Online Appendix for "Getting Rich Too Fast? Voters' Reactions to Politicians' Wealth Accumulation"

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Contents

A1 Frequency of Mentions of Financial Disclosures

Figure A1 graphs the mentions of "asset disclosures" in the written corpus maintained by Google Ngrams (`https://books.google.com/ngrams`), as a percent share of one of the most common two-word syntaxes, "to the", for the period 1980-2008.[1] The figure shows that there was about a 14-fold increase in the frequency of mentions of asset disclosures.

Figure A2 graphs the frequency of mentions of asset disclosures in the English-language Indian press from the enactment of the mandatory disclosure system in 2004 until 2016. We searched through 95 Indian publications available through Access World News, a media aggregation service.[2] We searched for articles mentioning a combination of "asset" and "affidavit". We used automated text analysis to confirm that the search returned meaningful hits, and also inspected the article titles to eliminate as many false positives as possible. The final search output included 5,301 relevant articles.[3]

The upper panel of Figure A2 shows the raw number of articles per month mentioning asset disclosures. The spikes correspond to important election months (e.g. the Lok Sabha election in 2014 and the recent Tamil Nadu election in 2016). The lower panel uses the Hodrick-Prescott filter to remove some of this recurring variation to show the stable time trend. Both panels show that the number of articles has increased manifold; the trend has increased about seven-fold since 2004.

A2 Wealth Accumulation and Reelection

Figure A3 shows the reelection rates of rerunning state legislators with different magnitudes of wealth accumulation, based on the latest election pair in all states where the data are available. The dots in the plot show the average reelection rate (y-axis) within each of the thirty equally-sized bins of wealth accumulation on the x-axis. The line is the linear best-fit line from a bivariate regression of reelection rates on the binned-out wealth accumulation variable.

A3 Sample Media Reports of Wealth Accumulation

Figures A4, A5, and A6 show examples of media and civil society reports of politicians' wealth accumulation based on information contained in the financial disclosures. Figure A4 shows an English-language article from the Times of India; Figure A5 shows an article in

[1] We combined the mentions of all the singular and plural variations of the words "asset disclosure" and "asset declaration."

[2] `http://www.newsbank.com/libraries/schools/solutions/us-international/access-world-news`. We chose Access World News over similar resources such as LexisNexis or Factiva because of greater coverage of news publications in India.

[3] 75 percent of the search hits came from the following publications: the Times of India, the Hindu, Hindustan Times, the Statesman, New Indian Express, United News of India, Indian Express, the Economic Times, the Pioneer, Daily News & Analysis, and the Calcutta Telegraph.

Hindi from Dainik Bhaskar, a Hindi Daily circulated in eleven states (as well as online); Figure A6 shows a screenshot from the website of the Association for Democratic Reforms, an NGO that digitizes candidates' affidavits and produces additional information based on them.

A4 Bihar and Madhepura Characteristics

Figure A7 shows that Bihar is close to the median in terms of average wealth accumulation of state legislators. The graph ranks states in terms of average wealth accumulation among rerunning incumbents for the latest pair of elections in each state.[4] Bihar is ranked as 15th, among 31 states for which the data are available.

Figure A8 shows the distribution of a number of characteristics across the four largest North Indian states (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh), and where Madhepura falls (indicated with a red line). The data for these characteristics are drawn from the Indian census (male population, scheduled caste, rural population, employed, permanently employed, part-time employed, farmers, non-agricultural workers, and share of illiterate), the Electoral Commission of India (turnout and the effective number of parties), and the Association for Democratic Reforms (wealth increase). Madhepura does not stand out compared to North India on all but two of the characteristics—the rural population and the illiteracy rate. Note, also, that for the rural population, most districts in North India are overwhelmingly rural (particularly in Bihar), and Madhepura falls in that range.

A5 Sampling and Lab Procedures

In order to maximize the social, age and ethnic diversity of participants in our experiment, recruiters from the survey team were tasked with finding potential participants blocked by age and ethnicity at a randomly selected sample of locations.

A location was either a group of adjacent villages or a section of the town of Madhepura, which we divided in four locations. Each location organized in this fashion, whether rural or urban, counted between 7,000 and 12,000 inhabitants.

We selected all the possible locations that were less than 20 kilometers away by car or motorcycle from our lab in the eastern side of the city of Madhepura. We identified a total of 22 locations of similar population size within this geographically-defined perimeter. We limited ourselves to this perimeter in order to maximize the chances that respondents would subsequently, upon receiving an invitation, be able to visit the lab. A previous study (Author 2016) had determined that a greater distance from the lab would severely lower the take-up rate.

We then randomly selected 9 of these 22 locations. This selection was stratified by geography. There are three major roads out of the city of Madhepura: one toward the

[4] State assembly elections in India are staggered, and therefore not all pairs of elections are from the same years.

North, one toward the South-West and one toward the South-East. We accordingly randomly selected 3 locations off of each of these roads in order to reach our total of 9 selected locations. One of the location off of the Northern road fell within the city of Madhepura, as did one of the locations off of the South-eastern road (hence 2/9 of our locations are urban, in line with the fact that roughly 23% of our sample lived in a location classified as urban).

Upon arriving to a randomly selected location, field team leaders collected information from local informants (usually gram panchayat secretaries) on caste and religious diversity in that location. This allowed the team to identify the four largest ethnic communities living at this location. Based on this, each of the enumerators in our field "recruitment" team were then directed toward settlements, neighborhoods or hamlets associated with these groups (in which a plurality belonged to these groups, but in which members of other groups occasionally resided). Overall, the allocation of enumerators to various settlements was meant to be broadly representative of the caste break-down of that location. Within each caste-related settlement, an equal number of flyers were distributed to people below and above 35 years of age.

Field enumerators belonged to all castes and were directed to invite one inhabitant of every n household (n depending here on the size of the settlement they were assigned to) after a short introduction. This strategy, as well as the fact that each enumerator was mandated to distribute an equal number of flyers to people below and above 35 years of age, in our opinion ensured that field enumerators could not pick and choose easy targets. In that sense, we do not believe that our sample of invitees could have been the result of major selection by enumerators. Our strategy ensured diversity and (relative) representativeness of our sample on urban/rural status, caste and age.

In the absence of good caste data on Madhepura or on these locations within Madhepura (neither caste or subcaste shares are systematically measured by the Census of India), we cannot provide definitive evidence that our sample of invitees is perfectly representative of Madhepura district or of Bihar in terms of caste. Data on who enumerators tried but failed to reach is similarly unavailable, as enumerators could not register information on citizens they could not meet. In light of the aforementioned enumeration rules, it is however important to note that our target sample of invitees was by design very diverse in terms of caste, precisely because enumerators could not pick and choose based on caste. Our lab sample reflects this, as it overall includes 56 different caste identities, with the mean and median size of a caste group in our lab sample being 18.23% and 3%, respectively. It was also by design diverse on age, since enumerators were constrained to invite citizens from two age groups (above and below 35 years of age). This is similarly reflected in our lab sample: 48.66% of lab respondents were below 35 years of age, while 50.34% were above 35 years old.

Also of importance is the fact that a relatively similar number of invitations were distributed in each of these randomly selected locations of relatively equal population size. Our original aim was to distribute 250 invitations in each location. As can be seen from Table A1 below, this was the case (with small deviations) in 6 of 9 locations (location 1, 3, 4, 5, 7, and 9). In our two most distant locations (location 6 and location 8), we distributed another 30 or so invitations after enumerators feedback suggested that fewer invitees would likely make it to the lab on the following day due to logistical difficulties. In the last location (location 2), enumerators were only able to distribute 202 invitations as they found fewer villagers at home on the day they visited, due to a funeral.

Moreover, as can be seen from Table A1, the take-up rate was high overall (close to a half of invited citizens subsequently visited the lab), and remarkably similar across locations, except for the aforementioned location 2.

1,047 people made it to the lab, of whom 1,023 completed the first part of the interview, and 1,020 completed both parts. Therefore, 24 people made it to the lab, checked in with our lab manager, but eventually left before the first interview, or did not respond when we looked for them in the waiting room (we have no data on these 24 people).

A6 Sample Composition

The 1,020 respondents who completed the conjoint experimental survey were diverse on a host of dimensions, as seen in columns 1-2 of Table A2. As discussed in the text, we conducted a second survey two months after finishing the conjoint survey, on a different sample of Madhepura citizens ($N = 323$). The two samples were nonetheless drawn from the same district population. Columns 3-4 of Table A2 show the composition of the second sample. The last two columns show that the two samples are broadly similar on a range of demographic and socioeconomic variables.[5]

How similar is our sample compared to Bihar and North India more generally? It is difficult to make comparisons, due to poor-quality or incomparable population data. The main difficulty comes from the fact that the census collects limited information, and that the most comprehensive national surveys usually record information about the household head rather than any respondent from the household (as we did in our survey). Columns 1-2 of Table A3 show the means and standard deviations of the comparable variables in our sample. The remaining columns show the same variables based on the (weighted) data for Bihar (columns 3-4) and North India (columns 5-6) from the second wave of the India Human Development Survey. As above, North India comprises of the four largest states: Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh. Our sample is similar to the populations of Bihar and North India in terms of education, household size, the share of Muslims, house size, and movable assets (such as a refrigerator or bicycle).

A7 Details on Conjoint Experiment

In this section, we provide additional information on our conjoint experiment.

After filling out the pre-treatment demographic survey, respondents were invited to wait for a few minutes in a waiting area of our lab until they could participate in a seemingly

[5]Notable differences between the two samples can be seen for age, share of farmers, and related to the latter, the number of cattle (cows, buffaloes, and goats). We reran all our results in both surveys controlling for: (a) the three imbalanced characteristics, as well as all of the characteristics listed in Table A2. Our results are substantively unchanged.

unrelated study on “political and social personalities.” This transition was necessary to ensure that our staff and enumerators had sufficient time to prepare the paper-based vignette experiment sheets. We used paper-based rather than digital questionnaires because of the lack of internet access and poor electricity access in the field. This transition did not pose any noticeable issues.[6]

Because of low rates of literacy among our respondents, rather than having them read the vignettes, interviewers relied on a carefully practiced script to summarize the information contained in the vignettes, while showing the prompt to the respondent. A sample vignette is shown in Figure A9.

Table A4 provides more details about each treatment within our vignettes. The second column shows the text presented to the respondents. The third column shows the text that the interviewers read out to the respondents.

The fictitious politicians used as part of the experimental vignettes were presented as incumbents in other, non-neighboring districts of Bihar, since some voters may have known the identity of candidates in their district.

The values used in the wealth accumulation treatment are nominal increases.[7] We chose to focus on nominal rather than real increases because: (a) public discussions almost exclusively focus on nominal wealth increases; (b) directing attention to real vs. nominal increases would likely confuse most respondents and complicate the experiment.

For the party and ethnicity treatments, we deliberately do not restrict the matches between parties and ethnic/caste groups since all four major parties—RJD, JD(U), BJP and the Congress (INC)—did in 2015 run candidates from each of these castes or religious groups.

In terms of randomization, all the attributes except ethnicity and the legality of wealth accumulation were randomized unconditionally and with repetition. The legality treatment was randomized conditional on the wealth accumulation treatment not being “did not increase.” The ethnicity treatment was partly conditional on the respondent’s stated ethnicity, according to the procedure detailed in the text. For the photograph, we chose six pictures of men approximately forty years of age who can pass as members of different castes. These six photographs were randomly drawn for each profile, without replacement to avoid repetition across the three vignettes. Finally, the district in each vignette was chosen from a list of eight real districts from a different sub-region in Bihar; none of the eight districts are geographically very close to Madhepura.

[6] Only three respondents who completed the first pre-treatment interview failed to complete the experimental survey. We discarded those cases.

[7] We draw the values from the sample of rerunning incumbents because otherwise we cannot calculate the wealth increase. While focusing on rerunning incumbents may produce some selection bias in the values of wealth accumulation we use, it covers the same sample that the voters would likely be most attentive to if they themselves focused on wealth accumulation. Also, these estimates of wealth increase are likely downward-biased due to likely under-reporting by the highest wealth accumulators.

A8 Estimating the Treatment Effect of Co-Ethnicity

As desribed in the text, our ethnicity treatment is somewhat different from the other treatments, in that we ensured that one of the three vignettes featured a candidate with the same subcaste as the one stated by the respondent in the pre-experiment survey. Since we are interested not in the effect of ethnicity per se, but of co-ethnicity, this choice ensured that each respondent rated at least one co-ethnic profile. For the remaining two vignettes, the candidate ethnicity was determined by a simple random draw from a list of 11 ethnicities. One might wonder if we would not have also achieved a sufficient number of co-ethnic profiles by having a simple randomization for all three vignettes. Unfortunately, this was infeasible, because the number of ethnicities in Bihar is very large. Therefore, using a simple random draw would have almost certainly not given us enough co-ethnic profiles. Indeed, in our data, the respondents declared 56 different ethnicities, and as a result only around 7 percent of the two vignettes with a simple random draw featured a co-ethnic.

