of BJP victories between 2015 and 2022 became significantly more pessimistic about the national economic outlook, but comparatively less so about their personal finances. We find no significant effect of close BJP wins on Hindus' individual and national economic sentiments. In terms of magnitude, an increase in BJP seat share from the 25^{th} to the 75^{th} percentile (0.20 to 0.67) causes a 0.24σ ($p < 0.01$) divergence in national economic sentiment between the Hindus and Muslims. For personal finance sentiment, the Hindu-Muslim divergence is smaller—ranging from 0.11σ to 0.18σ ($p < 0.01$–0.06), depending on the particular measure used. This asymmetric relevance of identity-based political leanings for national economic sentiment vis-à-vis personal finance sentiment is important, given that our data shows that sentiment regarding personal finances is a much stronger predictor of household consumption changes than national sentiment, conditional on household income changes. Moreover, we find no evidence of large-scale religious targeting by the BJP that would affect household incomes. The only detectable impact is a reduction in reported government transfers for Muslim households, but these transfers constitute a small share of total income and do not meaningfully alter overall household income. Taken together, these results imply that household consumption is unlikely to be significantly affected by electoral outcomes, since neither resources nor the consumption-relevant component of economic sentiment shifts by a large enough margin to translate into meaningful changes in spending. We corroborate this null effect of BJP victories on household consumption of both Hindu and Muslim households in the data.

We rationalize the observed insulation of household consumption from political shifts, despite the latter's relevance to national economic sentiment, using a Bayesian learning framework. We model the differing priors of Hindu and Muslim households regarding the economic impact of a BJP victory. Following an election, every household observes (i) a public, economy-wide signal about where national income is heading, and (ii) a private cue, hinting at how much national conditions will move their personal finances. Because Hindus start out more optimistic and Muslims more pessimistic about the BJP, the Hindu-Muslim gap in national outlook is naturally large after a BJP win. Yet, two frictions—uncertainty about transmission (if the average passthrough from GDP to household income is weak) and idiosyncratic noise in private income (which makes the cue noisy and thus down-weighted)—dampen how much that gap in macro-beliefs translates into personal senti-

[3] Even at the peak of the pro-BJP wave between August and November 2014, the Samaj Survey Project by the Centre for Monitoring the Indian Economy Pvt. Ltd. found that more than 67% of Muslim respondents did not vote for the BJP, likely understating the true figure due to fear of backlash. Related research shows that Muslims are substantially more likely to express disapproval of the BJP, its leadership, and party-backed legislation widely seen as discriminatory (Ghosh et al., 2024; Ghosh, 2025).

ment differences. Whenever these frictions are large enough, as would be the case for developing economies like India, the model predicts a strictly smaller Hindu-Muslim difference in personal sentiment than in national sentiment. Finally, because consumption reacts primarily to personal, and not national sentiment, the resulting gap in actual spending is even more muted.

The theoretical framework not only rationalizes our key empirical findings but also offers other testable implications. For instance, the framework posits that households facing greater idiosyncratic income risk or weaker (expected) macro–micro linkages are more likely to *compartmentalize* their beliefs from their spending behavior, reacting less to changes in perceived national conditions.[4] To test this mechanism, we construct an index of income risk and macro exposure using CPHS data on occupation, education, urban residence, and age structure. Households with a working-age demographic profile, white-collar occupations, and urban residence score higher on this index, suggesting greater (expected) macroeconomic exposure and lower income risk. Consistent with our framework's prediction, we find that households with an above-median score on this index exhibit a tighter linkage between political sentiment and expenditure, leading to larger Hindu–Muslim gaps in discretionary spending. By contrast, those facing greater idiosyncratic volatility exhibit muted consumption responses despite comparable shifts in sentiment. Beyond corroborating our theoretical mechanism, these patterns suggest that "sentiment" itself may be a heterogeneous construct—capturing partisan beliefs or perceived vulnerability for some households, and genuine economic expectations for others. In this sense, consumption polarization based on political orientation, often observed in advanced democracies, may be an economic "luxury" that is less accessible in environments where uncertainty and income volatility compel households to insulate their economic behavior from political mood swings (Enke, Polborn and Wu, 2025).

We believe the muted behavioral response to politically induced sentiment shifts is informative. In settings with limited consumption insurance and high resource volatility, people may *rationally* separate their political and macroeconomic beliefs from actual economic choices, recognizing that economy-wide shifts often do not alter personal economic fundamentals. More broadly, our findings suggest that belief–behavior linkages are not mechanical, but contingent on the economic environment: when uncertainty is high, insulation may be a rational, not an inattentive, response.

Figure 1.1 summarizes the potential channels of influence and our core results. Politics produces large shifts in national sentiment (solid arrow), but the transmission to individual sentiment and income is weak (dashed arrows). Because spending is primarily predicted by individual sentiment, these weaker links yield muted consumption effects. Our model rationalizes this attenuation and implies that its strength should vary across households, which we confirm using heterogeneity in income risk and macro exposure.

[4]This mechanism is similar in spirit to Roth and Wohlfart (2020), who show that in the U.S., extrapolation of macroeconomic outlook to expectations about personal economic condition is driven by individuals with higher exposure to macroeconomic risk.

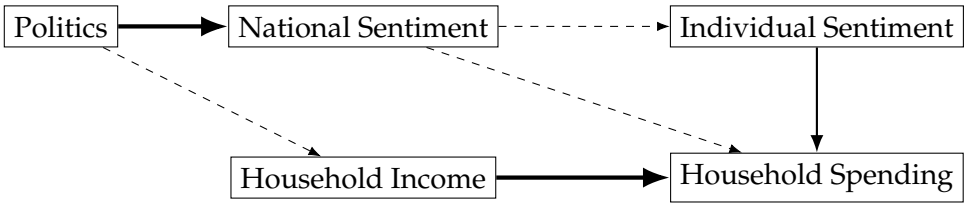


Figure 1.1: Conceptual Framework

Note: The flowchart shows the channels through which electoral politics might affect household spending. The degree of boldness of the arrows corresponds to the strength of the relation between two objects, as we find in the data. In the empirics, we causally identify the direct impact of political shifts on the four other variables in the flowchart. So, all links in the flowchart that do not originate from 'Politics' are not causally identified; they merely show conceptual channels of influence.

Contribution to the literature. Our work is primarily related to the literature documenting the role of households' political affiliation in driving exogenous movements in their sentiment and economic choices around election time.[5] Papers such as Coibion, Gorodnichenko and Weber (2020) and Binder, Kamdar and Ryngaert (2024) for the U.S., Guirola (2025) for European countries, and Gillitzer, Prasad and Robinson (2021) for Australia and the U.S. study the heterogeneous dynamics of expected economic outcomes based on households' political affiliation. Other works extend these findings by examining whether shifts in economic sentiment around election time lead to changes in actual economic behavior. For example, Gerber and Huber (2009), Benhabib and Spiegel (2018), and Kamdar and Ray (2022) find that household consumption demand increases when constituents are politically aligned with the party of the sitting U.S. President. Using Australian data, Gillitzer and Prasad (2018) also find that shocks to the economic sentiment of partisan households during elections affect consumption expenditure. In contrast, Mian, Sufi and Khoshkhou (2015, 2023) find that while individuals in U.S. counties, which are more ideologically predisposed toward the losing party, turn more pessimistic about government economic policy after the election, such sentiment shifts do not translate into changes in consumer spending. Our results for India are thus the closest to findings in Mian, Sufi and Khoshkhou (2015, 2023). While Mian, Sufi and Khoshkhou (2023) hypothesized that one potential explanation for the null effect of politically induced sentiment changes on household spending could be that "*...partisans are more optimistic about the overall economy when their preferred candidate wins, but they are not more optimistic about their own economic situation*", they did not find any empirical evidence for this distinction between individual and national sentiment. Our work not only provides empirical evidence for the heterogeneity in responses of national and individual sentiment to political shifts, but also offers a theoretical framework for understanding why some studies find strong effects of sentiment on consumption while others do not. Unlike most existing studies that use geographically aggregated data, we exploit household-level panel variation in individual

[5] For brevity, we focus on the part of the literature most relevant to our work—that is, studies linking politics with households' sentiment and consumption decisions. Related strands examine the relationship between political ideology and non-economic household choices, such as vaccine uptake and COVID-19 preventive behaviors, as well as the influence of politics on firms' and investors' behavior. As an alternative to the political channel, Lagerborg, Pappa and Ravn (2023) use fatalities in mass shootings in the US as an exogenous source of variation for consumer sentiment to study the impact of sentiment on real macroeconomic outcomes.

and national economic sentiments, alongside income and expenditure data, to examine how differences in priors about the role of a political party in the national economy across two identity groups can be amplified for national economic sentiment but potentially muted for individual sentiment and consumption.

This paper is the first to provide causal estimates of the effect of partisan sentiment on economic choices in any developing country. All existing evidence on the matter comes from developed economies, where researchers use self-reported partisanship to identify households' political leanings. While this identification strategy may be valid in rich democracies with stable political preferences and largely ideological party affiliation, in developing countries, where clientelistic links between political parties and voters are rife, relying on self-reported political affiliation, which is influenced by economic conditions and expectations about electoral outcomes, is problematic. Our use of a largely immutable identity—namely, religion, to determine the political affiliation of households bypasses this potential endogeneity. The use of the close-election instrument in the context of political consolidation along religious lines is a novel identification strategy in the literature examining the causal effect of politically motivated sentiment shifts on economic outcomes.

Our paper also contributes to research on party control and group-specific outcomes. Beland (2015) shows Democratic governors narrow the Black–White earnings gap in the U.S., and in India, BJP rule is linked to heightened Hindu–Muslim tensions and anti-Muslim rhetoric (Nellis, Weaver and Rosenzweig 2016; Jaffrelot 2021). Although extensive work explores how a political leader's identity (e.g., caste or gender) shapes economic outcomes in India (Chattopadhyay and Duflo 2004; Bardhan, Mookherjee and Torrado 2005; Aneja and Ritadhi 2022), we are not aware of studies exploring how *party* control overall affects *economic* outcomes. We fill this gap by showing that, in close elections, Muslim households' income and consumption under narrow BJP victories are statistically indistinguishable from those under narrow BJP defeats—implying limited economic spillovers from broader political change. Of course, violence itself remains harmful and may have significant non-economic consequences for the affected group.

Finally, our work speaks to a strand of literature that examines the relationship between economic sentiment and consumption, without reference to households' political affiliations. A growing body of work argues that shifts in optimism or pessimism—captured in expectations not directly tied to economic fundamentals—can influence real economic behavior, including household consumption (Angeletos and La'O, 2013; Benhabib, Wang and Wen, 2015; Acharya, Benhabib and Huo, 2021; D'Acunto and Weber, 2024). The empirical literature on how economic sentiment impacts consumption has typically focused on the time series correlation between economy-wide sentiment indices and aggregate consumption (see, for example, Blanchard (1993), Hall (1993), Friend and Adams (1964), Carroll, Fuhrer and Wilcox (1994), Ludvigson (1996, 2004), Bram and Ludvigson (1998) and Howrey (2001) for US-based evidence, Acemoglu and Scott (1994) for the UK, Kwan and Cotsomitis (2006) for Canada, Fan and Wong (1998) for Hong Kong, and Juhro and Iyke (2020) for Indonesia). Nevertheless, Attanasio and Weber (1995) argue that in the absence of individual or household-level

data, aggregation across consumers to estimate the intertemporal consumption choice equation can lead to spurious correlations between consumption and household expectations. Papers such as Jappelli and Pistaferri (2000), Souleles (2004), Attanasio, Kovacs and Molnar (2020), and Stoltenberg and Uhlendorff (2024) address this criticism by using disaggregated data on sentiment, income, and expenditure from household panel surveys. Our work is closest to this latter approach. The household panel data allows us to study heterogeneity in the relationship across different identity groups within India, but more importantly, to control for permanent idiosyncratic differences across households in their general optimism and pessimism through household fixed effects and aggregate economic conditions through state×year fixed effects. We also contribute to this literature by examining how household sentiment differentially affects spending on necessities, such as food, versus more discretionary expenditures, like luxury goods and human capital investments in health and education. Such heterogeneous links between sentiment and different spending categories make our findings particularly policy-relevant in a developing country context.

Organization of the paper. The rest of the paper is organized as follows. Section 2 provides details of the datasets used in the analyses and discusses the survey questionnaire on economic sentiment, specifying how we construct the sentiment variables for our empirical analyses from the categorical responses in the survey. In this section, we also motivate and discuss the regression models that we use to study the relationship between sentiment and expenditures, and identify the causal effect of identity politics on economic sentiment. Section 3 then presents key summary statistics and discusses the plausible empirical validity of the instrumental variable, while Section 4 presents the empirical findings. Section 5 rationalizes the empirical findings through a Bayesian learning framework and validates the theoretical framework with empirical tests. We also present alternative explanations for our main findings in this section. Finally, Section 6 concludes.

2 Data and Research Design

In this section, we first provide details of the datasets used in our analyses (Section 2.1). Second, we outline the construction of the sentiment variables that we use throughout the paper, based on household responses in the survey (Section 2.2). Finally, we motivate our empirical specifications to study how sentiment influences expenditure (Section 2.3), and how identity politics can drive economic sentiment of households (Section 2.4).

2.1 Data

Our primary data source is the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE). The nationally representative panel survey started in 2014 and has till date surveyed more than 236,000 households. We use data on

income, expenditure, sentiments and demographic characteristics from household interviews conducted every four months (quadrimesterly) between May 2015 and August 2022. During each interview, respondents report their current sentiments and provide details on their consumption and income for the preceding four months. Therefore, we have monthly data on income and expenditure and quadrimesterly data on economic sentiments. We attribute the average income and consumption data for the four months included in the recall to the quadrimester of the interview. In other words, even if income/consumption from a particular month would typically fall into a different quadrimester, we assign it based on the interview's quadrimester. This method ensures that the sentiments expressed are consistently aligned with the associated consumption and income data. Barring the exception of the Australian household panel data used by Gillitzer and Prasad (2018), this dataset is the only one that measures spending, income and economic sentiments of the same panel of households over time.[6] We control for state-by-year fixed effects in all our results to mitigate the obvious concern of the COVID-19 pandemic impacting survey data collection and household income and expenditure patterns in the 2020-2021 period.

We combine CPHS data with constituency-level state assembly election outcomes and candidate information between 2015 and 2022 (obtained from the Election Commission of India and compiled by the Trivedi Centre for Political Data (TCPD) at Ashoka University) to analyze how electoral outcomes shape sentiment formation and household consumption behavior. Data on candidates include information on gender, number of votes, party affiliation, and other candidate characteristics, allowing us to identify the winners and runners-up, as well as the victory margins. We define an election to be close if the margin of victory in terms of the vote share is less than 5% between the winner and the runner-up candidate. We show the robustness of our results by varying this victory-margin threshold to define a close election. Since we only know the district of residence of households from the CPHS data, we aggregate data from electoral constituencies to the district level following Bhalotra and Clots-Figueras (2014) and Aneja and Ritadhi (2022), in order to merge the electoral data with household income, expenditure, and sentiments data in the CPHS.[7]

2.2 Consumer Sentiment: Survey Questions and Variable Construction

The CPHS questionnaire has a consumer sentiment module with the following five questions – each with three possible responses (reported in parentheses):

1. Compared to a year ago, how is your family faring financially these days? [Better/Same/Worse]

2. How do you think that a year from now, your family will be faring financially? [Better/Same/Worse]

[6] In contrast, in the US datasets, household sentiment from the Michigan Survey of Consumers needs to be matched with the expenditure and income information from the Panel Study of Income Dynamics or the Consumption Expenditure Survey for different socio-economic groups, since the sets of interviewed households in the two datasets are different.

[7] The mapping of constituencies to districts is sourced from TCPD, which assigns each assembly constituency to a corresponding district based on the 2001 Census administrative boundaries. See the TCPD Lok Dhaba Codebook for further details (https://lokdhaba.ashoka.edu.in/static/media/2022Feb12LokDhabaCodebook.21040cf7.pdf).

3. How would you describe the financial and business conditions in our country in the next 12 months? [Good/Uncertain/Bad]

4. What do you think would be the financial and business conditions in our country in the next 5 years? [Continuously good times/Uncertain with ups and downs/Continuously bad times]

5. Do you think that this is generally a good or bad time to buy things like furniture, refrigerator, television, two-wheeler, car? [Good/Uncertain/Bad]

This set of five questions is identical to that in the Thomson Reuters/University of Michigan Survey of Consumers in the US as well as the Westpac-Melbourne Institute Survey of Consumer Sentiment in Australia, thereby aiding cross-country comparability. However, unlike the repeated cross-sectional data of the other consumer sentiment surveys, a unique feature of the CPHS is its panel structure, which allows us to effectively control for household fixed effects in sentiment, that is, control for the general optimism or pessimism of particular households.[8] While the Australian survey asks respondents for whom they would vote in a federal election, this information is not available in the CPHS. Therefore, while Gillitzer and Prasad (2018) rely on households' voting intention in the Australian dataset to inform the relation between political outcomes and economic sentiment, we use religious identity, which is highly correlated with voting patterns in India, to establish a causal relationship between political outcomes and economic sentiment.

We standardize the categorical responses to the sentiment questions, that is, create a mean-zero unit-variance variable based on the survey responses to each of the five sentiment questions. For tractability, we construct a Country Sentiment Index based on the two standardized variables for the national sentiment questions (questions 3 and 4 above), and an Individual Sentiment Index based on the three standardized variables for the individual sentiment questions (questions 1, 2 and 5 above). In constructing these indices, we follow the methodology in Anderson (2008), where the constituent standardized variables are weighted by the inverse of their covariance matrix.

Since the three individual sentiment questions capture different concepts, namely, perception of the present financial condition relative to the past in question 1 (backward-looking sentiment), expectations about the future financial condition relative to the present in question 2 (forward-looking sentiment), and the current readiness to buy durables in question 5, we show our main results for each of the three constituent variables separately. The Country Sentiment Index does not suffer from this issue because both of its constituent questions 3 and 4 are forward-looking (one-year and five-year ahead expectations). An important contribution of this work lies in distinguishing how electoral shocks transmit through both national and individual sentiments to shape household expenditure, which, to our knowledge, has not been systematically examined in prior work.[9]

[8] In the CPHS, a household is defined by the existence of a physical structure in which a group of people live. There exist physical structures and facilities (such as a kitchen, a verandah or an electricity connection) that are shared by this group of people. Households that do not have such shared physical structures as a kitchen, for example, 'nomadic households', are not included in the CPHS. The CPHS also does not follow households if all members of the household migrate.

