# Social Status, Economic Development and Female Labor Force (Non) Participation

Kaivan Munshi and Swapnil Singh *

July 4, 2025

**Abstract**

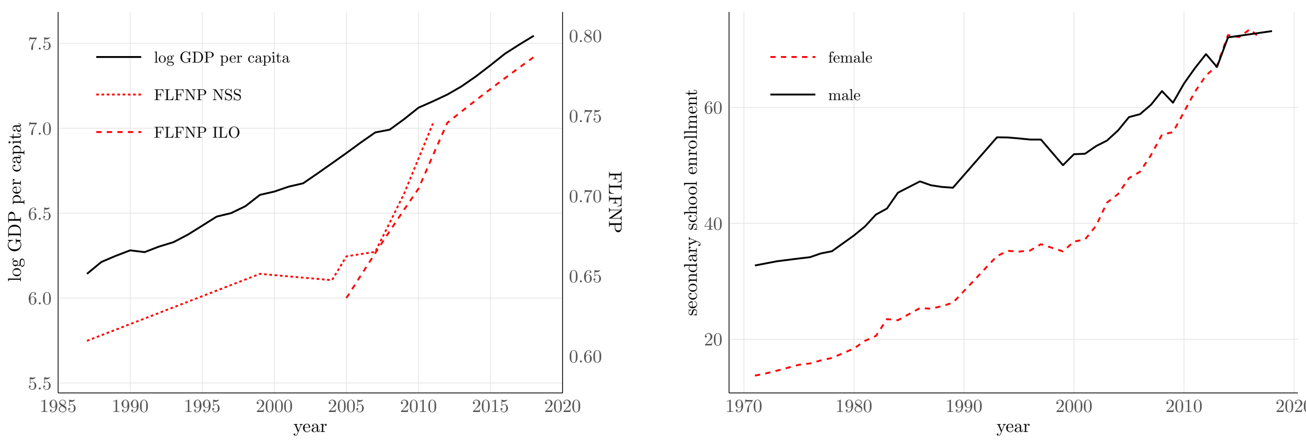
This research provides a status-based explanation for the high rates of female labor force non-participation (FLFNP) and the sustained increase in these rates over time that have been documented in many developing economies. This explanation is based on the idea that households or ethnic groups can signal their wealth, and thereby increase their social status, by withdrawing women from the labor force. If the value of social status or the willingness to bear the signaling cost is increasing with economic development, then this would explain the persistent increase in FLFNP. To provide empirical support for this argument, we utilize two independent sources of exogenous variation – across Indian districts in the cross-section and within districts over time – to establish that status considerations determine rural FLFNP. Our status-based model, which is used to derive the preceding tests, is able to match the high levels and the increase in rural Indian FLFNP that motivate our analysis. Counterfactual simulations of the estimated model identify policies that could potentially reduce FLFNP in economies where the status mechanism is relevant.

*Munshi: Yale University and Toulouse School of Economics, kaivan.munshi@yale.edu. Singh: Bank of Lithuania and Kaunas University of Technology, ssingh@lb.lt. We are grateful to Noah Sobel-Lewin for outstanding research assistance and to Shoumitro Chatterjee for initial collaboration on this project. Research support from Cambridge-INET and the Keynes Fund at the University of Cambridge, and the Agence Nationale de la Recherche (ANR) under the EUR Project ANR-17-EURE-0010 is gratefully acknowledged.

# 1 Introduction

Female labor force participation is extremely low, and has declined even further over time in many developing economies (Klasen, 2019). Consider, for instance, the Indian economy, which has been growing since the 1950's after centuries of economic stagnation. As observed in Figure 1a, per capita GDP has increased at an approximately constant rate for many decades now, but rural female labor force non-participation, which we refer to as FLFNP henceforth, was high to begin with and continues to rise, with no evidence of a reversal in this trend. By 2018, which is the last year for which data are available, 80 percent of rural Indian women had withdrawn from the labor force. To add to the puzzle, we see in Figure 1b that (higher secondary) education levels for males and females have converged over time. Female education is often accompanied by an increase in labor force participation, but this does not appear to be the case in India.

Figure 1: GDP per capita, FLFNP, and education (India)




(a) GDP per capita and FLFNP

(b) Secondary school enrollment

*Source:* NSS, ILO, World Bank

A number of factors have been proposed to explain the empirical patterns described above. Some of these factors, such as traditional gender norms, can explain why FLFNP is unusually high in developing countries. Other factors, such as an income effect or reduced employment opportunities in agriculture with economic development, can explain why FLFNP has increased over time. The additional, potentially coexisting, explanation that we propose in this paper is based on a mechanism – social status – that is the subject of a long-standing literature in economics, going back to Veblen (1899). In this literature, social status is increasing in *relative* wealth, but wealth is not publicly observed and thus must be revealed.[1] Veblen posits that conspicuous consumption is one way to signal wealth. Alternatively, conspicuous leisure or abstention from labor can be used as signals. The latter strategy is especially relevant for our analysis because households or ethnic groups in developing economies could potentially withdraw women from the labor force as a way of visibly reducing their income and thereby signaling their wealth.

[1]As Veblen (1899: 19) puts it: "In order to gain and to hold the esteem of men it is not sufficient merely to possess wealth or power. The wealth or power must be put in evidence, for esteem is awarded only on evidence."

Social status is valuable, beyond peer esteem, because it provides preferred access to non-market goods and services (Cole et al., 1992; Postlewaite, 1998; Weiss and Fershtman, 1998). Status signaling, with the preferential treatment that it generates, will thus have an especially high return in developing economies where many markets are missing or incomplete.[2] This would explain, in part, why FLFNP is relatively high in such economies. While the social status mechanism will become less useful in the long run as markets develop, as also noted by Weber (1922), it could generate an increase in FLFNP over time in the medium term. In particular, if the value of status or the willingness to bear the signaling cost is increasing with economic development, then this would explain the sustained increase in FLFNP that we observe in Figure 1a. Moreover, an increase in female education will increase households' *potential* income, which increases the competition for social status, as elucidated in the model described below. This explains why the increase in education that we observe does not result in a decline in FLFNP; indeed, it could increase FLFNP even further as we will see, reconciling Figures 1a and 1b.

While our ultimate objective is to explain the level and the dynamics of FLFNP in India, mediated by the status mechanism, we must first establish that there is indeed a link between FLFNP and social status. The challenge, which is also faced by previous studies that explore the status mechanism; e.g. Charles et al. (2009) is that its benefits are not directly observed. Our empirical strategy, taking the lead from these studies, is to derive conditions under which the value of status or the willingness to bear the signaling cost are predicted to be relatively large, and then document that FLFNP is relatively high under precisely those conditions. Atkin et al. (2021) follow the same strategy, and use the same core data as we do, in their analysis of ethnic identity in India. While they endogenize the choice of identity, taking social status as given, we do the converse.

Indian society, with its hierarchy of castes, is especially amenable to an analysis of status. The majority Hindu population is vertically stratified into broad caste categories or *varnas*, within which are numerous endogamous castes or *jatis*. Caste networks serving different economic roles have historically been organized, and continue to be organized, at the level of the *jati* (Munshi, 2019). For an analysis of status, however, it is the *varnas* that are relevant. All the surveys that we use for the analysis in this paper indicate whether a household is Scheduled Caste (SC), Scheduled Tribe (ST) or unclassified. The Scheduled Castes and Tribes had lower wealth and social status historically, and they continue to be economically and socially disadvantaged today. We will thus treat households in these groups as *low* status, while all other Hindu households are treated as *high* status. While this ranking may be fixed, the relative social position of these groups could vary across space and over time. Srinivas (1956, 1967) describes a process of "Sanskritization" with economic development in which the low castes attempt to raise their social position by adopting behaviors traditionally associated with the high castes.[3] Withdrawal of women from the labor force is one such behavior.

Both sources of exogenous variation that we use to link FLFNP and status – in the cross-section and over time – only apply to rural populations and, hence, the analysis in this paper is restricted to those populations. Indian districts are divided into urban and rural areas, and based on the most recent population census,

[2] The wealthy could also use bribes to gain preferred access to non-market goods and services. However, corruption has obvious risks and is not always feasible.

[3] The Scheduled Tribes are not Hindus *per se*, but Srinivas (1956, 1967) documents that these historically marginalized groups also attempt to improve their social position through Sanskritization.

conducted in 2011, 69 percent of the Indian population is rural. It is well known that lower castes face discrimination in rural health and educational facilities (both public and private) on account of their lower status (Shah et al., 2006; Oxfam, 2021; PROBE, 1999). We expect that such discrimination extends to many other spheres of rural life. The staff in local facilities will be aware of an individual's caste affiliation from their name or address.[4] However, individual-specific information on wealth or the behaviors that signal status are unlikely to be available. What the staff will observe are status signals, including FLFNP, at the caste level in the local area. This will determine how the different caste-groups are treated, which is consistent with Srinivas' (1967) view that social status is determined at the level of the caste in rural India.[5]

Since the status game plays out at the caste level, the model that we develop in Section 2 specifies that the local population consists of two (caste) groups, with all households in a group having the same wealth or income endowment. Households derive utility from the consumption of market goods and from a non-market good that is allocated through the status mechanism. The status of a group is increasing in the wealth of its members, but since wealth is unobserved by the staff in local facilities who are allocating the non-market good, it must be signaled by a costly choice. Each household chooses its signal independently, with the signaling expenditures aggregated up to the level of the group. Status, and the resulting allocation, are then based on the *relative* expenditure of each group. In the equilibrium of this game, the average signaling cost in the local population, which we associate empirically with FLFNP is (i) increasing in the per capita value of status, (ii) increasing in the mean income endowment, and (iii) decreasing in the income endowment gap between the groups. As a corollary to these results, we show that they also apply to each group separately.

The first theoretical result that we derive, with respect to the value of status, is relatively straightforward. The second result is new, but FLFNP could be increasing in the mean income endowment due to an income effect. The third result, which implies that both lower castes and higher castes will compete more vigorously as the income endowment gap narrows, arises because the status signals are strategic complements and, hence, mutually reinforcing. This last result is especially useful in ruling out alternative explanations and also distinguishes our model from previous analyses that incorporate a role for status. In Bursztyn et al. (2018); Atkin et al. (2021); Macchi (2023); Dupas et al. (2024) there is no reference group. Observed signals could thus reveal absolute rather than relative income.[6] Charles et al. (2009) incorporate relative income in their analysis, but individuals are trying to distinguish themselves from their own (racial) group and, hence, conspicuous consumption is *increasing* in the gap between their own income and the group's mean income.[7] The set up of our model, and the key result with respect to the income gap between groups, is actually more closely related to models of conflict that have been proposed in the literature; e.g. Esteban and Ray (2011);

[4]Indian villages are highly spatially segregated, with Scheduled Castes and Scheduled Tribes typically residing in neighborhoods outside the main village (Munshi, 2019; Asher et al., 2024).

[5]The idea that status can be determined at the level of the group, rather than the individual, goes back to Weber (1922). While caste affiliation will also determine status in urban India, that relationship is more complex because castes from different origin regions coexist in cities and there is also an additional layer of anonymity.

[6]To clarify this distinction, consider an illustrative example, following Macchi (2023) in which a loan officer is deciding the level of credit to offer an applicant. This level depends on the applicant's (collateralizable) wealth, but wealth is unobserved. Wealth is increasing in BMI (body weight) in the population and, hence, BMI can be used as an observable proxy. If potential applicants take account of this and choose their BMI strategically, then this is a signaling game. However, it will only be a status game if the loan amount depends on the applicant's wealth *and* the wealth of other applicants.

[7]In Genicot and Ray (2017) and Kim et al. (2024), parents similarly derive utility when their children's income (education) exceeds that of their peers, which increases expenditures on education in equilibrium. However, these models are specified at the individual rather than the group level.

Mitra and Ray (2014), and this is not a coincidence. Social status and conflict are alternative (costly) mechanisms to allocate resources between groups. When a hierarchy is absent, as is the case for Hindus versus Muslims in India or between tribes in Sub-Saharan Africa, it will be more difficult to coordinate on an equilibrium that utilizes the status mechanism and conflict is more likely.

We test the implications of the model in Section 3 with data from multiple rounds of the National Sample Survey (NSS). While incomes will be derived from labor and land in a rural (agrarian) economy, we focus on wage income for the core tests of the model. In each district-time period, the mean *potential* income, which corresponds to the mean income endowment in the model, is computed as the weighted average of the mean wage in each caste-gender category. The weight for each category is based on the size of its working-age population, regardless of the occupational status of its members. The caste-gap in the income endowment is similarly constructed as the difference between the caste-specific potential incomes. The status mechanism or any unobserved factor that shifts female labor *supply*, such as changes in gender norms, will also affect the equilibrium wage, which, as noted, is used to construct potential incomes. We account for this reverse causation, as well as for omitted variable bias and measurement error, by constructing statistical instruments for potential incomes that are based on rainfall shocks in each district-time period. Rainfall in a rural economy will determine wages and, by extension, potential incomes through the *demand* for labor and, hence, our instruments plausibly satisfy the exclusion restriction.[8] Our estimates indicate that FLFNP is increasing in mean potential income and decreasing in the caste-gap in potential income, net of district and time period effects (which incorporate the value of status in the benchmark specification). These results are obtained separately for the low castes and the high castes, as implied by the model.[9] As discussed in Section 3, our instrumental variable estimates are robust to a wide range of non-status explanations.

The tests of the model described above are based on exogenous variation in the willingness to compete for social status, conditional on its value. However, the model also tells us that the signalling cost (FLFNP) will be independently increasing in the value of status. While the received literature tells us why social status is useful, it does not tell us where this will be the case. There is a long standing view, recently refined by Mayshar et al. (2022) as discussed below, that appropriable agricultural surplus is a prerequisite for the emergence of hierarchical pre-modern societies. We posit that *conditional* on a society being stratified, social status will be more valuable and, hence, hierarchies will be more salient in more productive rural areas. One obvious reason for this association is that amenities will be of higher quality where there is greater output to fund them. Reinforcing this effect, there will be greater competition for amenities because higher productivity is associated with a larger population (density) at early stages of economic development (Ashraf and Galor, 2011). If the status mechanism is used to allocate scarce amenities, then the implication of the preceding argument is that the value of status, and the associated signalling cost, measured by FLFNP, will be increasing in agricultural productivity, proxied by population density.

While a positive association between FLFNP and population density, which we use henceforth as a summary measure of agricultural productivity, is consistent with the status mechanism, other explanations for this association are available. The additional advantage of focussing on India in our analysis is that it

[8] As discussed in Section 3, this instrument also allows us to relax an assumption in our model and in our construction of potential incomes, which is that individuals are homogeneous at the caste-gender level in a given district-time period.

[9] The model generates additional predictions for the magnitude of the coefficients on mean potential income and the caste-gap in potential income, by caste. We are able to verify these implications as well.

is not enough to be wealthy to achieve high status in highly stratified, caste-based, Hindu society. A central premise of Indian sociology, going back to Srinivas (1956, 1967) is that status-seeking groups (castes) must also make particular consumption choices – vegetarianism and teetotalism – that are associated with ritual purity and were traditionally adopted by the high castes. These choices do not increase household expenditures; indeed, vegetarian food products are less expensive than non-vegetarian products and teetotalism eliminates the cost of alcohol consumption. However, they will diverge from the household's preferred consumption bundle, causing it to incur a non-pecuniary cost. If the value of social status in rural India is increasing with population density, as we posit, then FLFNP, vegetarianism, and teetotalism should be increasing in that variable. Based on the status game that we described above, this should be true for the low castes who are attempting to improve their status and for the high castes who seek to maintain their social position.