There are two implications of this design for the analysis of the average marginal component effect (AMCE) of co-ethnicity. The first implication is the subtle difference in the interpretation of the co-ethnicity AMCE compared to the other AMCEs. For the other AMCEs, the average is taken over the joint distribution of all the possible combinations of the remaining attributes. This joint distribution is determined fully by the random draws in the experiment. For the ethnicity AMCE, the distribution of ethnicity over which the averages are taken is a mixture of the observed distribution of respondent ethnicity, as well as the experimentally-produced distribution of our pre-specified set of main subcastes.

The second implication of our design is in terms of the estimation of the co-ethnicity AMCE. There are two ways that a respondent can get a co-ethnic politician profile: through one of the three vignettes where we ensure a co-ethnic profile, and possibly through the luck of the draw in the remaining two vignettes. To properly account for this distinction, we use an indicator variable for the co-ethnic vignette as an instrument for the actual co-ethnicity status of the politician profile.[8] The calculation of the quantities of interest for ethnicity are therefore based on the two-stage least squares estimates, but otherwise follow the same calculation as the quantities of interest for the other treatments. The results are substantively very similar if we use a simpler OLS model instead of the two-stage model. Also, the results for the other treatments are very similar if we exclude the round which featured a co-ethnic vignette, or if we estimate them separately from the ethnicity effects.

[8]This instrument is valid. First, it is strong, because roughly 90 percent of the co-ethnic profiles are generated through the co-ethnic vignette. Second, it satisfies the exclusion restriction, because the treatment is orthogonal to all the other treatments. The instrumental variable approach changes somewhat the interpretation of the ethnicity effects, being confined to those respondents whose co-ethnicity with the politician was induced by the co-ethnicity vignette.

A9 Diagnostic Tests

This section reports several diagnostics tests of the validity of our experimental manipulations. Table A5 suggests that our treatments were successfully randomized. The table shows that a number of pre-treatment respondent characteristics are balanced in the conjoint experiment. The entries in column 1 represent the p-values of an F-test, from a regression of each pre-treatment characteristic indicated in the left-most column on all conjoint treatment conditions. None of the p-values in column 1 is below the conventional level of $p < 0.05$, implying that the the treatment conditions are not jointly statistically significant predictors of any of the listed pre-treatment variables. Column 2 takes a different approach, and reports the p-value of the effect of each pre-treatment characteristic on the profile rated by respondents in the conjoint experiment. Again, all p-values imply that profiles rated did not differ systematically across respondents' pre-treatment characteristics.

As discussed in the main text, the conjoint experiment involved respondents rating three politician profiles (or vignettes). The ordering of the profiles was randomized. Table A6 examines how much the treatment effects vary from one vignette to another, i.e. whether there are any profile order effects. The dependent variable is the vote intention. The main entries in columns 1-3 report the average marginal component effects (AMCEs) for each vignette separately. The main entries in column 4 represent the F-statistic from the test of whether the treatment effects for vignettes 2 and 3 are jointly statistically significantly different from the treatment effects in vignette 1; the entries in brackets are the p-values from this test. Overall, there are no systematic order effects, as the AMCEs for each treatment component in the conjoint experiment are similar across the three vignettes.[9]

In addition to the order of the vignettes, the order of the profile attributes was also randomized. We can evaluate the successfulness of the attribute order randomization by comparing the treatment effects across the profile rows. As there are seven bullet points (and ten attributes) shown in each profile, we can compare seven AMCEs for each treatment component—one for each row. For simplicity, Figure A10 compares the seven AMCEs only for our wealth accumulation treatments.[10] The left panel shows the AMCEs for each row for a politician profile with below-median wealth increase (relative to the no-increase condition). The right panel shows the seven AMCEs for a politician profile with above-median wealth increase (relative to the no-increase condition). The dependent variable is the vote intention. Both panels show that the treatment effects are quite stable across rows.

Because of the large number of treatment components, the concern is that some of the statistically significant AMCEs we report in the main text may have arisen simply by chance as a consequence of multiple comparisons. Figure A11 shows the results when a Benjamini-Hochberg multiple-comparison correction is applied (Benjamini and Hochberg, 1995).[11] This

[9] There is one instance where the treatment effect based on the last profile rated is somewhat different from the first two profiles: the AMCE for a politician coming from a rich family. Our results are substantively very similar when we reestimate the main results based only on the first two vignettes.

[10] The results for the other treatment components are similar and available upon request.

[11] This procedure controls the false discovery rate, by ordering the p-values of all the AMCEs from lowest to highest, and designating as statistically significant only those p-values that satisfy the condition $p_k \leq \frac{k}{m}\alpha$,

correction makes it increasingly harder to pass a significance test as the number of tests grows. We focus on $\alpha = 0.05$. In Figure A11, the plotted dots represent the p-values of all the AMCEs shown in the main text. The full dots indicate the AMCEs that remain significant after the correction (i.e. the p-value satisfies the Benjamini-Hochberg criterion), the hollow dots indicate the AMCEs that are not statistically significant according to this correction. The top panel plots the AMCE p-values for vote intention, the middle panel for the corruption rating, and the bottom panel for the violence rating, respectively. The results show that all of our main results are statistically unchanged when the potential multiple-comparison problem is addressed.

A10 How Aware are Voters of Disclosures and Wealth Accumulation?

As briefly discussed in the text, we asked the respondents whether they knew the approximate 2010 wealth of their own representative (MLA), available in their MLAs' 2010 affidavits. Our respondents came from one of two constituencies in the Madhepura district, represented by Chandra Shekhar (the constituency of Madhepura), or Ramesh Rishidev (the constituency of Singheshwar). To guide the respondents' answers, we offered the same seven categories as those in our conjoint experiment (5 lakhs, 8 lakhs, 20 lakhs, 45 lakhs, 85 lakhs, 2 crores, and 8 crores). The 2010 wealth of both MLAs was approximately 20 lakhs. As in Figure **??** in the text, Figure A12 plots for each MLA the proportion of respondents by category (in bars, dark gray being the correct category), and the difference in the predicted probability of each category response from the correct response, with the associated 95% confidence intervals (in caps).[12]

The Figure indicates that while the probability of a correct recall of their MLA's 2010 wealth is statistically significantly more likely than particularly bad guesses (of the order of magnitude greater than the MLAs' actual wealth), our respondents were also statistically as likely to choose a level considerably lower (8 lakhs for Shekhar, 8 or 5 lakhs for Rishidev) as they were to choose the correct level (20 lakhs). Overall, more than two-thirds of respondents chose a level of 2010 wealth different than that reported on the MLA's 2010 affidavit. Also, respondents made systematic errors: they were statistically significantly more likely (based on the Wilcoxon-Mann-Whitney median rank-sum test) to underestimate Rishidev's wealth and overestimate Shekhar's wealth, even though their reported wealth in 2010 is roughly equal.

In addition to the recalls and guesses about their own representatives, we asked our respondents the same for an *average* MLA in Bihar. Perhaps unsurprisingly, Figure A13 shows that the responses are of even lower precision than for the respondents' own MLAs:

where k is the position in the order of each p-value, m is the number of AMCEs, and α is the target significance level.

[12] The predicted differences are based on a multinomial logit model of the respondents' answers on their demographic and socioeconomic characteristics (age, education, income, own assets, and whether employed in government).

the respondents substantially underestimate both the average Bihar MLA's 2010 wealth (left panel) and the expected 2010-2015 wealth increase (right panel). What is more, the errors were strongly correlated with the errors made for own MLAs.

Moreover, Table A7 shows that those who reported being aware of the disclosures were not statistically more likely to furnish correct responses (on 2010 wealth, the first two rows) and guesses (about the anticipated 2010-2015 wealth increase, third and fourth row), either for their own representatives (first and third row) or for the Bihari MLAs (second and fourth row).

A11 Interactions between Wealth Accumulation and Other Politician Attributes?

Here, we show the results for the interactions between wealth accumulation treatments and other politician characteristics. These effects are calculated in a straightforward fashion, by adding the appropriate interaction terms to our regressions and incorporating them when calculating the AMCEs.

The most theoretically relevant potential moderators in Indian politics are record in office, party and ethnicity. Figure A14, however, shows that there are no significant interaction effects between wealth accumulation and record in office (top panel), co-partisanship (middle panel), or co-ethnicity (lower panel).

Table A8 similarly shows no consistent and statistically significant interaction effects between wealth accumulation and family background, criminal charges, or the initial level of wealth.

Finally, we do not find consistent interaction effects between respondents' wealth and a candidate's wealth accumulation, as seen in Table A9. We measure respondent wealth with a factor score derived from the respondents' assets, their self-reported income, and land size (see Table A3).

A12 Additional Results

For greater clarity, in the main text we grouped the seven 2010 wealth conditions and the seven wealth increase conditions into three groups of each. Figure A15 shows the main results—the treatment effects on the respondents' vote intention—for all seven categories of each treatment. The results are quite similar to those for the grouped treatments.

As mentioned in the text, information about wealth accumulation significantly increased respondents' propensity to view the candidate as both more corrupt (left panel) and more violent (right panel). These results are shown in Figure A16.

In the main text, we reported the results for the vote outcome. Here, we present the results for the two "representation" ratings: how good a representative the respondent thought the politician was (Figure A17), and how useful personally the respondent though the politicians was for them (Figure A18). Both outcomes were on a scale from 1 (very bad) to 5 (very good). Both figures show that the results are very similar to those for the vote intention. These results are reassuring because the vote question does not capture real voting, which may lead to concerns that it does not capture fully the respondents' true preferences. It is also noteworthy that our respondents do not perceive greater wealth accumulators as more useful for them personally, suggesting (at least in the context of our survey) that respondents did not expect greater wealth accumulation to increase the chance of clientelistic or patronage goods.

We omitted the AMCEs for photograph and district attributes from the main text to avoid cluttering the presentation, given that we do not have clear theoretical priors about the direction and magnitude of potential effects. Table A10 shows the AMCEs for these attributes across the three main outcomes. For the most part, the AMCEs are statistically insignificant.[13] There is a consistently strong effect of a politician being from Jahanabad (relative to a politician from Banka, a district arbitrarily chosen as the base category); respondents are more likely to vote for a politician from this district and less likely to perceive him as corrupt or violent. We do not have a clear explanation for this. However, these patterns do not seem consequential for our key findings about the effects of wealth accumulation. The last two rows of Table A10 show the p-values from an F-test of joint significance of the interactions between the photograph or district treatments and the wealth increase treatments. Neither of the two sets of interactions are jointly statistically significant.

Figure A19 shows the effect of wealth accumulation separately when it is presented as unsuspicious (left panel) and potentially illegal (right panel). Since this information was only provided when there was an increase in wealth, the baseline category is the "slight" increase (of 20 percent), rather than no increase. Intuitively, when there are suspicions of illegality, information about wealth increase further lowers the voting probability (the same goes for the corruption and violence rating outcomes). However, even when the press is said to report no suspicion of illegality, information about wealth increase of ten-fold or 30-fold results in a statistically significant lower probability of vote.

Because both our legality treatment conditions mention the press, the size and significance of the wealth increase effects depend somewhat on the extent to which respondents trust the media (which we asked separately). If we differentiate those respondents who "very much" trust the media (32% of respondents) from the rest, then they are statistically significantly more likely than respondents with lower media trust to vote for candidate profiles with the two highest wealth accumulation conditions with *no* suspicion of illegality. However, we find no obvious differences for the wealth accumulation conditions presented as illegal (the only significant difference is for the five-fold increase condition, but we see no systematic patterns for the other treatment conditions). These results are shown in Table A11 below.[14]

In the main text, we showed in Figure **??** that our respondents put greater weight on a politician's record in office than on wealth accumulation. Consequently, "wealth accumu-

[13] This is even more clearly the case when the multiple-testing correction is applied (Figure A11).

[14] If we differentiate those who "very much" or "somewhat" trust the news (75% of respondents) from the rest, than we find only one statistically significant difference: the high-trust respondents are less likely than the low-trust respondents to support profiles with the lowest but suspicious wealth increase condition (20% increase).

lators" with good record were preferred over politicians with a bad record but much lower wealth increase. Figure A20 below shows that this is the case even when wealth accumulation is presented as illegal.

A13 Survey Instruments

This section replicates the background pre-treatment survey, the experimental outcome questions, the post-treatment survey, and the information survey questions about wealth and wealth accumulation.

A13.1 Demographic Pre-Treatment Survey

1. Gender (do not ask)
2. In which year were you born?
3. For how many years have you lived at your current location?
4. Are you currently married?
    1. Yes
    0. No
    98. Refuses to answer
5. Did you go to school?
    1. Yes (Go to next question)
    0. No (Skip next question)
    99. Not sure/does not apply/no answer (Skip next question)
6. Until which class did you complete school?
    1. Class 1
    2. Class 2
    3. Class 3
    4. Class 4
    5. Class 5
    6. Class 6
    7. Class 7
    8. Class 8
    9. Class 9

10. Class 10
11. Intermediate (Class 11 & 12)
12. Graduate (College or University)
13. Post-graduate (Masters or Doctorate/Ph.D.)