[9] A large literature studies household expectations about specific variables like inflation, unemployment, or expected

2.3 The Relationship between Economic Sentiment and Consumption

Before establishing a causal link between identity politics and household sentiment and expenditures, which is the primary focus of this paper, we investigate whether survey-elicited sentiment has any explanatory power for changes in spending, after controlling for shifts in income and aggregate economic conditions. To that end, we run household-level panel regressions of the following form:

$$\Delta \ln C_{hsyt} = \beta S_{hsyt-1} + \delta_c \Delta \ln Y_{hsyt} + \delta_f \Delta \ln Y_{hsyt+1} + \theta_{sy} + \gamma_h + \epsilon_{hsyt} \tag{2.1}$$

Here, h indexes the household, s denotes the state of residence of the household, y denotes the calendar year, and t denotes the quadrimester when the household is interviewed. The time difference Δ is calculated between two consecutive quadrimesters $t-1$ and t, whenever data are available for a household in the two consecutive periods.[10] The variables C and Y denote consumption expenditure and total household income, respectively. S denotes a vector of household sentiment variables, namely, the standardized variables for forward-looking and backward-looking individual sentiments, and the Country Sentiment Index.

The parameter estimates from the empirical specification in equation (2.1) should not be treated as causal because of the obvious endogeneity of economic sentiment with both income and consumption changes. Still, one can motivate this reduced-form regression using a linearized Euler equation arising from optimal consumption choices of expected-utility-maximizing households subject to a budget constraint. We outline this motivation in Appendix B.

The main objective of regression (2.1) is to test whether the sentiment variables have any explanatory power for expenditure growth over and above the role of income growth. The joint statistical significance of the β vector will indicate the relevance of extra information contained in the survey questions on sentiments that are not contained in realized income changes.

The coefficient δ_c captures the degree of pass-through of income fluctuations to contemporaneous expenditure changes, and can be interpreted as an inverse measure of the consumption insurance against current income changes. Similarly, δ_f captures the marginal effect of future income growth on current expenditure growth. We include the one-period-ahead income growth as an additional regressor to check if the forward-looking sentiment variables capture private information of the households about their future income growth (see Barsky and Sims (2012)). As an extreme example, if the sentiments are only reflecting private information about future income changes, then β should be

future household income. However, given the nature of the CPHS sentiment questions, we desist from interpreting our sentiment indices as capturing expectations about any particular variable, like inflation, unemployment, or income.

[10] If a household for any reason is not surveyed in that quadrimester, that household would have missing values for both income, consumption, and sentiments. The CPHS weights explicitly factor in these missing data. Although the survey questions on individual sentiment ask about the current perception compared to *last year* and the expectations of the financial condition *next year* relative to the present, household may recall their financial situation *since their most immediate interview in the previous quadrimester* or form expectations about the financial situation *in the immediate future of the next quadrimester*. That is why we use quadrimesterly differences as our baseline. Nevertheless, we find similar results using a year as the time frame instead of a quadrimester (not shown for brevity).

zero when $\Delta \ln Y_{hsyt+1}$ is controlled for.

In addition to the sentiment and income growth variables as regressors, we include state×year fixed effects θ_{sy} as controls to account for state-level aggregate economic conditions in each calendar year, including, for instance, state-specific inflation. All our results are virtually the same if we instead include district×year fixed effects (not shown for brevity). We also include household fixed effects γ_h to control for time-invariant household characteristics like general optimism or pessimism of individual households, so that the effect of the sentiment variables can be interpreted as those arising from deviations from the household norm.[11] This is in contrast to earlier works, such as those by Carroll, Fuhrer and Wilcox (1994) and Ludvigson (1996), where only time-series analyses could be performed to estimate the effect of a national average sentiment index on aggregate private consumption in the economy, without allowing for any cross-sectional heterogeneity in the relation between sentiment and expenditure.

2.4 The Role of Identity Politics

Election results are likely among the most significant events shaping people's future outlook on a country's political and economic landscape. However, there is no causal micro-evidence for developing countries on how elections influence individual sentiments and consumption patterns.[12] We extend this line of inquiry of the impact of partisanship on economic perceptions and behavior from high-income countries like the U.S. (Gerber and Huber, 2009, 2010; Benhabib and Spiegel, 2018; Mian, Sufi and Khoshkhou, 2015, 2023) and Australia (Gillitzer and Prasad, 2018) to a vastly different setting—India—where political partisanship is intertwined with religious identity. Given the BJP's longstanding Hindu-nationalist stance and majoritarian religious overtones, Muslims—India's largest religious minority, have consistently voted against the party in both federal and state elections, with polarization intensifying over the past decade (Heath, 2020). Therefore, we examine whether the electoral victory of the BJP affects economic sentiment among Muslims relative to Hindus.

Unlike prior studies that directly observe individuals' political affiliations, our data lack self-reported partisan identification. We therefore exploit religious identity as a proxy, leveraging the strong and persistent association between religion and voting patterns in India. In doing so, we move beyond contemporaneous voting intentions, which may themselves be shaped by economic conditions, to identities assigned at birth, providing a plausibly exogenous and complementary source of variation for causal inference. Whereas prior work faces potential endogeneity from shifting partisan loyalties (see Erikson, MacKuen and Stimson (1998)), religious conversions in response to political outcomes are virtually non-existent. Our setting thus isolates a more deeply rooted and credibly

[11] CPHS assigns sampling weights to household-month level observations to ensure that consumption and income measures are representative of the Indian population. When conducting regressions at the household-quadrimester level, we average these weights across months within the quadrimester and use the resulting value as probability weights in our regressions. For regressions at the household-month level, we apply the original weights as provided.

[12] The bulk of the literature on the impact of elections in India focuses on the effect of political reservations on various socio-economic indicators (see, for example, Chattopadhyay and Duflo, 2004 and Chin and Prakash, 2011).

exogenous political channel through which economic sentiment is shaped.

2.4.1 Background

Voting based on religious and caste identities is pervasive in Indian politics. Despite India's Election Commission explicitly prohibiting campaign speeches invoking caste or religious affiliations that jeopardize the secular fabric of the country, politicians frequently employ such rhetoric to gain electoral advantage.[13] Going beyond mere campaign slogans, research also finds ingroup favouritism in public service delivery, where politicians tend to prioritize their own caste and religious communities (see Munshi and Rosenzweig (2015), Jensenius (2015) and Dunning and Nilekani (2013)).

The rise of the Hindu nationalist BJP in India's national politics since 2014 has been accompanied by a significant increase in hate speech and vigilante attacks targeting Muslims (see Jaffrelot (2021)). While direct evidence on the impact of the BJP's electoral performance on religious and caste group outcomes is limited, the BJP government has enacted policies like the Citizenship Amendment Act (CAA), which has faced widespread criticism for discriminating against Muslims.[14] Additionally, there is anecdotal evidence of far-right Hindu nationalist groups, such as Bajrang Dal, undermining Muslim livelihoods through attacks on their businesses for using Hindu names for their shops or selling products in Hindu-majority areas.[15] Muslim representation within the BJP's political ranks remains strikingly low — marking a first in India's history, the ruling BJP party at the federal level has no Muslim Member of Parliament (MP) in 2024.[16] Indeed, research indicates that victories by the Indian National Congress (INC) — the other major pan-India national party, in state assembly elections, helped reduce Hindu-Muslim violence between 1962 and 2000 (see Nellis, Weaver and Rosenzweig (2016)). Consequently, the Muslim electorate in India tends to vote overwhelmingly against the BJP, further entrenching the party's reliance on religious voting patterns.

Given the strong consolidation of Muslim votes against the BJP at various levels of elections in India, which has intensified over the past decade, we hypothesize that electoral victories by the BJP are likely to result in negative economic sentiment among Muslims. We further test whether actual household income and consumption are influenced by the political context outlined above.

2.4.2 Empirical Framework

We analyze the impact of the electoral performance of the BJP on household-level outcome, $\mathcal{O}$, for different religious groups using the following regression specification:

$$\mathcal{O}_{hsdyt} = \alpha_1 BJPSh_{sdyt} \times Hindu_h + \alpha_2 BJPSh_{sdyt} \times Muslim_h + \theta_{sy} + \gamma_h + \psi_{hsdyt} \tag{2.2}$$

[13] "EC comes down heavily on BJP, Congress for religious and casteist Lok Sabha election campaigns" (Economic Times, May 2024)

[14] "India enacts citizenship law criticised as 'discriminatory' to Muslims" (The Guardian, 2019).

[15] "'Shown their place': Muslim livelihoods under attack in India" (Aljazeera, September, 2021).

[16] "Eighteenth Lok Sabha has lowest share of Muslim MPs in six decades" (The Hindu, June 2024).

Here, $\mathcal{O}_{hsdyt}$ denotes the different types of sentiment, consumption, or income measures for household h living in state s, district d, in calendar year y and quadrimester t. $BJPSh_{sdt}$ is the share of Vidhan Sabha (state assembly) constituencies won by the BJP in district d of state s in the most recently concluded state-assembly election. We interact it with the religious identity of the household (Hindu or Muslim) to estimate the effect of the BJP's seat share on the sentiments of Hindu and Muslim households. Our primary coefficient of interest is $(\alpha_1 - \alpha_2)$, which captures the differential effect of the BJP's electoral success on Hindu households relative to Muslim households. A positive and statistically significant estimate of $(\widehat{\alpha_1} - \widehat{\alpha_2})$ would indicate that Hindu households benefit disproportionately compared to Muslim households. We also include a state×year fixed effect, θ_{sy}, and a household fixed effect, γ_h, in these regressions to control for state-level aggregate conditions in each calendar year and household-specific, time-invariant factors. Because households do not migrate across districts in the CPHS, household fixed effects remove all time-invariant differences across households[17] and locations, including long-run factors correlated with the religious composition of constituencies or the BJP's historical support base. This mitigates concerns arising from level differences between districts with high and low Muslim population shares, for example. In addition, our state×year fixed effects absorb all time-varying shocks at the state level, such as changes in political strategy, economic conditions, or campaign intensity—that could jointly influence electoral outcomes and household sentiment.

Nevertheless, estimating the specification above through an OLS regression will likely yield biased estimates. There may be omitted variables that determine both the seat share of the BJP and the household sentiments in a district. The direction of this bias is unclear a priori. On the one hand, if households in richer and more urban neighbourhoods have more positive sentiments and are also more likely to vote for the BJP, the estimates could be upward-biased. Alternatively, given the BJP's rising popularity among Hindu low-caste voters, there could be a downward bias if economic sentiments are more negative among these voters due to lower income.

To deal with this endogeneity problem, we use an instrumental variable (IV) for the seat share of BJP in each district, which is similar in spirit to the IVs used in Clots-Figueras (2011), Bhalotra and Clots-Figueras (2014), and Aneja and Ritadhi (2022), among others. We utilize district-level variation in the share of state assembly constituency seats won by the BJP in close elections. The intuition is simple – when the margin of victory is arbitrarily small, the outcome may be influenced by exogenous factors such as turnout, weather conditions, etc. If politicians have imperfect control over these factors, the outcome of such close elections can be considered as good as random.

The instrument we use for the share of seats won by the BJP in a district is the share of close elections won by the BJP. The mathematical formula for the instrument is the following:

$$BJPcloseShWin_{sdyt} = \frac{BJPcloseWin_{sdyt}}{TotalBJPcloseElections_{sdyt}} \tag{2.3}$$

[17]This holds unless household membership changes entirely, which is possible but likely rare, and less of a concern given that our outcomes are measured in short differences.

The numerator in equation (2.3) is the total number of close elections (with a victory margin of less than 5%) won by the BJP in district d during the most recently concluded state-assembly election, measured at calendar year y and quadrimester t. The denominator is the total number of close elections that involved the BJP. If both candidates have the same chance of winning a close election, the instrument would take a value of 0.5 by construction. Using the instrument, we estimate a two-stage least squares (2SLS) design. The first stage is:

$$BJPSh_{sdyt} = \phi BJPcloseShWin_{sdyt} + \theta_{sy} + \mu_{sdyt} \tag{2.4}$$

and the second stage is:

$$\mathcal{O}_{hsdyt} = \alpha_1 \widehat{BJPSh_{sdyt}} \times Hindu_h + \alpha_2 \widehat{BJPSh_{sdyt}} \times Muslim_h + \theta_{sy} + \gamma_h + \psi_{hsdyt}{}^{18} \tag{2.5}$$

In their practical guide for implementing regression discontinuity designs, Imbens and Lemieux (2008) recommend validity checks for the soundness of identification strategies like the one above. We discuss such validity tests in Section 3.3 below.

3 Summary Statistics and Validity of Instrument

In this section, we present descriptive statistics for income, expenditure and the individual and national sentiment measures — both in the cross-section and over time for Hindus and Muslims (Section 3.1). We also test whether the sentiment responses are consistent with the actual income and expenditure recorded in the survey (Section 3.2). Finally, we provide evidence for the validity of our close-election instrument (Section 3.3).

3.1 Summary Statistics

In line with widely acknowledged socio-economic patterns in India, our CPHS sample of households shows that Hindus are better off than Muslims, both in terms of income and different expenditure categories (see Appendix Table B.1). There is a greater disparity in income than in expenditure across the two religious groups, highlighting the role of cross-sectional consumption insurance through both public taxes and transfers, as well as private means, such as savings and borrowing.

Next, to get a sense of how household sentiment has evolved in India, we plot the dynamics of the survey-based sentiment measures. This descriptive exercise illustrates potential shifts in public perceptions around major political and economic events. Figure 3.1, which plots the net fraction of households reporting positive responses to these questions in the survey, shows that economic sentiment was largely stagnant on average between mid-2015 and late-2019, then declined sharply

[18] In practice, we estimate this specification in one step using STATA's *ivreghdfe* command with $BJPcloseShWin_{sdyt} \times Hindu_h$ and $BJPcloseShWin_{sdyt} \times Muslim_h$ as instruments for $BJPSh_{sdyt} \times Hindu_h$ and $BJPSh_{sdyt} \times Muslim_h$, respectively.

around the time of the pandemic, and recovered thereafter. Appendix Figure B.1 corroborates similar dynamics for the Individual and Country Sentiment Indices, separately for Hindus and Muslims.

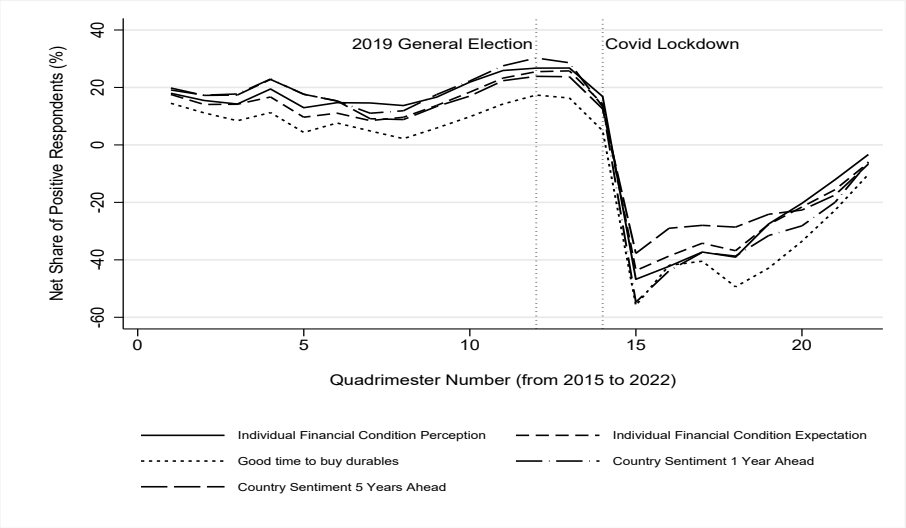


Figure 3.1: Difference between Shares of Positive and Negative Sentiment Response over Time

Note: The graph plots the difference between the fractions of households reporting a positive response and those reporting a negative response to each of the 5 sentiment questions in the CPHS survey for 30 quarters between the third quarter of 2015 and the fourth quarter of 2022. The timings of the 2019 general election and the onset of the COVID-19 lockdown are shown by dotted vertical lines.

The sharp drop in economic optimism at the onset of the COVID-19 lockdown, seen in Figure 3.1, is intuitive, given that a pandemic-induced lockdown severely damaged economic activity. What is more interesting, however, is that the decline in sentiment is more pronounced in districts with a higher number of confirmed COVID-19 cases (see Appendix Figure B.2). Although our main focus is on political events, the consistent correlation between COVID-19 cases and sentiments in both the time-series and cross-section provides a strong validation of the survey measures and underscores a key determinant of economic sentiment in this period.

Apart from the pandemic, another major economic shock during this period was demonetization in November 2016. In Appendix Figure B.3, we focus on the period surrounding the Indian government's demonetization announcement and find that both Hindus and Muslims exhibit more negative individual- and country-level sentiments in response. Interestingly, national sentiments seem to rebound swiftly, in contrast to individual sentiments. This divergence might hint at why demonetization may not have been politically costly—perhaps individuals viewed the policy as serving the national interest, even as it imposed personal costs.

3.2 Validation of Sentiment Measures

Do households change their sentiments? One concern with survey-based sentiment measures is that household responses may be highly persistent over time — some households are systematically optimistic while others are pessimistic, regardless of circumstances. Such persistence could

undermine the identification of our regression specifications, which relies on residual variation in sentiments after accounting for household fixed effects and state×year fixed effects. Appendix Figure B.4 shows that only 16–22% of the total variation in sentiments is absorbed by these fixed effects. This implies that substantial variation remains within households and across quadrimesters, lending credibility to both our identification strategy and empirical findings.

Are individual and national sentiments really different? A second concern is whether the individual and country sentiment measures capture distinct concepts, or whether respondents simply project one onto the other. This concern is particularly salient because in Figure 3.1, we find that the responses to all five questions have very similar dynamics. Since our analysis hinges on tracing the transmission of national sentiment to personal sentiment and ultimately to consumption behavior, validating this distinction is crucial. Beyond showing in our core results in Section 4.2.1 that elections affect the two types of sentiments to different degrees, we further illustrate the distinction in Appendix Figure B.5, where we plot household-level sentiments aggregated to the district level across the full sample. While the two measures are broadly correlated, clear differences emerge. For instance, in western Rajasthan, personal financial sentiment is more positive than national sentiment, whereas in neighboring northern Gujarat national sentiment is relatively stronger than personal finances. Similar contrasts across other regions suggest that, although related, the two indices capture distinct dimensions of household perceptions. A simple correlation matrix among the different sentiment measures in Appendix Table B.2 also reveals that the correlations among the different components of individual sentiment are much higher than those between the individual sentiment components and the Country Sentiment Index — further highlighting that the individual and country sentiment measures are distinct objects.