In Section 4 of the paper, we use data from the population census, the India Human Development Survey (IHDS), and multiple rounds of the NSS to provide empirical support for the argument laid out above. In particular, we show that there is a positive association between population density, instrumented by exogenous agricultural productivity, and (i) the quality and the competition for scarce local amenities, and (ii) FLFNP, vegetarianism, and teetotalism, separately by caste. In addition, FLFNP, vegetarianism, and teetotalism are higher on average for the high castes, which implies that they have higher status in equilibrium, as we assume. As with the tests of the model in Section 3, we consider and rule out a comprehensive set of alternative, non-status, explanations for the FLFNP-population density association in Section 4.[10]

Having established a link between FLFNP and social status with two independent sources of exogenous variation, we complete the analysis in Section 5 by estimating the structural parameters of the model. For this analysis, we extend the analytical model developed in Section 2 by introducing education choices and by allowing wages to be determined endogenously. (Predicted) population density determines aggregate TFP and the value of status in each district-time period, which, in turn, jointly determine education, wages, and FLFNP. We find that the model fits the data very well, with respect to these variables, across districts in each NSS round, and over time. The positive cross-sectional association between FLFNP and population density that we estimate in Section 4 is assumed to arise because the value of status is increasing in the latter variable. Although this value cannot be observed directly in the data, our parameter estimates indicate that it is indeed increasing in population density.

With regard to the observed increase in FLFNP over time, changes in a number of non-status factors could potentially generate this trend. Based on our structural estimates, however, changes in these factors would have actually led to a net *decline* in FLFNP. This leaves us with the status mechanism with its three components, and our estimates indicate that the observed increase in FLFNP was largely driven by an underlying increase in the value of status and mean potential income. While district-level shocks to the caste-gap in potential income were especially useful in identifying a status effect in Section 3, this factor does not contribute appreciably to the increase in aggregate FLFNP over time.

[10]We also extend the analysis beyond India in that section by comparing the FLFNP-population density association in Asia and Africa. This association is positive in Asia, as in India, but absent in Africa. Inter-regional differences in historical social stratification and female labor force participation are used to explain this result in Section 4.

While the status-based factors that generate the increase in FLFNP may evolve naturally over the course of the development process, we are nevertheless interested in identifying policies that would ameliorate the inefficient signaling. Goldin (1994) posits that increases in female education at later stages of economic development encourage women to enter the labor force. One possible policy would thus be to invest in female education. We evaluate this policy by exogenously reducing the cost of education and find that FLFNP actually *increases* substantially. While this result may be surprising at first glance, it is easily interpreted through the lens of our model: the decline in the cost of education and, for that matter, any scheme that offers a monetary incentive for women to work will increase their households' potential incomes. This will, in turn, increase the competition for status and its accompanying signaling costs. The steep increase in female education over time that we documented at the outset in India, very likely increased FLFNP even further.

While the preceding discussion tells us that standard prescriptions to increase female labor force participation may not be effective, and even backfire, in economies where status considerations are relevant, our structural model does provide an alternative solution. The second counterfactual policy simulation that we consider reduces the non-pecuniary constraints to female labor force participation, by weakening gender norms for instance. This effectively increases the cost of withdrawing women from the workforce, without changing potential incomes, and our simulations indicate that this strategy would result in a substantial *decline* in FLFNP. It is not easy to weaken gender norms, but recent experimental evidence that we discuss in the concluding section indicates that appropriately designed interventions, which take account of the status mechanism, could potentially achieve this objective.

## 2 The Status Game

### 2.1 Ingredients of the Model

Our model is based on previous characterizations of social status in the economics literature; e.g. Frank (1985); Cole et al. (1992); Bagwell and Bernheim (1996); Fershtman et al. (1996); Postlewaite (1998); Weiss and Fershtman (1998). These papers, in turn, build on the seminal contributions of Veblen (1899) and Weber (1922) and have the following features in common:

1. Wealth is not publicly observed and, hence, households signal their wealth by making costly visible choices; for example, by withdrawing women from the labor force. Status is increasing in relative wealth in equilibrium.

2. Households have a concern for relative standing, and are willing to bear the associated signaling costs, because it is instrumental in determining their consumption of non-market goods and services; i.e. they do not necessarily value status *per se*. These instrumental concerns arise because markets are incomplete or function imperfectly.

3. The status game can be played between individuals or groups. Either way, social status is inherently relative and, hence, the allocation of non-market goods and services through this mechanism is a zero-sum game. Based on the discussion in the previous section, an individual's identity and their status is determined by their caste in rural India. The status game will thus be played between caste groups.

## 2.2 Population and Preferences

The status game is played by the local population in each village. This population consists of two (caste) groups: $H$ and $L$. Each group consists of $N$ households.[11] We are interested in modeling the status game between groups and, hence, all households within a group $k \in \{H, L\}$ are assumed to have the same wealth or income endowment, $y_k$, in a given village. The income endowments $y_k \in \{y_H, y_L\}$ vary across villages and their levels in a given village are private information; i.e. the external agents who are using the status mechanism to allocate resources do not know their value. $y_H > y_L$ in all villages and, hence, the $H$ group always has a higher social position than the $L$ group (the rank is fixed). However, the magnitude of this advantage will vary across villages, depending on the levels of $y_H$, $y_L$, which are revealed in equilibrium.

Households derive utility from the consumption of market goods and from a non-market good, which has per capita (or, to be more precise, per household) value, $v$. The non-market good is allocated through the status mechanism. The status of a group is increasing in the wealth of its members, but since wealth is unobserved it must be signaled by a costly choice. Denote the income of household $i$ belonging to group $k$ by $y_{i,k}$ and its costly signal by $c_{i,k}$. Assuming that preferences over the consumption of market goods are logarithmic and normalizing so that the price of the consumption bundle is equal to one, household $i$ in group $k \in \{H, L\}$ derives the following utility from consumption:

$$\log(y_{i,k} - c_{i,k}) + \frac{\mathbb{C}_k}{\mathbb{C}_k + \mathbb{C}_{-k}} \cdot 2v, \tag{1}$$

where $\mathbb{C}_k$ is the total signaling cost borne by group $k$ and $\mathbb{C}_{-k}$ is the corresponding statistic for the other group. As in Esteban and Ray's (2011) model of inter-group conflict, each household makes its signaling choice independently, with the signaling expenditures aggregated up to the level of the group. Status, and the resulting allocation of the non-market good, are then based on the *relative* expenditure of each group.[12] It is easy to verify that this specification of the status function satisfies two budget-balance conditions: (i) Each household receives $v$ when there is no heterogeneity in the status signals. (ii) If households in group $-k$ incur no costs on signaling, then group-$k$ households consume $2v$. A convenient feature of the functional form we have chosen is that these budget-balance conditions will also be satisfied when the model is extended to allow for differences in group size in Section 5.

Note that households could derive utility from the consumption component of the status signal. For example, if conspicuous consumption of positional goods is used as a signal, then individuals in the household might benefit from the consumption of such goods. Alternatively, if FLFNP is used as the signal, then the woman's time could be used for leisure or home production, which includes investments in children's human capital. In the Indian context, $c_{i,k}$ will also incorporate the monetized value of the non-pecuniary costs that must be simultaneously borne to achieve high status, such as vegetarianism and teetotalism. The only restriction on the signaling cost is that the household must be worse off on net; i.e. $c_{i,k}$ must be positive,

[11] We make this assumption for analytical convenience. Later in Section 5, when we estimate the model, we will allow group sizes to vary.

[12] As discussed in the previous section, the presumption is that the external agents who are allocating the non-market good only observe group-level expenditures, which is why the status game is played at the group level. Recall also from the previous section that our model and the Esteban-Ray model are conceptually closely related because status and conflict are alternative (costly) mechanisms that can be used to allocated resources between groups in an economy.

for the signal to reveal its underlying wealth.

### 2.3 The Status Equilibrium

Household $i$ in group $k$ chooses its wealth signal $c_{i,k}$ to maximize expression (1), taking the signaling choices of the remaining households in its group and all households in the other group as given. Since all households in a group have the same income endowment, this is a symmetric equilibrium and, hence, the optimal signaling choice for the representative household in $k \in \{H, L\}$ is determined by the following first-order condition:

$$\frac{1}{y_k - c_k} = \frac{c_{-k}}{(c_k + c_{-k})^2} \cdot 2\frac{v}{N}. \tag{2}$$

This constitutes a system of two equations with two unknowns, $c_H$ and $c_L$. To solve these equations, we divide the first-order condition for the $H$ group by the first-order condition for the $L$ group and rearrange terms to obtain:

$$\frac{c_H}{y_H} = \frac{c_L}{y_L}. \tag{3}$$

Both groups expend the same share of their income endowment on signaling in equilibrium. It follows that the non-market good would be allocated in exactly the same way if $y_H$, $y_L$ were observed, in which case incomes would enter the status function directly and the inefficient signaling costs would not be incurred.

Notice from equation (3) that the expenditures on signaling are strategic complements. It is well known that games with strategic complements typically admit multiple equilibria, one of which could be that no one signals. There is a unique equilibrium in our model, as in Esteban and Ray (2011), because we are restricting attention to strategy profiles in which at least one household has a positive expenditure on status signaling (the utility maximization problem is otherwise not well defined). The model thus applies to an environment in which groups have coordinated to play the status game, which is more likely in populations that are stratified. In Hindu society, for example, upper castes historically withdrew women from the labor force. With the onset of economic development, both upper castes and lower castes now withdraw women from the labor force as a way of signaling their wealth. In other contexts, with different preconditions, competing groups could coordinate on conspicuous consumption instead. For populations without a social hierarchy, any type of coordination may be challenging and other non-status mechanisms (outside the model) will be needed to allocate resources between groups.

One strategy to test for status signaling would be to exploit the fact that the signals are strategic complements. Notice from equation (3) that an exogenous increase in $c_{-k}$ will be accompanied by a corresponding increase in $c_k$. This is the approach taken by Kim et al. (2024) in their status-based analysis of educational investments in Korea. We take an alternative approach, which is more closely related to Charles et al. (2009); Atkin et al. (2021) that exploits exogenous variation in the per capita value of status, $v$, and group-specific incomes, $y_H$ and $y_L$.

**Proposition 1** *The average signaling cost in a local population is (i) increasing in the per capita value of status, (ii) increasing in the mean income endowment, and (iii) decreasing in the income endowment gap between the groups.*

To prove the proposition (see Appendix B for the complete derivation) we substitute $c_{-k} = \frac{c_k y_{-k}}{y_k}$, as implied by (3), in (2) to derive an expression for $c_k$ as a function of the exogenous variables in the model:

$$c_k = \frac{y_k}{1 + Kw}, \tag{4}$$

where $K \equiv \frac{(y_H + y_L)^2}{y_H y_L}$ and $w \equiv \frac{N}{2v}$.

Taking the average over $k = H, L$ and denoting the average signaling cost by $\overline{c} = \frac{c_H + c_L}{2}$ and the mean income endowment by $\overline{y} = \frac{y_H + y_L}{2}$:

$$\overline{c} = \frac{\overline{y}}{1 + Kw} \tag{5}$$

Observe that $K$ in the denominator of equation (5) can be expressed as a function of the mean income endowment, $\overline{y}$, and the income endowment gap, $\Delta y \equiv \frac{y_H - y_L}{2}$:

$$K = \frac{4\overline{y}^2}{\overline{y}^2 - \Delta y^2}$$

Differentiating the preceding equation, it is straightforward to verify that $K$ is increasing in $\Delta y$ since that term only appears in the denominator on the right hand side. It can also be shown that $K$ is decreasing in $\overline{y}$ (see Appendix B). This implies, from equation (5), that $\overline{c}$ is decreasing in $\Delta y$ and increasing in $\overline{y}$, since $\overline{y}$ also appears in the numerator of that equation. Notice also from equation (5) that $\overline{c}$ is increasing in the per capita value of status, since $w$ is decreasing in $v$, to complete the proof of Proposition 1.

$\overline{c}$ is increasing in $\overline{y}$ because there is diminishing marginal utility from the consumption of the market good. An exogenous increase in wealth in the population consequently increases the competition for status. $\overline{c}$ is decreasing in $\Delta y$ because the status signals are strategic complements. When the income of one group is infinitesimally small, it cannot participate in the status game and, as a result, status signals are infinitesimally small in equilibrium. As the income of the less wealthy group increases, the mechanics of our model come into play and both groups incur positive signalling costs. Since the strategies in this game are mutually reinforcing, total signalling costs reach their maximum value when both groups have equal income.

As a corollary to Proposition 1, we can derive implications for group-specific investments in social status. From equation (4),

$$c_H = \frac{\overline{y} + \Delta y}{1 + Kw} \tag{6}$$

$$c_L = \frac{\overline{y} - \Delta y}{1 + Kw} \tag{7}$$

Differentiating equations (6) and (7), it is straightforward to verify that the qualitative implications of the model, derived in Proposition 1 for $\overline{c}$, apply to $c_H$, $c_L$ as well, with the exception of the $\Delta y$ effect. Conditional on $\overline{y}$, an increase in $\Delta y$ implies that $y_H$ must increase and $y_L$ must decline. The resulting income effects, captured by the $\Delta y$ terms in the numerator of equations (6) and (7), will increase $c_H$ and reduce $c_L$, independently of the negative $\Delta y$ effect that works through the $K$ term. It follows that the negative $\Delta y$ effect that we derived in Proposition 1 for $\overline{c}$ is strengthened for $c_L$ and weakened for $c_H$. Consequently, the sign of the association between $c_H$ and $\Delta y$ is now ambiguous.

If we make the additional assumption that $\frac{\Delta y}{(1+Kw)^2} \approx 0$, then the model also has testable implications for the magnitude of these effects (see Appendix B):[13]

$$\frac{\partial \overline{c}}{\partial \overline{y}} = \frac{\partial c_L}{\partial \overline{y}} = \frac{\partial c_H}{\partial \overline{y}} \tag{8}$$

$$\left|\frac{\partial c_L}{\partial \Delta y}\right| > \left|\frac{\partial \overline{c}}{\partial \Delta y}\right| > \left|\frac{\partial c_H}{\partial \Delta y}\right| \tag{9}$$

We will test a linear approximation to the model in the section that follows and, hence, we do not want to take these quantitative implications too literally. With regard to (8), a more reasonable expectation is that the $\overline{y}$ effect will be of comparable magnitude with $\overline{c}$, $c_L$, $c_H$ as outcomes. Intuitively, a secular increase in the income endowment for both groups, holding $\Delta y$ constant, will generate a similar increase in their status signals. In addition, (9) tells us that the lower castes, who are seeking to raise their social position, will respond more to a narrowing of the income endowment gap than the high castes, who are pushing back to maintain their position. This result follows directly from equations (6) and (7) and the discussion that accompanied them. The differential increase in FLFNP, as the income endowment between caste groups narrows, is a very specific implication of the status model and if it can be verified, then this would increase our confidence in that model.