7. What is your community? (As reported by the respondent)
8. Current occupation?
    1. Farmer
    2. Agricultural worker
    3. Shop-owner
    4. Government Employee (specify)
    5. Private sector job (specify)
    6. Other (specify)
9. Total Agricultural land owned by household?
    1. 0 3 bigha
    2. 3 6 bigha
    3. 6 9 bigha
    4. 9 12 bigha
    5. 12 15 bigha
    6. 15 18 bigha
    7. 18 21 bigha
    8. 21 25 bigha
    9. 25+ bigha
10. Type of House?
    1. Pucca (both wall and roof made of pucca material)
    2. Pucca-kucha (either wall or roof is made of pucca material and of other kutcha material)
    3. Kutcha (both wall and roof made of kutcha material other than materials mentioned in category 4)
    4. Hut (both wall and roof are made of grass, leaves, mud, un-burnt brick or bamboo)
    99. Not available/don't know
11. Number of rooms?

12. Number of members in household?

13. Do you or your family member have the following: Yes (1) No (0)

    a. Car/jeep/van/tractor
    b. Colour or B/W television set
    c. Scooter/motorcycle/moped
    d. Bicycle
    e. Mobile phone
    f. Electric fan/cooler
    g. Radio/transistor
    h. Pumping set
    i. Fridge
    j. Cow (enter actual number)
    k. Buffalo (enter actual number)
    l. Goat or sheep (enter actual number)

14. Total monthly household income (in rupees)?

A13.2 Treatment Outcome Questions

1. Would you consider voting for such a candidate?

    1. Yes
    2. No
    3. Don't know

2. Politicians' job is to address their constituents' problems. On a scale from 1 to 5, how good a representative do you think this politician would be in that respect?

    1. Very bad
    2. Bad
    3. Neither bad not good
    4. Good
    5. Very good

3. Politicians sometimes help some of their constituents more than they help others. On a scale from 1 to 5, how good a representative do you think this politician would be for you personally?

1. Very bad
2. Bad
3. Neither bad not good
4. Good
5. Very good

4. On a scale from 1 to 5, how likely do you think this person is corrupt?

    1. Very unlikely
    2. Unlikely
    3. Neither unlikely nor likely
    4. Likely
    5. Very likely

5. On a scale from 1 to 5, how likely do you think this politician engages in violent activities?

    1. Very unlikely
    2. Unlikely
    3. Neither unlikely nor likely
    4. Likely
    5. Very likely

A13.3 Post-Treatment Survey

1. Which party do you usually support in elections?

    1. RJD
    2. JD(U)
    3. BJP
    4. Congress
    5. LJP
    6. BSP
    7. Other (specify)
    88. Don't know/don't remember
    98. Refuses to say
    99. NA

2. Did you vote in 2010 (last state assembly elections)?

   1. Yes
   0. No
   88. Don't know/don't remember
   98. Refuses to say
   99. NA (if respondent was not of voting age in 2010)

3. If yes, could you tell me which party you voted for?

   1. RJD
   2. JD(U)
   3. BJP
   4. Congress
   5. LJP
   6. BSP
   7. Other (specify)
   88. Don't know/don't remember
   98. Refuses to say
   99. NA

4. Did you vote in 2014 (Lok Sabha elections)?

   1. Yes
   0. No
   88. Don't know/don't remember
   98. Refuses to say
   99. NA (if respondent was not of voting age in 2010)

5. If yes, could you tell me which party you voted for?

   1. RJD
   2. JD(U)
   3. BJP
   4. Congress
   5. LJP
   6. BSP

7. Other (specify)
88. Don't know/don't remember
98. Refuses to say
99. NA

6. Let me now ask you about politicians here in Madhepura. Let's start with your MLA.
   a. Can you identify the name of your current MLA for me? (Write name)
      1. Cannot identify
      2. Wrongly identifies
      3. Partially identifies
      4. Identifies correctly
      88. Don't know/don't remember
      98. Refuses to answer
   b. Can you identify his/her party? (Write party name)
      1. Cannot identify
      2. Wrongly identifies
      3. Partially identifies
      4. Identifies correctly
      88. Don't know/don't remember
      98. Refuses to answer

7. Let us now speak about your MP.
   a. Can you identify the name of your current MP for me? (Write name)
      1. Cannot identify
      2. Wrongly identifies
      3. Partially identifies
      4. Identifies correctly
      88. Don't know/don't remember
      98. Refuses to answer
   b. Can you identify his/her party? (Write party name)
      1. Cannot identify
      2. Wrongly identifies
      3. Partially identifies
      4. Identifies correctly
      88. Don't know/don't remember
      98. Refuses to answer

8. In general, how often do you follow news about politics in the papers or on TV?
    1. Every day
    2. Every Few days (several times a week)
    3. Once a week
    4. Once a month
    5. Almost never
    6. Never
    88. Don't know
    98. Refuses to say
9. In general, how often do you discuss news about politics with others around you?
    1. Every day
    2. Every Few days (several times a week)
    3. Once a week
    4. Once a month
    5. Almost never
    6. Never
    88. Don't know
    98. Refuses to say
10. On a scale from 1 to 5 (5 being the most), how much do you trust news about politicians in the media?
    1. Not at all
    2. Somewhat not
    3. Neither trust nor distrust
    4. Somewhat
    5. Very Much
    88. Dont know
    98. Refuses to say
11. On a scale from 1 to 5 (5 being the most), how much do you believe that accusations brought against politicians in the media?
    1. Not at all
    2. Somewhat not

3. Neither trust nor distrust
4. Somewhat
5. Very Much
88. Dont know
98. Refuses to say

12. Who is the current chief minister of Bihar? (Write name)
    1. Cannot identify
    2. Wrongly identifies
    3. Partially identifies
    4. Identifies correctly
    88. Don't know/don't remember
    98. Refuses to answer

13. Who is the current prime minister of India? (Write name)
    1. Cannot identify
    2. Wrongly identifies
    3. Partially identifies
    4. Identifies correctly
    88. Don't know/don't remember
    98. Refuses to answer

14. Which party currently holds the majority in the state assembly in Bihar? (Write party name)
    1. Cannot identify
    2. Wrongly identifies
    3. Partially identifies
    4. Identifies correctly
    88. Don't know/don't remember
    98. Refuses to answer

15. Which party currently holds the majority in the Lok Sabha? (Write party name)
    1. Cannot identify
    2. Wrongly identifies

3. Partially identifies
4. Identifies correctly
88. Don't know/don't remember
98. Refuses to answer

A13.4 Second Survey Questions

Let me now ask you a few questions about your views on the wealth of politicians from Bihar. Before they can register their candidacy for an election, politicians have to make a declaration of everything they own, i.e. their assets: land, houses, cars, gold, jewels, etc. So, we currently know for example about the assets that politicians declared before the 2010 elections.

1. Have you heard about these declarations before?
    1. Yes
    0. No
    98. Refuses to answer
2. Did you know that these declarations are publicly available to everyone?
    1. Yes
    0. No
    98. Refuses to answer
3. Thinking about MLAs in general (on average), what is your best guess of their total assets (including all of these things) in 2010 among the following options? (*Guide the respondent toward choosing one of the substantive options. Only if they really cannot choose from that list, use the last two options.*)
    1. 5 lakhs
    2. 8 lakhs
    3. 20 lakhs
    4. 45 lakhs
    5. 85 lakhs
    6. 2 crores
    7. 4 crores
    88. Don't know/don't remember
    98. Refuses to answer

4. Do you think the average MLA in Bihar has gotten richer since then?

   1. Yes
   0. No (Skip the next question)
   98. Refuses to answer

5. If yes, What is your best guess of approximately how much the average Bihar MLA's assets have increased since then among the following options?

   1. slightly increased
   2. increased two times
   3. increased three times
   4. increased 5 times
   5. increased 10 times
   6. increased thirty times
   88. Dont know/dont remember
   98. Refuses to answer

6. Now think about your own MLA right here in Madhepura. What is your best guess of his total assets (including all of these things) in 2010 among the following options?

   1. 5 lakhs
   2. 8 lakhs
   3. 20 lakhs
   4. 45 lakhs
   5. 85 lakhs
   6. 2 crores
   7. 4 crores
   88. Don't know/don't remember
   98. Refuses to answer

7. Do think your MLA has gotten richer since then?

   1. Yes
   0. No (Skip the next question)
   98. Refuses to answer

8. What is your best guess of approximately how much your MLA's total assets have increased since then among the following options?

1. slightly increased
2. increased two times
3. increased three times
4. increased 5 times
5. increased 10 times
6. increased thirty times

88. Dont know/dont remember
98. Refuses to answer

9. Of the three parties, RJD, JD(U) and BJP, for which party do you think the average MLA accumulates the most wealth?
   - RJD
   - JD(U)
   - BJP
10. Tell us why you think that is the case?

References

Benjamini, Yoav and Yosef Hochberg. 1995. "Controlling the False Discovery Rate: a Practical and Powerful Approach to Multiple Testing." *Journal of the Royal Statistical Society. Series B (Methodological)* 57(1):289–300.

A14 Sample Affidavit

Below, we show several pages from a sample affidavit (the 2015 affidavit of Lalit Kumar Yadav, a member of the Bihar state legislature from the RJD party).

GOVT. OF BIHAR भारत STAMP DUTY बिहार JUDICIAL
COURT FEE
Rs.≈0000100≈ 14.10.2015
375279 BIHAR
INDIA ··Zero·Zero·Zero·Zero·One··Zero·Zero···
2673 0910934

"प्ररूप 26"
(नियम 4क देखिए)

NOTARY
DARBHAGNA, BIHAR INDIA
Authorised u/s 297 (1) (c) of Cr/P/C
8 (1) (a) of The Notaries Act and
u/s 139 (a a) of C.P.C 1908

No. 04 Date 14.10.2015

82 दरभंगा ग्रामीण विधान सभा

निर्वाचन क्षेत्र से (निर्वाचन क्षेत्र का नाम) बिहार विधान सभा (सदन का नाम) के लिए निर्वाचन के लिए रिटर्निंग आफिसर के समक्ष अभ्यर्थी द्वारा प्रस्तुत किया जाने वाला शपथपत्र

भाग–क

मैं ललित कुमार यादव **पुत्र/~~पुत्री~~/~~पत्नी~~ गणेश यादव आयु 49 वर्ष, जो ग्राम–तारडीह फकीराना, पोस्ट–कैथवार, थाना–सकतपुर प्रखण्ड तारडीह, अनुमंडल–दरभंगा सदर, जिला–दरभंगा, बिहार, पिन– 847204 (डाक का पूरा पता लिखें) का/~~की~~ निवासी हूँ और उपरोक्त निर्वाचन से अभ्यर्थी हूँ सत्यनिष्ठा से प्रतिज्ञा करता हूं/~~करती~~ हूं, शपथ पर निम्नलिखित कथन करता हूं/~~करती~~ हूं:-

(1) मैं राष्ट्रीय जनता दल (**राजनैतिक दल का नाम) द्वारा खड़ा किया गया अभ्यर्थी/~~**एक स्वतंत्र अभ्यर्थी के रुप में लड़ रहा हूँ।~~

(**जो लागू न हो उसे काट दे)

(2) मेरा नाम 81 अलीनगर (सामान्य) बिहार (निर्वाचन क्षेत्र और राज्य का नाम) में भाग सं 26 के क्रम सं 495 पर प्रविष्ट है।

(3) मेरा संपर्क टेलीफोन नं. 06272–251410, 9431821873 है/हैं और मेरा ई–मेल आईडी (यदि कोई हो तो) mlalalitkryadav@gmail.com है। मेरा सोशल मीडिया एकाउंट्स (अगर कोई हो) शून्य है।

(4) स्थाई लेखा संख्याक (पैन) के ब्यौरे और आयकर विवरणी फाइल करने की प्रास्थिति :

क्रम सं.	नाम		पैन	वित्तीय वर्ष जिसके लिए अंतिम आयकर विवरणी फाइल की गई है।	आयकर विवरणी में उपदर्शित कुल आय (रुपए में)
1.	स्वयं	ललित कुमार यादव	ABBPY 7738D	2012-2013 (A Year 2013-14)	24,61,730.00
2.	पति या पत्नी	शिव कुमारी	AGLPK 4835E	2012-2013 (A Year 2013-14)	25,23,700.00
3.	आश्रित–1	अस्मिता	BISPA 5634 H	शून्य	शून्य
4.	आश्रित–2	स्मृति साहानी	FBLPS 3597 F	शून्य	शून्य
5.	आश्रित–3	खुशबू	शून्य	शून्य	शून्य
6	आश्रित– 4	विजय प्रकाश	शून्य	शून्य	शून्य
7	आश्रित– 5	विनय प्रकाश	शून्य	शून्य	शून्य

(5) मैं ऐसे किसी लंबित मामले में दो वर्ष या अधिक के कारावास से दंडनीय किसी अपराध (अपराधों) का/की अभियुक्त नहीं हूं जिसमें सक्षम अधिकारिता वाले न्यायालय द्वारा आरोप विरचित किया गया है/किए गए हैं। लागु नहीं होता