Do households correctly recall changes in their economic conditions? The backward-looking individual sentiment question allows us to check whether household perceptions about past events (relative to present) align with reality. One can view this as a sanity check for the sentiment responses in the survey. In particular, in Appendix Table B.3, we examine whether household income growth over the past quadrimester (i.e., between quadrimesters $t-1$ and t) or the past year (i.e., between quadrimesters $t-3$ and t) is positively correlated with the household's perception of changes in its financial situation during the same period. We find a significant positive correlation between the perceived change in financial condition and realized income growth, both over the past quadrimester (Panel A) and over the past year (Panel B). This is reassuring for the validity of the survey-based sentiment measures.

Can households predict their future economic condition? The forward-looking individual sentiment records households' beliefs about their financial condition in the future compared to their current condition. We use this to verify whether households' subjective expectations about their future

financial conditions are aligned with the actual changes in future income. In Appendix Table B.4, we find that households' subjective expectations about their future financial conditions are not aligned, in fact negatively correlated, with the actual change in future income, both over a quadrimester (Panel A) and a year (Panel B). This implies that while households correctly perceive realized changes in their income, they make systematic errors in forming subjective expectations about their future income. One way to rationalize this finding is that households feel optimistic about their future financial prospects when they are better off in the present compared to their past. In other words, households ignore the typical mean reversion in income shocks, wherein positive income shocks are more likely to be followed by negative ones. In fact, in our data, the pooled correlation between the income growth rates in two consecutive periods, $Corr\left(\Delta y_{it}, \Delta y_{it+1}\right)$ is -0.41, which highlights the mean reversion in actual income shocks and provides an explanation for the systematic error in subjective expectations about households' future incomes based on past income changes.[19]

Do households follow through on their readiness to buy durables? The third survey question on individual sentiment speaks directly to a household's readiness to buy durable items. Therefore, it is natural to ask whether the stated intention of the household matches actual spending on durables. In Appendix Table B.5, we show that all households, irrespective of their religious identity, increase their spending on durable items in the period in which they state that it is a good time to buy such items.

3.3 Instrument Validity and Relevance

As discussed in Section 2.4, our identification of the role of political outcomes in driving economic sentiments hinges on the election outcome being quasi-random so that the impact of a close election outcome on the economic sentiments of Hindus and Muslims can be deemed causal. The validity of the close-election instrumental variable proposed here depends on (a) the density of the BJP win margin being continuous at the zero threshold, where the electoral outcome changes discontinuously from a BJP loss to a BJP victory, and (b) candidate and constituency-level covariates like age, education, gender of candidates, and the number of contenders in a constituency, etc., being smooth around the BJP victory threshold.

Figure 3.2 shows the manipulation testing plot from a McCrary (2008) test of discontinuity of the running variable - BJP win margin, at the zero threshold. It plots the density of elections by the running variable, where a positive value of the running variable indicates a BJP victory, a negative value indicates a BJP loss, and values close to zero on either side of the zero threshold indicate a close election outcome. The absence of a statistically discernible discontinuity in the density of elections around the zero-threshold of win margin suggests no sorting of candidates into winner and loser

[19] Our findings are similar to experimental evidence in Armona, Fuster and Zafar (2019), who find that home price expectations are revised in a way consistent with short-term momentum in home price growth but respondents do not expect the empirically-occurring mean reversion in home price growth.

status. In other words, we find no evidence to reject that a BJP victory in a close election is a random event. This lends credence to using the share of constituency seats won by the BJP in all close elections as an instrumental variable.

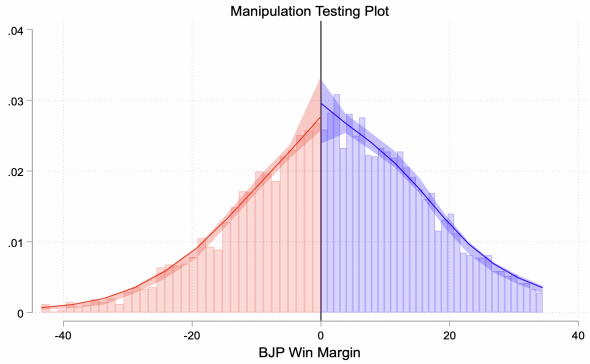


Figure 3.2: Instrument Validity: McCrary Test for Discontinuity of BJP Victory Margin around Zero

Note: Each bar indicates the density of the BJP win margin for one of the bins corresponding to the victory margin in individual constituencies in state-level elections between 2015 and 2022. The fitted curves, along with their shaded confidence bands, test for discontinuity in the BJP victory margin at the winning threshold of zero, as proposed in McCrary (2008).

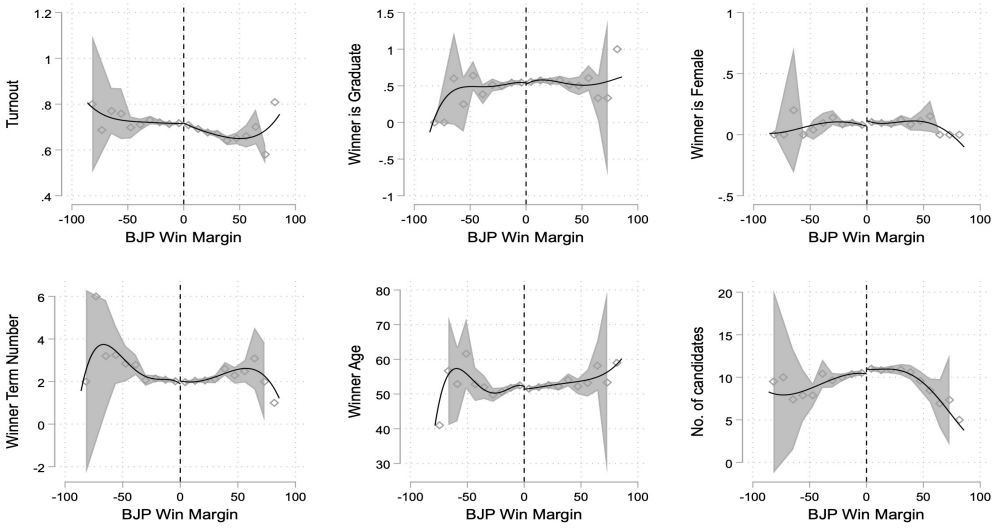


Figure 3.3: Instrument Validity: Constituency-level Covariate Balance across BJP Victory Margin

Note: The first five figures present covariate balance checks across winning candidate characteristics, while the last figure corresponding to the number of candidates is at the level of constituencies. The solid lines show the best-fit curve from local polynomial regressions, while the shaded regions represent the 95% confidence bands.

In addition to the absence of candidate sorting around the discontinuity of victory status, Meyersson (2014) suggests that constituency and candidate-specific observable characteristics should also be smooth at the victory threshold. We carry out such smoothness checks for six observables, namely, (a) voter turnout in the constituency (valid votes as a share of the number of registered electors), (b)

whether the winning candidate is a graduate, (c) the sex of the winning candidate, (d) the term number of the winning candidate, (e) the age of the winner, and (f) the number of candidates contesting in the constituency. Figure 3.3 shows no discontinuity at the threshold of BJP win or loss for any of the six observable characteristics of candidates and constituencies. Taken together, the evidence in Figures 3.2 and 3.3 suggests the quasi-randomness of a BJP close win in tightly contested constituencies, supporting the validity of our instrumental variable.

In Figure 3.4, we show the relevance of our instrument by illustrating how BJP's win margins at the assembly constituency level influence its overall seat share at the district level. The figure highlights the strong relevance of our instrument, showing that an additional constituency-level win corresponds to an approximately 20 percentage point increase in the district-level seat share. This is intuitive, given that the average number of constituencies per district in our sample period is 5.13.[20]

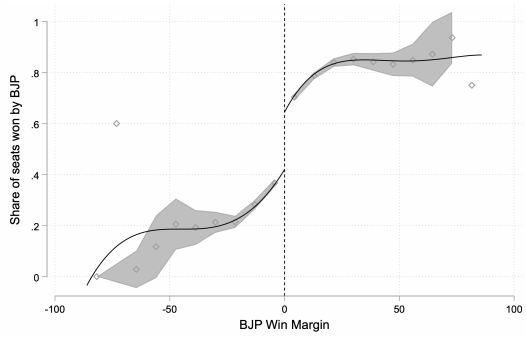


Figure 3.4: Instrument Relevance: The Impact of BJP Win Margin on Share of Seats Won in the District

Note: The outcome variable is the share of seats won at the district-level by BJP. The running variable is the BJP's win margin at the constituency level. The solid lines represent the best-fit curve from local polynomial regressions, while the shaded regions denote the 95% confidence bands.

Finally, we notice that constructing the instrument restricts the sample to districts with at least one election in which the BJP was in a close contest. Since the occurrence of close elections involving the BJP is not random, we thus implicitly restrict our sample to areas where the BJP has a strong presence. Appendix Figure B.6 shows a map of India, highlighting all districts in our sample where at least one state assembly constituency had the BJP involved in a close election during the study period. As is evident from the map, such close-election districts are widely spread across India, except in some southern states, where the BJP is not a formidable political force.

4 Results

In this section, we first examine how household sentiment about their personal finances and the national economy influences household expenditure (Section 4.1). Then, we demonstrate how close

[20] Regressing BJP seat share on the share of close seats won, along with state-by-year fixed effects (essentially the first stage (2.4) of the 2SLS regressions), yields a coefficient of 0.29 with an F-statistic of 332.24.

electoral victories by the BJP in state assembly constituencies differentially impact the two types of economic sentiment, income and expenditure of local Hindu and Muslim households (Section 4.2).

4.1 Effect of Economic Sentiment on Household Expenditure

As a first step towards understanding the impact of economic sentiment on changes in household expenditure following the modified Euler equation-type specification in equation (2.1), we examine the simple correlation between economic sentiment and contemporaneous household spending, conditional on income growth. In column (1) of Table 4.1, we regress the log total household expenditure on the forward and backward-looking components of individual sentiment about personal finances, along with the income growth from the last period and household and state-by-year fixed effects. We find that the two individual sentiment components have a statistically significant positive pass-through to contemporaneous household spending.[21] This finding continues to hold when we additionally control for future income growth and the forward-looking sentiment about the national economy (see column (2) of Table 4.1). In terms of magnitudes, a one standard deviation increase in forward (backward) looking sentiment leads to a rise in contemporaneous spending by 1.5%-1.7% (1.6%-2%) depending on the specification. The pass-through of sentiment about the national economy to household consumption, as captured through the coefficient on the Country Sentiment Index, is markedly smaller in magnitude than the pass-through of sentiment about personal finances. This aligns with the intuition of personal economic expectations being more relevant for spending choices.

The positive correlation between economic sentiment and contemporaneous expenditure implies that households with a more positive outlook, whether regarding their future relative to the present, or their present relative to the past, tend to spend more in the current period. This higher current spending, however, leaves less room for spending in the subsequent period, thereby driving down expenditure growth. We corroborate this negative effect of individual sentiment on household expenditure growth in columns (3) and (4) of Table 4.1. Column (4), which corresponds to the full regression specification in equation (2.1), shows that after accounting for current and future income growth, a one-standard-deviation increase in forward (backward) looking sentiment is associated with a 0.89% (0.74%) reduction in household spending growth between the current quadrimester and the next, while the Country Sentiment Index has a negligible impact on spending growth. Thus, we find no additional predictive power of the Country Sentiment Index for household expenditure growth, once individual sentiment and income growth are controlled for. Nevertheless, the three sentiment variables continue to be jointly significant in predicting expenditure growth. In Appendix Table C.1, we show that individual sentiment remains a strong predictor of consumption changes even for a broader range of income-related controls, namely, a third-degree polynomial in income growth as well as the full set of interactions between income growth and income quartile dummies.

[21] Our finding of current economic sentiment being positively correlated with current expenditure is consistent with results in Stoltenberg and Uhlendorff (2024), who use Italian household survey data and find that current expenditure is not only driven by current earnings but is also positively correlated with expectations of future earnings.

Table 4.1: Effect of Economic Sentiment on Household Expenditure

	Log Expenditure at t		**Δ Log Expenditure between t & $t+1$**	
	(1)	(2)	(3)	(4)
Forward looking individual sentiment at t	0.0171***	0.0145***	-0.0078***	-0.0089***
	(0.0005)	(0.0006)	(0.0006)	(0.0007)
Backward looking individual sentiment at t	0.0193***	0.0162***	-0.0066***	-0.0074***
	(0.0005)	(0.0006)	(0.0006)	(0.0007)
Country Sentiment Index at t		0.0042***		0.0002
		(0.0005)		(0.0006)
Δ Log Income between $t-1$ & t	0.056***	0.0394***		
	(0.0009)	(0.0008)		
Δ Log Income between t & $t+1$		-0.0468***	0.1223***	0.1288***
		(0.0008)	(0.0016)	(0.0019)
Δ Log Income between $t+1$ & $t+2$				0.0020**
				(0.0006)
F-test for Joint Significance of Sentiment Variables	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
No. of Observations	2,134,924	1,723,573	2,134,924	1,723,573
No. of Household-Level Clusters	168,148	160,880	168,148	160,880
Mean of Dependent Variable	9.31	9.31	0.03	0.03

Note: Robust standard errors clustered at the household level are reported in parentheses. All regressions include state-by-year fixed effects and household fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

The role of economic sentiment in explaining household expenditure growth varies by spending category and across Hindu and Muslim households (see Appendix Table C.2). Consistent with economic theory, we find that the pass-through of sentiment variables, as well as the contemporaneous relationship between income growth and expenditure growth, is higher for more discretionary spending categories, such as luxury expenses, than for necessities like food.

4.2 Effect of Identity Politics on Household Sentiment, Income and Expenditure

4.2.1 Impact of BJP Seat Share on Economic Sentiment

Having established a link between economic sentiment and household consumption, we now examine, following the empirical strategy in Section 2.4.2, whether election outcomes influence individuals' sentiment about their financial condition and their broader economic outlook for the country.

Table 4.2 shows how the BJP's seat share affects Hindu and Muslim households' sentiments

about individual and national financial conditions. For each household–quadrimester observation, we assign the BJP's seat share from the most recent prior election in that district. For results in Panel B, we instrument this share using the *ratio of close elections the BJP won to the number it contested* in the district. The table reports the group-specific effects (*BJP Seat Share* $\times$ *Hindu* and *BJP Seat Share* $\times$ *Muslim*) and their divergence, which is the difference between these coefficients. The sample covers all state assembly elections for which CPHS sentiment and consumption data are available.

Table 4.2: Effect of BJP Seat Share on Each Component of Economic Sentiments by Religion

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Country Sentiment Index**	**Individual Sentiment Variables**		
		Backward Looking	**Forward Looking**	**Good Time to Buy Durables**
	(1)	(2)	(3)	(4)
Panel A: OLS				
BJP Seat Share × Hindu	-0.154*	-0.0560	0.0200	0.00396
	(0.0875)	(0.0754)	(0.0718)	(0.0731)
BJP Seat Share × Muslim	-0.329***	-0.216*	-0.0924	-0.191*
	(0.126)	(0.114)	(0.106)	(0.110)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	0.175**	0.160**	0.112*	0.195***
	(0.078)	(0.070)	(0.069)	(0.072)
Panel B: IV				
BJP Seat Share × Hindu	-0.0310	-0.008	0.0320	0.113
	(0.168)	(0.140)	(0.129)	(0.131)
BJP Seat Share × Muslim	-0.526**	-0.351*	-0.203	-0.118
	(0.236)	(0.205)	(0.189)	(0.180)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**0.500*** **	**0.343*** **	**0.235***	**0.232***
	(0.148)	(0.127)	(0.128)	(0.126)
Kleibergen-Paap F-Stat (First Stage)	65.2	65.2	65.2	65.2
No. of Observations	1,486,856	1,486,856	1,486,856	1,486,856
No. of District×Year Clusters	1,961	1,961	1,961	1,961

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Close elections are those with a victory margin of 5% or less.

Column (1) shows that a higher BJP seat share is associated with a significantly larger negative impact on Muslims' national economic outlook compared to Hindus, based on a composite index combining expectations about the national economy over the next 1 and 5 years. An increase in the BJP's seat share from the 25^{th} percentile (0.20) to the 75^{th} percentile (0.67) causes a divergence in Hindu-Muslim national sentiment of 0.24 standard deviations ($p < 0.01$) in the IV regression.

Columns (2)–(4) of Table 4.2 report the effects of increases in BJP seat share on household financial sentiment. Across all three sentiment components, once again, both the OLS and IV estimates consistently show more negative effects for Muslims than for Hindus. Moving the BJP's seat share from the 25^{th} percentile (0.20) to the 75^{th} percentile (0.67) yields a Hindu–Muslim divergence of roughly 0.11–0.18 standard deviations ($p < 0.01$ to 0.06) in the IV specifications (using a combined

index as the outcome yields an effect size of 0.14 standard deviations, with a *p-value* of 0.016). The individual interaction coefficients—*BJP Seat Share* × *Hindu* and *BJP Seat Share* × *Muslim*—vary in magnitude and precision, but their difference is always statistically significant, indicating a clear divergence in household sentiment between the two groups. Notably, the Hindu-Muslim divergence in sentiment regarding individual finances is smaller in magnitude than that for national finance sentiment.

For Hindus, although the OLS estimate indicates a negative effect on country sentiment, the impact is small in the IV specification. This suggests that the OLS estimate for Hindus is downward-biased, whereas for Muslims, it is upward-biased. It is difficult to determine the exact reason for this intriguing pattern in biases. It is plausible that the growing popularity of the BJP among low-caste Hindus (and the resulting higher seat share in these regions), who are generally of lower income and may hold more negative sentiments, leads to a downward bias in the OLS estimate for Hindus. Conversely, the BJP's increased popularity in higher-income regions with Muslim populations may cause an upward bias in the OLS estimate for Muslims relative to the IV estimate.