# 3 Testing the Model

**Estimating equation**: We use the NSS Employment and Unemployment surveys to test the model. These surveys include repeated cross-sections of households over the 1987-2011 period, selected through stratified random sampling, that are representative of the country's population in each round. The labor force participation statistics are derived from the usual activity status of all working-age adults in each sampled rural household (see Appendix A for details of variable construction). Individual responses are aggregated up to the district level in each survey round, by caste and gender, to construct the statistics that we use for the analysis. While household incomes will be derived from labor and land in an agrarian economy, we focus on the former factor when constructing the income endowments to test the model because incomes from land are unavailable at the caste-district level over time. We will, however, incorporate land incomes in extensions to these tests below. Individual wages are also obtained from the Employment and Unemployment surveys, as described in Appendix A, and then aggregated up to the caste-gender-district-time period level.

We test the model's implications, as specified in Proposition 1 and its caste-specific corollary, by estimating the following equation with NSS data, across districts $j$ and over rounds or time periods $t$:[14]

$$c_{jt} = \beta_1 \overline{y}_{jt} + \beta_2 \Delta y_{jt} + \delta_j + \gamma_t + \epsilon_{jt}. \tag{10}$$

[13] This assumption will be satisfied if the quadratic term, $(1 + Kw)^2$, is an order of magnitude larger than the income-gap between the two groups, $\Delta y$. However, we still need to assume that $\frac{\overline{y}}{(1+Kw)^2}$ has finite value (see Appendix B). This may not be unreasonable since $\overline{y}$ is seven times larger than $\Delta y$ on average in our data.

[14] The status game, as we model it in Section 2, is played between *jatis* at the level of the village. The NSS does not provide village identifiers or *jati* information. Our empirical analysis thus aggregates decisions from many underlying status games. The implicit assumption is that villages are homogeneous within district-time periods.

$c_{jt}$ denotes the signaling cost, which is measured by average or caste-specific FLFNP. $\overline{y}_{jt}$ measures the mean income endowment across the two caste groups and $\Delta y_{jt}$ measures the difference between the high-caste and low-caste endowments. When discussing the empirical results, we will refer to the income endowments as *potential* incomes; i.e. the incomes that would be obtained if women were not withdrawn from the labor force. The district effects, $\delta_j$, incorporate the per capita value of social status, $v$, as well as other fixed factors outside the model, such as gender norms, that independently determine FLFNP. The time-period effects, $\gamma_t$, account for secular changes that affect FLFNP in all districts, while unobserved district-time period effects are captured by the $\epsilon_{jt}$ term. Time varying components of the value of social status or gender norms will also be incorporated in this term. Note that the additive separability in equation (10) accounts for an important feature of Proposition 1, which is that the effect of each determinant of the signaling cost – $v$, $\overline{y}$, $\Delta y$ – is derived *conditional* on the other determinants. Based on that proposition, we expect $\beta_1 > 0$, $\beta_2 < 0$.

To match more closely with the model, we would want to multiply FLFNP by the female market wage to give us a measure of the *monetary* cost of withdrawing women from the labor market, and we will do this when estimating the structural parameters of the model in Section 5. We omit the wage multiplier from the current analysis because its presence could potentially undermine the validity of the instruments that we construct for $\overline{y}_{jt}$ and $\Delta y_{jt}$, as discussed below. This omission does not affect the signs of $\beta_1$ and $\beta_2$, as implied by Proposition 1, because any factor that increases (decreases) FLFNP would also increase (decrease) female wages through its general equilibrium effect. The relative magnitudes of these coefficients, as implied by equations (8) and (9), are also robust to this adjustment as shown below.

Our model describes household decisions, whereas its implications are tested at the district level. To map the model to the data, we assume that the 'representative' household in each caste has two members – a male and a female – each of whom is endowed with a single unit of time (Hansen, 1985). The male devotes all his available time to work and receives the market wage, while the female's time is allocated optimally at the intensive margin, trading off her wage income against the gain in social status when she reduces her presence in the labor market. While employment lotteries at the household level, as in Rogerson (1988) generate discrete labor market outcomes – women either enter the labor force or stay at home – the average FLFNP in a given district corresponds to underlying household-level choices at the intensive margin in our model.

**Variable construction**: To construct the potential (labor) income terms, which appear on the right hand side of equation (10), we first measure the average wage in each district-time period at the caste ($k$) and gender ($g$) level: $w_{kg}$, where $k \in \{H, L\}$ and $g \in \{m, f\}$. If there was an equal share of low-caste and high-caste households in the population, as assumed in the model, and a single male and female in each household, as assumed above, then $\overline{y}$ would be constructed as an unweighted average of $w_{kg}$ across castes and genders. In practice, castes and genders will not be balanced and, hence, we construct $\overline{y}$, and $\Delta y$, as follows in each district $j$ and time period $t$:

$$\overline{y} = \sum_k x_k \sum_g x_{kg} w_{kg} \tag{11}$$

$$\Delta y = \sum_g x_{Hg} w_{Hg} - \sum_g x_{Lg} w_{Lg}. \tag{12}$$

where $x_k$ measures the share of caste-$k$ households, $x_H + x_L = 1$, and $x_{kg}$ measures the share of working-age individuals by gender in each caste, $x_{km} + x_{kf} = 1$.

As in the model, the implicit assumption when constructing these statistics is that individuals are homogeneous within caste-gender sub-populations in a given district-time period. This allows us to assign the observed wage to all working-age individuals when constructing potential incomes, even if they are self employed (owner-cultivators) or withdrawn from the labor force.[15] As discussed below, this 'representative' agent assumption can be relaxed once we instrument for potential incomes, but it will be retained when we estimate the model in Section 5.

There are three potential sources of bias when $\overline{y}$, $\Delta y$ are measured as above: reverse causality, omitted variables, and measurement error. We describe each source of bias below, proposing an instrumental variable strategy that addresses all of them.

Equation (10) is derived from a model in which households are making independent choices, taking the market wage (which determines their income endowment) as given. Once we aggregate up to the district level, variation in the *supply* of female labor, due to the status mechanism or unobserved factors incorporated in the $\epsilon_{jt}$ term, will affect the equilibrium female wage, which, in turn, determines $\overline{y}_{jt}$, $\Delta y_{jt}$ in each district-time period. This reverse causation will arise if the production technology exhibits diminishing marginal productivity with respect to labor or if there is heterogeneity in individual ability (and selection into the labor force varies with ability). Omitted variable bias will arise if unobserved supply-side shifters that appear in the $\epsilon_{jt}$ term are correlated with $\overline{y}_{jt}$, $\Delta y_{jt}$ in equation (10). Measurement error arises because our potential income measures are based on contemporaneous wages in each NSS round. Although this specification is consistent with our static model, we expect that status signals at the caste-district level will evolve more gradually over time in practice. These signals will thus be determined by current wages and by the (recent) history of wage realizations, with the omission of the latter giving rise to the measurement error.

To address the potential biases listed above, we construct statistical instruments for $\overline{y}$, $\Delta y$ that leverage exogenous variation in the *demand* for labor. This is the classical approach to identify the supply response to price changes (wages in our context) and will also address omitted variable bias caused by supply-side factors as well as measurement error, as discussed below. Our analysis is based on a sample of rural households and in an agrarian economy, the demand for labor at any point in time will depend on local contemporaneous rainfall shocks (Jayachandran, 2006). This is true not only for individuals engaged in agriculture, but also for those employed in other occupations (through general equilibrium effects). We thus use rainfall, available annually at the district level over the 1901-2018 period from the Climate Research Unit Time Series (CRU TS), as described in Appendix A, to construct the statistical instruments.

The objective when constructing the statistical instruments is to isolate that part of the variation in $\overline{y}$, $\Delta y$ that is generated by exogenous rainfall shocks. While rainfall may affect incomes in all occupations in an agrarian economy, this effect will not be uniform. The NSS provides the "primary occupation"

[15]The additional assumption is that the shadow price of labor for a self-employed individual is equal to the market wage. This implies that there is no restriction on movement between self employment and wage labor in the local economy.

of each household: (i) technical, (ii) administrative, (iii) clerical, (iv) sales and services, (v) agriculture, and (vi) others. While individuals may change jobs temporarily in response to economic shocks, it is reasonable to assume that the household's primary occupation is fixed and predetermined. The first step in constructing the statistical instruments is to nonparametrically estimate the relationship between average wages, measured at the caste-gender-occupation level, and rainfall shocks in each district-time period.[16] These estimates are reported in Appendix Figure B1, after partialling out district and time period effects with the Robinson (1988) procedure. We see in the figure that wages are increasing in rainfall shocks across all occupations for the men, and that there is variation in the slope of this relationship by caste and occupation. In contrast, the associations are weaker, with less variation by caste and occupation, for the women. Predicted wages based on these estimates, $\hat{w}_{kg}$ are then used to construct instruments for $\overline{y}$, $\Delta y$ in each district-time period:

$$\overline{y}_{IV} = \sum_k \overline{x}_k \sum_g \overline{x}_{kg} \hat{w}_{kg} \tag{13}$$

$$\Delta y_{IV} = \sum_g \overline{x}_{Hg} \hat{w}_{Hg} - \sum_g \overline{x}_{Lg} \hat{w}_{Lg} \tag{14}$$

where $\overline{x}_k$, $\overline{x}_{kg}$ denote district-level averages of $x_k$, $x_{kg}$ computed over all time periods. This averaging accounts for the possibility that changes in the population shares $x_k$, $x_{kg}$, within a district over time, are correlated with unobserved factors that determine female labor supply, such as changes in gender norms. The direct effect of $\overline{x}_k$, $\overline{x}_{kg}$ on FLFNP is, moreover, subsumed in the district fixed effects that are also included in the estimating equation.

Our rainfall-shock instruments, which shift wages through the demand for labor, will be uncorrelated with any (unobserved) labor supply shifters that appear in the error term of equations (10). They will also account for reverse causality; i.e. the effect of FLFNP on wages. As noted, the remaining source of bias – measurement error – arises because we are ignoring lagged wages when constructing potential incomes. Our instrumental variable estimates address this source of bias as well because the serially uncorrelated contemporaneous rainfall shocks that we use to predict the wage are uncorrelated with lagged wages (the measurement error).[17] While our instruments thus address the potential sources of bias that we listed above, notice that they are potentially correlated with female wages, $w_{kf}$. This is why we do not multiply FLFNP by that variable when constructing the dependent variable in equation (10).

**Estimation results**: Table 1, Columns 1-3 report OLS estimates of equation (10), with $\overline{c}$, $c_H$, $c_L$ as the dependent variables. Table 1, Columns 4-6 report the corresponding IV estimates. As discussed above, the signalling costs are measured by FLFNP.

As implied by the model, the coefficient on mean potential income, $\overline{y}$, is positive and significant with all specifications in Table 1. The coefficient on the caste-gap in potential incomes, $\Delta y$, is negative, and significant with one exception (when the dependent variable is high-caste FLFNP). Recall that the model

[16] The rainfall shock is measured by the difference between contemporaneous rainfall and average rainfall in the district over the 1901-2018 period.

[17] Although wages are only observed in years in which the NSS was conducted, rainfall at the district level is available in all years. We can thus test the assumption that rainfall shocks are serially uncorrelated. Denote an NSS-round year by $t$. In our data, the correlation in the rainfall shock between year $t$ and $t-1$ is -0.1, the correlation between $t$ and $t-2$ is 0.1, and the correlation between $t$ and $t-3$ is -0.09.

Table 1: Female labor force non-participation within districts over time

| Dep. variable | FLFNP | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.251*** | 0.181*** | 0.357*** | 0.896*** | 0.907*** | 1.072*** |
| | (0.060) | (0.063) | (0.078) | (0.158) | (0.174) | (0.209) |
| caste-gap in potential income | -0.096** | -0.014 | -0.221*** | -0.266** | -0.143 | -0.555*** |
| | (0.038) | (0.041) | (0.050) | (0.111) | (0.114) | (0.159) |
| Kleibergen-Paap LM statistic | – | – | – | 102.65 | 102.65 | 102.65 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 98.45 | 98.45 | 98.45 |
| Dep. var. mean | 0.649 | 0.684 | 0.583 | 0.649 | 0.684 | 0.583 |
| Observations | 2840 | 2840 | 2840 | 2840 | 2840 | 2840 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

does not unambiguously sign this particular coefficient and, hence, this result is not unexpected.[18]

In the corollary to Proposition 1, we derived additional implications with respect to the coefficients across caste groups: (i) We expect the magnitudes of the $\overline{y}$ coefficients to be roughly comparable. (ii) We expect to observe an ordering in the (absolute) magnitude of the $\Delta y$ coefficients; the low castes should have the largest coefficient and the high castes the smallest coefficient, with the average coefficient lying in between. Focussing on the IV estimates in Columns 4-6 of Table 1, we see that the results match the more specific predictions of the model.

Since we have one source of exogenous variation – rainfall shocks – and two endogenous variables – $\overline{y}$, $\Delta y$ – one important requirement for our two instruments to be valid is that rainfall shocks should have a differential effect on wages (potential incomes) by caste. We expect to observe such a differential effect because there is heterogeneity in occupations and education (which determines occupational choice and the assignment of tasks within occupations) across these groups. Appendix Table B1 estimates the effect of rainfall shocks on wages, as well as their differential effect by caste. Male and female wages are both significantly higher, on average, for the upper castes. The rainfall effects, however, are restricted to the males, in line with Appendix Figure B1. Rainfall shocks have a positive and significant effect on male wages, with this effect varying significantly by caste. We are ignoring variation across occupations in these estimating equations, which we do exploit when constructing the statistical instruments. Not surprisingly, the Keibergen-Paap LM statistic, which tests for under-identification is above 100 in Table 1. The additional requirement for our instruments to be valid is that they should have sufficient statistical power. Based on the first-stage regressions reported in Appendix Table B2, we do not face a weak instrument problem and

[18]Indian districts will often divide over time and we take account of this by measuring outcomes at the level of contemporaneous administrative boundaries in the analysis. However, standard errors are clustered at the level of the original 1981 boundaries, as discussed in Appendix A.

the Kleibergen-Paap F statistic in Table 1 is also above 90. We complete the tests of the model by verifying the robustness of the results in various ways in Appendix B.

1. Previous analyses utilizing NSS data in the economics literature have typically restricted attention to the "thick" rounds, conducted in 1987-1988, 1999-2000, 2004-2005, 2009-2010 and 2011-2012; e.g. Mitra and Ray (2014); Afridi et al. (2018); Atkin et al. (2021).[19] We follow these studies and use the five "thick" rounds for the analysis of consumption in Section 4 and to estimate the model in Section 5. However, for the tests of the model in Table 1, which exploit variation over time within districts, we also utilize data from three additional "thin" rounds, conducted in 2004, 2005-2006, and 2007-2008. As a robustness check, we only include the five "thick" rounds in Appendix Table B3.