यदि अभिसाक्षी ऐसे किसी अपराध (अपराधों) का /की अभियुक्त है तो वह निम्नलिखित जानकारी प्रस्तुत करेगा/करेगी :– लागु नहीं होता

(i) निम्नलिखित मामला (मामले) मेरे विरुद्ध लंबित है जिसमें दो वर्ष या अधिक के कारावास से दंडनीय किसी अपराध के लिए न्यायालय द्वारा आरोप विरचित किया गया है/ किए गए हैं। नहीं

(क)	मामला/प्रथम सूचना रिपोर्ट संख्या/संख्याओं सहित संबंधित पुलिस थाना/जिला/राज्य के पूर्ण ब्यौरे	लागु नहीं होता
(ख)	संबंधित अधिनियम (अधिनियमों) की धारा (धाराएं) और अपराध (अपराधों) का संक्षिप्त विवरण जिसके (जिनके) लिए आरोपित किया गया है	लागु नहीं होता
(ग)	न्यायालय का नाम, मामला संख्या और संज्ञान लेने के आदेश की तारीख	लागु नहीं होता

Md. Shahid Wajeeh Darbhanga Reg. No. GOVT. OF BIHAR INDIA NOTARY

14.10.15

(घ)	न्यायालय, जिसके (जिनके) द्वारा आरोप (आरोपों) की विरचना की गई	लागु नहीं होता
(ड.)	तारीख (तारीखें) जिनको आरोप विरचित किए गए थे	लागु नहीं होता
(च)	क्या सभी या कोई कार्यवाही किसी सक्षम अधिकारिता वाले न्यायालय द्वारा रोकी गई है/हैं	लागु नहीं होता

(ii) निम्नलिखित मामला (मामले) मेरे विरूद्ध लंबित है/हैं जिनमें न्यायालय द्वारा संज्ञान लिया गया है {पूर्वोक्त मदद (i) में वर्णित मामलों से भिन्न}:- कुछ भी नहीं

(क)	न्यायालय का नाम, मामला संख्या और संज्ञान लेने के आदेश की तारीख	लागु नहीं होता
(ख)	उन मामलों के ब्योरे जहां न्यायालय ने संज्ञान लिया है, अधिनियम (अधिनियमों) की धारा (धाराएं) और अपराध (अपराधों) का संक्षिप्त विवरण जिसके (जिनके) लिए संज्ञान लिया गया है	लागु नहीं होता
(ग)	पूर्वोक्त आदेश (आदशों) के विरूद्ध पुनरीक्षण के लिए फाइल की गई अपील (अपीलों)/आवेदन (आवेदनों) (यदि कोई हों) के ब्यौरे	लागु नहीं होता

(6) मुझे किसी अपराध (अपराधों) (लोक प्रतिनिधित्व अधिनियम, 1951 (1951 का 43)की धारा 8 की उपधारा (1) या उपधारा (2) में निर्दिष्ट या उपधारा (3) के अंतर्गत आने वाले किसी अपराध (अपराधों) से भिन्न, के लिए सिद्धदोष ठहराया गया है/नहीं ठहराया गया है, और एक वर्ष या अधिक के लिए कारावास का दंडादेश दिया गया है/नहीं दिया गया है: लागु नहीं होता

यदि अभिसाक्षी उपर्युक्त रूप में सिद्धदोष ठहराया गया और दंडादिष्ट किया गया है तो वह निम्नलिखित जानकारी प्रस्तुत करेगाः लागु नहीं होता

निम्नलिखित मामलों में मुझे सिद्धदोष ठहराया गया है और न्यायालय द्वारा कारावास का दंडादेश दिया गया है:

(क)	उन मामलों के ब्यौरे, अधिनियम (अधिनियमों) की धारा (धाराएं) और अपराध (अपराधों) का संक्षिप्त विवरण जिसके (जिनके) लिए सिद्धदोष ठहराया गया है	लागु नहीं होता
(ख)	न्यायालय (न्यायालयों) का नाम, मामला संख्या और आदेश (आदेशों) की तारीख (तारीखें)	लागु नहीं होता
(ग)	अधिरोपित दंड	लागु नहीं होता
(घ)	क्या सिद्धदोष ठहराने के आदेश के विरूद्ध कोई अपील फाइल की गई थी/है। यदि हां, तो अपील के ब्यौरे और वर्तमान प्रास्थिति	लागु नहीं होता

(7) मैं मेरे, मेरे पति या पत्नी और सभी आश्रितों की आस्तियों (जंगम और स्थावर आदि) के ब्यौरे नीचे देता हूँ

अ. जंगम आस्तियों के ब्यौरे :

टिप्पणी 1 – संयुक्त स्वामित्व की सीमा को उपदर्शित करते हुए संयुक्त नाम में आस्तियों का भी विवरण दिया जाना है।

टिप्पणी 2 – जमा/विनिधान की दशा में क्रम सं., रकम, जमा की तारीख, स्कीम, बैंक/संस्था का नाम और शाखा सहित ब्यौरे दिए जाने है।

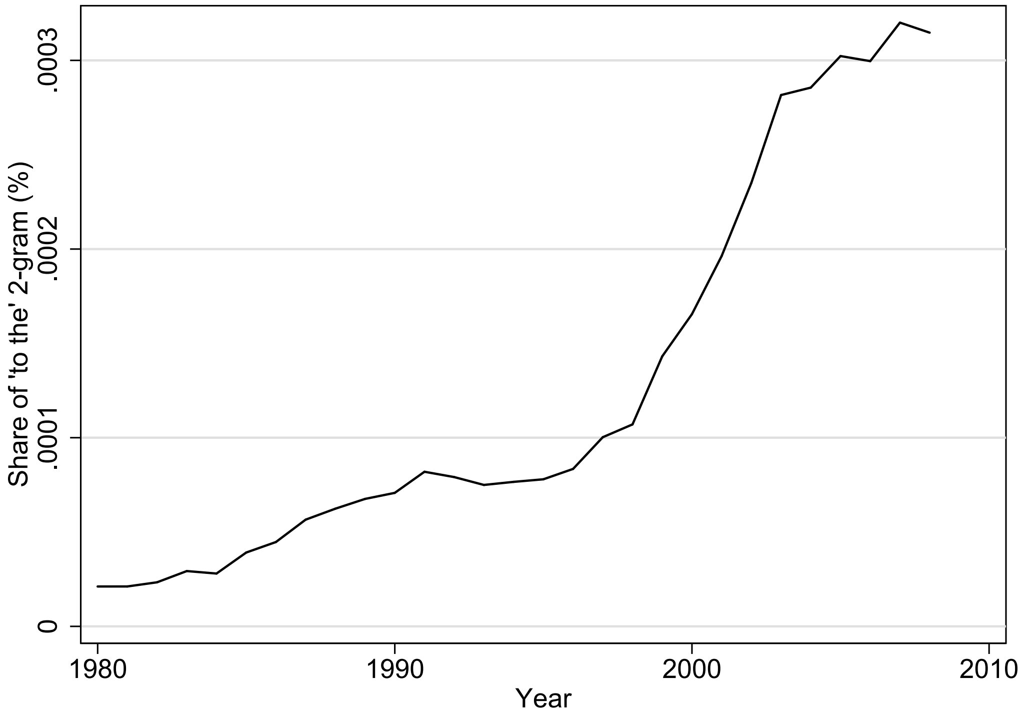
टिप्पणी 3 – सूचीबद्ध कंपनियों के संबंध में बंधपत्रों/शेयर डिबेंचरों का मूल्य स्टॉक एक्सचेंजों मे चालू बाजार मूल्य के अनुसार और गैर सूचीबद्ध कंपनियों की दशा में लेखाबहियों के अनुसार दिया जाना चाहिए।

टिप्पणी 4 – यहां आश्रित का वही अर्थ है जो उसका लोक प्रतिनिधित्व अधिनियम, 1951 की धारा 75क के अधीन स्पष्टीकरण (5) में है।

टिप्पणी 5 – रकम सहित ब्यौरे प्रत्येक विनिधान के संबंध में पृथकतया दिए जाने हैं।

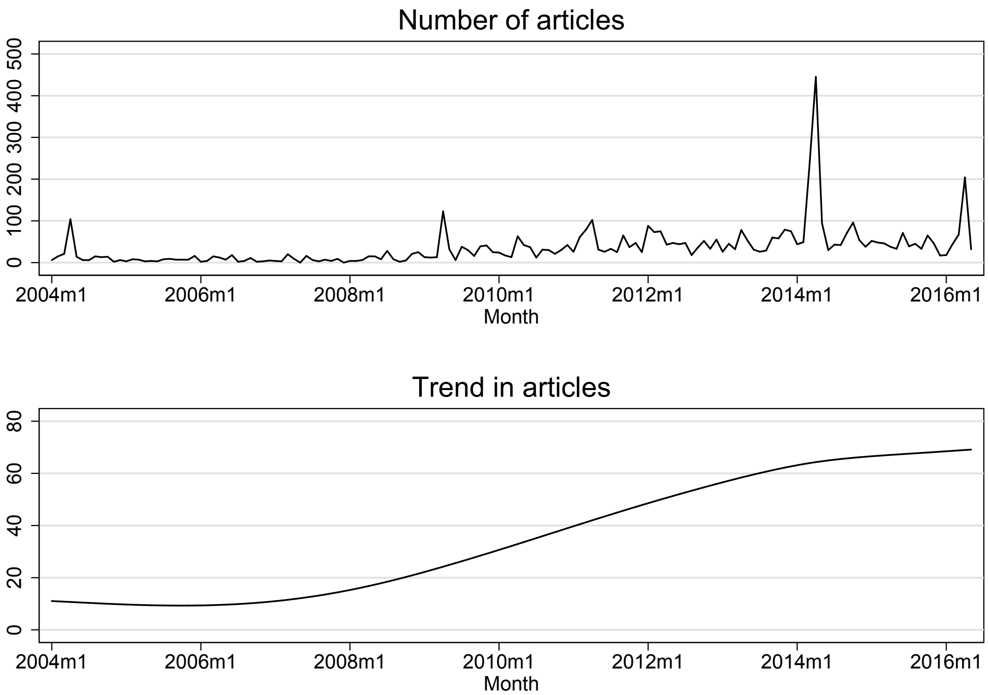
क्रम सं	विवरण	स्वयं ललित कुमार यादव	पति या पत्नी शिव कुमारी	आश्रित – 1 अस्मिता	आश्रित – 2 स्मृति साहानी	आश्रित – 3 खुसबू	आश्रित – 4 विजय प्रकाश	आश्रित – 5 विनय प्रकाश
(i)	हाथ में नकदी	4,80,000.00	3,16,000.00	शून्य	शून्य	शून्य	शून्य	शून्य
(ii)	बैंक खातों में जमा के ब्यौरे (नियत जमा, आवधिक जमा और अन्य सभी प्रकार के जमा	1. भारतीय स्टेट बैंक बिहार विधान मंडल पटना शाखा, बचत खाता सं0–10839461657 रुपया–5,29,185.79 दिनांक–22.09.2015 2. इलाहाबाद बैंक दरभंगा शाखा (शिव कुमार के साथ) बचत खाता सं0–20338994363 रुपया– शून्य दिनांक–01.10.2015 3 सिन्डीकेट बैंक दरभंगा शाखा बचत खाता सं0–74402200035687 रुपया– 11270.00 दिनांक–03.10.2015 4. भारतीय स्टेट बैंक मनीगाछी ,शाखा बचत खाता सं0–31445414110,रुपया–11143.00 दिनांक–03.10.2015	1. भारतीय स्टेट बैंक बिहार विधान मंडल पटना शाखा, बचत खाता सं0–10839475003 रुपया–2,00,770.59 दिनांक–22.09.2015 2. भारतीय स्टेट बैंक डी.एम.सी.सी. शाखा, दरभंगा बचत खाता सं0–10436734261 रुपया– 2935.90 दिनांक–25.06.2015 3 एच.डी.एफ.सी. एक्जीबीशन रोड शाखा, बचत खाता सं0–01861870000991.00 रुपया– 18167.00 दिनांक–21.09.2015 4. सिन्डीकेट बैंक दरभंगा शाखा बचत खाता सं0–74402200034950 रुपया– 12155.00 दिनांक–07.10.2015	1. भारतीय स्टेट बैंक बिहार विधान मंडल पटना शाखा, बचत खाता सं0–30278950666 रुपया–2084.54 दिनांक–22.09.2015	1. भारतीय स्टेट बैंक बिहार विधान मंडल पटना शाखा, बचत खाता सं0–33111488033 रुपया–9061.73 दिनांक– 22.09.2015	1. भारतीय स्टेट बैंक बिहार विधान मंडल पटना शाखा, बचत खाता सं0–33111487197 रुपया–11885.41 दिनांक–22.09.2015	शून्य	शून्य

Figure A1: Increased mentions of asset disclosures globally



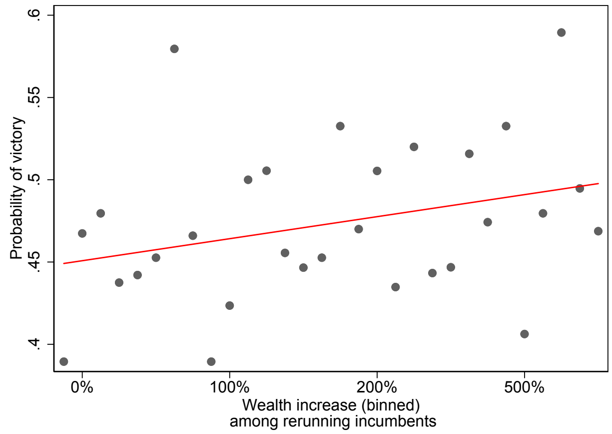
Source: `books.google.com/ngrams`. The figure shows the mentions of "asset disclosures" as a share of mentions of "to the," one of the most common two-word syntaxes in the English language.