Notably, Hindu households' sentiments do *not* appear to improve when the BJP wins more seats compared to other parties, even though the difference with Muslim households is statistically significant. Thus, the BJP's Hindu-nationalist position seems to have little effect on the sentiments of the majority Hindus, at least regarding their outlook on personal economic and financial conditions and their broader perceptions of the country's financial future. This could be due to a lack of political consolidation of Hindus in favor of the BJP throughout India, owing to significant caste, linguistic, regional, and other internal cleavages.

We show that these results are robust to the inclusion of district-level electoral controls—specifically, the average turnout across constituencies in the district in the previous election, the effective number of parties (averaged across constituencies), the number of constituency seats contested by the BJP, and the share of reserved seats in each district (see Appendix Table C.3). Appendix Table C.4 further demonstrates robustness to varying the win-margin threshold to 4% and 6%.

Overall, the results are consistent with BJP victories being perceived more negatively by Muslim citizens, which prompts a more pessimistic outlook on both national and personal finances compared to Hindus, with the effects being markedly stronger for perceptions of the national economy.

A Placebo Test: Close election wins by the Indian National Congress (INC). One potential concern is that the differential effects of BJP victories across Hindus and Muslims could arise from divergent preferences for national versus local parties rather than solely reflecting the BJP's Hindu-nationalist stance that drives its higher popularity among Hindus and lower support among Muslims. For instance, regional or state-specific parties may be more responsive to minority populations due to their deeper local knowledge. In contrast, national parties might lack the same state-specific insight and responsiveness. This could be in part due to the fact that decision-making is influenced or controlled by the central leadership of such larger parties, limiting their ability to address local

concerns as effectively. Since our research design compares close elections won by the BJP against both regional and national parties, this might explain part of our results.

To rule out this alternative explanation, we study (using a similar identification strategy) whether an increase in the seat share of the Indian National Congress (INC) — the only other pan-Indian party, in state assembly elections, has different effects on Hindu and Muslim households. We do not find this to be the case (see Table 4.3). The impact of an increase in INC seat share does not seem to have differential effects on Hindus and Muslims. If anything, in the OLS specifications, a higher seat share for the INC has a negative impact on Muslim personal finance sentiments, but the effects are statistically indistinguishable from zero in the IV specification. In fact, a downward bias in the OLS specification is what one would expect – given that poorer Muslims (with more negative sentiments) are perhaps more likely to vote for the INC.

Table 4.3: Effect of INC Seat Share on Each Component of Economic Sentiments by Religion: Placebo Test

Instrument = $\frac{\text{Share of close elections INC won}}{\text{Share of close elections INC involved}}$	**Country Sentiment Index**	**Individual Sentiment Variables**		
		Backward Looking	**Forward Looking**	**Good Time to Buy Durables**
	(1)	(2)	(3)	(4)
Panel A: OLS				
INC Seat Share × Hindu	-0.0007	-0.0259	-0.0696	-0.125*
	(0.0872)	(0.0748)	(0.0750)	(0.0735)
INC Seat Share × Muslim	-0.0722	-0.223**	-0.224**	-0.286***
	(0.107)	(0.0971)	(0.0966)	(0.0910)
(INC Seat Share × Hindu - INC Seat Share × Muslim)	0.0714	0.197***	0.154**	0.160**
	(0.148)	(0.072)	(0.069)	(0.126)
Panel B: IV				
INC Seat Share × Hindu	0.246	0.0552	-0.185	-0.114
	(0.210)	(0.187)	(0.183)	(0.164)
INC Seat Share × Muslim	0.407	0.0144	-0.275	-0.398
	(0.303)	(0.282)	(0.276)	(0.285)
(INC Seat Share × Hindu - INC Seat Share × Muslim)	**-0.161**	**0.041**	**0.089**	**0.283**
	(0.178)	(0.180)	(0.183)	(0.203)
Kleibergen-Paap F-Stat (First Stage)	108.4	108.4	108.4	108.4
No. of Observations	1,311,188	1,311,188	1,311,188	1,311,188
No. of District×Year Clusters	1,891	1,891	1,891	1,891

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. In the instrumental variable, close elections are defined as those with a victory margin of 5% or less.

One might worry that the INC may have been involved in fewer close elections during this period relative to the BJP, in which case the absence of IV effects could reflect limited statistical power. This, however, is not the case. Over the period studied, the INC contested 1,401 close elections at the constituency level, while the BJP contested 1,546. Of these, 764 were direct head-to-head contests between the two parties, accounting for about 54% of the INC's close races and 49% of the BJP's.

Taken together, the results suggest that the BJP's specific political history and stance, rather than a broader distinction between national and regional parties, is likely driving the negative sentiments among Muslims when the party secures a higher share of assembly seats. Notably, Hindu households' sentiments do *not* improve when the BJP secures more seats relative to other parties. Thus, the BJP's Hindu nationalist stance seems to have little discernible effect on the majority community's views—whether about their own financial situation or about the country's economic future. While we lack systematic evidence comparing the economic performance of BJP- versus non-BJP-governed states (or legislators), the available data indicate that aggregate growth rates across states have been broadly similar regardless of which party is in power.[22] This pattern is consistent with our finding that Hindus do not appear to adjust their financial expectations based on the BJP's electoral victories. The statistically significant divergence between Hindus and Muslims is therefore driven primarily by more negative responses among the latter.

4.2.2 Impact of BJP Seat Share on Income and Expenditure

What impact do heightened negative sentiments among Muslims—fueled by an increasing BJP seat share—have on their spending behavior? Combining our finding in Section 4.1 that personal finance sentiment is more tightly linked to consumption than national economic sentiment, with the evidence in Section 4.2.1 that BJP victories depress national sentiment for Muslim households more strongly than their personal finance sentiment, we can expect that the consumption impact of BJP victories operating through the sentiment channel should be limited for Muslims. However, consumption can also be affected if household resources change. Prior research suggests that the BJP's electoral gains are often accompanied by surges in Hindu-Muslim violence, potentially generating supply-side shocks that depress Muslims' real incomes relative to those of Hindus (Nellis, Weaver and Rosenzweig, 2016). Consequently, BJP victories may have disproportionately adverse economic effects on Muslim households. If such impacts are substantial, they could also contribute to long-term majority–minority disparities in income and upward mobility. Yet, the broader consequences of party-level electoral shifts for India's identity groups have remained largely unexplored.

To understand this, we study whether an increase in the BJP seat share affects the income and expenditure patterns of Hindu and Muslim households. Table 4.4 reports these results. The outcome in column (1) is the total income of the household from both labor and non-labor sources. We find no evidence that the BJP winning more seats significantly affects the incomes of Hindu or Muslim households. Both coefficients are positive, although *economically small* and *not* statistically significant. The magnitudes of the coefficients suggest that an increase in the BJP seat share from 0.20 (25^{th} percentile) to 0.67 (75^{th} percentile) (nearly a 50 p.p. increase) would raise monthly incomes by roughly 2.4-3.7% and expenditures by 3.1-3.4% relative to the mean.[23] For different income categories — labor, private

[22] "Congress versus BJP: Who has fared better in the last five years," The Economic Times, 2013.

[23] Please note that the outcomes are not defined on a per capita basis. However, we include household fixed effects, which account for differences in household size unless the number of members changes over time. The results remain the

and government transfers, and business income, reported in Appendix Table C.6, we again observe largely non-significant effects, both within and between religious groups. The notable exception is government transfer income. Specifically, Muslims report a negative effect (p = 0.07) while Hindus report no significant effect, and this difference is statistically significant (p = 0.02). This finding may suggest religious targeting in the allocation of public funds by the BJP, or a negative perception of Muslims about their local BJP leadership. Nevertheless, government transfers constitute only a small portion of overall household income, thus limiting their impact.

Table 4.4: Effect of BJP Seat Share on Income and Expenditure by Religion (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Total Income**	**Total Expenditure**
	2SLS	**2SLS**
	(1)	(2)
BJP Seat Share × Hindu	1031.219	890.961
	(1059.932)	(656.995)
BJP Seat Share × Muslim	1568.275	823.053
	(1572.904)	(855.396)
% effect due to an increase in BJP seat share from 25^{th} to 75^{th} percentile (47 p.p. increase)	(Hindu = 2.4%, Muslim=3.7%)	(Hindu = 3.1%, Muslim=3.4%)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	-537.06	67.91
	(1158.47)	(653.04)
No. of Observations	5,694,113	5,696,192
No. of District×Year Clusters	1,961	1,961
Mean of Dependent Variable	19,586	12,343
Kleibergen-Paap F-Stat (First Stage)	52.8	65.1

Note: All regressions include household fixed effects and state-by-year fixed effects. Robust standard errors clustered at the district-by-year level are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Similar to total income, we find positive but statistically non-significant effect on total household expenditure. The null effect of the BJP victory on total expenditure may conceal important heterogeneity across various types of spending. For instance, essential expenditures, such as those on food, are insulated from changes in political sentiment that accompany electoral cycles. In contrast, more discretionary spending on items such as health, education, and luxury goods (even though they account for a smaller share of overall spending) may be more sensitive to households' expectations about the future or shifts in the political mood. To investigate this possibility, Appendix Table C.7 disaggregates household expenditure into the following categories: food, education, healthcare, luxury items, and durable goods. The evidence suggests some heterogeneity across these categories. Specifically, the impact of an increase in the BJP seat share on food, education, and durable spending is nearly identical for both Hindu and Muslim households. However, for healthcare and luxury items,

same if we instead use per capita measures.

the effects differ: we observe positive coefficients for Hindu households and negative ones for Muslim households, with the difference being statistically significant for healthcare spending ($p = 0.01$) and suggestive, though less robust, for luxury expenditure ($p = 0.16$).

Short-lived income and consumption responses, appearing only in the years immediately following an election, may not be apparent in our estimates, which are pooled over the full five-year electoral cycle. Appendix Table C.5 shows that this is not the case: we detect no effect on total expenditure or income either in the first two years post-election or in the third to fifth years (despite divergent effects on sentiments across the full five-year electoral term, as seen in Table 4.2).

Despite the BJP's strong Hindu nationalist stance, we do not find evidence that the party has implemented large-scale supply-side policies (such as restrictions on employment opportunities or access to public services) that directly harm Muslim household consumption (even though sentiments might reflect such threats). Of course, there is substantial evidence of the BJP's negative effects on Muslims documented in other research—particularly in the form of increased violence and discrimination (Jaffrelot (2021); Nellis, Weaver and Rosenzweig (2016)). These are serious consequences in their own right, even if they do not manifest directly in broader household consumption patterns.

5 Discussion of Results

Why do electoral victories by the BJP, despite generating substantial divergence in economic sentiment between Hindu and Muslim households, not translate into proportionate differences in consumption between the two groups? In Section 5.1, we shed light on this question through a Bayesian learning framework, showing how individuals might combine a noisy public signal about the national economy with their private individual cues to form beliefs about personal finances. We take as given the difference in the subjective beliefs of Hindus and Muslims in India regarding the contribution of the BJP to the national economy. We then show that, after the election results are announced, when households update their beliefs about the national economy and how it influences their individual income, the difference in sentiment about personal finances between Hindus and Muslims can be smaller than their difference in national economic sentiment. Since consumption differences are explained more by differences in personal economic sentiments than by those in national economic sentiments, the resulting consumption gap between Hindus and Muslims is muted. This model not only rationalizes our key empirical findings in Section 4 but also provides testable predictions that we corroborate in the data in Section 5.1.1. Finally, in Section 5.2, we discuss alternative explanations for our core findings.

5.1 A Model of Individual Sentiment Formation from Noisy Signals about the National Economy

Set-up and timeline. Each household i belongs to either of the two religious groups - Hindu or Muslim, $g \in \{H, M\}$. There are two periods $t \in \{0, 1\}$. In period 0, elections are held and the

outcome is denoted by $e \in \{0,1\}$, with $e = 1$ denoting a BJP victory. Immediately after election results are announced, households form beliefs about the future state of the national economy as well as their personal finances. This, then, determines household consumption in period 1.

The true processes determining national income and personal finances are given as follows:

$$Y^N = \bar{Y}^N + \theta e + \varepsilon^N; \quad \text{where} \quad \varepsilon^N \sim N\left(0, \sigma_N^2\right) \tag{5.1}$$

$$Y_i^P = \alpha X_i + \beta_i Y^N + \varepsilon_i^P; \quad \text{where} \quad \varepsilon_i^P \overset{\text{i.i.d.}}{\sim} N(0, \sigma_P^2) \quad \& \quad \beta_i \overset{\text{i.i.d.}}{\sim} N\left(\bar{\beta}, v_0^2\right) \tag{5.2}$$

In the national income equation (5.1), $\bar{Y}^N$ denotes a baseline level of national income, θ denotes the "true" national deviation from the baseline level due to the election outcome and ε^N is an error term. The personal financial condition or household income Y_i^P in equation (5.2) is determined by household characteristics X_i, the household's latent sensitivity of how the national economy influences individual finances β_i, and an error term ε_i^P.

In period 0, households hold group-specific priors about the impact of the election outcome on the national economy $\theta|g$, and after the election results are announced, they observe a noisy signal s of the true national income Y^N:

$$\theta|g \sim N\left(\bar{\theta} + \lambda_g, v_\theta^2\right); \quad \text{where} \quad \lambda_H > 0 > \lambda_M \tag{5.3}$$

$$s = Y^N + \eta; \quad \text{where} \quad \eta \sim N\left(0, \tau^2\right), \quad \eta \perp (\varepsilon^N, \varepsilon_i^P, \theta, \beta_i) \tag{5.4}$$

The specification of the group-specific prior in equation (5.3) reflects increased optimism (pessimism) about the national economy for Hindus (Muslims) after a BJP victory. Since Y^N is affine in θ and ε^N (without loss of generality, considering $\bar{\theta} = 0$), we obtain:

$$Y^N|g \sim N\left(\bar{Y}^N + \lambda_g,\, V_0\right) \quad \text{where} \quad V_0 \equiv v_\theta^2 + \sigma_N^2 \tag{5.5}$$

Updating belief about the national economy. Once the signal s is realized, households update their beliefs about the national economy using conjugate-normal learning as follows:

$$Y^N|s, g \sim N\left(S_g^N, V^N\right) \tag{5.6}$$

The posterior mean of national income given religious identity and signal realization is a precision-weighted combination of the prior mean and the observed signal, $S_g^N = (1 - \omega_s)\left(\bar{Y}^N + \lambda_g\right) + \omega_s s$, with the weight $\omega_s \equiv \frac{Q_s}{Q_0 + Q_s}$, where we use Q's to denote the precision of the variables: $Q_0 \equiv \frac{1}{V_0}$ and $Q_s \equiv \frac{1}{\tau^2}$. The variance of the posterior distribution is given by $V^N = \frac{1}{Q_0 + Q_s}$.

Updating belief about how the national economy influences household income. Once the public signal s (and hence the national posterior S_g^N) is observed, each household updates its prior on β_i - the latent sensitivity of how the national economy impacts individual finances, using the observed

private cue $z_i \equiv \frac{Y_i^P - \alpha X_i}{Y^N} = \beta_i + \frac{\varepsilon_i^P}{Y^N}$, via conjugate-normal learning. Under these model assumptions, we get the following lemma about the predictive variance of z_i.

Lemma (Proof in Appendix D.1): The private cue, z_i has predictive variance $\sigma_z^2(s) \approx \sigma_P^2 (S_g^N)^{-2} \left(1 + 3\frac{V^N}{(S_g^N)^2}\right)$, and the corresponding Kalman-gain weight placed on z_i in the update for β_i is $\kappa(s) \equiv \frac{v_0^2}{v_0^2 + \sigma_z^2(s)}$.

Between-group gaps in national and individual sentiments. We define the gap in sentiment about the national economy between the two groups H and M as $\Delta^N \equiv S_H^N - S_M^N$, where $S_g^N = \mathbb{E}\left[Y^N \mid s, g\right]$ for $g \in \{H, M\}$. Similarly, the between-group gap in sentiment about individual household finances can be defined as $\Delta^P \equiv P_H - P_M$, where $P_g = \mathbb{E}\left[Y_i^P \mid z_i, s, g\right]$ for $g \in \{H, M\}$.

Proposition (Proof in Appendix D.2): The individual or personal sentiment gap Δ^P is strictly smaller than the national sentiment gap Δ^N, if (a) $\sigma_P^2 > v_0^2 S_H^N S_M^N$ and (b) $\bar{\beta}$ is sufficiently small.

We provide some intuition for the proof here. The attenuation of the between-group difference in personal economic sentiment emerges from how households balance two signals: (1) the national economic outlook (shaped by election-driven priors λ_H, λ_M), and (2) their expectations of how national conditions will translate to personal income through β_i. When $\bar{\beta}$ is small, personal finances are less tied to macro trends on average, so election-induced optimism/pessimism has limited downstream effects. This mechanically shrinks Δ^P relative to Δ^N. Similarly, when idiosyncratic noise in personal finances, σ_P^2 is high, making private signals unreliable (e.g., due to shocks to one's health or a job loss event), households discount their own experiences and rely more on national news, *but* the noise prevents their personal beliefs from fully mirroring identity-driven gaps. So long as the noise σ_P^2 dominates prior uncertainty, v_0^2, scaled by the levels of national income expected by both groups, $S_N^H S_N^M$, the personal sentiment gap will again be smaller than the national sentiment gap. The proposition formalizes why political polarization might not fully translate to consumption disparities: real-world randomness (high σ_P^2) and/or weak macro-micro linkages (small $\bar{\beta}$) act as friction against belief spillovers to individual economic decisions.

While we do not explicitly model consumption choice in this framework, it is easy to see that whenever the pass-through of expected household income to consumption is imperfect – a fact widely established empirically – the difference in household spending between the two groups will be even smaller than the difference in personal economic sentiment.

5.1.1 Testing Model Implications

Our theoretical framework argues that households face multiple layers of uncertainty that complicate their ability to interpret how national- or state-level developments (such as elections) might affect their personal finances. The first is ambiguity about the national economic condition itself, perceived

through group-specific biases. The second is uncertainty over how changes in national conditions translate into household-level outcomes. Together, these factors dampen the divergence in personal sentiment, even when national sentiment differs sharply between Hindu and Muslim households. Since personal sentiment is a key driver of consumption, the effect on actual spending behavior is correspondingly even weaker.