2. We replace the district-level averages, $\overline{x}_k$, $\overline{x}_{kg}$ by the corresponding time-period averages when constructing the instruments in Appendix Table B4. The time-period effects that are also included in the estimating equation will now subsume the direct effect of the national-level population shares on FLFNP. While there are hundreds of districts, there are only eight time periods (NSS rounds) in our sample. There is consequently much less variation in these instruments relative to the benchmark specification in Table 1. Nevertheless, the $\overline{y}$, $\Delta y$ coefficients retain their statistical significance and are very similar in magnitude to the point estimates in that table.

3. We replaced the signaling cost by FLFNP as the dependent variable in equation (10) because the rainfall-shock instruments determine wages. However, as reported in Appendix Table B1, these shocks determine male wages, but not female wages. While these heterogeneous effects do not undermine the validity of our instruments, they do imply that FLFNP can be multiplied by the relevant female wage to construct the dependent variable: average FLFNP is multiplied by the average female wage and caste-specific FLFNP is multiplied by the caste-specific female wage. Comparing the estimates in Appendix Table B5 and Table 1, this adjustment to the dependent variable does affect the absolute magnitude of the $\overline{y}$, $\Delta y$ coefficients. However, the relative magnitude of these coefficients across outcomes, as implied by equations (8) and (9), is retained.[20]

4. The per capita value of status, $v$, is subsumed in the district fixed effect in equation (10). However, it is possible that $v$ changes over time with economic development. As the economy grows larger, the quality of amenities will improve, with an accompanying increase in the value of status. At the same time, markets will expand with economic development, with an accompanying decline in the need for the social status mechanism. While the nature of the variation in $v$ over time within a district is thus theoretically ambiguous, we allow for such variation by including population density interacted with NSS round (time period) effects in the estimating equation. Recall from the discussion in the Introduction that exogenous agricultural productivity, proxied by population density, will determine the value of status in an agrarian developing economy. The results with this augmented specification of equation (10) are reported in Appendix Table B6, where we see, once again, that the point estimates are very similar to the corresponding estimates with the benchmark specification in Table 1.

[19]Mitra and Ray (2014) also use the 1983 NSS round in their analysis, but this round does not include district identifiers.

[20]When we multiply FLFNP by the relevant female wage, we are effectively measuring the pecuniary value of the signaling cost. In particular, we do not account for the value of the woman's leisure or the benefit of home production when measuring the signaling cost. We will, however, allow for these compensatory effects when we estimate the structural model.

5. While the tests of the model thus far have focused on income from labor, income from land will also be relevant in a rural economy. If land ownership and productivity were available by caste in each district-time period, then we could construct measures of $\overline{y}$, $\Delta y$ based on land incomes and test the model independently. However, district-level information on land in the NSS is restricted to the Land and Livestock Holding Survey, conducted in the 2003 round, which lists the amount of land owned by each caste group. Without information on land productivity, and time varying data more generally, we cannot independently test the model. Nevertheless, we would like to control for land incomes in the estimating equation because they will vary with rainfall (our instrument). Land markets are extremely thin in India and it is thus reasonable to assume that land holdings are fixed over time. For each caste group $k$, the 'representative' household's income from land in district $j$ and time period $t$ can then be parsimoniously specified as $\gamma_k R_{jt} \frac{A_{jk}}{N_{jk}}$, where the $\gamma_k$ parameters (to be estimated) measure caste-specific land productivity, $R_{jt}$ is rainfall, $A_{jk}$ is total acreage owned by caste $k$ in district $j$ in 2003, and $N_{jk}$ is the number of households in that caste in that district in that year (obtained from the NSS Employment and Unemployment Survey). The robust results with an augmented specification of equation (10) that includes the land income terms are reported in Appendix Table B7.

**Alternative Explanations**: Any fixed determinant of FLFNP is subsumed in the district fixed effects that are included in the estimating equation (10). Any secular change is subsumed in the time effects that are also included in the estimating equation. The estimates in Table 1 can thus only be biased by unobserved district-time varying factors, subsumed in the $\epsilon_{jt}$ term, that shift female labor supply. Among the supply-side constraints that have been proposed in the literature, it has been hypothesized that marriage and accompanying home production (child care) could be responsible for the withdrawal of women from the workforce in developing economies (Goldin, 1994; Afridi et al., 2018). Women may also be less likely to work if they have less education or if the new (non-agricultural) jobs that become available with economic development are distasteful to them. Finally, gender norms determine women's status within their households and, by extension, their decision-making power and autonomy (Srinivas, 1977; Basu, 1992; Chakravarti, 1993). The presumption in the gender norms literature is that women would like to work for pay, but their low status, on account of the norms, prevents them from exercising their preferences.

As discussed above, changes in such supply-side factors, within the district over time, are orthogonal to our high-frequency rainfall shock instruments that shift labor demand, and thus do not pose a threat to identification. There is, however, one alternative explanation, associated with the increase in income that accompanies economic development, that now requires particular attention because potential incomes appear as covariates in Table 1. Consider a model in which status considerations are absent, but female leisure or, equivalently, FLFNP is increasing in household income (Goldin, 1994). Let these income effects vary by caste. To simplify the exposition, we omit district and time effects, as well as the error term in the equations that follow.

$$c_{Hjt} = \beta_H y_{Hjt}, \quad c_{Ljt} = \beta_L y_{Ljt} \tag{15}$$

Now rewrite equation (10), which we estimated in Table 1, in terms of $y_{Hjt}$, $y_{Ljt}$ rather than $\overline{y}_{jt}$, $\Delta y_{jt}$:

$$c_{jt} = \left(\frac{\beta_1 + \beta_2}{2}\right) y_{Hjt} + \left(\frac{\beta_1 - \beta_2}{2}\right) y_{Ljt} \tag{16}$$

Where the status and income effects models diverge is in their implications with $c_{Hjt}$, $c_{Ljt}$ as the dependent variables. In particular, cross-caste income effects are present in equation (16) with the status model, but not with the alternative income effects model, as specified in equation (15). With $c_{Hjt}$ as the dependent variable, the alternative model implies that $\beta_1 - \beta_2 = 0$. Since $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ in Table 1, Column 5, this implication is evidently at odds with our estimates. Based on these estimates, we can also reject the hypothesis that $\beta_1 - \beta_2 = 0$ with a high degree of statistical confidence ($F = 17.3$, $p = 0.000$). With $c_{Ljt}$ as the dependent variable, the alternative model implies that $\beta_1 + \beta_2 = 0$. $\hat{\beta}_1$, $\hat{\beta}_2$ have very different magnitudes in Table 1, Column 6, and hence we do not expect this implication to be satisfied. Based on our estimates, we can formally reject the restriction that $\beta_1 + \beta_2 = 0$ with a high degree of statistical confidence ($F = 8.46$, $p = 0.004$). The parametric restrictions imposed by the alternative model are thus rejected by the data. In Section 4.4, we will take a less structured approach to rule out income effects as an explanation for the results in Table 1.

# 4 Cross-Sectional Evidence

## 4.1 Labor Force Non-Participation Across Indian Districts

The tests of the model described above are based on exogenous variation in the willingness to compete for social status, conditional on its value. However, the model also tells us that the willingness to bear the signalling cost, which we measure by FLFNP, will be independently increasing in the value of status. The cross-sectional measure of the value of status that we use to test this implication and to later estimate the structural model is motivated by the following argument: Amenities will be of higher quality in more productive rural areas, where there is greater aggregate output to fund them. Since population density is increasing in agricultural productivity at early stages of economic development, there will also be greater competition for these amenities. If the status mechanism is used to allocate scarce amenities, then this implies that the value of social status will be increasing in population density. It follows that FLFNP will be increasing in population density.

**Population density and agricultural productivity**: Since agricultural productivity is crop-specific, we measure overall productivity by population density, based on the assumption that more productive areas will support a larger population at early stages of economic development (Ashraf and Galor, 2011). In our analysis, population density at the district level is derived from the 1951 population census, which is just around the time the Indian economy was starting to develop and is as far back as we can go. While it may be reasonable to assume that population density at this early stage of development was largely determined by agricultural productivity, this variable could, in principle, have been affected by other factors such as historical famines and conflicts in the district. When we report associations with respect to population density in regression tables, we thus always instrument for population density with potential crop yields, and when we present figures, the population density variable is always predicted population density. The FAO GAEZ database provides potential yields for 42 crops at different levels of technology and irrigation. Following Galor and Özak (2016) we use low technology-rain fed agriculture to measure the crop yields, so that population density is predicted by exogenous geo-climatic conditions alone.[21]

Although population density is measured in 1951, the implied assumption in our analysis is that this statistic (instrumented by potential crop yields) determines the quality and per capita supply of local amenities and, by extension, the value of status over the 1987-2011 period. In Section 5, we will use the estimated structural parameters to verify that the value of status is increasing in (predicted) population density in the first (1987) period and the last (2011) period. In the analysis that follows, we verify that scarce amenities are of higher quality and in shorter supply in more densely populated districts in 2011 with an illustrative example from the public health system

**Local amenities and population density**: In the Indian rural health system, Primary Health Centers (PHC's) serve as the first point of contact with the population, followed by Community Health Centers (CHC's) and rural (sub-district) hospitals at the next level. Cases that cannot be handled within the local system are referred to the district hospital. In principle, the level of service and the population that is served should be the same in all districts, conditional on the type of health facility. However, we show in Appendix Figure C1 and Appendix Table C1, with data from the village directory of the 2011 population census and the 2011 round of the IHDS, that (i) each type of facility is larger and provides a wider range of services in more densely populated districts, and (ii) that the number of facilities per capita, by type, is decreasing in population density.[22] It follows that health services are of higher quality, but there is also greater competition for these services, in more densely populated districts. If the staff in the rural health facilities use social status, among other factors, to determine which patients get preferential access to treatment, then the preceding results imply that the value of status is increasing in population density.

**Labor force non-participation and population density**: Proposition 1 tells us that FLFNP (status signaling) is increasing in the value of status. If the value of status is increasing in population density, then this implies that there should be a positive association between FLFNP and population density (instrumented by agricultural productivity). As with the tests of the model in Section 3, we use the eight NSS rounds, conducted over the 1987-2011 period, to estimate this association at the district level. Figure 2a reports the nonparametric association between rural FLFNP and population density in the earliest available (1987) and last available (2011) NSS round.[23] FLFNP is increasing in population density, measured in 1951, across Indian districts in each round. The fraction of working age (18-65 year old) women who are withdrawn from the labor force ranges from 0.45 to 0.8 in 1987. While this enormous cross-sectional variation does decline over time, reflected in the flatter slope in 2011, notice that there is an overall increase

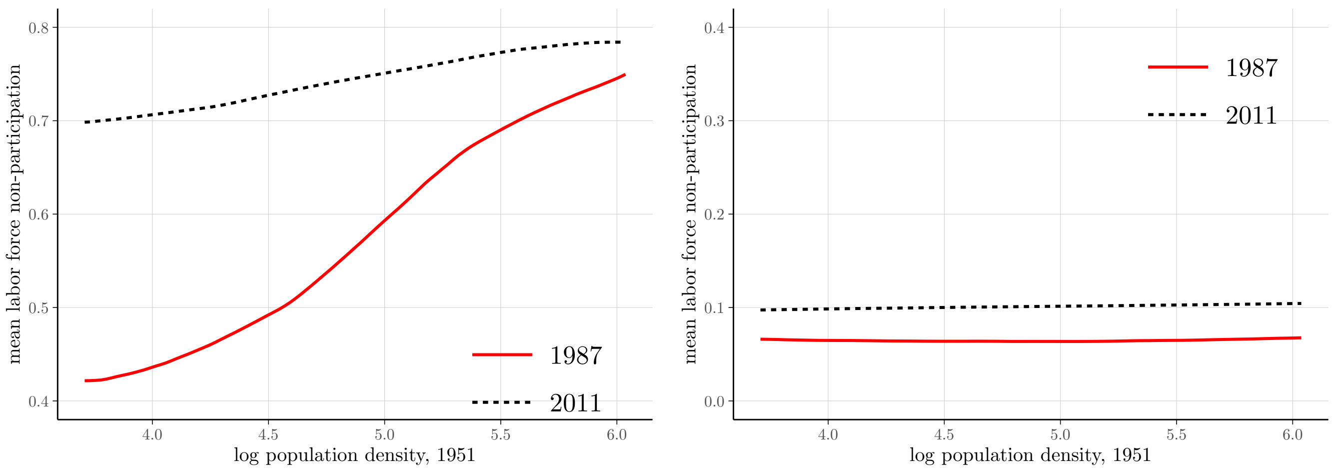
[21]The association between population density and potential crop yields arises for two reasons: (i) higher yields increase the demand for labor, and (ii) higher yields increase food supply, which, in turn, increase the population through the fertility (Malthusian) channel. We include all 42 crops in the first-stage equation for completeness and to be consistent with the cross-regional analysis that follows in Section 4.3.

[22]The 2011 population census provides information on the health facilities in each village. We measure the size of a facility by the number of doctors in place and document that average size, measured at the district level, is increasing in population density for each type of facility. While we would expect larger facilities to provide a wider range of services, this information is not available in the census. However, the 2011 round of the IHDS did collect information on both size (the number of doctors) as well as the services that were provided by all health facilities in the Primary Sampling Units (PSU's) that it covered. Focussing on PHC's, CHC's, and rural hospitals, we see that the number of procedures and tests, as well as the range of equipment, is increasing in size for each type of facility.

[23]All the analyses with district-level data in this section of the paper control for state effects. These fixed effects are partialled out nonparametrically using the Robinson (1988) procedure, as described in Appendix C.

in FLFNP from 1987 to 2011 (at all levels of population density). Labor force non-participation for the men (Figure 2b), in contrast with the women, does not vary with population density.

Figure 2: Rural labor force non-participation (Indian districts, NSS)




(a) Female (b) Male

*Source:* 1987 and 2011 NSS rounds and 1951 population census
Population density in 1951, measured in logs, is predicted by FAO GAEZ potential crop yields.
State fixed effects are partialled out prior to nonparametric estimation using the Robinson (1988) procedure.

Table 2 pools all eight NSS rounds to estimate the association between labor force non-participation and population density, as well as the change in this association over time. Column 1 reports the association between FLFNP and population density. Matching Figure 2a, the population density coefficient, which corresponds to the association in 1987, is positive and significant, while the interaction with the time trend is negative and significant. Columns 2-3 replace FLFNP, measured across all rural households in each district-time period, with the corresponding statistics for high castes and low castes, respectively. The same pattern of coefficients is obtained, in contrast with the men, where all coefficients are close to zero in Columns 4-6. While FLFNP is increasing with population density for both caste groups, notice that it is higher on average for the high castes. This difference in means implies that the high castes have higher status than the low castes in equilibrium, as assumed in the model.

We verify the robustness of the results that we have presented in Table 2 in a number of ways in Appendix C: (i) As with the tests of the model in Section 3, we only include the five "thick" NSS rounds in Table C2. (ii) Muslim, Christian and Sikh societies in India are also stratified (Ahmad, 1967; Luke and Munshi, 2011; Judge, 2002). We thus expect the status game to play out within these other religious groups as well, resulting in a positive association between FLFNP and population density, and this is indeed what we observe in Table C3. We will see that this finding extends to other vertically stratified Asian populations as well in Section 4.3. (iii) Recall that the positive association between FLFNP and the value of status in Proposition 1 is derived conditional on $\overline{y}$, $\Delta y$. Since Table 2 reports the unconditional association between FLFNP and our measure of the value of status – population density – we complete the robustness tests by verifying that the results are retained when $\overline{y}$, $\Delta y$ are included as covariates in the estimating equation in Appendix Table C4.