Figure A2: Increased frequency of mentions of asset disclosures in India



Source: English-language Indian sources available through Access News World. The upper panel of Figure A2 shows the raw count of the joint 4mentions of "asset" and "affidavits." The lower panel smooths the raw counts using a Hodrick-Prescott filter, in order to more clearly depict the trend. The data draw on 5,301 relevant articles identified as having mentioned the key words.

Figure A3: Wealth accumulation and reelection rates among Indian state legislators



The dots in the plot show the average reelection rate (y-axis) among rerunning state legislators within each of the thirty equally-sized bins of wealth accumulation on the x-axis. The data are from the latest election pair in all the states with available information. The line is the linear best-fit line through the data. The source of data for electoral victory is: "Indian State Assembly Election and Candidates Data (1962-Present)," Trivedi Centre for Political Data, Ashoka University. The source of data for wealth accumulation is the Association for Democratic Reforms, `myneta.info`.

Figure A4: Sample report of politicians' wealth accumulation

Printed from

THE TIMES OF INDIA

Mayawati's wealth doubled to Rs 111.64 crore during her term as chief minister

TNN | Mar 13, 2012, 06.23 PM IST

Mayawati's wealth doubled to Rs 111.64 crore during her term as chief minister

LUCKNOW: Bahujan Samaj Party (BSP) president Mayawati's assets doubled to Rs. 111.64 crores (approx. $22 million) during her term as chief minister of Uttar Pradesh.

In her affidavit filed along with the nomination for the Rajya Sabha (upper house of Parliament) elections on Tuesday, Mayawati has declared total assets of Rs 111.64 crore, which is more than double of Rs. 52 crore she declared in May 2007 when she contested for the state legislative council elections after becoming chief minister. In 2010, when she contested for the state legislative council elections again, she had declared total assets of Rs 88 crore.

On Tuesday, her affidavit showed immovable assets worth Rs 96.38 crore and movable over Rs 15.26 crore.

She owns two commercial properties in Connaught Place (B-34 ground floor and B-34 1st floor with area respectively of 3628.02 and 4535.02 square feet) costing Rs 9.36 and Rs 9.45 crores in Delhi. She has two residential buildings one in New Delhi (23,24 SP Marg New Delhi) one in Lucknow (9 Mall Avenue) currently valued at Rs 61.86 crores and Rs 15.68 crores. Both

https://timesofindia.indiatimes.com/india/Mayawatis-wealth-doubled-to-Rs-111-64-crore-during-her-term-as-chief-minister/articleshowprint/12249319.cms 1/3

Source: The Times of India, https://timesofindia.indiatimes.com/.

Figure A5: Sample report of politicians' wealth accumulation

14 Millionaires Candidates In Bharuch And Narmada Districts | Surat News in Hindi

www.bhaskar.com/gujarat/surat/news/GUJ-SUR-OMC-14-millionaires-candidates-in-bharuch-and-narmada-districts-5752482-PHO.html

भरूच. भरूच और नर्मदा जिले में 14 उम्मीदवारों के पास करोड़ों की संपत्ति है। हलफनामा में उम्मीदवार तथा आश्रितों के साथ घोषित चल व अचल संपत्ति में वागरा से भाजपा उम्मीदवार अरुणसिंह राणा 13.87 करोड़ की संपत्ति के साथ सबसे अमीर हैं। अंकलेश्वर के कांग्रेस उम्मीदवार अनिल भगत 12.84 करोड़ की संपत्ति के साथ दूसरे स्थान हैं। जंबूसर के एनसीपी के महेश सोलंकी 07.45 करोड़ के साथ तीसरे स्थान पर हैं।

वहीं देडियापाडा में निर्दलीय उम्मीदवार अमरसिंह वसावा 24 लाख की संपत्ति के साथ सूची में आखिरी स्थान पर हैं। भाजपा के 6, कांग्रेस के 4, बीटीपी के 2, निर्दलीय 1 तथा एनसीपी का एक उम्मीदवार करोड़पति उम्मीदवार की सूची में शामिल हैं। बता दें कि भरूच और नर्मदा जिले में कुल 127 उम्मीदवारों ने फॉर्म भरे हैं, जिसमें 14 करोड़पति हैं।

माननीयों की संपत्ति 5 साल में कई गुना बढ़ी

विधायक	2012	2017
दुष्यंत पटेल	01.87 करोड़	03.56 करोड़
अरुणसिंह राणा	07.19 करोड़	13.87 करोड़

1/3

Source: Dainik Bhaskar, `https://www.bhaskar.com`.

Figure A6: Sample report of politicians' wealth accumulation

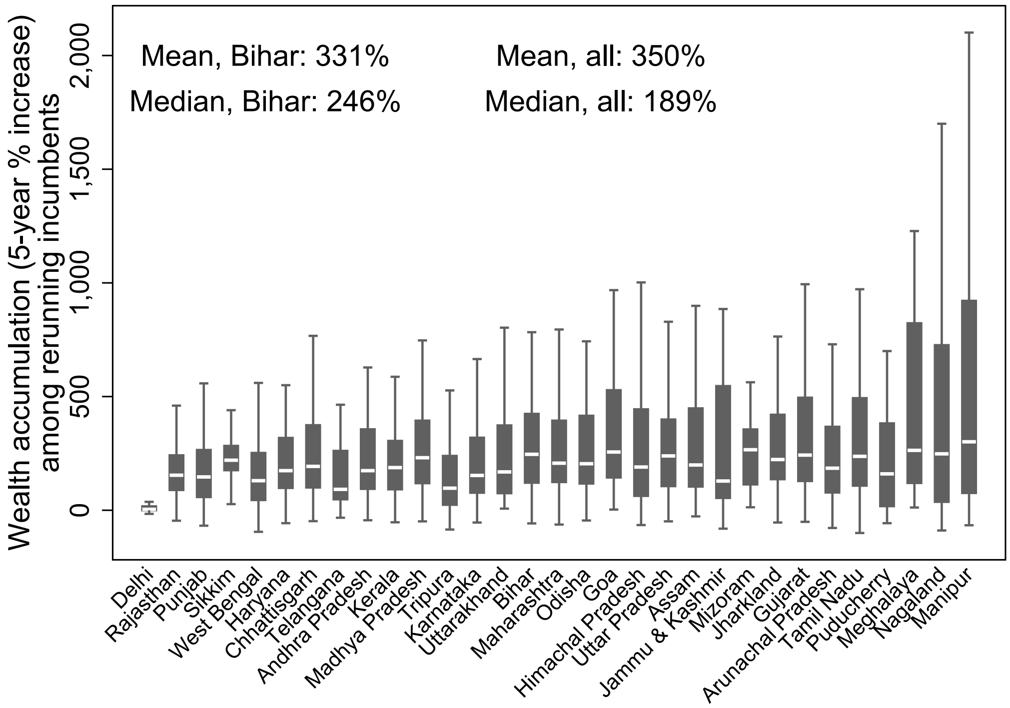
Re-contest Winners

**Click on candidate's name to see complete profile comparison

Sno	Name (Party)	Total Assets in Bihar 2010	Total Assets in Bihar 2005	Asset Increase	% Increase in Asset	Remarks
1	Purnima Yadav (JD(U))	2,78,60,001 2 Crore+	56,70,850 56 Lacs+	2,21,89,151 2 Crore+	391%	PAN is missing this time Party in last election was IND
2	NARENDRA KUMAR SINGH URF BOGO SINGH (JD(U))	2,83,06,092 2 Crore+	66,27,025 66 Lacs+	2,16,79,067 2 Crore+	327%	Party in last election was IND
3	Renu Devi (BJP)	2,11,99,691 2 Crore+	41,31,163 41 Lacs+	1,70,68,528 1 Crore+	413%	PAN is Different
4	Shrawan Kumar (JD(U))	1,83,23,658 1 Crore+	22,25,334 22 Lacs+	1,60,98,324 1 Crore+	723%	PAN is Different
5	SURENDRA PRASAD YADAV (RJD)	2,29,08,662 2 Crore+	89,66,000 89 Lacs+	1,39,42,662 1 Crore+	156%	
6	Pradip Kumar Das (BJP)	1,66,92,623 1 Crore+	32,66,627 32 Lacs+	1,34,25,996 1 Crore+	411%	Age Difference=3
7	SANJAY SARAWGI (BJP)	1,94,97,277 1 Crore+	72,51,222 72 Lacs+	1,22,46,055 1 Crore+	169%	
8	Pashupati Kumar Paras (LJP)	1,93,61,973 1 Crore+	84,69,683 84 Lacs+	1,08,92,290 1 Crore+	129%	
9	MAHESHWAR PD YADAV (RJD)	1,17,51,330 1 Crore+	20,38,137 20 Lacs+	97,13,193 97 Lacs+	477%	Age Difference=3 PAN is Different
10	Anil Kumar (BJP)	1,27,60,423 1 Crore+	31,47,000 31 Lacs+	96,13,423 96 Lacs+	305%	Age Difference=1
11	TARKISHORE PRASAD (BJP)	1,72,55,328 1 Crore+	76,90,182 76 Lacs+	95,65,146 95 Lacs+	124%	Age Difference=1
12	Nitish Mishra (JD(U))	1,32,46,806 1 Crore+	37,49,988 37 Lacs+	94,96,818 94 Lacs+	253%	
13	Sunil Kumar (JD(U))	2,02,47,978 2 Crore+	1,20,15,392 1 Crore+	82,32,586 82 Lacs+	69%	Age Difference=7 PAN is Different
14	SATYADEO NARAIN ARYA (BJP)	1,06,74,807 1 Crore+	24,78,540 24 Lacs+	81,96,267 81 Lacs+	331%	PAN is Different
15	Pannalal Singh Patel (JD(U))	93,96,142 93 Lacs+	13,37,729 13 Lacs+	80,58,413 80 Lacs+	602%	Age Difference=3 PAN was missing last time

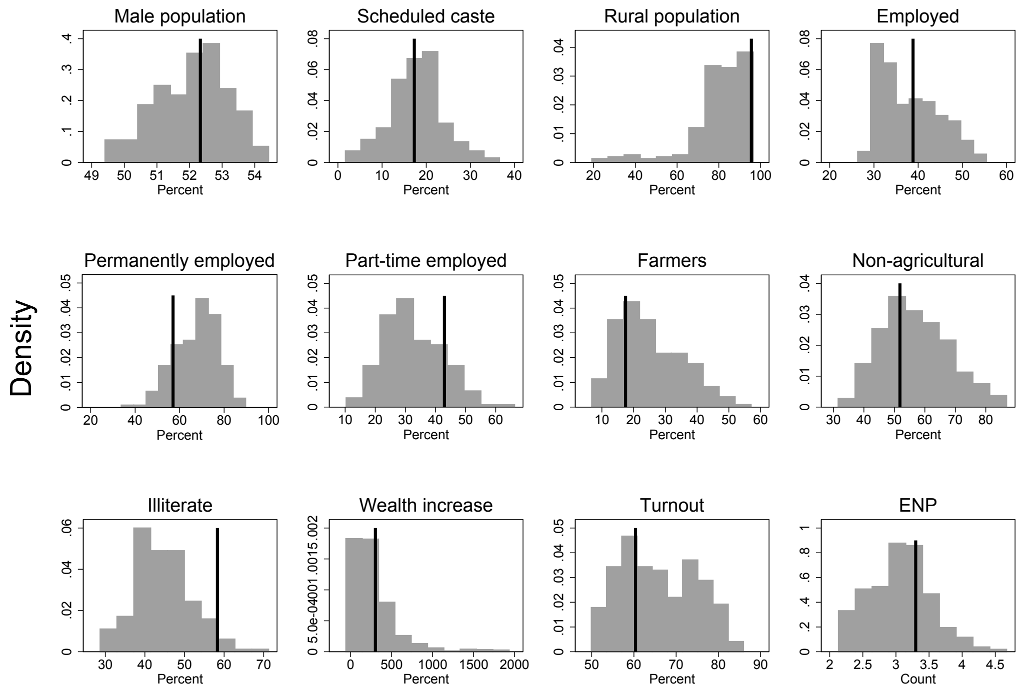
Source: The Association for Democratic Reforms, `myneta.info`.