In contexts characterized by greater dispersion of idiosyncratic income shocks, or by heightened uncertainty about how aggregate economic trends translate into household finances, the link between politically driven sentiment and consumption should be weaker. This may help explain why our results in a developing-country setting diverge from those in richer economies like Australia (Gillitzer and Prasad, 2018). In fact, the absence of detectable effects on consumption is consistent with the psychology of poverty literature, which emphasizes that households facing tighter resource constraints and greater uncertainty tend to be more cautious and deliberative in their spending, and thus less responsive to non-economic stimuli (Mullainathan and Shafir, 2013). Together, this contrast highlights how financial constraints in poorer environments influence economic behavior in ways that differ fundamentally from those in wealthier contexts.

The theoretical framework not only aligns with our core empirical findings but also generates broader predictions. A key testable implication of our model is that households more exposed to the macroeconomy—either because they expect aggregate trends to transmit strongly into their own circumstances or because they face fewer idiosyncratic income shocks—should translate their sentiments more directly into spending behavior. The CPHS data allows us to examine this by leveraging heterogeneity in household characteristics. Specifically, we construct an index using the first principal component of four variables that can proxy for stronger macro–micro linkages or lower susceptibility to idiosyncratic shocks: (i) white- versus blue-collar occupations, (ii) age composition (working age versus seniors), (iii) urban versus rural location, and (iv) education composition of household members (please refer to Appendix D.3 for more details regarding how these variables are constructed). Intuitively, households that are more educated, urban, engaged in white-collar professions, and are of working age rank higher on this index and, according to our model, should experience a larger transmission of sentiments into spending behavior.

Appendix Tables D.1 and D.2 report heterogeneous results based on a median split of households on this index, for sentiments and consumption, respectively. BJP victories generate a clear Hindu-Muslim divergence in national sentiment across both groups. In each case, the gap narrows for personal sentiment, as predicted by the model. The reduction in the Hindu-Muslim divergence when moving from national sentiment to forward-looking personal sentiment is relatively stronger among below-median households, consistent with weaker transmission of national shocks into individual assessments for more vulnerable households. While these patterns should be interpreted as suggestive, given the reduced power from the sample split and the multiple interactions in the IV specifications, they align well with the model's predictions.

The consumption results in Appendix Table D.2 show a sharper Hindu-Muslim divergence

among households ranked *above* the median on this index. For households below the median, Hindu-Muslim differences in consumption remain small and not statistically significant. Across each of the consumption categories reported in Appendix Table D.2, the Hindu-Muslim gap for the above-median sample is roughly 2 to 12 times larger than that for the below-median sample, with statistically significant differences for luxury expenditures, durables, and health expenditures.

Overall, these results indicate that for economically vulnerable households, the transmission of political sentiments into consumption behavior is limited. This muted response likely reflects greater uncertainty over income flows and/or weaker links between national shocks and personal circumstances, creating a separation between expressed sentiment and actual spending. In contrast, more affluent households exhibit clearer polarization in consumption, suggesting a stronger mapping from sentiment to economic action. By distinguishing between national and personal sentiments and leveraging household panel data to study this heterogeneity, our analysis uncovers behavioral patterns that are often obscured in aggregate data.

5.2 Alternative Explanations

While the explanation above is consistent with our empirical findings, we acknowledge other potential mechanisms that may also account for these patterns. One possibility is that changes in reported national *economic* sentiment primarily reflect shifts in *political* attitudes, particularly given the BJP's association with Hindu nationalism and anti-minority rhetoric. For Muslim households, negative political views toward the ruling party may spill over into perceptions of the economy, making it difficult to express optimism about economic conditions when political sentiments are negative. In this case, a deterioration in economic sentiment driven by political factors may not translate into changes in actual household spending, suggesting that politically driven sentiment and consumption are governed by distinct underlying processes. Another related explanation is that Muslim households may form beliefs by taking cues from political elites or media sources (Broockman and Butler, 2017). If influential figures within the Muslim community highlight the adverse consequences of BJP rule, economic or otherwise, these messages may shape public perceptions even in the absence of immediate changes in personal economic conditions. Future work could focus on disentangling these channels.

Whether due to uncertainties about the national economy and its implications for personal finances (as emphasized in our model), or due to limited discretionary spending, informal insurance networks, or other institutional buffers that shield consumption from political shocks, Indian households appear broadly capable of *compartmentalizing* their views of national economic health from their own financial circumstances (the attenuation in our model and empirics). This compartmentalization lies at the heart of our core empirical findings. In this sense, the sharp electoral polarization in consumption documented in richer countries may itself be a kind of economic "luxury"—one that households in developing contexts, facing tighter constraints and greater uncertainty, are less able or willing to indulge in. These patterns are also consistent with the idea that sentiment formation in poorer settings may often be tied to tangible risks—such as greater vulnerability to government

actions, violence, or marginalization—rather than the more diffuse "negative feelings" that appear to drive consumption behavior in wealthier environments. The finding that below-median households display strong(er) shifts in sentiment but very little consumption response (relative to above-median households) is consistent with this interpretation.

6 Conclusion

We document several facets of the nexus among identity politics, partisan beliefs, and household economic decisions in the context of a large, multiparty democracy where ethnopolitical divisions are highly salient. Our empirical findings show that a close electoral victory by the Hindu-majoritarian BJP turns Muslims more pessimistic about the future of the Indian economy, while their personal finance sentiment does not change as much. In conjunction with another finding that national sentiment plays a more limited role in consumption decisions than individual sentiment, it is natural that we find that politically driven shifts in economic sentiment do not have a significant pass-through to household consumption. Contrary to the commonly held prior belief about religious targeting by the BJP in the allocation of state resources, we do not find evidence of decreases in Muslim household income following a local BJP victory. Taken together, these results suggest that despite the deep-rooted influence of religion-based identity politics in India, such politics have a limited impact on household consumption, either through the demand channel of sentiment shifts or through the supply channel of income changes.

We develop a Bayesian learning framework to rationalize our empirical findings. The model highlights that uncertainty at multiple levels—about the national economy, its personal financial implications, and actual income volatility—can attenuate the transmission of national sentiment differences between Hindus and Muslims into differences in their personal sentiment and consumption behavior. Consistent with this framework, we also find that households with smaller income risk or higher macro-exposure are more likely to follow through on their sentiments resulting from political shifts.

Although we outline a framework for why Indian households can separate politically induced sentiment from actual economic behavior, the precise micro-behavioral channels remain an important avenue for further work. Future research could focus on understanding this behavioral non-response in a more systematic way. One promising direction would be to experimentally manipulate perceptions—perhaps through an information experiment like in Fuster et al. (2022) and Faia et al. (2024)—and observe whether shifts in national sentiment translate into changes in personal sentiment. Such designs could also help disentangle the precise psychological mechanisms underlying consumer responses to political or macroeconomic information. With better micro-level data, it may be possible to structurally estimate some of the key parameters in our theoretical model—such as income shock variances or the precision of national signals—and examine how different subpopulations respond to a common aggregate shock based on these characteristics.

Finally, an open question remains: which types of shocks, by shaping individual sentiments, meaningfully influence consumption, and to what extent? These are likely to be shocks that affect individuals' financial outlooks without necessarily altering their current incomes. For instance, witnessing layoffs in one's workplace or industry—while remaining personally unaffected—could still undermine confidence in future financial stability. Exploring these dynamics using suitable data also remains an important direction for future research.

References

Acemoglu, Daron, and Andrew Scott. 1994. "Consumer Confidence and Rational Expectations: Are Agents' Beliefs Consistent with the Theory?" *The Economic Journal*, 104(422): 1–19.

Acharya, Sushant, Jess Benhabib, and Zhen Huo. 2021. "The anatomy of sentiment-driven fluctuations." *Journal of Economic Theory*, 195.

Anderson, Michael L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association*, 103(484): 1481–1495.

Anderson, Siwan, Patrick Francois, and Ashok Kotwal. 2015. "Clientelism in Indian Villages." *The American Economic Review*, 105(6): 1780–1816.

Aneja, Abhay, and S.K. Ritadhi. 2022. "Can political parties improve minority wellbeing? Evidence from India's "Silent Revolution"." *Journal of Development Economics*, 158.

Angeletos, George-Marios, and Jennifer La'O. 2013. "Sentiments." *Econometrica*, 81(2): 739–779.

Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. "Home Price Expectations and Behaviour." *The Review of Economic Studies*, 86(4): 1371–1410.

Attanasio, Orazio, Agnes Kovacs, and Krisztina Molnar. 2020. "Euler Equations, Subjective Expectations and Income Shocks." *Economica*, 87: 406–441.

Attanasio, Orazio P., and Guglielmo Weber. 1995. "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey." *Journal of Political Economy*, 103(6): 1121–1157.

Attanasio, Orazio P., and Hamish Low. 2004. "Estimating Euler equations." *Review of Economic Dynamics*, 7: 406–435.

Bardhan, Pranab, Dilip Mookherjee, and Monica Parra Torrado. 2005. "Impact of reservations of panchayat pradhans on targeting in West Bengal." *University of California at Berkeley, department of economics, typescript*.

Barsky, Robert B., and Eric R. Sims. 2012. "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence." *The American Economic Review*, 102(4): 1343–1377.

Beland, Louis-Philippe. 2015. "Political Parties and Labor-Market Outcomes: Evidence from US States." *American Economic Journal: Applied Economics*, 7(4): 198–220.

Benhabib, Jess, and Mark M. Spiegel. 2018. "Sentiments and Economic Activity: Evidence from US States." *The Economic Journal*, https://doi.org/10.1111/ecoj.12605.

Benhabib, Jess, Pegfei Wang, and Yi Wen. 2015. "Sentiments and Aggregate Demand Fluctuations." *Econometrica*, 83(2): 549–585.

Bhalotra, Sonia, and Irma Clots-Figueras. 2014. "Health and the Political Agency of Women." *American Economic Journal: Economic Policy*, 6(2): 164–197.

Binder, Carola Conces, Rupal Kamdar, and Jane M. Ryngaert. 2024. "Partisan expectations and COVID-era inflation." *Journal of Monetary Economics*, 148.

Blanchard, Olivier. 1993. "Consumption and the Recession of 1990-91." *AEA Papers and Proceedings*, 83(2): 270–274.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *The American Economic Review*, 98(5): 1887–1921.

Bram, Jason, and Sydney Ludvigson. 1998. "Does Consumer Confidence Forecast Household Expenditure? A Sentiment Index Horse Race." *FRBNY Economic Policy Review*, 4(2): 59–78.

Broockman, David E, and Daniel M Butler. 2017. "The causal effects of elite position-taking on voter attitudes: Field experiments with elite communication." *American Journal of Political Science*, 61(1): 208–221.

Carroll, Christopher D., Jeffrey C. Fuhrer, and David W. Wilcox. 1994. "Does Consumer Sentiment Forecast Household Spending? If So, Why?" *The American Economic Review*, 84(5): 1397–1408.

Chattopadhyay, Raghabendra, and Esther Duflo. 2004. "Impact of reservation in Panchayati Raj: Evidence from a nationwide randomised experiment." *Economic and Political Weekly*, 979–986.

Chin, Aimee, and Nishith Prakash. 2011. "The redistributive effects of political reservation for minorities: Evidence from India." *Journal of Development Economics*, 96(2): 265–277.

Clots-Figueras, Irma. 2011. "Women in politics: Evidence from the Indian States." *Journal of Public Economics*, 95: 664–690.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. "Political Polarization and Expected Economic Outcomes." *NBER Working Paper*, 28044.

D'Acunto, Francesco, and Michael Weber. 2024. "Why Survey-Based Subjective Expectations are Meaningful and Important." *NBER Working Paper*, 32199.

Dunning, Thad, and Janhavi Nilekani. 2013. "Ethnic Quotas and Political Mobilization: Caste, Parties, and Distribution in Indian Village Councils." *American Political Science Review*, 107(1): 35–56.

Enke, Benjamin, Mattias K. Polborn, and Alex A. Wu. 2025. "Values as Luxury Goods and Political Behavior." *Journal of the European Economic Association*, 23(5): 1635–1668.

Erikson, Robert S., Michael B. MacKuen, and James A. Stimson. 1998. "What Moves Macropartisanship? A Response to Green, Palmquist, and Schickler." *American Political Science Review*, 92(4): 901–912.

Faia, Ester, Andreas Fuster, Vincenzo Pezone, and Basit Zafar. 2024. "Biases in Information Selection and Processing: Survey Evidence from the Pandemic." *The Review of Economics and Statistics*, 106(3): 829–847.

Fan, Chengze Simon, and Phoebe Wong. 1998. "Does consumer sentiment forecast household spending? The Hong Kong case." *Economic Letters*, 58: 77–84.

Friend, Irwin, and F. Gerard Adams. 1964. "The Predictive Ability of Consumer Attitudes, Stock Prices, and Non-Attitudinal Variables." *Journal of the American Statistical Association*, 59(308): 987–1005.

Fuster, Andreas, Ricardo Perez-Truglia, Mirko Wiederholt, and Basit Zafar. 2022. "Expectations with Endogenous Information Acquisition: An Experimental Investigation." *The Review of Economics and Statistics*, 104(5): 1059–1078.

Gerber, Alan S., and Gregory A. Huber. 2009. "Partisanship and Economic Behavior: Do Partisan Differences in Economic Forecasts Predict Real Economic Behavior?" *American Political Science Review*, 103(3): 407–426.

Gerber, Alan S., and Gregory A. Huber. 2010. "Partisanship, Political Control, and Economic Assessments." *American Journal of Political Science*, 54(1): 153–173.

Ghosh, Arkadev. 2025. "Religious Divisions and Production Technology: Experimental Evidence from India." *Journal of Political Economy*, 133(10): 3249–3304.

Ghosh, Arkadev, Prerna Kundu, Matt Lowe, and Gareth Nellis. 2024. "Creating Cohesive Communities: A Youth Camp Experiment in India." *The Review of Economic Studies*, forthcoming.

Gillitzer, Christian, and Nalini Prasad. 2018. "The Effect of Consumer Sentiment on Consumption." *American Economic Journal: Macroeconomics*, 10(4): 234–269.

Gillitzer, Christian, Nalini Prasad, and Tim Robinson. 2021. "Political Attitudes and Inflation Expectations: Evidence and Implications." *Journal of Money, Credit and Banking*, 53(4): 605–634.

Guirola, Luis. 2025. "Economic expectations under the shadow of party polarization: Evidence from 135 government changes." *European Economic Review*, 171.

Hall, Robert E. 1993. "Macro Theory and the Recession of 1990-91." *AEA Papers and Proceedings*, 83(2): 275–279.

Hansen, Lars Peter, and Kenneth J. Singleton. 1983. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns." *Journal of Political Economy*, 91(2): 249–265.

Heath, Oliver. 2020. "Communal realignment and support for the BJP, 2009–2019." *Contemporary South Asia*, 28(2): 195–208.

Howrey, E. Philip. 2001. "The Predictive Power of the Index of Consumer Sentiment." *Brookings Papers on Economic Activity*, 2001(1): 175–207.

Imbens, Guido, and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." *Journal of Econometrics*, 142: 615–635.

Jaffrelot, Christophe. 2021. *Modi's India: Hindu Nationalism and the Rise of Ethnic Democracy.* Princeton, NJ:Princeton University Press.

Jappelli, Tullio, and Luigi Pistaferri. 2000. "Using subjective income expectations to test for excess sensitivity of consumption to predicted income growth." *European Economic Review*, 44: 337–358.

Jensenius, Francesca Refsum. 2015. "Development from Representation? A Study of Quotas for the Scheduled Castes in India." *American Economic Journal: Applied Economics*, 7(3): 196–220.

Juhro, Solikin M., and Bernard Njindan Iyke. 2020. "Consumer confidence and consumption expenditure in Indonesia." *Economic Modelling*, 89: 367–377.

Kamdar, Rupal, and Walker Ray. 2022. "Polarized Expectations, Polarized Consumption." *Working Paper*.

Kwan, Andy C.C., and John A. Cotsomitis. 2006. "The Usefulness of Consumer Confidence in Forecasting Household Spending in Canada: A National and Regional Analysis." *Economic Inquiry*, 44(1): 185–197.

Lagerborg, Andresa, Evi Pappa, and Morten O. Ravn. 2023. "Sentimental Business Cycles." *Review of Economic Studies*, 90: 1358–1393.

Ludvigson, Sydney. 1996. "Consumer Sentiment and Household Expenditure: Reevaluating the Forecasting Equations." *Federal Reserve Bank of New York Research Paper*, No. 9636.

Ludvigson, Sydney C. 2004. "Consumer Confidence and Consumer Spending." *The Journal of Economic Perspectives*, 18(2): 29–50.

McCrary, Justin. 2008. "Manipulation of the running variable in the regression discontinuity design: A density test." *Journal of Econometrics*, 142: 698–714.

Meyersson, Erik. 2014. "Islamic Rule and the Empowerment of the Poor and Pious." *Econometrica*, 82(1): 229–269.

Mian, Atif, Amir Sufi, and Nasim Khoshkhou. 2015. "Government Economic Policy, Sentiments, and Consumption." *NBER Working Paper*, 21316.

Mian, Atif, Amir Sufi, and Nasim Khoshkhou. 2023. "Partisan Bias, Economic Expectations, and Household Spending." *The Review of Economics and Statistics*, 105(3): 493–510.

Mitra, Aruni, and Ronit Mukherji. 2025. "Class, Caste and Conspicuous Consumption in India." *Economica*, forthcoming.

Mullainathan, Sendhil, and Eldar Shafir. 2013. *Scarcity: Why having too little means so much.* Penguin Books.

Munshi, Kaivan, and Mark Rosenzweig. 2015. "Insiders and Outsiders: Local Ethnic Politics and Public Goods Provision." *NBER Working Paper*, 21720.

Nellis, Gareth, Michael Weaver, and Steven C. Rosenzweig. 2016. "Do Parties Matter for Ethnic Violence? Evidence from India." *Quarterly Journal of Political Science*, 11(3): 249–277.

Roth, Chris, and Johannes Wohlfart. 2020. "How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?" *The Review of Economics and Statistics*, 102(4): 731–748.

Souleles, Nicholas S. 2004. "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys." *Journal of Money, Credit and Banking*, 36(1): 39–72.

Stoltenberg, Christian A., and Arne Uhlendorff. 2024. "Consumption Choices and Earnings Expectations: Empirical Evidence and Structural Estimation." *Working Paper*.