Table 2: Rural labor force non-participation (Indian districts, NSS)

| Dependent variable | rural labor force non-participation | | | | | |
|---|---|---|---|---|---|---|
| Gender | female | | | male | | |
| Caste group | all<br>(1) | high<br>(2) | low<br>(3) | all<br>(4) | high<br>(5) | low<br>(6) |
| Population density | 0.124***<br>(0.029) | 0.132***<br>(0.031) | 0.097***<br>(0.027) | 0.001<br>(0.003) | 0.000<br>(0.005) | -0.002<br>(0.006) |
| Population density × time trend | -0.003***<br>(0.001) | -0.004***<br>(0.001) | -0.002**<br>(0.001) | 0.000**<br>(0.000) | 0.000<br>(0.000) | 0.000<br>(0.000) |
| Kleibergen-Paap F-statistic | 22.61 | 28.16 | 22.35 | 22.61 | 28.20 | 22.21 |
| Dep. var. mean | 0.658 | 0.692 | 0.595 | 0.085 | 0.091 | 0.073 |
| Observations | 3418 | 3401 | 3368 | 3420 | 3404 | 3370 |

*Source:* NSS ("thick" and "thin" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

### 4.2 Vegetarianism, Teetotalism and Population Density

While a positive association between FLFNP and population density is consistent with the status mechanism, other explanations are available. An additional implication of the status mechanism, which will help us rule out these explanations, is that complementary consumption choices – vegetarianism and teetotalism – should also vary with population density. As discussed in the Introduction, these consumption choices were traditionally associated with the high castes and must also be made to achieve high status in India. We use the NSS Household Consumer Expenditure surveys for the analysis of vegetarianism and teetotalism. Table 3 replaces FLFNP with vegetarianism and teetotalism as the dependent variables when estimating the association with population density (see Appendix A for a detailed description of the construction of these variables). Providing independent support for the status mechanism, the pattern of coefficients and the mean of the dependent variable across caste groups with these complementary outcomes matches what we obtained with FLFNP as the dependent variable.

Variation in vegetarianism and teetotalism across districts could, in principle, be driven by standard determinants of consumption demand; i.e. income and prices. Non-vegetarian foods are relatively expensive and our results could thus be obtained if household incomes (expenditures) were declining in population density. Alternatively, supply-side effects could result in higher prices for non-vegetarian food items and alcohol in more densely populated districts. As seen in Appendix Table C5, these alternative explanations do not appear to be relevant. Total expenditures and food expenditures per household are increasing in population density. Moreover, the relevant prices are (weakly) decreasing in population density. This last result is indicative of a reduced demand for these products, in line with the status mechanism.

Notice that the coefficient on the population density variable is positive and significant, while the co-

Table 3: Rural vegetarianism and teetotalism (Indian districts, NSS)

| Dep. variable | vegetarianism | | | teetotalism | | |
|---|---|---|---|---|---|---|
| Caste group | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Population density | 0.043** | 0.042** | 0.049** | 0.087*** | 0.061*** | 0.084*** |
| | (0.017) | (0.017) | (0.021) | (0.020) | (0.016) | (0.023) |
| Population density × time trend | -0.002*** | -0.002*** | -0.002** | -0.002*** | -0.001** | -0.002** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.001) |
| Kleibergen-Paap F-statistic | 23.59 | 22.67 | 15.53 | 23.59 | 22.67 | 15.53 |
| Dep. var. mean | 0.608 | 0.640 | 0.540 | 0.848 | 0.887 | 0.782 |
| Observations | 2083 | 2078 | 2068 | 2083 | 2078 | 2068 |

*Source:* NSS ("thick" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

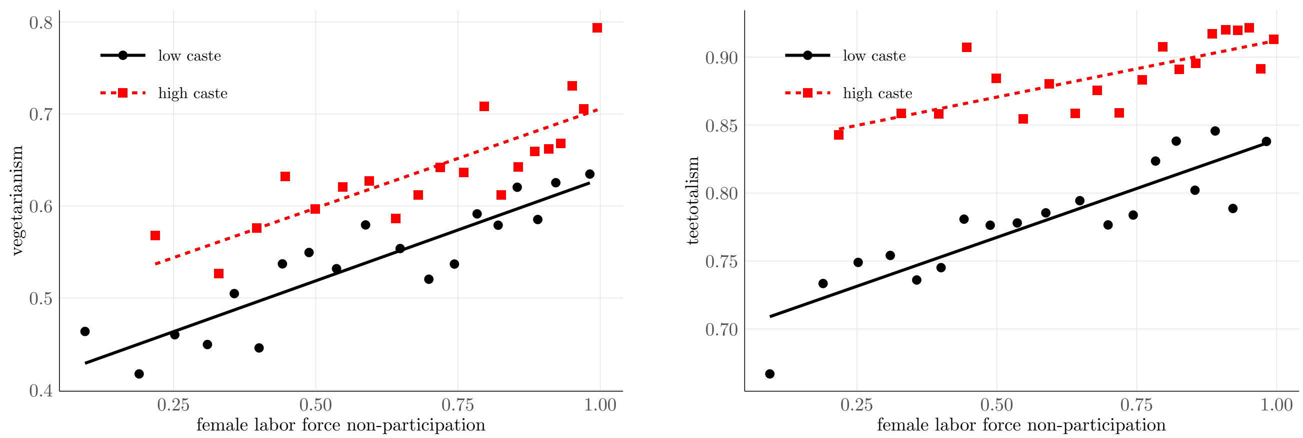
efficient on the population density-time trend interaction is negative and significant, without exception, in Table 2 with FLFNP as the outcome and in Table 3 with vegetarianism and teetotalism as outcomes. This consistency indicates that these outcomes are linked. We provide direct support for the preceding claim in Figure 3 by reporting the correlation between FLFNP and the complementary consumption behaviors, across districts and over NSS rounds. The binned scatter plots reported in the figure indicate that these correlations are indeed strongly positive, both for low castes and high castes, at all levels of FLFNP, to complete the cross-sectional analysis of the status mechanism with Indian data.

### 4.3 Labor Force Non-Participation Across Regions

The analysis in the preceding section provided support for a status-based interpretation of the positive FLFNP-population density association by documenting that this association was also observed for other variables that are linked to status in rural India. We now take a different approach by comparing regions with and without social stratification. Recall that without stratification, it is difficult for groups to coordinate on behaviors that signal higher status. We thus expect the FLFNP-population density association to be observed in (historically) stratified regions, but not where such stratification is absent.

It has long been believed that social stratification in pre-modern societies was positively associated with agricultural productivity (Cancian, 1976; Diamond, 1998). However, Mayshar et al. (2022) have recently shown that it is *not* agricultural productivity, but the type of crop that matters. In particular, the cultivation of storable cereals, which can be appropriated, as opposed to perishable roots and tubers, is a pre-requisite for the emergence of a hierarchy. Although Mayshar et al. are not concerned with inter-regional differences, a distinct Asia-Africa divide is evident in Figure 2 of their paper: roots and tubers are grown in abundance in Africa, whereas agriculture in Asia is restricted to the cultivation of cereals. Goody (1971) uses differences

Figure 3: Rural vegetarianism, teetotalism, and female labor force non-participation (Indian districts, NSS)




(a) Vegetarianism (b) Teetotalism

*Source:* NSS "thick" rounds

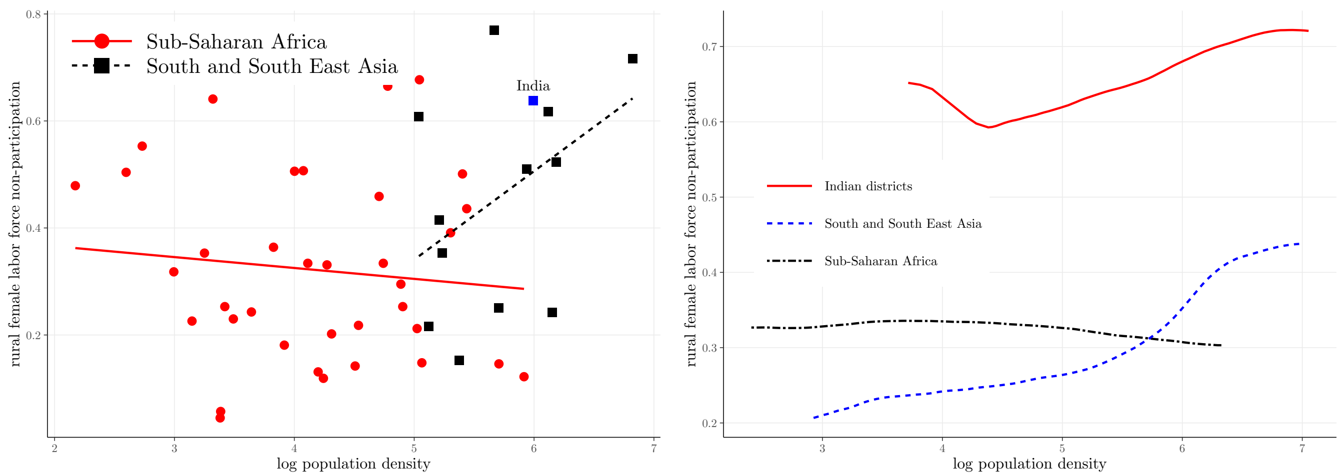
in marital arrangements to provide independent support for the inter-regional divide: his argument is that status-group endogamy, as observed in Eurasia, must be present in a stratified society, and this was not observed in Africa.

High-status women historically did not work outside the home in Asia.[24] FLFNP is thus likely to serve as a focal point in the status game that commences with economic development in that (stratified) region of the world. In contrast, while individuals could independently signal their wealth in Africa, it will be challenging for groups to coordinate on a status signal in the absence of a traditional social hierarchy. Even if coordination can be achieved, it is unlikely to involve FLFNP since all women worked historically. Based on the preceding discussion, we expect to observe a positive association between FLFNP and population density (agricultural productivity) in Asia, but not in Africa.

Figure 4a reports the association between rural FLFNP and population density across countries, separately in South and South East Asia and in Sub-Saharan Africa. Rural labor force participation rates are obtained at the country level in 2005 from the ILO UN STATS database and population densities, derived from the NASA SEDAC database, are measured in 2000 (see Appendix A for details). As above, we only use that part of the variation in population density that can be explained by exogenous crop suitability, obtained from the FAO GAEZ database, in our analysis. As observed in Figure 4a, rural FLFNP is increasing steeply with population density across Asian countries. However, this relationship is not observed across African countries, where the association is (if anything) mildly negative. Based on the figure, the well documented difference in FLFNP between these regions can be almost entirely explained by the positive association with respect to population density in Asia but not Africa. For the men, in contrast, these inter-regional differences are absent in Appendix Figure C2a and there is no association between labor force non-participation and population density in Asia or Africa.

[24] Boserup (1970) characterizes the historical seclusion of women as a distinctly Asian phenomenon, and posits that this arose because there was a social hierarchy, with a large class of landless workers, in that region. However, she does not make the distinction between high-status and low-status women. The latter traditionally worked outside the home, even in Asia.

Figure 4: Rural female labor force non-participation across regions (country data, ILO; district data, DHS)




(a) Country data

(b) District data

*Source:* ILO UN STATS, DHS, and NASA SEDAC
Labor force non-participation is measured by unemployment in panel (b) with DHS data.
Population density in 2000, measured in logs, is predicted by FAO GAEZ potential crop yields. For DHS, first administrative unit (state) fixed effects and survey year effects are partialled out prior to nonparametric estimation using the Robinson (1988) procedure.

We subject the preceding facts to closer scrutiny with DHS data. Rural employment rates, which are closely related to labor force participation rates, can be constructed at the district (second administrative unit) level with these data, which are available for eight Asian countries and 29 African countries at different points in time (see Appendix Table A1). Although there is now much greater overlap in population densities across regions in Figure 4b, the same patterns are observed: (i) there is a positive association between female unemployment and population density across districts in Asia but not Africa, and (ii) there is no association for the men in either region (see Appendix Figure C2b). Appendix Table C10 reports regressions corresponding to the DHS figures, showing that the slope of the association between FLFNP and population density is very similar for India and Asia.[25] To the best of our knowledge, the fact that Asian women in *more* agriculturally productive rural areas are *less* likely to participate in the labor force has not been previously documented in the literature. While the inter-regional differences in the FLFNP-population density association that we have documented have a status-based interpretation, other explanations are also available. In the section that follows, we systematically consider such explanations.

## 4.4 Alternative Explanations

The discussion in this section examines alternative (non-status) factors that have been proposed in the literature as determinants of female labor force participation in developing countries. While they could potentially coexist with the status mechanism and we will allow for their presence in the structural model, they do not explain the associations with population density that we have estimated.

[25] While the rural FLFNP-population density association may be very similar in India and the rest of Asia, the *level* of FLFNP is much higher in India. Other non-status determinants of FLFNP, such as gender norms, presumably contribute to this intra-regional difference.

**1. Income effects**: With economic development, there will be an increase in household income. Female leisure or, equivalently, FLFNP could then rise on account of this income effect (Goldin, 1994). The same mechanism could potentially apply across districts in the cross-section if (potential) incomes are increasing in population density. One strategy to rule out income effects is based on the idea that the status mechanism only affects FLFNP. In contrast, income effects apply to both males and females. Male wages are significantly higher than female wages, and women contribute disproportionately to home production. As a result, the magnitude of the income effects could vary by gender. However, the absence of an economically meaningful association between male labor force non-participation and population density, as documented across Indian and Asian districts, would appear to rule out this alternative mechanism. A second, more direct, strategy to rule out income effects is to include potential incomes, suitably instrumented, in the estimating equation. Recall that the FLFNP-population density association across Indian districts is retained in Appendix Table C4 when the potential income variables, $\overline{y}$ and $\Delta y$, are included as covariates.

We see in Appendix Table C4, with FLFNP as the dependent variable, that the coefficient on $\overline{y}$ is positive and significant, while the coefficient on $\Delta y$ is negative and significant. In contrast, with male labor force non-participation as the dependent variable, the coefficient on $\overline{y}$ is positive and significant, but six times smaller than the corresponding coefficient with FLFNP as the outcome. More importantly, the coefficient on $\Delta y$ is *positive*, small in magnitude, and insignificant. The specification in Appendix Table C4 is the same as in Table 1, except that district fixed effects are replaced by population density and its interaction with the time trend. Our rejection of the model's implications with male labor force non-participation as the dependent variable serves as a useful placebo test of the status mechanism, and also provides independent evidence that income effects are not responsible for the results in Table 1. Following the argument above, if income effects were driving our results, then we would expect to observe qualitatively similar estimates for males and females.