Figure A7: Wealth accumulation among state legislators in Indian States



The graph ranks states in terms of the average wealth accumulation among rerunning incumbents for the latest pair of elections in each state. Source: The Association for Democratic Reforms, `myneta.info`.

Figure A8: Comparison of Madhepura to North India



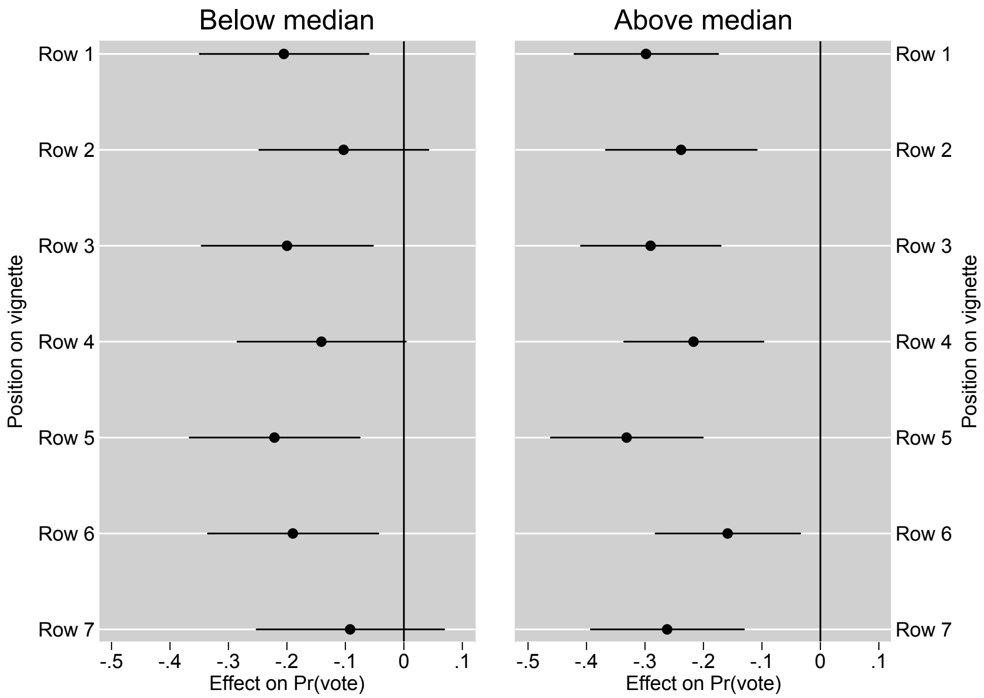
The distribution of each characteristic is for the four largest states in North India (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh). The black line indicates where the Madhepura district falls. The data for the following characteristics are drawn from the Indian Census: male population, scheduled caste, rural population, employed (labeled “workers” in the Census), permanently employed (“main workers”), part-time employed (“marginal workers”), farmers (“cultivators”), non-agricultural workers (employed minus farmers and agricultural laborers), and illiterate. All are expressed as percent shares; permanently employed, part-time employed, farmers, and non-agricultural workers are expressed as a share of employed; the remaining variables are expressed as a share of the total population. The data for turnout and the effective number of parties (ENP) are drawn from the Electoral Commission of India, and refer to the latest state legislative elections in each state. The wealth increase data among rerunning incumbents, for the latest pair of elections in each state, are drawn from the Association for Democratic Reforms.

Figure A9: Sample experimental vignette

	समुदाय: भूमिहार
	विकास: बहुत कम किया
	मध्य वर्ग परिवार
	जिला: मधुबनी
	कई आपराधिक आरोप हैं
	बीजेपी
	5 लाख, थोड़ी बढ़ी 6 लाख तक, गैरकानूनी कामों का संदेह हैं

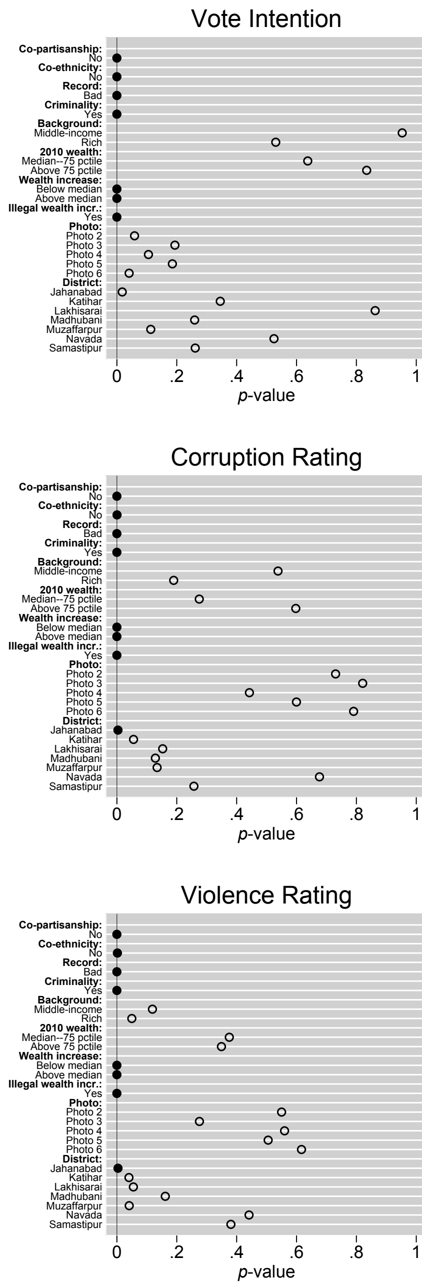
The vignette is in Hindi, as shown to the respondents. The conditions in the vignette are as follows: ethnicity – Bhumihar; record in office – did very little; family background: middle-class; district – Madhubhani; criminal charges – several; party – BJP; wealth information – 5 Lakhs, increased a little bit to 6 lakhs, suspicion of illegality.

Figure A10: Row order estimates for wealth increase effects



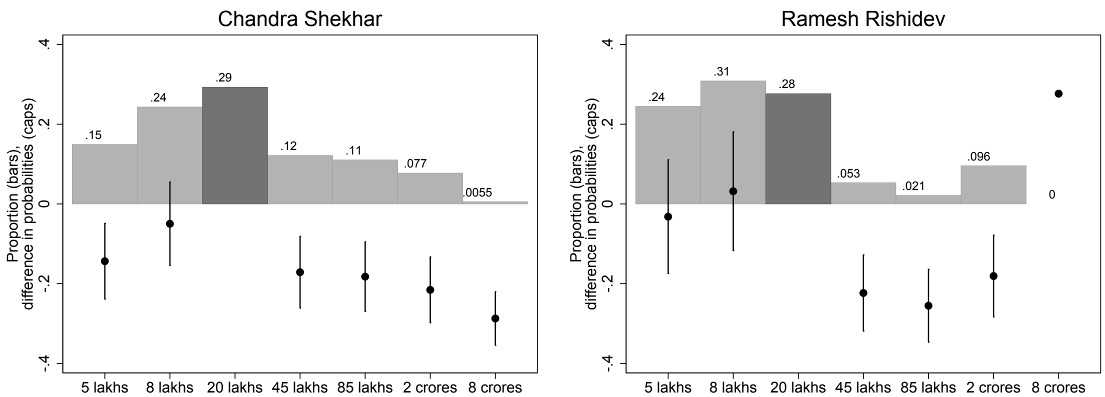
The dependent variable is the vote intention. The left panel shows the AMCEs for median-wealth increase (relative to the no-increase condition), separately for each row of the vignette profile where it was presented (example shown in Figure A9). The right panel shows the same for the above-median wealth increase AMCE (relative to the no-increase condition).

Figure A11: Multiple comparison corrected results



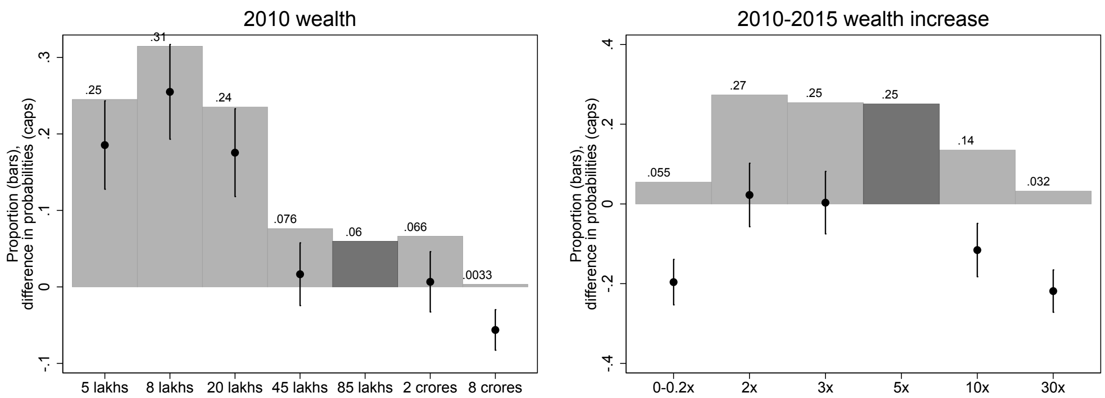
The figure shows the Benjamini-Hochberg multiple-comparison corrected results. This procedure orders the p-values of all the AMCEs from lowest to highest, and designates as statistically significant only those p-values that satisfy the condition $p_k \leq \frac{k}{m}\alpha$, where k is the position in the order of each p-value, m is the number of AMCEs, and α is the target significance level. We focus on $\alpha = 0.05$. The plotted dots represent the p-values of all the AMCEs shown in the main text. The full dots indicate the AMCEs that remain significant after the correction (i.e. the p-value satisfies the Benjamini-Hochberg criterion), the hollow dots indicate the AMCEs that are not statistically significant. The dependent variable is indicated above each of the three panels.

Figure A12: Respondents' recall of their MLA's 2010 wealth



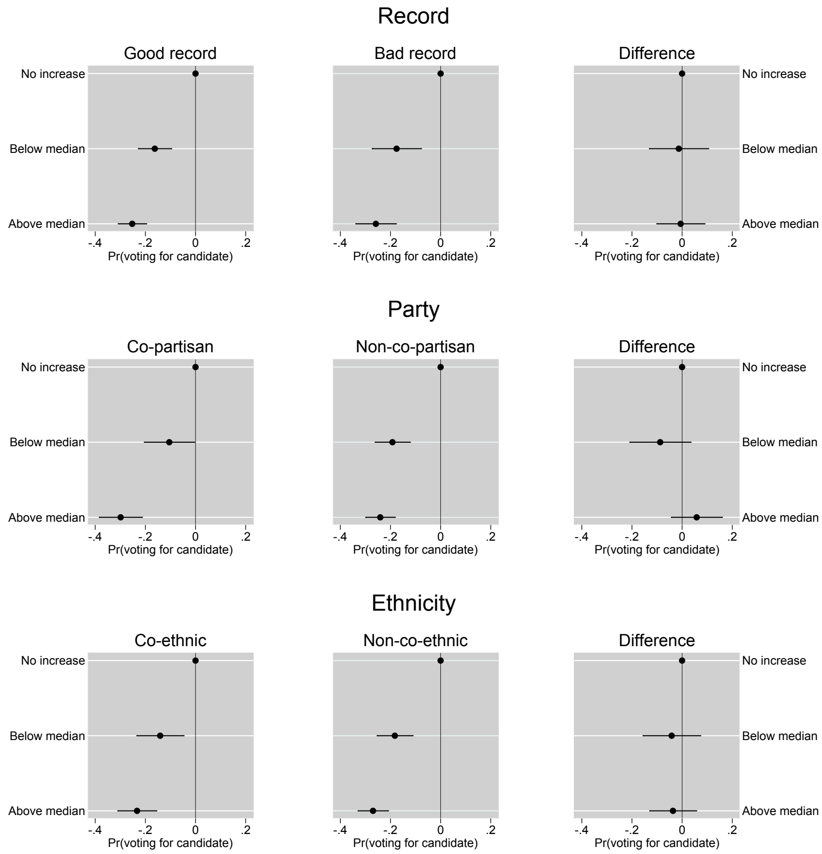
The plot shows the distribution of respondents' answers about their MLA's 2010 wealth (in bars, dark gray being the correct category), and the difference in the predicted probability of each category response from the correct response (dots), with the associated 95% confidence intervals (caps). The predicted probability differences are based on a multinomial logit model of the respondents' answers on their demographic and socioeconomic characteristics (age, education, income, own assets, and whether employed in government).