Appendix

There are four appendices, A through D corresponding to Sections 2 through 5, respectively in the main paper.

A Appendix to Section 2

Motivation for the Expenditure Growth Regression Specification

In a standard life-cycle model of expected utility maximization by a household choosing consumption subject to a budget constraint, one can derive the intertemporal optimality condition or the Euler equation by equating the discounted expected marginal utilities of consumption in two consecutive periods. Assuming a power utility function like the CRRA, the Euler equation can be used to express consumption growth as a linear function of the (log) real interest rate, changes in any utility-shifting variables that are exogenous and deterministic from the point of view of the household and observable to the econometrician (e.g., age, location, etc.), and an error term.[24] Attanasio, Kovacs and Molnar (2020) argue that the error term, in turn, contains several important components: (i) the expectational error in consumption growth, (ii) the expectational error in real interest rate, (iii) any unobserved heterogeneity across households that influences utility, (iv) any measurement error in consumption, and (v) deviations of conditional higher-order moments of consumption growth and real interest rate from their unconditional means. Of these, we are particularly interested in the two expectational error components, (i) and (ii).

Blundell, Pistaferri and Preston (2008) show that the expectational error in consumption growth can be approximated by a linear function of the permanent and transitory shocks to a log-linear income process. Without assuming a log-linear income process or delving into the structural identification of the permanent and transitory income shocks, it can still be argued that the expectational error in consumption growth is a function of income growth. The coefficient of the income growth variable in a regression of consumption growth on income growth can be interpreted similarly to the loading factors for permanent and transitory income shocks in Blundell, Pistaferri and Preston (2008). A coefficient close to one means that income fluctuations are transmitted almost entirely to consumption changes, implying little consumption insurance against income shocks. On the other hand, a coefficient close to zero implies high levels of consumption smoothing.

The expectational error in the interest rate is the deviation of the realized interest rate from the rationally expected value of the interest rate. Not only does the interest rate contain information regarding the aggregate economic condition, e.g., the inflation rate, the real return on investment,

[24] Log-linearizing an Euler equation helps obtain consistent estimates of the relationship (see Attanasio and Low (2004)), particularly when the income process is assumed to be log-linear. Factors like the elasticity of intertemporal substitution and the unconditional means of the higher-order moments of consumption growth and real interest rate are subsumed in constant terms in the log-linear Euler equation (see Hansen and Singleton (1983)).

etc., but also individual households' portfolio choices. Therefore, any expectational error in the interest rate can be considered a function of household sentiment about their personal finances and the national economy.

Taking the two expectational error terms in the Euler equation into consideration, we can, therefore, express the change in log expenditure as a linear function of initial consumer sentiment, the change in log income, and an error term capturing measurement error, higher-order moments, and unobserved heterogeneity. This is the basis of our estimation equation (2.1), where we test whether sentiments can predict expenditure growth above and beyond the role played by income growth. It is worth noting that despite equation (2.1) describing consumption growth and not log consumption levels, we include household fixed effects in that regression. This is because the sentiment variables are measured at the initial period, and changes in these sentiment variables are not meaningful objects, given that the survey questions on sentiments already measure perception or expectation about *changes* in financial conditions. Therefore, to control for the household-specific optimism or pessimism, we must include household fixed effects in the consumption growth equation.

It is worth noting that equation (2.1) can be viewed as a generalized version of the standard log-linear consumption function derived, for example, in Blundell, Pistaferri and Preston (2008) – augmented with individual and national sentiment, one-period-ahead income growth and household fixed effects. Thus, by constraining $\beta = \delta_f = \gamma_h = 0$, we can get back the standard consumption growth function.

B Appendix to Section 3

Table B.1: Summary Statistics of Household-Level Per Capita Income & Expenditure by Religion

Income & Expenditure Categories	**Hindu + Muslim** (1)	**Hindu** (2)	**Muslim** (3)
Total Monthly Income			
Mean	5,868.98	6,010.15	4,635.88
Standard Deviation	2,596.35	2,674.97	1,631.80
Total Monthly Expenditure			
Mean	3,346.47	3,389.09	2,974.23
Standard Deviation	3,877.06	4,083.50	805.96
Food Expenditure			
Mean	1,652.75	1,658.71	1,600.72
Standard Deviation	3,762.15	3,970.27	305.17
Health Expenditure			
Mean	94.59	96.62	76.88
Standard Deviation	232.21	240.68	136.47
Education Expenditure			
Mean	91.46	92.74	80.29
Standard Deviation	209.96	206.13	240.07
Luxury Expenditure			
Mean	271.46	275.01	240.50
Standard Deviation	502.19	517.34	339.85
Durable Expenditure			
Mean	34.58	35.44	27.09
Standard Deviation	106.64	110.55	62.17
No. of unique households	*178,663*	*160,310*	*18,353*

Note: All statistics correspond to data from the CPHS survey between May 2015 and August 2022 in current Indian Rupees, collapsed at the unique household-level using survey weights that are adjusted for non-response, and divided by the family size to convert into per capita measures. **Luxury expenditure** includes spending on clothing, footwear, jewellery, wallets, gems, automobile EMIs, electronics, entertainment and recreation, and social or religious activities. This basket of luxury items has an income elasticity of greater than one for both Hindus and Muslims (see Mitra and Mukherji (2025)). The four non-durable spending categories considered here, namely, food, health, education and luxury items, taken together, constitute about 60% of total household monthly expenditure in our sample. **Durable expenditure** includes spending on furniture, refrigerator, television, two-wheeler and car — the same items that are listed in the sentiment question on whether the household finds it a good time to purchase durables.

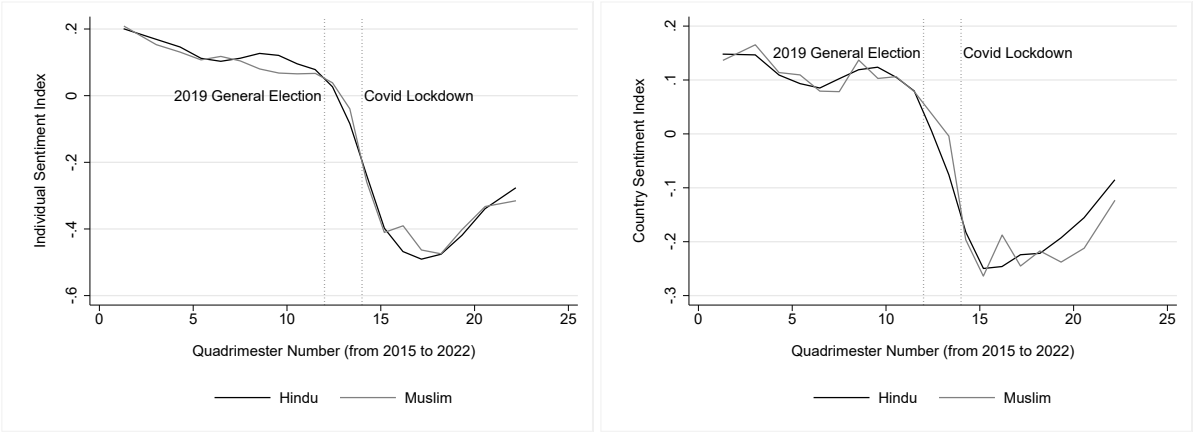


Figure B.1: Individual & Country Sentiment Indices by Religion over Time

Note: The figure shows the time series of the Individual (left) and Country (right) Sentiment Indices residualized by household fixed effects, separately for Hindus and Muslims. The timings of the 2019 general election and the onset of the COVID-19 lockdown are shown by dotted vertical lines.

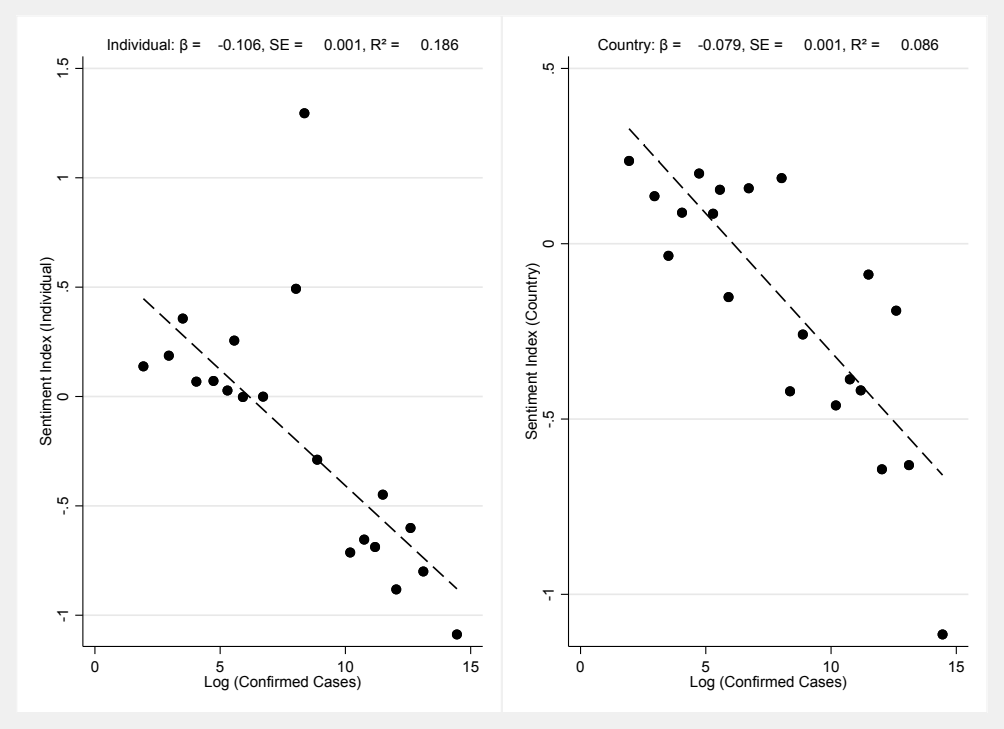


Figure B.2: Correlations of Sentiment Indices with Covid-19 Cases across Indian Districts

Note: The two panels of the figure show the bin scatter plots of Individual Sentiment Index (left panel) and Country Sentiment Index (right panel) against the logarithm of total confirmed cases of COVID-19 across Indian districts during the second and third quarters of 2020. In estimating the fitted lines, observations are weighted by the district-level population estimates in 2021. Estimates of the slope coefficients (β) along with their standard errors, and the R-squared of the regressions are reported.

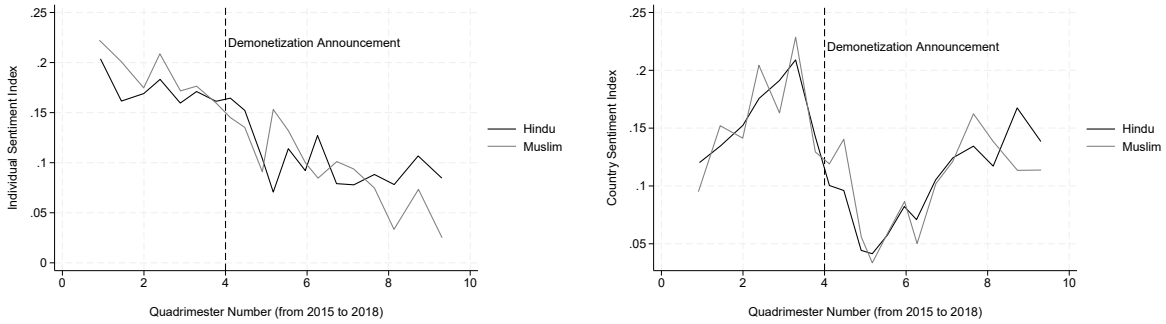
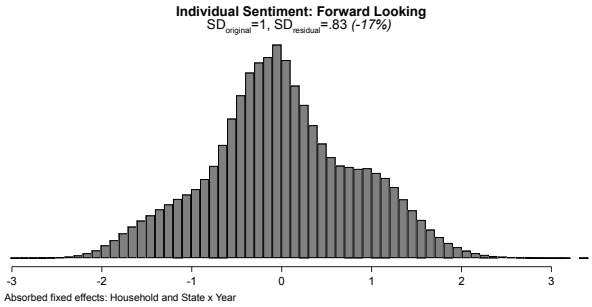
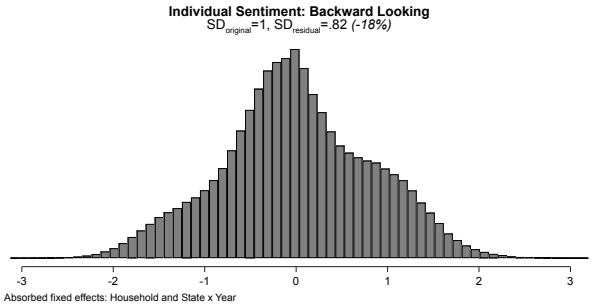


Figure B.3: Individual & Country Sentiment Indices around Demonetization Announcement

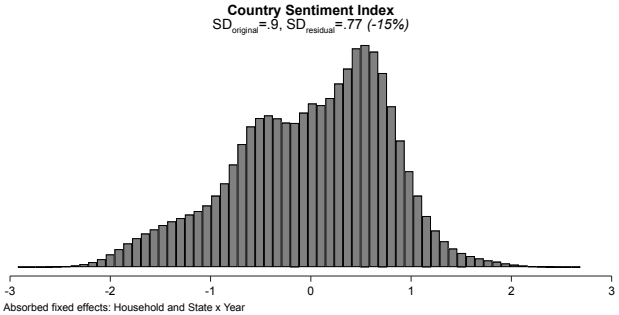
Note: The two panels of the figure show the dynamics of the average values of the Individual Sentiment Index (left panel) and the Country Sentiment Index (right panel), separately for Hindu and Muslim households, around the time of the announcement of demonetization - November 2016, that is, the third quadrimester of 2016, or equivalently, the fourth quadrimester of our dataset.



(a) Forward Looking Individual Sentiment



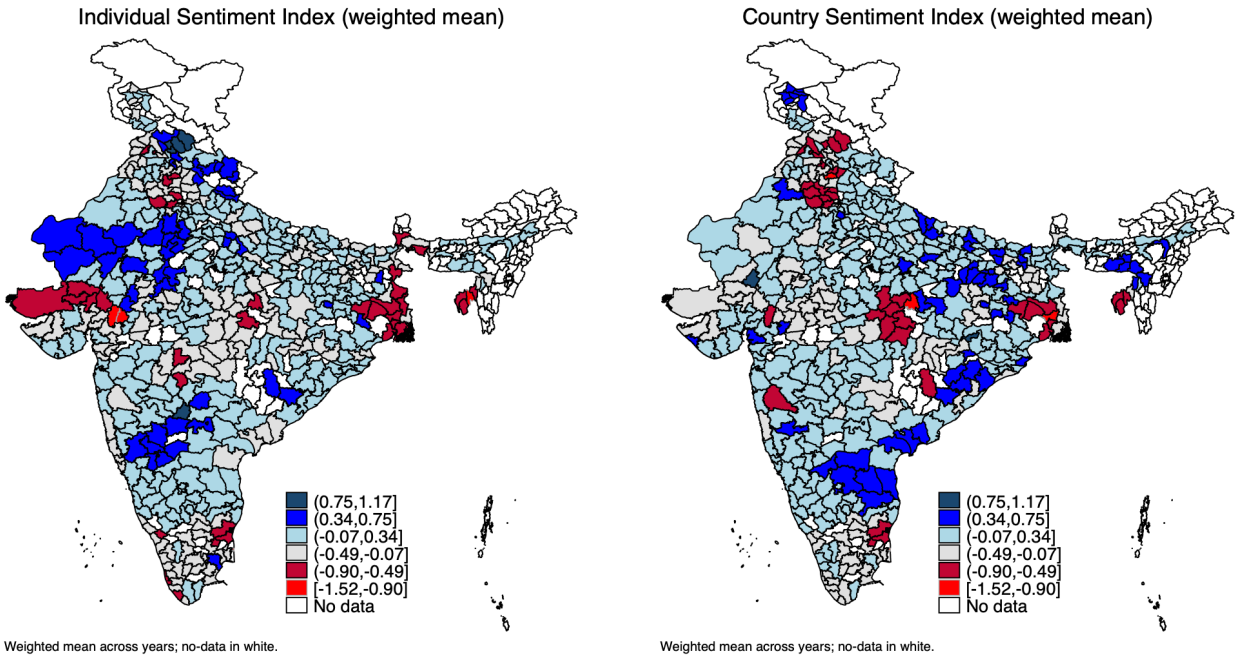
(b) Backward Looking Individual Sentiment



(c) Country Sentiment Index

Figure B.4: Residual variation in sentiment indices after accounting for fixed effects

Note: This figure displays the distribution of various sentiment measures after residualizing them with respect to household and state×year fixed effects. These fixed effects account for 16–22% of the variation in the sentiment measures.



(a) Individual Sentiment Index

(b) Country Sentiment Index

Figure B.5: District-level Sentiment Maps

Note: This figure shows Individual and Country Sentiment Indices, as defined in Section 2.2, aggregated to the district level for the full sample period (2015–2022). Household–quadrimester level sentiment indices are first averaged to the district–year level using household weights, and then further collapsed to the district level across all years, weighting by the number of households used to construct each district–year mean.

Table B.2: Correlation Matrix for Different Sentiment Measures

	Forward-looking Individual Sentiment	**Backward-looking Individual Sentiment**	**Good Time to Buy Durables**	**Country Sentiment Index**
Forward-looking Individual Sentiment	**1.00**			
Backward-looking Individual Sentiment	0.71	**1.00**		
Good Time to Buy Durables	0.51	0.52	**1.00**	
Country Sentiment Index	0.25	0.24	0.31	**1.00**

Note: This table is a correlation matrix of the three individual sentiment questions and the Country Sentiment Index. Since both sentiment questions about the national economy are forward-looking, we do not show results for the two questions separately, and instead focus on the Country Sentiment Index.