**2. Demand for female labor**: The demand for female labor in agriculture will depend on geo-climatic conditions. For example, it is well known that this demand has historically been higher in Africa than in Asia due to differences in growing conditions (Boserup, 1970). Historical work patterns could, in addition, have crystallized into gender norms that continue to shape female labor force participation today (Alesina et al., 2013). A similar argument, based on exogenous variation in growing conditions, has been used to explain differences in the demand for female agricultural labor across Indian districts (Carranza, 2014). With the onset of economic development, new manufacturing jobs will open up. The demand for female labor in these jobs could also vary across space at early stages of economic development (Goldin, 1994).

If the demand for female labor is decreasing in more densely populated districts in India (and Asia), as argued by Boserup (1970), then this would explain why women residing in these districts are less likely to work, with an accompanying decline in the equilibrium wage. In contrast, if women are less likely to work due to a supply-side constraint associated with the status mechanism, then female wages should be *increasing* in population density. The NSS reports wages for women who work for pay (see Appendix A for details) and we see in Appendix Table C6 that there is a positive and significant association between wages and population density. This positive association is also obtained separately for high caste and low caste women.

**3. Female labor supply**: We posit that female labor supply in more densely populated districts is constrained due to the status mechanism. However, there could be other constraints on labor supply. For example, increases in female education with economic development have been seen to raise labor supply (Heath and Jayachandran, 2017). If more densely populated districts have lower female education, then this could explain the positive association between FLFNP and population density that we have uncovered. As seen in Appendix Table C6, however, female education (see Appendix A for details) is *increasing* in population density. This result is obtained for high castes and low castes.

Apart from human capital, demographic characteristics can also affect female labor supply. It has been hypothesized that marriage and accompanying home production (child care) could be responsible for the withdrawal of women from the workforce in developing economies (Goldin, 1994; Afridi et al., 2018). If marriage rates or fertility rates are increasing in population density, then the observed positive association with FLFNP could be obtained without a role for status. While the NSS provides information on each adult and child in the household, it does not link mothers to their children.[26] We thus turn to the DHS, which provides information on marriage and fertility for a nationally representative sample of women. We begin in Appendix Table C7 by verifying that there is a positive and significant association between female unemployment and population density, measured at the district level, with the DHS data.[27] However, there is no association between population density and either marriage rates or fertility (measured by the number of surviving children or the number of children ever born).

**4. Gender norms**: While the preceding discussion has focussed on economic and demographic factors, traditional gender norms have also been seen to determine female labor force participation in India. These norms determine a woman's status within her household, which, in turn, determines her decision-making power and autonomy (Srinivas, 1977; Basu, 1992; Chakravarti, 1993). The presumption in the gender norms literature is that women would like to work for pay, but their low status on account of the norms, keeps them at home. Spatial variation in women's status could then explain the positive association between FLFNP and population density. High caste women traditionally had low status within their households (Srinivas, 1977; Chakravarti, 1993). This would explain the additional observation that high caste women are less likely to work.

Gender norms and social status are directly related. In particular, the norm that upper caste, high-status, women traditionally did not work serves as a focal point in the status game between castes that subsequently commences with economic development. One way to disentangle these coexisting mechanisms would be to examine the dynamics of FLFNP. We would expect the gender norms to weaken over time, whereas the status effect could grow stronger with economic development. The structural estimates reported in Section 5 are in line with this prediction. To disentangle these mechanisms in the cross-section, we proceed to examine decision-making and autonomy within the household, which determines women's status but not social status. The DHS elicits information from female respondents about their decision-making power. As seen in Appendix Table C7, the fraction of women who report they have a say with regard to household decisions about health and expenditures, and who do not need permission to visit their relatives,

[26]The NSS household roster reports the relationship between the head and each member, but this does not link mothers to their children in joint families, which are common in India.

[27]The DHS collects information on employment rather than labor force participation (see Appendix A) but these variables are highly correlated in practice. Restricted-use DHS data, which we utilize for the analysis, provide geo-codes for each survey cluster, which can be mapped to the district in which it is located.

is independent of population density. Appendix Table C8 reports estimates with measures of autonomy obtained from the India Human Development Survey (IHDS) where we see, once again, that there is no association with population density.[28] There is no evidence that women's status is declining with population density, although we note that this evidence is based on a limited set of outcomes and the crop suitability instruments have less statistical power with DHS and IHDS data.

Taking a different approach, our results on vegetarianism and teetotalism, particularly the positive association between these variables and population density for the upwardly mobile lower castes, provide additional and independent support for the social status mechanism. Agte and Bernhardt (2023) exploit a different source of exogenous cross-sectional variation to document that upper castes are less likely to make choices that are traditionally associate with their high status – FLFNP, vegetarianism, teetotalism – when their incomes are relatively low.[29] However, this could simply reflect a weakening of their caste identity, as in Atkin et al. (2021). To uncover the social status mechanism, an ethnic group must be seen to adopt the traditional behaviors of a *higher* status group, when the value of status is high, as we document in our data.[30]

# 5 Quantitative Analysis

The empirical tests thus far have been based on the qualitative implications of the model. The next step in the analysis is to estimate its structural parameters. After evaluating the model fit, we will use the estimated model to (i) validate the assumption that the value of status is increasing in population density, and (ii) conduct counterfactual analyses that shed light on the factors that are responsible for the increase in FLFNP over time, with implications for policy.

In our analytical model, households choose the signaling cost, which we measure in practice by FLFNP, taking potential incomes (and market wages) as given. When testing the implications of this model, we accounted for the reverse effect of FLFNP on wages by instrumenting for them. For the counterfactual policy analysis mentioned above, we will want to allow for general equilibrium effects and so wages will be endogenized in the structural model. Since we are also interested in making sense of the positive association between FLFNP and female education, as documented in Figure 1, we will add education choice to the structural model, which implies that potential income is also endogenously determined.

## 5.1 Structural Estimation

**Set up of the model**: As in the analytical model, the household consists of a male and a female member, each of whom is endowed with a single unit of time. In addition, we now specify that household $i$ belonging

[28] The IHDS is a nationally representative survey of households that was conducted in 2005 and 2011. Data from the second round can be used to construct measures of FLFNP, vegetarianism and teetotalism. Matching the core NSS results, we see in Appendix Table C9 that each of these variables is positively associated with population density.

[29] In our model, an exogenous narrowing of the income endowment gap increases FLFNP in both caste groups. While this would appear to be at odds with Agte and Bernhardt's findings, we note that their analysis is situated in a very unusual setting in which Scheduled Tribes have substantially *higher* income than upper castes. Our model, in which upper castes always have higher incomes than lower castes, does not apply to such a setting.

[30] Atkin et al. (2021) also show that lower castes adopt a religious (upper caste) identity, with an increase in vegetarianism and teetotalism, at times of Hindu-Muslim conflict. However, such events are rare in practice and are unrelated to social status (within the Hindu population).

to caste $k$ can allocate each member's time to skilled tasks, $\xi_{i,kg}$, or unskilled tasks, $(1-\xi_{i,kg})$. Skilled tasks require investments in education, which cost $e_{kg}(\xi_{i,kg})$.[31] The household's potential income can then be expressed as follows:

$$y_{i,k} = \sum_{g} w_{skg}\xi_{i,kg} + w_{ukg}(1-\xi_{i,kg}) - e_{kg}(\xi_{i,kg}) \tag{17}$$

where $w_{skg}$, $w_{ukg}$ are the wages faced by the household, which vary by skill, caste, and gender in each district-time period.[32]

The household's expenditure on status signaling, by skill, can be expressed as follows:

$$c_{i,sk} = w_{skf}\xi_{i,kf}\tau_{i,sk}\eta_{sk} \tag{18}$$

$$c_{i,uk} = w_{ukf}(1-\xi_{i,kf})\tau_{i,uk}\eta_{uk}, \tag{19}$$

where $\tau_{i,sk}$, $\tau_{i,uk}$ are the fractions of the skilled-task time and the unskilled-task time that are withdrawn from the labor market for the female member of household $i$. The $\eta_{sk}$, $\eta_{uk}$ parameters, which are positive, incorporate a number of factors: (i) the utility from leisure for a woman who is withdrawn from the labor market, (ii) the value of her home production, (iii) gender norms that restrict female labor force participation and thus effectively dampen the cost to the household of keeping the woman at home, and (iv) The consumption disutility associated with complementary behaviors such as vegetarianism and teetotalism, which will amplify the monetary cost of FLFNP. If (iv) dominates (i), (ii) and (iii), then $\eta_{sk}$, $\eta_{uk}$ will be greater than one, whereas if the converse is true, these parameters will be less than one. Notice that $\eta_{sk}$, $\eta_{uk}$ vary by skill and caste group, since an educated woman could contribute more to home production (child rearing) and gender norms vary by caste, as discussed in Section 4.

**Solving for education and FLFNP, taking wages as given**: Household $i$ chooses $\xi_{i,kg}$, $c_{i,sk}$, $c_{i,uk}$, which in turn determine $\tau_{i,sk}$, $\tau_{i,uk}$ from equations (18) and (19), to maximize its utility:

$$U = \log(y_{i,k} - c_{i,sk} - c_{i,uk}) + \frac{\mathbb{C}_k}{\mathbb{C}_k + \mathbb{C}_{-k}} \frac{N_k + N_{-k}}{N_k} v \tag{20}$$

where $c_{i,k} = \left(c_{i,sk}^{\phi} + c_{i,uk}^{\phi}\right)^{1/\phi}$ and $\mathbb{C}_k = \sum_i c_{i,k}$. Note that this specification of the signaling cost allows the skilled and unskilled costs, $c_{i,sk}$ and $c_{i,uk}$, to enter as substitutes or complements in the status function.

The utility function specified in (20) is the same as the corresponding function in the analytical model, as described by (1), except that the household separately chooses skilled and unskilled signaling costs, and group sizes vary, since we are now interested in matching the model to the data. There are $N_k$ households in group $k$ and $N_{-k}$ households in group $-k$, but the status function in equation (20) still satisfies the required budget-balance conditions: (i) Each household receives $v$ when all households make the same signaling choice. (ii) If households in group $-k$ incur no signaling costs, then group $k$ households receive $v \cdot (N_k + N_{-k})/N_k$.

[31] We allow the cost of education to vary by ethnicity (caste in this case) and gender, as in Hsieh et al. (2019). This generates differences in education levels, by caste and gender, as observed in our data.

[32] In contrast, we let wages vary by caste, gender, and the household's primary occupation in Section 3. This is because we were estimating the wage response to rainfall shocks (our instrument) in that section, and this response will vary by the type of occupation in an agrarian economy.

To derive educational choices, we maximize $U$ in (20) with respect to $\xi_{i,kg}$, after substituting the expression for $y_{i,k}$ from (17). Specifying that the cost of education is a quadratic function, $e_{kg}(\xi_{i,kg}) = \beta_{1,kg}\xi_{i,kg} + \beta_{2,kg}\xi_{i,kg}^2$, and making the symmetry assumption once the first-order condition is derived, as we did when solving the analytical model, we obtain:[33]

$$\xi_{kg} = \frac{(w_{skg} - w_{ukg}) - \beta_{1,kg}}{2\beta_{2,kg}} \tag{21}$$

Although education choices are made long before the individual enters the labor market, there is no uncertainty in the model and, hence, $\xi_{kg}$ is determined by $w_{skg}$, $w_{ukg}$, where $w_{skg} > w_{ukg}$. As with the tests of the analytical model in Section 3, we assume that these choices at the intensive margin by the representative household map into district-time period outcomes once *ex post* lotteries are introduced. $\xi_{kg}$ can thus be interpreted as the fraction of educated individuals, measured in practice by the fraction of individuals who have completed secondary schooling, by caste-gender.

The education levels that we have derived as functions of wages in equation (21) can be plugged into the expression for the representative household's potential income (equation (17) without the $i$ subscripts). We take this potential income, $y_k$, as given, when solving next for the signaling costs, $c_{sk}$ and $c_{uk}$. To derive these costs, we follow the same steps that we took with the analytical model (see Appendix D for details). The first step is to maximize $U$ in (20) with respect to $c_{i,sk}$ and $c_{i,uk}$. Making the symmetry assumption as usual, the two first-order conditions are shown to imply that

$$c_{sk} = c_{uk}. \tag{22}$$

As discussed in Appendix D, the $\phi$ parameter plays a key role in generating this result. If this parameter was equal to one and the signaling costs entered additively in the status function, then we would be unable to solve separately for $c_{sk}$ and $c_{uk}$. At the same time, it conveniently drops out of the equations that follow. The $\phi$ parameter could thus be arbitrarily close to one in practice, in which case the skilled and unskilled signaling costs would be (close to) perfect substitutes.

Since $c_{sk} = c_{uk}$, one of the first-order conditions that we derived above is redundant. We thus select one of them and substitute $c_{sk} = c_{uk}$ to obtain:

$$\frac{1}{y_k - 2c_{sk}} = \frac{c_{-sk}N_{-k}}{(c_{sk}N_k + c_{-sk}N_{-k})^2} \cdot \frac{N_k + N_{-k}}{N_k} \cdot \frac{v}{2} \tag{23}$$

Notice the similarity between this equation and equation (2) in Section 2. Following the same steps as in that section, we construct an equation corresponding to (23) for the $-k$ group, with $k$ and $-k$ subscripts reversed, and then divide the two resulting equations to derive an expression for $c_{-sk}$ as a function of $c_{sk}$:

$$c_{-sk} = \frac{c_{sk}y_{-k}N_k^2}{B(c_{sk})} \tag{24}$$

where $B(c_{sk}) \equiv y_k N_{-k}^2 + 2c_{sk}(N_k^2 - N_{-k}^2)$. Without loss of generality, let $N_k > N_{-k}$, which implies that

[33]Note that female education, $\xi_{i,kf}$ also enters the status function in (20) through the $c_{i,sk}$, $c_{i,uk}$ terms, but the associated partial derivatives drop out due to the Envelope Condition: $\frac{\partial U}{\partial c_{i,sk}} \cdot \frac{\partial c_{i,sk}}{\partial \xi_{i,kf}} = \frac{\partial U}{\partial c_{i,uk}} \cdot \frac{\partial c_{i,uk}}{\partial \xi_{i,kf}} = 0$.

$B'(c_{sk}) > 0$. Substituting the expression for $c_{-sk}$ from (24) in (23), and rearranging terms, we finally arrive at an equation that can be used to solve for $c_{sk}$:

$$\frac{c_{sk}\left[B(c_{sk}) + y_{-k}N_k N_{-k}\right]^2}{B(c_{sk})y_{-k}N_{-k}} = (y_k - 2c_{sk}) \cdot \frac{N_k + N_{-k}}{N_k} \cdot \frac{v}{2} \tag{25}$$

Since $N_k$ is assumed to be greater than $N_{-k}$, the $k$ group corresponds to the majority $H$ caste and $-k$ corresponds to the minority $L$ caste in equations (23)-(25). The first challenge that arises when solving equation (25) is that $N_H$, $N_L$, which are measured at the village level (since the status game is played at that level) are not observed. However, the NSS does provide the share of low caste households, and the complementary share of high caste households (which is 69% on average) in each district. Assuming that the caste distribution is homogeneous across villages within a district in each NSS round, we can rewrite the preceding equation in terms of $f \equiv N_H/N_L$, which is observed:

$$\frac{c_{sH}\left[B(c_{sH}) + y_L f\right]^2}{B(c_{sH})y_L} = (y_H - 2c_{sH}) \cdot \frac{f+1}{f} \cdot \frac{v/N_L}{2} \tag{26}$$

where $B(c_{sH}) \equiv y_H + 2c_{sH}(f^2 - 1)$ and $B'(c_{sH}) > 0$. We will thus estimate $\widetilde{v} \equiv v/N_L$ rather than $v$, but this has no bearing on the analysis.