Figure A13: Respondents' guesses about average Bihar MLA's wealth and wealth increase



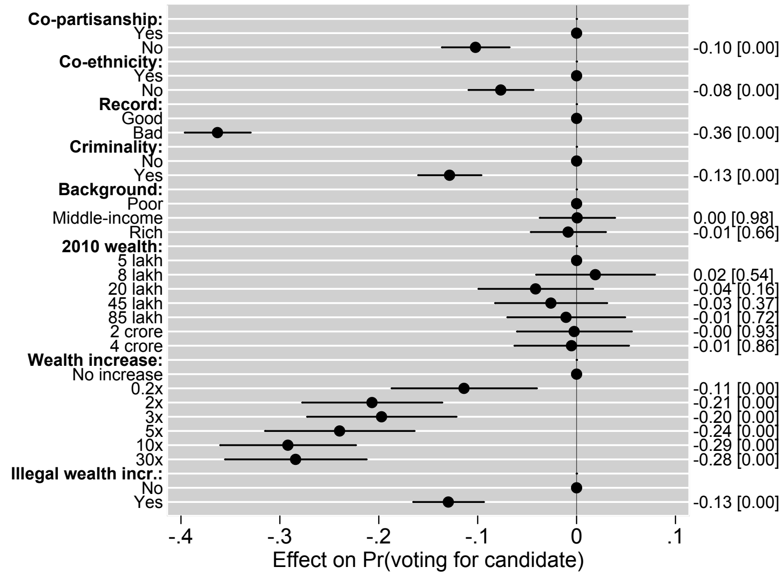
In each panel, the plot shows the distribution of respondents' answers (in bars, gray being the correct category), and the difference in the predicted probability of each category response from the correct response (dots), with the associated 95% confidence intervals (caps). The left (right) panel shows the distribution of answers and predicted probabilities about an average Bihar MLA's 2010 wealth (anticipated 2010-2015 wealth accumulation). The predicted probability differences are based on a multinomial logit model of the respondents' answers on their demographic and socioeconomic characteristics (age, education, income, own assets, and whether employed in government).

Figure A14: Interaction between wealth increase and record, co-partisanship, and co-ethnicity



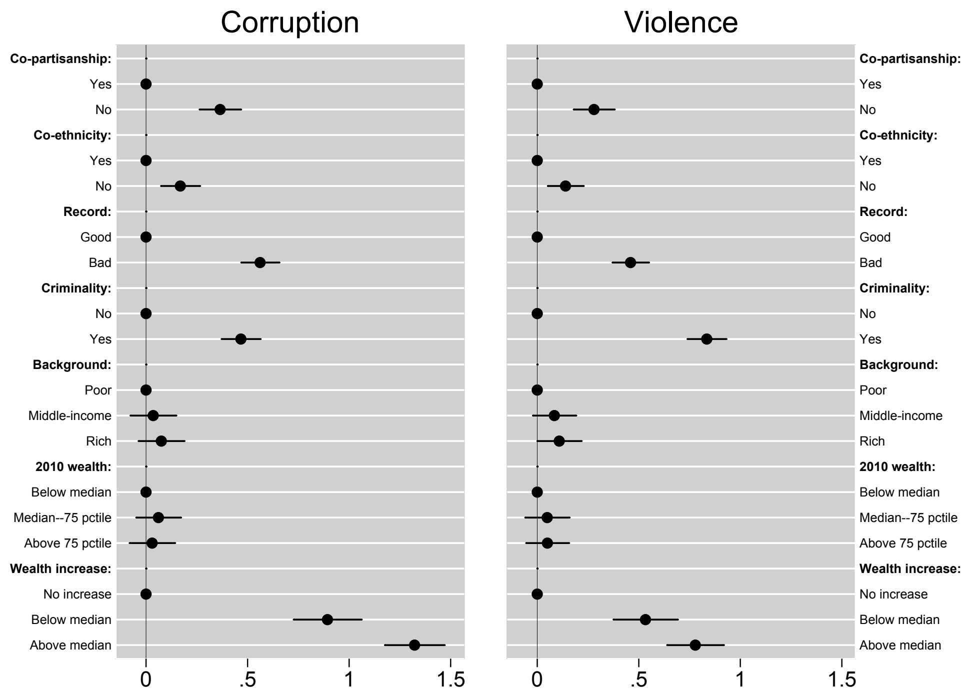
The dependent variable is the vote intention. The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors.

Figure A15: Attribute AMCEs with all levels of initial wealth and wealth increase



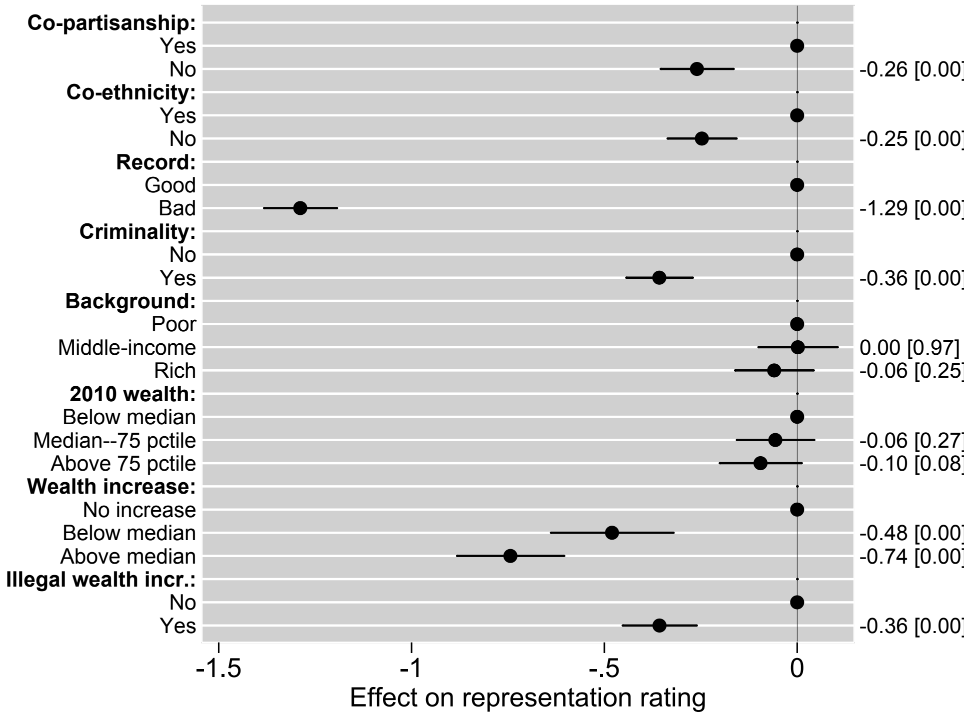
The dependent variable is the vote intention. The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors. The point estimate and p-value (in brackets) for each treatment effect are shown on the right side of the plot.

Figure A16: Candidate attribute effects on corruption and violence ratings



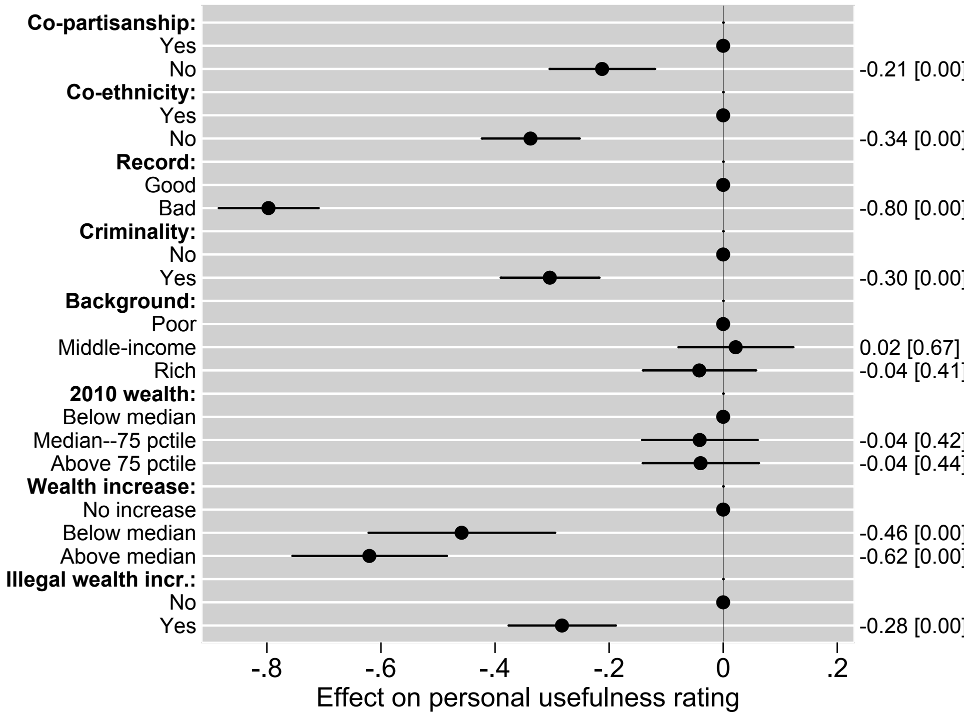
The dependent variables are the corruption rating (left panel) and the violence rating (right panel). The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors.

Figure A17: Candidate attribute effects on representation quality rating



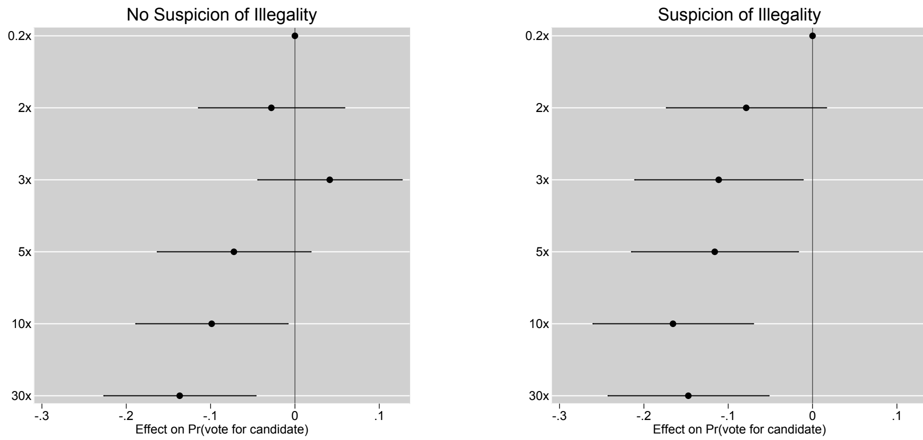
The dependent variable is the representation quality rating. The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors. The point estimate and p-value (in brackets) for each treatment effect are shown on the right side of the plot.

Figure A18: Candidate attribute effects on personal usefulness rating



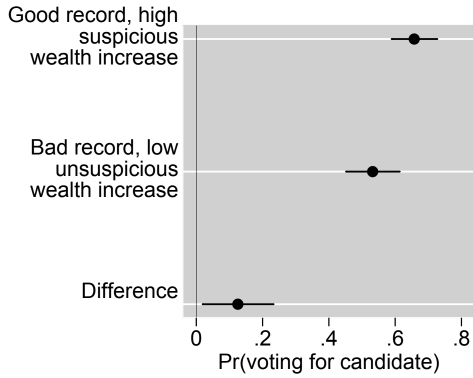
The dependent variable is the personal usefulness rating. The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors. The point estimate and p-value (in brackets) for each treatment effect are shown on the right side of the plot.

Figure A19: Effect of wealth increase based on legality



The dependent variable is the vote intention. The dots are the average marginal component effects. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors.

Figure A20: Relative importance of politician record and wealth increase, by legality



The dependent variable is the vote intention. The dots are the average predicted values for profiles with characteristics indicated on the y axis. The horizontal caps are the 95 percent confidence intervals based on respondent clustered standard errors. “High” wealth increase is the 30-fold increase. “Low” wealth increase refers to the “slight” increase of 20%.

Table A1: Sampling procedure details

Location number	Direction from lab	Number of lab interviews	Invitations distributed	Take-up rate
1	N	104	251	41.43%
2	N	68	202	33.66%
3	N	130	246	52.85%
4	SE	134	252	53.17%
5	SE	110	238	46.22%
6	SE	128	281	45.55%
7	SW	106	243	43.62%
8	SW	146	285	51.23%
9	SW	121	243	49.79%
Total		1047	2241	46.72%

Of the 1,047 people who showed up to the lab, 24 did not finish the pre-treatment survey, and three did not take the experimental and post-treatment survey. Therefore, our final sample contains 1,020 respondents. For the explanation of locations and the sampling procedure, see Section A5.