Table B.3: Correlation between Past Income Growth and Individual Sentiment about Current Financial Condition Compared to Last Year by Religion

Dependent Variable:	**Hindu**	**Muslim**
How is the family faring financially compared to a year ago?	(1)	(2)
Panel A: *Income Growth from Last Quadrimester*		
Δ Log Income between $t-1$ and t	0.0484***	0.0864***
	(0.0013)	(0.0060)
No. of Observations	1,927,297	207,627
No. of Household-Level Clusters	151,223	16,925
Mean of Dependent Variable	0.02	0.00
Panel B: *Income Growth from Last Year*		
Δ Log Income between $t-3$ and t	0.0688***	0.0812***
	(0.0014)	(0.0055)
No. of Observations	1,687,487	181,248
No. of Household-Level Clusters	146,621	16,228
Mean of Dependent Variable	-0.01	-0.02

Note: The unit of time is a quadrimester. Since there are three quadrimesters in a year, an annual change in any variable x is calculated as $x_t - x_{t-3}$. Panel A uses income growth between the last quadrimester and the current period, while Panel B uses the annual income growth since last year as the explanatory variable. In both panels, the dependent variable is measured at the current period t. Robust standard errors clustered at the household level are reported in parentheses. All regressions include state-by-year fixed effects and household fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table B.4: Correlation between Future Income Growth and Individual Sentiment about One Year Ahead Financial Condition by Religion

	Hindu	**Muslim**
	(1)	(2)
Panel A. *Dependent Variable:* Δ *Log Income between* t *and* $t+1$		
How will the family fare financially a year from now?	-0.0417***	-0.0488***
	(0.0010)	(0.0024)
No. of Observations	1,927,297	207,611
No. of Household-Level Clusters	151,223	16,925
Mean of Dependent Variable	0.03	0.03
Panel B. *Dependent Variable:* Δ *Log Income between* t *and* $t+3$		
How will the family fare financially a year from now?	-0.0586***	-0.0599***
	(0.0012)	(0.0032)
No. of Observations	1,687,487	181,248
No. of Household-Level Clusters	146,621	16,228
Mean of Dependent Variable	0.07	0.08

Note: The unit of time is a quadrimester. Since there are three quadrimesters in a year, an annual change in any variable x is calculated as $x_t - x_{t-3}$. Panel A uses income growth between the current quadrimester and the next one, while Panel B uses the annual income growth between the current period and next year as the dependent variable. In both panels, the explanatory variable is measured at the current period t. Robust standard errors clustered at the household level are reported in parentheses. All regressions include state-by-year fixed effects and household fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table B.5: Follow-Through of Stated Position of Whether It Is a Good Time to Buy Durables by Religion

Dependent Variable:	**Hindu**	**Muslim**
Log Durable Expenditure at time t	(1)	(2)
Sentiment about durable expenditure at t	0.1278***	0.0656***
	(0.0031)	(0.0090)
Δ Log Income between $t-1$ and t	0.0863***	0.1399***
	(0.0035)	(0.0138)
Δ Log Income between t and $t+1$	-0.0859***	-0.1156***
	(0.0035)	(0.0133)
No. of Observations	1,558,375	165,197
No. of Household-Level Clusters	144,903	15,977
Mean of Dependent Variable	2.45	2.12

Note: Robust standard errors clustered at the household level are reported in parentheses. All regressions include state-by-year fixed effects and household fixed effects. For the definition of durable expenditure, see Note to Table B.1. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

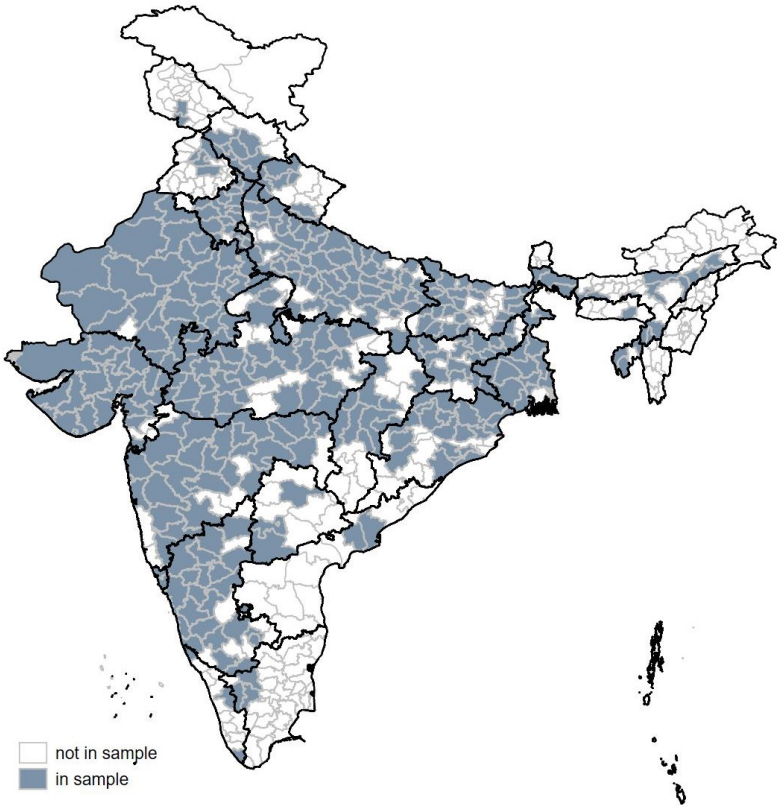


Figure B.6: Districts with At Least One State Assembly Constituency with BJP in a Close Electoral Contest

Note: The map shows all district boundaries of India in light grey lines and all state boundaries in black lines. The districts in dark grey colour had at least one state assembly constituency with the BJP involved in a close electoral contest, i.e., less than 5% vote share difference with the nearest competitor. The white (uncoloured) districts had no constituency where the BJP was involved in a close contest during the period under study.

C Appendix to Section 4

Table C.1: Effect of Individual Economic Sentiment on Total Expenditure Growth: Robustness to Income Growth Polynomials and Income Quartile Controls

	(1)	(2)	(3)
Forward looking individual sentiment at t	-0.0062***	-0.0121***	-0.0086***
	(0.0006)	(0.0006)	(0.0006)
Backward looking individual sentiment at t	-0.0042***	-0.0130***	-0.0075***
	(0.0006)	(0.0006)	(0.0006)
Δ Log Income between $t-1$ and t	0.2140***		0.0671***
	(0.0013)		(0.0017)
$(\Delta$ Log Income$)^2$	-0.0005***		
	(0.0002)		
$(\Delta$ Log Income$)^3$	-0.0023***		
	(0.0000)		
Income Quartile 2		0.1131***	0.0659***
		(0.0012)	(0.0012)
Income Quartile 3		0.1830***	0.0961***
		(0.0014)	(0.0016)
Income Quartile 4		0.2730***	0.1274***
		(0.0017)	(0.0021)
Income Quartile 2 $\times$ Δ Log Income			0.1055***
			(0.0037)
Income Quartile 3 $\times$ Δ Log Income			0.0801***
			(0.0032)
Income Quartile 4 $\times$ Δ Log Income			0.0982***
			(0.0035)
F-test for Joint Significance of Sentiment Variables	$p < 0.01$	$p < 0.01$	$p < 0.01$
No. of Observations	2,134,924	2,134,924	2,134,924
No. of Household-Level Clusters	168,148	168,148	168,148
Mean of Dependent Variable	0.03	0.03	0.03

Note: Robust standard errors clustered at the household level are reported in parentheses. All columns include household fixed effects and state$\times$year fixed effects as controls. Column (1) includes a third-degree polynomial of household income growth as controls. Column (2) excludes income growth but includes as controls three categorical variables for whether a household belongs to the second, third or fourth quartile of average household income (averaged over all timepoints for which data is available). Column (3) includes as controls the full set of interaction terms between household income growth and the income quartile dummies. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.2: Effects of Forward and Backward Looking Individual Sentiments on Growth in Different Expenditure Categories over a Quadrimester for Hindu and Muslim Households

	Δ Log Expenditure between $t-1$ and t in Different Categories					
	Total	**Food**	**Health**	**Education**	**Luxury**	**Durables**
	(1)	(2)	(3)	(4)	(5)	(6)
A. Forward Looking Individual Sentiment at $t-1$						
Forward-looking individual sentiment at $t-1$ x Hindu	-0.0112***	-0.0056***	-0.0082***	-0.0242***	-0.0849***	-0.0678***
	(0.0005)	(0.0005)	(0.0021)	(0.0037)	(0.0025)	(0.0032)
Forward-looking individual sentiment at $t-1$ x Muslim	-0.0185***	-0.0119***	-0.0351***	-0.0260**	-0.1244***	-0.0968***
	(0.0014)	(0.0013)	(0.0062)	(0.0113)	(0.0087)	(0.0090)
Δ Log Income between $t-1$ and t	0.1224***	0.0859***	0.1565***	0.1793***	0.3331***	0.2683***
	(0.0016)	(0.0013)	(0.0032)	(0.0051)	(0.0047)	(0.0051)
Difference between Hindu & Muslim Coefficients	0.0073***	0.0063***	0.0269***	0.0018	0.0395***	0.0290***
	(0.0015)	(0.0014)	(0.0064)	(0.0117)	(0.0090)	(0.0094)
No. of Observations	2,134,924	2,134,924	2,134,924	2,134,924	2,134,924	2,134,924
No. of Household-Level Clusters	168,148	168,148	168,148	168,148	168,148	168,148
Mean of Dependent Variable	0.03	0.02	0.04	0.04	0.05	0.05
B. Backward Looking Individual Sentiment at $t-1$						
Backward-looking individual sentiment at $t-1$ x Hindu	-0.0110***	-0.0070***	-0.0078***	-0.0144***	-0.0940***	-0.0696***
	(0.0005)	(0.0005)	(0.0021)	(0.0038)	(0.0025)	(0.0033)
Backward-looking individual sentiment at $t-1$ x Muslim	-0.0177***	-0.0134***	-0.0405***	0.0188*	-0.1368***	-0.0934***
	(0.0014)	(0.0013)	(0.0060)	(0.0114)	(0.0086)	(0.0094)
Δ Log Income between $t-1$ and t	0.1224***	0.0858***	0.1564***	0.1799***	0.3320***	0.2677***
	(0.0016)	(0.0013)	(0.0032)	(0.0051)	(0.0047)	(0.0051)
Difference between Hindu & Muslim Coefficients	0.0067***	0.0064***	0.0327***	-0.0332***	0.0428***	0.0244**
	(0.0014)	(0.0014)	(0.0062)	(0.0117)	(0.0088)	(0.0097)
No. of Observations	2,134,924	2,134,924	2,134,924	2,134,924	2,134,924	2,134,924
No. of Household-Level Clusters	168,148	168,148	168,148	168,148	168,148	168,148
Mean of Dependent Variable	0.03	0.02	0.04	0.04	0.05	0.05

Note: Robust standard errors clustered at the household level are reported in parentheses. All regressions include state-by-year fixed effects and household fixed effects. See Note to Appendix Table B.1 for the definitions of luxury and durable expenditures. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table C.3: Effect of BJP Seat Share on Economic Sentiments by Religion: Robustness to District-level Controls (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Country Sentiment Index**	**Individual Sentiment Variables**		
		Backward Looking	**Forward Looking**	**Good Time to Buy Durables**
	(1)	(2)	(3)	(4)
BJP Seat Share × Hindu	0.0683	0.0422	0.127	0.0535
	(0.159)	(0.136)	(0.124)	(0.122)
BJP Seat Share × Muslim	-0.417*	-0.298	-0.103	-0.170
	(0.223)	(0.200)	(0.182)	(0.173)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**0.484*** **	**0.340*** **	**0.231***	**0.223***
	(0.145)	(0.125)	(0.125)	(0.118)
Kleibergen-Paap F-Stat (First Stage)	64.5	64.5	64.5	64.5
No. of Observations	1,486,051	1,486,051	1,486,051	1,486,051
No. of District×Year Clusters	1,961	1,961	1,961	1,961
District-level Controls	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects, like in the baseline results in Table 4.2. **Additionally, the regressions in this table include district-level controls, namely, the average turnout across constituencies in the district in the past election, the effective number of parties in the district (average across constituencies), the number of seats the BJP put up a candidate for, and the share of reserved seats in each district.** ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Close elections are those with a victory margin of 5% or less.

Table C.4: Effect of BJP Seat Share on Economic Sentiments by Religion: Robustness to Close Election Threshold (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Country Sentiment Index**	**Individual Sentiment Variables**		
		Backward Looking	**Forward Looking**	**Good Time to Buy Durables**
	(1)	(2)	(3)	(4)
Panel A: *Close election threshold = 4%*				
BJP Seat Share × Hindu	0.322*	0.258*	0.356**	0.232
	(0.179)	(0.153)	(0.154)	(0.145)
BJP Seat Share × Muslim	-0.140	0.0193	0.0252	0.106
	(0.315)	(0.243)	(0.242)	(0.211)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**0.462****	**0.240**	**0.330***	**0.126**
	(0.227)	(0.166)	(0.178)	(0.150)
Kleibergen-Paap F-Stat (First Stage)	32.52	32.52	32.52	32.52
No. of Observations	1,322,588	1,322,588	1,322,588	1,322,588
No. of District×Year Clusters	1,771	1,771	1,771	1,771
Panel B: *Close election threshold = 6%*				
BJP Seat Share × Hindu	-0.288*	-0.0480	-0.0437	0.0291
	(0.156)	(0.124)	(0.114)	(0.117)
BJP Seat Share × Muslim	-0.698***	-0.412**	-0.260	-0.163
	(0.219)	(0.184)	(0.160)	(0.161)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**0.410*****	**0.363*****	**0.216***	**0.1920***
	(0.1454)	(0.1233)	(0.1122)	(0.1087)
Kleibergen-Paap F-Stat (First Stage)	90.10	90.10	90.10	90.10
No. of Observations	1,583,001	1,583,001	1,583,001	1,583,001
No. of District×Year Clusters	2,121	2,121	2,121	2,121

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Close elections are those with a victory margin of 4% in Panel A and 6% in Panel B.

Table C.5: Effect of BJP Seat Share on Income and Expenditure by Religion over the Electoral Cycle (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Total Income**	**Total Expenditure**
	2SLS	**2SLS**
	(1)	(2)
Panel A: Within 2 years after an election		
BJP Seat Share × Hindu	275.033	-437.413
	(1537.245)	(1005.461)
BJP Seat Share × Muslim	692.610	309.587
	(1948.212)	(1127.214)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**-417.5**	**-747.00**
	(1576.5)	(1038.27)
No. of Observations	2,732,483	2,728,954
No. of District×Year Clusters	1,010	1,010
Mean of Dependent Variable	19,770	12,174
Kleibergen-Paap F-Stat (First Stage)	32.32	32.64
Panel B: Between 3-5 years after an election		
BJP Seat Share × Hindu	2059.341	2365.601**
	(1716.895)	(1010.652)
BJP Seat Share × Muslim	2939.356	1830.049
	(2282.416)	(1197.979)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**-880.02**	**535.52**
	(1679.5)	(704.96)
No. of Observations	2,961,409	2,967,003
No. of District×Year Clusters	1,026	1,026
Mean of Dependent Variable	19,933	12,498
Kleibergen-Paap F-Stat (First Stage)	27.74	27.92

Note: All regressions include household fixed effects and state-by-year fixed effects. Robust standard errors clustered at the district-by-year level are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table C.6: Effect of BJP Seat Share on Income Categories by Religion (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Wage** (1)	**Private Transfer** (2)	**Government Transfer** (3)	**Business** (4)
BJP Seat Share × Hindu	-273.898	98.756**	10.105	872.019
	(787.409)	(49.393)	(21.803)	(565.091)
BJP Seat Share × Muslim	785.687	290.772	-54.875*	812.767
	(1253.387)	(200.785)	(29.945)	(635.372)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**-1059.59**	**-192.02**	**64.98****	**59.25**
	(1216.79)	(169.47)	(27.79)	(599.14)
No. of Observations	5,697,033	5,714,356	5,702,263	5,693,077
No. of District×Year Clusters	1,961	1,961	1,961	1,961
Mean of Dependent Variable	15,206	122	117	3,026
Kleibergen-Paap F-Stat (First Stage)	52.8	52.9	52.3	52.6

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table C.7: Effect of BJP Seat Share on Expenditure Categories by Religion (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Food** (1)	**Health** (2)	**Education** (3)	**Luxury** (4)	**Durables** (5)
BJP Seat Share × Hindu	442.861*	34.775	-31.884	108.242	98.62***
	(262.336)	(28.998)	(40.596)	(131.634)	(24.115)
BJP Seat Share × Muslim	409.579	-44.072	-45.341	-119.376	71.274**
	(386.118)	(40.898)	(76.781)	(195.764)	(25.856)
(BJP Seat Share × Hindu - BJP Seat Share × Muslim)	**33.28**	**78.85*****	**13.46**	**227.62**	**27.34**
	(283.44)	(30.37)	(63.05)	(161.95)	(23.34)
No. of Observations	5,638,337	5,698,782	5,705,652	5,757,812	5,757,812
No. of District×Year Clusters	1,961	1,961	1,961	1,961	1961
Mean of Dependent Variable	5,702	278	308	934	134.7
Kleibergen-Paap F-Stat (First Stage)	53.13	65.2	65.2	52.3	52.37

Note: Robust standard errors clustered at the district-by-year level are reported in parentheses. All regressions include household fixed effects and state-by-year fixed effects. See Note to Appendix Table B.1 for the definition of luxury and durable expenditures. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

D Appendix to Section 5

D.1 Proof of Lemma

We have defined: $z_i \equiv \frac{Y_i^P - \alpha X_i}{Y^N} = \beta_i + \frac{\varepsilon_i^P}{Y^N}$. Then, $z_i | \left(Y^N, s\right) \sim N\left(\beta_i, \frac{\sigma_P^2}{(Y^N)^2}\right)$. Since $Y^N | s, g \sim N\left(S_g^N, V^N\right)$, and Y^N being the national income is sufficiently away from zero, we have the following approximate expression for the predictive variance of z_i at time $t = 0$:

$$\sigma_z^2(s) \equiv \mathbb{E}\left[\frac{\sigma_P^2}{(Y^N)^2}\middle| s, g\right] \approx \sigma_P^2 \left(S_g^N\right)^{-2} \left(1 + 3\frac{V^N}{\left(S_g^N\right)^2}\right)$$

To see this, define a function $f(x) = \frac{1}{x^2}$. A second order Taylor expansion of this function $f(x)$ around a fixed point $x = a$ is given by $f(x) \approx \frac{1}{a^2} - \frac{2}{a^3}(x-a) + \frac{3}{a^4}(x-a)^2$. Applying this approximation of the function for the random variable Y^N around S_g^N, we get,

$$\begin{aligned} \frac{1}{(Y^N)^2} &\approx \frac{1}{\left(S_g^N\right)^2} - \frac{2}{\left(S_g^N\right)^3}\left(Y^N - S_g^N\right) + \frac{3}{\left(S_g^N\right)^4}\left(Y^N - S_g^N\right)^2 \\ \implies \mathbb{E}\left[\frac{1}{(Y^N)^2}\middle| s, g\right] &\approx \frac{1}{\left(S_g^N\right)^2} + 3\frac{V^N}{\left(S_g^N\right)^4} = \left(S_g^N\right)^{-2}\left(1 + 3\frac{V^N}{\left(S_g^N\right)^2}\right) \end{aligned} \tag{D.1}$$

The last step follows from the posterior mean and variance of $Y^N | s, g$ in equation (5.6). Then the expression for the predictive variance of z_i at $t = 0$, $\sigma_z^2(s)$ can be readily derived by multiplying both sides of equation (D.1) by σ_P^2.