We are able to derive a closed-form expression for the signaling cost in Section 2 because group sizes are equal in the analytical model. With the more general specification of the structural model, equation (26) must be solved numerically to derive $c_{sH}$. As shown in Appendix D, a unique solution for the signaling cost, with $c_{sH} \in (0, y_H/2)$, nevertheless exists.[34] Once we have solved for $c_{sH}$, we can derive $c_{sL}$, $c_{uH}$, $c_{uL}$ from equations (22) and (24).[35] This, in turn, allows us to derive $\tau_{sk}$, $\tau_{uk}$, for $k \in \{H, L,\}$ from equations (18) and (19), suitably modified to apply to the representative household by dropping the $i$ subscripts. The fraction of time that is withdrawn from the labor market at the intensive margin, $\tau_{sk}$, $\tau_{uk}$ maps into FLFNP, by skill, at the district-time period level, once we introduce *ex post* lotteries at the household level. Note that signaling costs and, hence, FLFNP are derived as functions of potential incomes in the equations above. These incomes, in turn, are functions of wages from equations (17) and (21).

**Solving for wages, taking education and FLFNP as given**: For the purpose of the structural model, we assume that the status game is played in each village between a finite number of households, while the wage is determined competitively at the district level. Assuming as above that the caste distribution does not vary across villages within a district-time period, each village has a fraction $x_L = \frac{N_L}{N_L + N_H}$ low-caste households and there is a corresponding mass $x_L$ of low caste households in that district, with $x_H \equiv 1 - x_L$. We assume that output in the district-time period is determined by a linear aggregate production function: $Y = AE$, where $A$ is total factor productivity and $E$ is aggregate labor. Labor is heterogeneous along three dimensions: gender, caste, and skill. We thus use a nested-CES structure, as in Card and Lemieux (2001),

[34] We show that the left hand side of equation (26) is monotonically increasing in $c_{sH}$ and cuts the right hand side, which is evidently decreasing in $c_{sH}$, from below.

[35] Note that equation (24) can also be rewritten in terms of $f$: $c_{sL} = \frac{c_{sH} y_L f^2}{B(c_{sH})}$.

Ottaviano and Peri (2012), to aggregate the different components of labor:

$$
\begin{aligned}
E &= \left[\theta_f E_f^{\rho} + \theta_m E_m^{\rho}\right]^{\frac{1}{\rho}} \\
E_g &= \left[\theta_{Lg} E_{Lg}^{\rho_g} + \theta_{Hg} E_{Hg}^{\rho_g}\right]^{\frac{1}{\rho_g}}, \quad g = \{f, m\} \\
E_{kg} &= \left[\theta_{skg} E_{skg}^{\rho_{kg}} + \theta_{ukg} E_{ukg}^{\rho_{kg}}\right]^{\frac{1}{\rho_{kg}}}, \quad k = \{H, L\} \\
E_{skf} &= \xi_{kf}(1 - \tau_{sk})x_k, \quad E_{ukf} = (1 - \xi_{kf})(1 - \tau_{uk})x_k \\
E_{skm} &= \xi_{km} x_k, \quad E_{ukm} = (1 - \xi_{km})x_k
\end{aligned}
$$

The labor productivity parameters vary by caste and gender, conditional on skill, in the preceding specification. This could be due to (i) discrimination by ethnicity (caste) and gender, as also assumed by Hsieh et al. (2019), (ii) an identity-based preference for caste-specific traditional occupations (Cassan et al., 2021; Oh, 2023) or the presence of caste networks in particular, not necessarily traditional, occupations (Munshi, 2019), and (iii) differences in land ownership and productivity by caste.[36] While we thus allow for market frictions, the assumption is that labor is allocated efficiently within a district-time period, conditional on the differences in productivity.[37] The wage for each skill-caste-gender category is thus determined by the associated marginal productivity of labor:

$$
w_{skg} = \frac{\partial Y}{\partial E_{skg}} = \frac{\partial Y}{\partial E} \times \frac{\partial E}{\partial E_g} \times \frac{\partial E_g}{\partial E_{kg}} \times \frac{\partial E_{kg}}{\partial E_{skg}} \tag{27}
$$

$$
w_{ukg} = \frac{\partial Y}{\partial E_{ukg}} = \frac{\partial Y}{\partial E} \times \frac{\partial E}{\partial E_g} \times \frac{\partial E_g}{\partial E_{kg}} \times \frac{\partial E_{kg}}{\partial E_{ukg}}. \tag{28}
$$

As shown in Appendix D, $w_{skg}$ and $w_{ukg}$ can be derived as functions of $E$, $E_g$, $E_{kg}$, and $E_{skf}$ or $E_{ukf}$ from equations (27) and (28). These variables are, in turn, determined by the education investment, $\xi_{kg}$, and the time withdrawn from the skilled-task and unskilled-task endowments, $\tau_{sk}$, $\tau_{uk}$, in the aggregate production function specified above.

**Solving and estimating the general equilibrium model**: As discussed in Section 4, (predicted) population density proxies for exogenous agricultural productivity, which, in turn, determines the value of status. This variable thus serves as the source of exogenous variation in the structural model, with both total factor productivity, $A$, and the value of status, $v$, specified as flexible power functions of population density. The model is estimated separately in each of the five "thick" NSS rounds: 1987, 1999, 2003, 2009,

[36] The amount of labor allocated to their own land by cultivators depends on the shadow price of their labor (the market wage) and the productivity of their land. The market wage, in turn, is determined by equilibrating the marginal value product of labor supplied for own cultivation and to the labor market within caste categories (under the assumption that the labor market is segmented by caste). Since upper castes own more productive land and are more likely to own land, the equilibrium wage and, by extension, the productivity parameters will vary by caste. We do not include land as a factor in the aggregate production function because caste-specific information on land ownership is only available in the 2003 NSS round.

[37] Hsieh et al. (2019) introduce a wedge between marginal productivity and the realized wage that is ethnicity (race) and gender specific, while assuming that productivity is the same in all groups. Regardless of the way in which distortions are introduced, market clearing wages will vary by ethnicity and gender in equilibrium.

and 2011. In each round, we construct a log population density grid, such that each grid interval contains an equal number of districts. The number of intervals is set at 20.[38] In each population density interval, given $A$, $v$, and the structural parameters, we can solve for the endogenous variables in the model using the following algorithm:

**Step 1.** Guess $w_{skg}$, $w_{ukg}$

**Step 2.** Given $w_{skg}$, $w_{ukg}$ from Step 1, solve for $\xi_{kg}$, $\tau_{sk}$, $\tau_{uk}$, as in the partial equilibrium analysis described above.

**Step 3.** Given $\xi_{kg}$, $\tau_{sk}$, $\tau_{uk}$ derived in Step 2, solve for $w_{skg}$, $w_{ukg}$, as also described above.

Use $w_{skg}$, $w_{ukg}$ derived from Step 3 as the guess in Step 1 for the next iteration and continue to iterate in this way until there is convergence; i.e. the guess in Step 1 matches the wages derived in Step 3.

The algorithm described above allows us to solve the 16 endogenous variables in the model in each population density interval, which gives us 320 model moments in each round.[39] To estimate the structural parameters, we compare these moments with the corresponding data moments. We search over all parameter values, using an algorithm described in Appendix D, to find the set of parameters that minimizes the (percentage) difference between the data moments and the model moments. There are 37 structural parameters, listed in Appendix Table D1, and 320 moments for matching, leaving us with sufficient degrees of freedom for estimation in each survey round.

## 5.2 Model Fit and the Value of Status

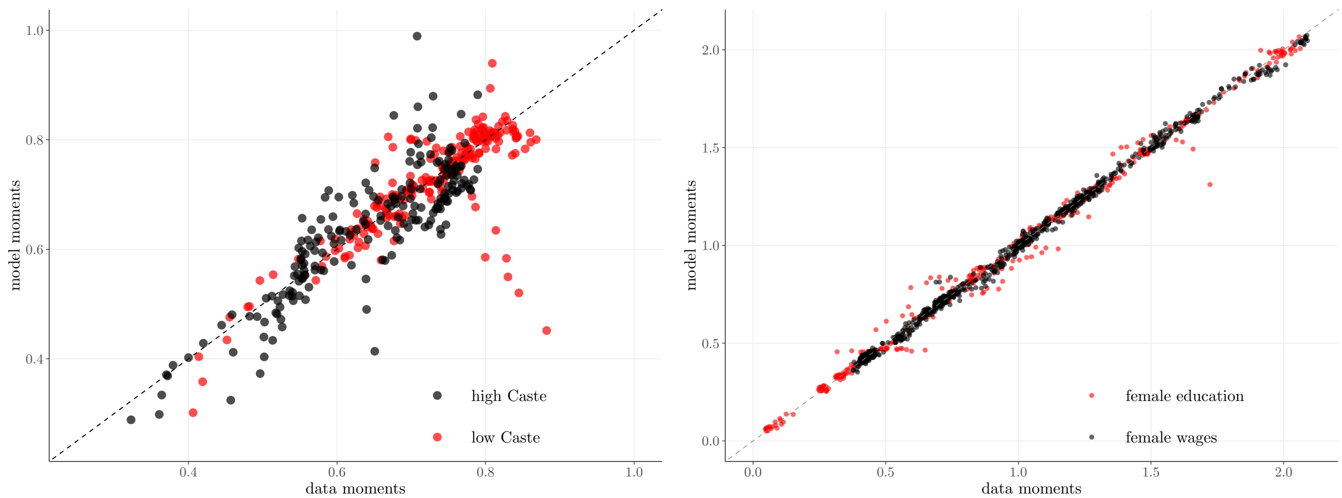
We match 320 data moments and model moments, as closely as possible, when estimating the structural parameters in each survey round. With five survey rounds, this leaves us with 1600 moments. Given the large number of moments, we first follow Oswald (2019), Heise and Porzio (2022), and take a graphical approach to report the model fit. Figure 5 plots that model moment on the $y$ axis that corresponds to each data moment (on the $x$ axis). If the moments match perfectly, then all points would lie on the 45 degree line. Figure 5a reports the goodness of fit for the FLFNP moments, separately by caste. Figure 5b reports the corresponding graph for the education and wage moments, combining castes and genders. For completeness, we report the education and wage moments separately by caste and gender in Appendix Figures D1 and D2. We see in the figures that (almost) all points are tightly clustered around the 45 degree line. Despite the model's parsimonious structure – we estimate 185 parameters by targeting 1600 moments across all survey rounds – it still fits the data very well.

While the graphical approach allows us to include all targeted moments in the figures that we present, it does not tell us how the model fit varies in the cross-section with respect to (predicted) population density or over time across survey rounds. Figure 6a reports the association between population density and FLFNP, female education, and female wages in the last (2011) NSS round. We see that all three outcomes are increasing in population density, and that the model matches the data across the range of

[38] The number of intervals we have chosen trades off two considerations: as the number of intervals increases, we will pick up finer grained variation in the data, but the precision of our estimated data moments will also decline.

[39] There are 4 education variables, corresponding to $\xi_{kg}$, 4 FLFNP variables, corresponding to $\tau_{sk}$, $\tau_{uk}$, and 8 wage variables, corresponding to $w_{skg}$, $w_{ukg}$.

Figure 5: Comparing model and data moments




(a) Female labor force non-participation

(b) Female education and wages

*Note:* NSS "thick rounds" and 1951 population census are used to estimate the structural model.
Since education and wages have different means, the data and model moments are divided by the mean of the relevant variable (at the caste-gender-time period level) in Figure 5b.

population densities. The cross-sectional associations that we document in 2011 are also observed in the first (1987) NSS round, with the model closely matching the data, as reported in Appendix Figure D3a.

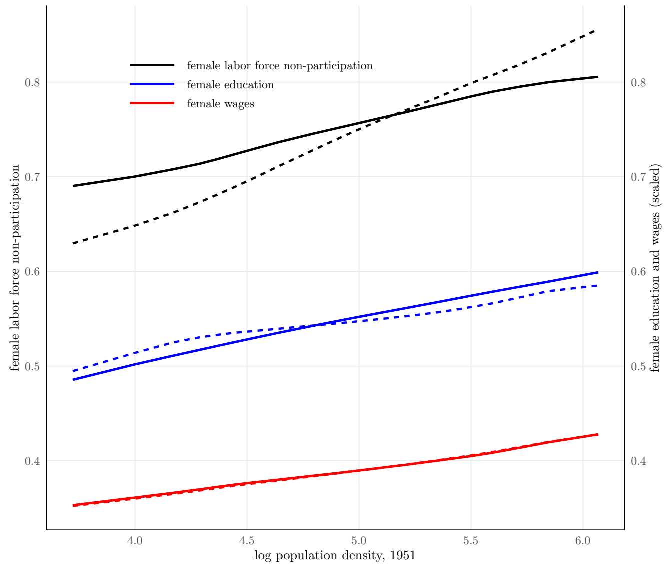
As discussed in Section 4, we are unaware of a non-status explanation for the positive FLFNP-population density association. Turning, therefore, to the status mechanism, either an increase in $v$, which we measure by $\tilde{v}$, an increase in $\overline{y}$, or a decline in $\Delta y$ with population density could generate this association. As seen in Figure 6b and Appendix Figure D3b, $\tilde{v}$ is increasing in population density in 2011 and 1987. While this result helps explain the positive FLFNP-population density association, it also provides independent support for the hypothesis put forward in Section 4 that the value of status is increasing in population density (agricultural productivity).[40] Turning to the remaining status factors in the figures, $\overline{y}$ is seen to be increasing in population density and, therefore, also contributing to the positive FLFNP-population density association, but $\Delta y$ is independent of the latter variable. The preceding discussion tells us that particular social status factors contributed to the variation in FLFNP in the cross-section. The analysis that follows will examine how these roles changed over time.

## 5.3 Changes in FLFNP Over Time

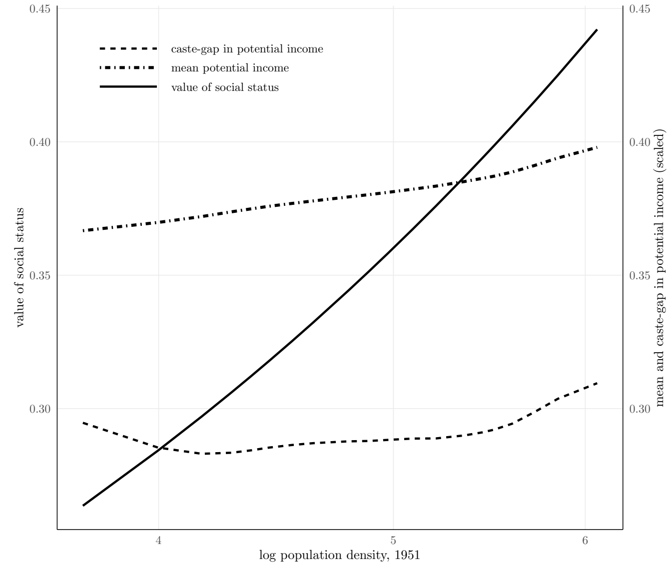
Figure 7a plots the change in aggregate FLFNP over NSS rounds. FLFNP is increasing over time and we see that the model matches the data very closely, as it did in the cross-section. For completeness, Appendix Figure D4a examines the fit of the model with respect to female education and wages. These statistics are

[40] Recall that $\tilde{v}$ is defined as $v$ divided by $N_L$, where $v$ is the value of status and $N_L$ is the number of low caste households in the village. The latter statistic is also increasing in population density, by construction. It follows that if $\tilde{v}$ is increasing in population density, then $v$ will also be increasing in that variable. Although we do not report the association between the aggregate productivity, $A$, parameter and population density for expositional convenience, this association is also positive as assumed in the model.