Table A2: Sample characteristics in our two surveys

	First survey (N=1,020)		Second survey (N=232)		Difference	
	Mean	St. dev.	Mean	St. dev.	Coef.	*p-value*
Age (years)	39.39	14.03	42.17	15.22	2.79	0.00
Years in residence	38.05	14.91	39.06	16.51	1.00	0.33
Schooling (years)	6.35	4.90	6.54	4.68	0.18	0.54
Married (prop.)	0.86	0.35	0.88	0.33	0.02	0.35
Yadav (prop.)	0.45	0.50	0.40	0.49	-0.05	0.12
Muslim (prop.)	0.11	0.32	0.09	0.29	-0.02	0.25
Agricultural land	1.25	0.82	1.27	1.01	0.02	0.79
House type: pucca (prop.)	0.11	0.32	0.15	0.36	0.04	0.08
House type: kutcha (prop.)	0.43	0.50	0.45	0.50	0.01	0.64
House type: hut (prop.)	0.46	0.50	0.40	0.49	-0.05	0.09
Farmer (prop.)	0.23	0.42	0.36	0.48	0.13	0.00
Agricultural laborer (prop.)	0.34	0.47	0.33	0.47	-0.01	0.71
Shop owner (prop.)	0.09	0.29	0.10	0.30	0.01	0.76
Government worker (prop.)	0.05	0.21	0.06	0.24	0.01	0.38
Private job (prop.)	0.11	0.31	0.11	0.32	0.01	0.67
Assets (count)	2.27	1.56	2.40	1.46	0.13	0.16
Cattle (count)	1.09	1.30	1.93	2.08	0.84	0.00
Income (rupees)	6,233.85	6,212.83	6,083.85	6,338.88	-150.00	0.71

The first survey is the experimental survey. The second survey is the "information" survey. Columns 5-6 show the coefficient and the p-value from a regression of each characteristic (indicated in row) on the binary indicator for the first survey (vs. the second survey), respectively. "Assets" represents the sum of the following binary variables indicating a possession of: a car, TV, motorcycle, bicycle, cell phone, fan, radio, water pump, and refrigerator. "Cattle" is a sum of the number of cows, buffaloes, and goats.

Table A3: Sample, state, and national demographics

	Survey		Bihar		North India	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Schooling (years)	6.35	4.90	5.96	4.69	6.61	4.35
Household size	6.05	2.64	5.69	2.53	5.49	2.55
Muslim (prop.)	0.11	0.32	0.14	0.30	0.14	0.26
Number of rooms	2.26	1.49	2.79	1.64	2.69	1.65
Assets (count)	2.27	1.56	2.44	1.45	2.92	1.53

Columns 1-2 show the summary statistics from our experimental survey. The weighted state (columns 3-4) and North India (columns 5-6) summary statistics are from Wave II of the India Human Development Survey. Throughout this section, we define North India as the four largest North Indian states: Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh. "Assets" represents the sum of the following binary variables indicating a possession of: a car, TV, motorcycle, bicycle, cell phone, fan, radio, water pump, and refrigerator.

Table A4: Summary of experimental manipulations

Attribute	**Text on the vignette which respondents can see**	**What the interviewer says to respondents**
District	Random draw among: Samastipur, Lakhisharai, Katihar, Kishanganj, Muzzafarpur, Jahanabad, Nawada, Banka	"This politician was elected in 2010 in [*district name*] disrict."
Wealth at beginning of term	Random draw among: 5 lakhs, 8 lakhs, 20 lakhs, 45 lakhs, 85 lakhs, 2 crores, 4 crores	"Candidates for office are required to report their assets and the assets of their immediate family members as they declare their candidacy. At the beginning of his term in 2010, this politician had [*initial wealth amount*] rupees in assets."
Wealth accumulation during current term	Random draw among: Did not increase, slightly increased, increased two times, increased three times, increased five times, increased ten times, increased thirty times	"The wealth of this incumbent increased [*number of times*] during his term in office. Since he had [*initial wealth amount*] in 2010, he now has [*current amount*]."
Perceived legality of wealth accumulation	Random draw, conditional on wealth accumulation not being "Did not increase," among: No suspicion of illegality, suspicion of illegality	"Wealth increase is mainly due to successful business deals and real estate operations in the district, [none of which/many of which] have been deemed suspicious by the press."
Social background	Random draw among: poor family, middle-income family, rich family	"The politician hails from a [poor/middle-income/rich family]."
Record in office	Random draw among: disappointing record, good record	"According to reports in the press, he [was/was not] very active in terms of development and infrastructures and he [did/did not] do very much for his constituency."
Ethnicity	Draw between: respondent's self-reported ethnicity and other salient ethnicities in Madhepura (according to the procedure detailed in Section A8)	"This politician belongs to the [*group name*] community."
Party	Random draw among: JD(U), RJD, BJP, INC	"This politician is from [*party name*]."
Criminal charges	Random draw among: No criminal charges, several criminal charges	"This politician is [not charged in any criminal cases/charged in several criminal cases]."

Table A5: Balance tests

	Omnibus test	Profile rated
Age	0.713	0.825
Married	0.873	0.196
Years of schooling	0.146	0.061
Occupation	0.624	0.405
Household size	0.236	0.867
Size of land owned	0.347	0.816
House type	0.629	0.558
Number of rooms	0.861	0.120
Household income	0.435	0.444
Ethnicity	0.325	0.882

The entries in column 1 represent the p-values of an F-test from a regression of each pre-treatment characteristic (indicated in rows) on all conjoint treatment conditions. Column 2 reports the p-value of the effect of each pre-treatment characteristic (indicated in rows) on the profile rated by respondents in the conjoint experiment.

Table A6: Variability in attribute effects on vote intention by vignette

	Vignette 1	Vignette 2	Vignette 3	F-test
Co-partisanship				
Base: Yes				
No	-0.114***	-0.069**	-0.112***	0.677
	(0.029)	(0.032)	(0.030)	[0.508]
Co-ethnicity				
Base: Yes				
No	-0.053*	-0.067**	-0.098***	0.622
	(0.029)	(0.031)	(0.029)	[0.537]
Record				
Base: Good				
Bad	-0.339***	-0.372***	-0.366***	0.451
	(0.027)	(0.029)	(0.028)	[0.637]
Criminality				
Base: No				
Yes	-0.128***	-0.146***	-0.124***	0.177
	(0.027)	(0.028)	(0.028)	[0.837]
Background				
Base: Poor				
Middle-income	-0.002	0.053	-0.050	2.264
	(0.034)	(0.035)	(0.034)	[0.104]
Rich	0.002	0.027	-0.071**	2.073
	(0.033)	(0.036)	(0.036)	[0.126]
2010 wealth				
Base: Below median				
Median–75 pctile	-0.025	0.012	-0.012	0.317
	(0.032)	(0.034)	(0.034)	[0.729]
Above 75 pctile	-0.023	0.032	0.011	0.701
	(0.034)	(0.034)	(0.034)	[0.496]
Wealth increase				
Base: No increase				
Below median	-0.157***	-0.140***	-0.158***	0.042
	(0.049)	(0.053)	(0.048)	[0.959]
Above median	-0.247***	-0.193***	-0.303***	1.756
	(0.040)	(0.045)	(0.042)	[0.173]
Illegal wealth incr.				
Base: No				
Yes	-0.121***	-0.102***	-0.101***	0.213
	(0.038)	(0.038)	(0.036)	[0.808]

The dependent variable is the vote intention. The main entries in columns 1-3 report the average marginal component effects for each profile separately; the entries in parentheses are the respondent-clustered standard errors. The main entries in column 4 represent the F-statistic from the test of whether the treatment effects for vignettes 2 and 3 are jointly statistically significantly different from the treatment effects in vignette 1; the entries in brackets are the p-values from this test.

Table A7: Knowledge of disclosures and precision of guesses

	Correct	Under-estimate	Over-estimate
Own MLA–2010 wealth	0.10	-0.05	-0.05
	(0.06)	(0.07)	(0.05)
Ave. Bihar MLA–2010 wealth	0.01	0.03	-0.05
	(0.03)	(0.04)	(0.03)
Own MLA–2010-2015 wealth increase	-0.08	-0.08	0.16**
	(0.05)	(0.06)	(0.06)
Ave. Bihar MLA–2010-2015 wealth increase	0.11*	-0.18***	0.07
	(0.06)	(0.06)	(0.05)

All three dependent variables, indicated in column headers, are binary. *Correct* equals one if a respondent chose a correct category (for 2010 wealth) or made a correct guess (for the 2010-2015 wealth increase). *Under-estimate* (*Over-estimate*) equals one if a respondent chose a category lower (higher) than a correct response or guess. The main entries are coefficients from a regression of the dependent variable on the indicator variable denoting whether the respondent had heard of the disclosures and that they are public. The models include controls for age, education, income, assets, land ownership, party affiliation, whether employed in government, and caste/ethnicity (Muslim or Yadav). Robust standard errors in parentheses.

Table A8: Interaction between wealth increase and initial wealth, family background, and criminality

	Below median wealth increase	Above median wealth increase
2010 wealth		
@ Below median 2010 wealth	-0.201***	-0.253***
	(0.048)	(0.040)
× Median – 75th pctile	0.039	-0.035
	(0.078)	(0.063)
× Above 75th pctile	0.014	-0.035
	(0.075)	(0.063)
Family background		
@ Poor family	-0.200***	-0.297***
	(0.051)	(0.044)
× Middle-class family	-0.025	0.034
	(0.075)	(0.064)
× Rich family	0.074	0.034
	(0.076)	(0.063)
Criminality		
@ No criminal record	-0.176***	-0.277***
	(0.042)	(0.036)
× Criminal record	-0.015	0.007
	(0.063)	(0.052)

The dependent variable is the vote intention. The first row of each set of interactions, indicated with a bold-face caption, shows the wealth increase AMCE at the base category of the interacting treatment component (the rows indicated with "@"); the other rows represent the interaction terms (i.e. the difference from the first row) for the remaining treatment conditions for each set of attributes (the rows indicated with "×").

Table A9: Interaction between wealth increase and respondent wealth

	Below median wealth increase	Above median wealth increase
Respondent wealth		
@ Lowest quartile	-0.263***	-0.280***
	(0.055)	(0.046)
× 2nd quartile	0.094	0.038
	(0.080)	(0.068)
× 3rd quartile	0.204**	0.071
	(0.079)	(0.069)
× Highest quartile	0.068	-0.016
	(0.084)	(0.068)

The dependent variable is the vote intention. The first row of each set of interactions, indicated with a bold-face caption, shows the wealth increase AMCE at the base category of the interacting treatment component (the rows indicated with "@"); the other rows represent the interaction terms (i.e. the difference from the first row) for the remaining treatment conditions for each set of attributes (the rows indicated with "×").

Table A10: Photo and district effects

	Vote	Corruption	Violence
Photograph			
Base: Photo 1			
Photo 2	0.050*	-0.026	-0.044
	(0.026)	(0.077)	(0.073)
Photo 3	0.037	-0.018	-0.083
	(0.028)	(0.078)	(0.076)
Photo 4	0.044	0.059	-0.043
	(0.027)	(0.076)	(0.074)
Photo 5	0.036	0.039	-0.049
	(0.027)	(0.075)	(0.073)
Photo 6	0.056**	-0.020	-0.039
	(0.028)	(0.075)	(0.077)
District			
Base: Banka			
Jahanabad	0.072**	-0.269***	-0.265***
	(0.030)	(0.093)	(0.091)
Katihar	0.029	-0.168*	-0.179**
	(0.031)	(0.088)	(0.087)
Lakhisarai	0.006	-0.129	-0.171*
	(0.032)	(0.090)	(0.089)
Madhubani	0.035	-0.134	-0.121
	(0.031)	(0.088)	(0.086)
Muzaffarpur	0.051	-0.155	-0.194**
	(0.032)	(0.103)	(0.095)
Navada	0.020	-0.037	-0.068
	(0.031)	(0.089)	(0.088)
Samastipur	0.034	-0.097	-0.077
	(0.030)	(0.086)	(0.088)
Photo $\times$ wealth increase (F-test p-value)	0.935	0.773	0.790
District $\times$ wealth increase (F-test p-value)	0.756	0.433	0.965

The dependent variables are indicated in the column headers. The main entries are the average marginal component effects. The entries in parentheses are the respondent-clustered standard errors. The last two rows show the p-values from an F-test of joint significance of the interactions between the photograph or district treatments and the wealth increase treatments.

Table A11: Results by trust in media

	Wealth increase with no suspicion of illegality			Wealth increase with suspicion of illegality		
	High trust	Low trust	Diff	High trust	Low trust	Diff
0.2x	0.71	0.69	0.02	0.58	0.63	-0.06
	(0.06)	(0.04)	(0.08)	(0.06)	(0.05)	(0.08)
2x	0.78	0.67	0.10	0.59	0.55	0.04
	(0.06)	(0.04)	(0.07)	(0.07)	(0.04)	(0.08)
3x	0.78	0.79	-0.01	0.58	0.48	0.10
	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)	(0.08)
5x	0.67	0.63	0.04	0.64	0.47	0.17**
	(0.06)	(0.04)	(0.08)	(0.07)	(0.05)	(0.08)
10x	0.76	0.57	0.19**	0.51	0.45	0.06
	(0.06)	(0.04)	(0.07)	(0.06)	(0.04)	(0.08)
30x	0.72	0.54	0.19**	0.44	0.48	-0.04
	(0.06)	(0.05)	(0.08)	(0.06)	(0.05)	(0.07)

The dependent variable is the vote intention. The main entries in the first two columns of each panel are the predicted vote probabilities for each level of wealth increase. The third column in each panel (*Diff*) is the difference between the predicted probabilities in the preceding two columns. The entries in parentheses are the respondent-clustered standard errors.