Given the variance of β_i as v_0^2 and the variance of z_i as $\sigma_z^2(s)$, it can be easily seen that the Kalman-gain weight placed on z_i in the update for β_i is given by

$$\kappa(s) = \frac{v_0^2}{v_0^2 + \sigma_z^2(s)}$$

Therefore, the posterior mean of β_i is given as follows:

$$E\left[\beta_i | z_i, Y^N\right] = \kappa\left(Y^N\right) z_i + \left(1 - \kappa\left(Y^N\right)\right)\bar{\beta} \tag{D.2}$$

D.2 Proof of Proposition

Taking conditional expectations on both sides of equation (5.2), and using the Law of Iterated Expectations (henceforth, LIE), we get

$$\begin{aligned} E\left[Y_i^P|X_i,s,g\right] &= \alpha X_i + E_{Y^N|s,g}\left[E_{\beta_i}\left[\beta_i Y^N|s,Y^N\right]\right] \\ &= \alpha X_i + E\left[\beta_i Y^N|s,g\right] \end{aligned} \tag{D.3}$$

Using the definition of covariance, $Cov(X,Y) = E(XY) - E(X)E(Y)$, we can write the last term of equation (D.3) as follows:

$$\begin{aligned} E\left[\beta_i Y^N|s,g\right] &= E\left[\beta_i|s,g\right]E\left[Y^N|s,g\right] + \text{Cov}\left(\beta_i, Y^N|s,g\right) \\ &= \bar{\beta}S_g^N + \text{Cov}\left(\beta_i, Y^N|s,g\right) \end{aligned} \tag{D.4}$$

Therefore, $E\left[Y_i^P|X_i,s,g\right]$ can be found if we can solve for $\text{Cov}\left(\beta_i, Y^N|s,g\right)$ in equation (D.4). Since the posterior mean of β_i is given by equation (D.2), we can express posterior β_i as $\bar{\beta}+\kappa\left(Y^N\right)\left(z_i-\bar{\beta}\right)$. Thus, we can rewrite the covariance term as $\text{Cov}\left(\beta_i, Y^N|s,g\right) = \text{Cov}\left[\kappa(Y^N)(z_i-\bar{\beta}), Y^N\right]$. To simplify the calculation of this covariance, we take a linear Taylor approximation of the function $\kappa(.)$ around the fixed point S_g^N, that is, $\kappa\left(Y^N\right) \approx \kappa\left(S_g^N\right) + \kappa'\left(S_g^N\right)\left(Y^N - S_g^N\right)$. Therefore, plugging this approximate expression of $\kappa\left(Y^n\right)$ into the covariance yields

$$\text{Cov}\left(\beta_i, Y^N|s,g\right) = \kappa\left(S_g^N\right)\text{Cov}\left(z_i-\bar{\beta}, Y^N\right) + \kappa'\left(S_g^N\right)\text{Cov}\left[\left(Y^N - S_g^N\right)\left(z_i-\bar{\beta}\right), Y^N\right] \tag{D.5}$$

We can rewrite the second covariance term on the right-hand side of equation (D.5) as follows:

$$\begin{aligned} \text{Cov}\left[\left(Y^N - S_g^N\right)\left(z_i-\bar{\beta}\right), Y^N\right] &= \text{Cov}\left[\left(Y^N - S_g^N\right)\left(z_i-\bar{\beta}\right), \left(Y^N - S_g^N\right)\right] \\ &= E\left[\left(Y^N - S_g^N\right)^2(z_i-\bar{\beta})\right] - E\left[Y^N - S_g^N\right]E\left[\left(Y^N - S_g^N\right)(z_i-\beta)\right] \\ &= E\left[\left(Y^N - S_g^N\right)^2\left(z_i-\bar{\beta}\right)\right] \quad (\because E\left(Y^N - S_g^N\right) = 0, \text{ by definition}) \\ &= E_{Y^N}\left[\left(Y^N - S_g^N\right)^2 E\left(z_i-\bar{\beta}\right)|Y^N\right] \quad \text{(applying LIE)} \\ &= 0 \quad (\because E\left(z_i-\bar{\beta}\right) = 0, \text{ by definition}) \end{aligned}$$

Then, equation (D.5) simplifies to

$$\begin{aligned} \text{Cov}\left(\beta_i, Y^N|s,g\right) &= \kappa\left(S_g^N\right)\text{Cov}\left(z_i-\bar{\beta}, Y^N\right) \\ &= \kappa\left(S_g^N\right)\text{Cov}\left(z_i, Y^N\right) \\ &= \kappa\left(S_g^N\right)\text{Cov}\left(\frac{Y_i^P - \alpha X_i}{Y^N}, Y^N\right) \end{aligned} \tag{D.6}$$

We notice that for any differentiable function $\phi\left(Y^N\right)$, we can approximate it using a first-order Taylor approximation around the fixed point $Y^N = S_g^N$ as follows: $\phi\left(Y^N\right) \approx \phi\left(S_g^N\right) + \phi'\left(S_g^N\right)\left(Y^N - S_g^N\right)$. Because $E\left(Y^N - S_g^N\right) = 0$, this allows us to write

$$E\left[\phi\left(Y^N\right)\right] \approx E\left[\phi\left(S_g^N\right)\right] \tag{D.7}$$

Stein's lemma states that for a normally distributed random variable X with expectation μ and variance σ^2, and a differentiable function $h(.)$ for which the two expectations $E\left[h(X)(X-\mu)\right]$ and $E\left[h'(X)\right]$ both exist, $E\left[h(X)(X-\mu)\right] = \sigma^2 E\left[h'(X)\right]$. Using Stein's lemma for the function $f\left(Y^N\right) = \frac{Y_i^P - \alpha X_i}{Y^N}$, we can write: $\text{Cov}\left(f\left(Y^N\right), Y^N\right) = V^N E\left[f'\left(Y^N\right)\right]$, since V^N is the variance of the normally distributed random variable Y^N. Now, using equation (D.7) for the function $f'\left(Y^N\right)$, we can write

$$\begin{aligned}
\text{Cov}\left(f\left(Y^N\right), Y^N\right) &\approx V^N E\left[f'\left(S_g^N\right)\right] \\
&= -V^N E\left[\frac{Y_i^P - \alpha X_i}{\left(S_g^N\right)^2}\right] \quad \text{(from the definition of } f(.) \text{ above)} \\
&= -\frac{V^N}{\left(S_g^N\right)^2} E\left(Y_i^P - \alpha X_i\right) \\
&= -\frac{V^N}{\left(S_g^N\right)^2} E\left(\beta_i Y^N + \varepsilon_i^P\right) \quad \text{(from equation (5.2))} \\
&= -\frac{V^N}{\left(S_g^N\right)^2} E\left(\beta_i Y^N\right) \quad (\because \varepsilon_i^p \text{ has mean zero}) \\
&= -\frac{V^N}{\left(S_g^N\right)^2} E\left[E\left(\beta_i Y^N | Y^N\right)\right] \quad \text{(applying LIE)} \\
&= -\frac{V^N \bar{\beta}}{\left(S_g^N\right)^2} E\left(Y^N\right) \quad (\because \beta_i \text{ has mean } \bar{\beta}) \\
&= -\frac{V^N \bar{\beta}}{S_g^N} \quad (\because Y^N \text{ has mean } S_g^N) \\
\implies \text{Cov}\left(\beta_i, Y^N | s, g\right) &\approx -\kappa\left(S_g^N\right) \frac{V^N \bar{\beta}}{S_g^N} \quad \text{(from equation (D.6))} \\
\implies E\left[\beta_i Y^N | s, g\right] &\approx \bar{\beta} S_g^N - \kappa\left(S_g^N\right) \frac{V^N \bar{\beta}}{S_g^N} \quad \text{(from equation (D.4))} \\
\implies E\left[Y_i^P | X_i, s, g\right] &\approx \alpha X_i + \bar{\beta} S_g^N - \kappa\left(S_g^N\right) \frac{V^N \bar{\beta}}{S_g^N} \quad \text{(from equation (D.3))}
\end{aligned} \tag{D.8}$$

Equation (D.8) can be used to define the between-group gap in personal or individual sentiment as follows:

$$\begin{aligned}\Delta^P &\equiv E\left[Y_i^P|X_i,s,H\right]-E\left[Y_i^P|X_i,s,M\right]\\ &\approx \bar{\beta}\left[\left(S_H^N-S_M^N\right)-V^N\left(\frac{\kappa\left(S_H^N\right)}{S_H^N}-\frac{\kappa\left(S_M^N\right)}{S_M^N}\right)\right]\\ &\equiv \bar{\beta}\left[\Delta^N-V^N\left(\frac{\kappa\left(S_H^N\right)}{S_H^N}-\frac{\kappa\left(S_M^N\right)}{S_M^N}\right)\right]\end{aligned} \tag{D.9}$$

The last step uses the definition of the between-group gap in national sentiment, $\Delta^N = S_H^N - S_M^N$.

For the case when $\bar{\beta} \leq 1$, a sufficient condition for $\Delta^P < \Delta^N$ to hold is $\frac{\kappa\left(S_H^N\right)}{S_H^N} > \frac{\kappa\left(S_M^N\right)}{S_M^N}$. Using the expression of $\kappa\left(S_g^N\right)$ from the Lemma and the definition of Δ^N, it is easy to show that

$$\frac{\kappa\left(S_H^N\right)}{S_H^N} > \frac{\kappa\left(S_M^N\right)}{S_M^N} \iff \sigma_P^2\left[1+\frac{3V^N\left[\left(S_H^N\right)^2+\left(S_M^N\right)^2+S_H^NS_M^N\right]}{\left(S_H^NS_M^N\right)^2}\right] > v_0^2S_H^NS_M^N$$

Therefore, a sufficient condition for $\frac{\kappa\left(S_H^N\right)}{S_H^N} > \frac{\kappa\left(S_M^N\right)}{S_M^N}$ is $\sigma_P^2 > v_0^2S_H^NS_M^N$. Therefore, for $\bar{\beta} \leq 1$, we have shown that the proposition holds if $\sigma_P^2 > v_0^2S_H^NS_M^N$. The proposition can hold even if $\bar{\beta} > 1$ provided $\bar{\beta}$ is not too large.

The necessary condition for $\Delta^P < \Delta^N$ is given as follows:

$$\bar{\beta} < \left[1-\frac{V^N}{\Delta^N}\left(\frac{\kappa\left(S_H^N\right)}{S_H^N}-\frac{\kappa\left(S_M^N\right)}{S_M^N}\right)\right]^{-1} \tag{D.10}$$

Note that the necessary condition in (D.10) has the same comparative statics as the original proposition. The condition is easier to satisfy if (a) $\bar{\beta}$ is smaller, making the left-hand side of the inequality smaller, or if (b) σ_P^2 is larger or v_0^2 is smaller – both of which make the right-hand side of the inequality larger.

D.3 Construction of Heterogeneity Variables

To examine heterogeneous effects by household characteristics in Section 5, we construct a set of categorical variables capturing socioeconomic position and demographic structure.

Occupation

Households are classified into *white-collar* and *blue-collar* groups based on the primary occupation category reported in the survey. The following are coded as **blue-collar**: *Agricultural Labourers*, *Industrial Workers*, *Organised Farmers*, *Small/Marginal Farmers*, *Wage Labourers*, and *Small Traders/Hawkers*. The following are coded as **white-collar**: *Business & Salaried Employees*, *Entrepreneurs*, *Legislators/Social Workers/Activists*, *Managers/Supervisors*, *Non-industrial Technical Employees*, *Qualified Self-employed Professionals*, *Self-employed Entrepreneurs*, *White-collar Clerical Employees*, and *White-collar Professional Employees*. Categories such as *Support Staff*, *Home-based Workers*, and *Retired/Aged* are intentionally left unclassified due to ambiguity. We then generate a binary indicator equal to 1 for white-collar, 0 for blue-collar, and missing otherwise.

Education

Educational attainment is coded as an ordinal index based on the highest education level of household members. We assign:

- 0 = *Illiterate* (all household members illiterate);
- 1 = *Literate* (some or all literate but none matriculate);
- 2 = *Matriculate* (any matriculate household);
- 3 = *Graduate* (any graduate household).

Observations marked "Not applicable" are coded as missing.

Age Composition

We construct a household *age exposure index* based on the dominant age group within the household. The index takes the value:

- 0 = *Young/child-dominated households*;
- 1 = *Senior-dominated households*;
- 2 = *Grown-up/senior mixed households*;
- 3 = *Grown-up dominant or balanced households (no seniors)*.

This variable proxies for variation in household exposure to the wider economy and public sphere.

Urban–Rural Status

Finally, households are classified by place of residence using survey location codes. A binary indicator is set equal to 1 for **urban** households and 0 for **rural** households.

D.4 Heterogeneity Results Validating the Bayesian Learning Framework

Table D.1: Effect of BJP Seat Share on Sentiment: Heterogeneity by Religion and Household Socio-economic Characteristics (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Country Sentiment**	**Individual Sentiment**	
	Index	**Forward Looking**	**Backward Looking**
	(1)	(2)	(3)
Heterogeneity by Proxies for High $\bar{\beta}$ or Low σ_p^2			
BJP Seat Share × Hindu × Above Median Proxy	0.291*	0.237	0.120
	(0.175)	(0.150)	(0.149)
BJP Seat Share × Muslim × Above Median Proxy	-0.224	-0.072	-0.147
	(0.247)	(0.227)	(0.230)
BJP Seat Share × Hindu × Below Median Proxy	-0.008	0.095	0.032
	(0.160)	(0.124)	(0.139)
BJP Seat Share × Muslim × Below Median Proxy	-0.584**	-0.133	-0.376*
	(0.240)	(0.196)	(0.215)
Differences in Coefficients			
(1) **Above Median Proxy: Hindu – Muslim**	**0.515*** **	**0.310***	**0.270***
	(0.172)	(0.170)	(0.153)
(2) **Below Median Proxy: Hindu – Muslim**	**0.576*** **	**0.229**	**0.408** **
	(0.176)	(0.151)	(0.153)
Kleibergen-Paap F-stat (First Stage)	156.47	156.47	156.47
No. of Observations	1,486,051	1,486,051	1,486,051
No. of District×Year Clusters	1,961	1,961	1,961

Note: We construct an index as the first principal component of four standardized variables that proxy for stronger macro–micro linkages, i.e., higher $\bar{\beta}$, or lower exposure to idiosyncratic shocks, i.e., lower σ_p^2: (i) white- versus blue-collar occupations, (ii) household age composition, (iii) rural versus urban residence, and (iv) education composition of household members. This table presents heterogeneity based on the above- and below-median values of this index. All regressions include household and state-by-year fixed effects, and the **full set of interacted controls formed from the three variables in the triple interaction, along with the corresponding instruments.** Standard errors clustered at the district-year level are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table D.2: Effect of BJP Seat Share on Expenditure Categories: Heterogeneity by Religion and Household Socio-economic Characteristics (IV Results)

Instrument = $\frac{\text{Share of close elections BJP won}}{\text{Share of close elections BJP involved}}$	**Total**	**Food**	**Health**	**Education**	**Luxury**	**Durables**
	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity by Proxies for High $\bar{\beta}$ or Low σ_p^2						
BJP share × Hindu × Above Median Proxy	1097.304	405.584	16.430	52.532	194.583	161.245***
	(902.759)	(327.824)	(44.439)	(58.987)	(226.993)	(40.108)
BJP share × Muslim × Above Median Proxy	399.801	153.338	-104.053	-41.046	-324.447	76.398*
	(1267.385)	(465.312)	(67.710)	(124.641)	(376.683)	(46.176)
BJP share × Hindu × Below Median Proxy	850.361	465.160*	41.507	-59.935	83.710	77.609***
	(637.777)	(262.970)	(26.621)	(40.047)	(114.225)	(20.790)
BJP share × Muslim × Below Median Proxy	1010.788	508.222	-25.844	-45.446	-51.491	70.705***
	(803.675)	(393.604)	(36.097)	(69.868)	(158.587)	(23.173)
Differences in Coefficients						
(1) **Above Median Proxy: Hindu – Muslim**	**697.503**	**252.246**	**120.484****	**93.578**	**519.030***	**84.847***
	(981.509)	(342.910)	(47.161)	(100.653)	(303.092)	(51.616)
(2) **Below Median Proxy: Hindu – Muslim**	**-160.428**	**-43.062**	**67.351****	**-14.489**	**135.201**	**6.904**
	(634.578)	(296.263)	(29.443)	(59.228)	(141.215)	(19.940)
No. of Observations	5,696,192	5,638,337	5,698,782	5,698,782	5,705,652	5,757,812
No. of District×Year Clusters	1,961	1,961	1,961	1,961	1,961	1,961
Mean of Dependent Variable	12,343.44	5,716.92	279.85	308.72	934.66	134.67
Kleibergen-Paap F-stat (First Stage)	149.1	149.3	149.13	149.8	149.8	149.8

Note: We construct an index as the first principal component of four standardized variables that proxy for stronger macro–micro linkages, i.e., higher $\bar{\beta}$, or lower exposure to idiosyncratic shocks, i.e., lower σ_p^2: (i) white- versus blue-collar occupations, (ii) household age composition, (iii) rural versus urban residence, and (iv) education composition of household members. This table presents heterogeneity based on the above- and below-median values of this index. All regressions include household and state-by-year fixed effects, and the **full set of interacted controls formed from the three variables in the triple interaction, along with the corresponding instruments**. See Note to Appendix Table B.1 for the definitions of luxury and durable expenditure. Standard errors clustered at the district-year level are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.