Figure 6: Model fit and status factors in the cross-section (2011)




(a) FLFNP, female education, and female wages




(b) Status factors

*Note:* NSS "thick" rounds and 1951 population census are used to estimate the structural model.
Solid lines denote the data and dashed lines denote model predictions in Figure 6a.
The value of social status is measured by $\tilde{v} \equiv v/N_L$ in Figure 6b, where $v$ is the value of social status and $N_L$ is the number of low caste households in the village.

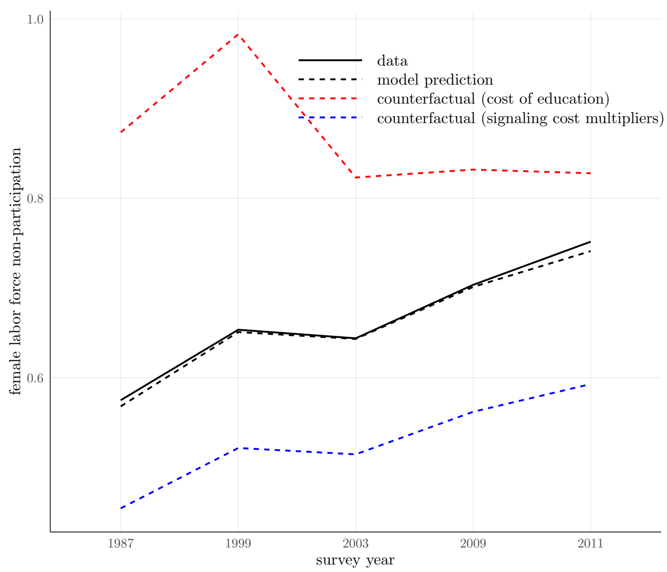
also increasing over time and our model can fit these trends extremely well.

The positive FLFNP trajectory that we document in Figure 7a can be generated by the structural model, holding constant the status effect, if the $\eta$ parameters change over time (across NSS rounds). Recall that these parameters incorporate the following factors: (i) the utility from female leisure, (ii) the value of home production, (iii) gender norms, and (iv) the consumption disutility associated with vegetarianism-teetotalism. If the $\eta$ parameters decline over time, then $\tau$ (FLFNP) will increase to maintain the equilibrium level of the signaling cost.

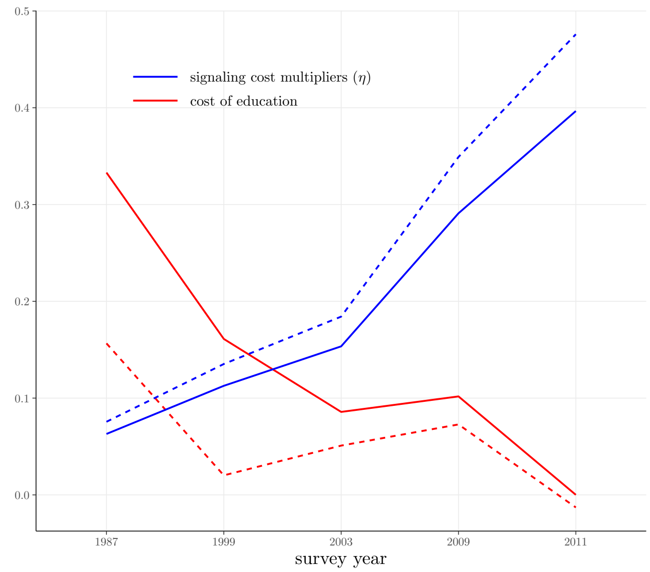
Figure 7b reports the change in $\eta$ (averaged across castes and skill levels) over NSS rounds. The first observation is that $\eta$ is less than one. This implies that (i), (ii), (iii) above, which make FLFNP less costly to the household, dominate (iv), which works in the opposite direction. The second observation is that $\eta$ is *increasing* over time. As an economy develops and household incomes increase, we expect to see an increase in female leisure and an increase in the returns to investing in children's human capital. These changes will shift the $\eta$ parameters down. We posit that the mechanism that is driving the increase in $\eta$ is a weakening in traditional gender norms, which effectively increases the cost of FLFNP and, hence, $\eta$, and we will return to this point below.

Based on the preceding discussion, changes in $\eta$ cannot explain the increase in FLFNP over time. As with the cross-sectional analysis, this leaves us with the status mechanism. We unpack this mechanism into its three components – $\tilde{v}$, $\overline{y}$, and $\Delta y$ – and see how they changed over time. As seen in Appendix Figure D4b, $\tilde{v}$ and $\overline{y}$ are increasing over time and thus responsible for the increase in FLFNP. The increase in $\tilde{v}$ over time is presumably driven by an improvement in the quality of scarce amenities and, hence, the value of status

Figure 7: Counterfactual policy simulations




(a) FLFNP: data, model prediction, and counterfactuals




(b) Signaling cost multipliers ($\eta$) and cost of education

*Source:* NSS "thick rounds" and 1951 population census are used to estimate the structural model.
Counterfactual FLFNP in Figure 7a is based on a 25% increase in the $\eta$ parameters and a 25% reduction in the quadratic cost of education parameter, $\beta_2$, shown by the dashed lines in Figure 7b.
Cost of education in Figure 7b is constructed by fixing education, by caste-gender, at its 2011 level in all periods.

with economic development, while the increase in mean potential income $\overline{y}$ is generated by an underlying increase in aggregate TFP, $A$ (not reported). While shocks to the caste-gap in potential incomes $\Delta y$ helped us identify a status effect in Section 3, this factor is less useful in explaining variation in FLFNP in the cross-section and over time.[41] The status-based factors underlying the increase in FLFNP that we have uncovered are natural consequences of economic development: incomes ($\overline{y}$) will increase, and so will the competition for increasingly valuable amenities ($v$) as an economy grows. In the long run, markets will thicken and expand, and the status mechanism will ultimately be less relevant. In the interim period, however, it is important to implement policies that will reduce FLFNP in an environment where an underlying status motivation is present, and we next use the estimated model to examine such policies.

The first policy that we consider, follows Goldin (1994) who posits that increasing female education at later stages of economic development encourages women to enter the labor force. Figure 7b reports the average estimated female cost of education, combining both caste groups, in each survey round. We see that this cost has been declining over time. Our policy experiment reduces the quadratic cost of education parameter, $\beta_2$, by an additional 25% in each time period.[42] We see that this results in an *increase* in

[41]Hnatkovska et al. (2012) document, using NSS data, that education levels for low castes and high castes have converged over time. Our estimates of the cost of education also reveal such convergence (not reported). However, many factors determine potential income and on net we do not observe a convergence in potential incomes over time.

[42]Given the separability in the cost of education function, a 25% reduction in the cost can be generated by reducing both the linear parameter ($\beta_1$) and the quadratic parameter ($\beta_2$) by that amount. However, $\beta_1$ is negative in some caste-gender-time periods, and it is straightforward to verify from equation (21) that a reduction in the (absolute) value of $\beta_1$ could then lead to a decline in the level of education. The $\beta_2$ parameter is always positive and so reducing its value unambiguously increases the level of education.

FLFNP in Figure 7a. Based on the model, this increase can be explained by the fact that the decline in the cost of education, together with the accompanying increase in education with its higher wages, would have increased *potential* household incomes. This, in turn, would have increased investments in the status game and, hence, signaling costs, with an accompanying increase in FLFNP.[43] Circling back to Figure 1, which motivated our analysis, the decline in the cost of education over time that we have just documented would have increased female education, as observed. The resulting increase in potential income would have increased the growth in FLFNP even further.

Our second counterfactual exercise increases the $\eta$ parameters by 25% in each period in Figure 7b. Following the argument made above, an increase in $\eta$ will result in a decline in $\tau$ (FLFNP) to maintain the equilibrium level of the signaling cost. This is what we observe in Figure 7a. Some components of $\eta$, such as the value of female leisure and the consumption disutility from vegetarianism-teetotalism are associated with preferences and are, therefore, less amenable to policy levers. Another component, the value of home production (child rearing) is likely increasing with economic development. While this would have led to a decline in $\eta$ over time, with an accompanying increase in FLFNP, it is not clear that policies that attempt to reverse this trend would be welfare enhancing. This leaves us with the final component, gender norms, whose weakening with economic development was seen to be responsible for the estimated increase in $\eta$ over time in Figure 7a. Based on our model and the counterfactual analysis, policies that weaken gender norms even further could substantially reduce FLFNP if designed correctly, and we will return to this point below.

## 6 Conclusion

This research provides a status-based explanation for the high rates of female labor force non-participation (FLFNP) and the increase in these rates over time, that have been documented in many developing economies. This explanation is based on the idea that households or ethnic groups can signal their wealth, and thereby increase their social status, by withdrawing women from the labor force. Higher status provides preferred access to non-market goods and services, which is especially valuable in developing economies. While status considerations will ultimately cease to be relevant, the value of status and the willingness to bear the signaling cost could increase in the medium term as an economy develops. This argument helps explain why FLFNP, which was high to begin with, has increased even further in countries like India.

To provide empirical support for the preceding argument, we first establish that there is a link between rural FLFNP and social status, across Indian districts in the cross-section and within districts over time. We then estimate the structural parameters of the model that is used to derive these tests. Based on the estimated parameters, the observed increase in FLFNP over time is largely driven by underlying increases in the value of status and mean income (which increases the willingness to bear the signaling cost). While these changes are a natural consequence of economic development, we would still want to design policies that will reduce FLFNP, since status considerations are likely to remain relevant for the foreseeable future.

The first policy simulation that we consider is based on an exogenous reduction in the cost of education and we find that this *increases* FLFNP. This is because potential household incomes increase and this, in

[43] A decline in the cost of education for both castes will also change $\Delta y$, but in a way that is not systematic and thus simply adds noise to the counterfactual prediction.

turn, increases the competition for social status with its associated signaling costs. The more general message is that any incentive-based policy, such as a monetary bonus for women who work, that raises potential incomes could backfire in an economy where status considerations are relevant. The rapid increase in female education over time, which is a noteworthy feature of Indian economic development, could paradoxically have increased FLFNP even further. The second simulation that we consider is based on a policy that reduces the non-pecuniary constraints to female labor force participation; for example, by weakening gender norms. This effectively increases the signaling cost, without changing potential incomes, and results in a substantial *decline* in FLFNP.

While our analysis treats the household as a unitary decision-making unit, the literature on gender norms assumes that women would like to work for pay but are prevented from doing so on account of their weak bargaining position within the home. One strategy to strengthen their position would be to improve their outside options through remunerative employment, but such a strategy is difficult to implement in economies were status considerations are relevant. Wage employment is typically visible, and the household thus signals that it is less wealthy when the female members accept such employment. There is, however, a way to escape the high-FLFNP trap, with recent experimental evidence indicating that a two-step process in which jobs are first offered in-home, allowing gender norms to weaken, after which work outside the home is made available may be feasible (Ho et al., 2023). This intervention, which implicitly incorporates the constraints imposed by the status mechanism, suggests a promising way forward if it can be implemented at scale.

## References


Afridi, F., T. Dinkelman, and K. Mahajan (2018): "Why are fewer married women joining the work force in rural India? A decomposition analysis over two decades," *Journal of Population Economics*, 31, 783–818.

Agte, P. and A. Bernhardt (2023): "The Economics of Caste Norms: Purity, Status, and Women's Work in India," *Typescript*.

Ahmad, I. (1967): "The Ashraf and Ajlaf categories in Indo-Muslim society," *Economic and Political Weekly*, 887–891.

Alesina, A., P. Giuliano, and N. Nunn (2013): "On the origins of gender roles: Women and the plough," *The Quarterly Journal of Economics*, 128, 469–530.

Asher, S., K. Jha, P. Novosad, A. Adukia, and B. Tan (2024): "Residential segregation and unequal access to local public services in India: Evidence from 1.5 m neighborhoods," Tech. rep., Working Paper.

Asher, S., T. Lunt, R. Matsuura, and P. Novosad (2021): "Development research at high geographic resolution: An analysis of night-lights, firms, and poverty in India using the SHRUG open data platform," *The World Bank Economic Review*, 35.

Ashraf, Q. and O. Galor (2011): "Dynamics and stagnation in the Malthusian epoch," *American Economic Review*, 101, 2003–41.

Atkin, D., E. Colson-Sihra, and M. Shayo (2021): "How do we choose our identity? A revealed preference approach using food consumption," *Journal of Political Economy*, 129, 1193–1251.

Bagwell, L. S. and B. D. Bernheim (1996): "Veblen effects in a theory of conspicuous consumption," *The American Economic Review*, 349–373.

Basu, A. M. (1992): *Culture, the status of women, and demographic behaviour: Illustrated with the case of India.*, Clarendon press.

Boserup, E. (1970): *Woman's role in economic development*, George Allen and Unwin Ltd.

Bursztyn, L., B. Ferman, S. Fiorin, M. Kanz, and G. Rao (2018): "Status goods: Experimental evidence from platinum credit cards," *The Quarterly Journal of Economics*, 133, 1561–1595.

Cancian, F. (1976): "Social stratification," *Annual Review of Anthropology*, 5, 227–248.

Card, D. and T. Lemieux (2001): "Can falling supply explain the rising return to college for younger men? A cohort-based analysis," *The Quarterly Journal of Economics*, 116, 705–746.

Carranza, E. (2014): "Soil endowments, female labor force participation, and the demographic deficit of women in India," *American Economic Journal: Applied Economics*, 6, 197–225.

Cassan, G., D. Keniston, and T. Kleineberg (2021): "A division of laborers: Identity and efficiency in India," Tech. rep., National Bureau of Economic Research.

Chakravarti, U. (1993): "Conceptualising Brahmanical patriarchy in early India: Gender, caste, class and state," *Economic and Political Weekly*, 579–585.

Charles, K. K., E. Hurst, and N. Roussanov (2009): "Conspicuous consumption and race," *The Quarterly Journal of Economics*, 124, 425–467.

Cole, H. L., G. J. Mailath, and A. Postlewaite (1992): "Social norms, savings behavior, and growth," *Journal of Political economy*, 100, 1092–1125.

Diamond, J. M. (1998): *Guns, germs and steel: A short history of everybody for the last 13,000 years*, Random House.

Dupas, P., M. Fafchamps, and L. Hernandez-Nunez (2024): "Keeping up appearances: An experimental investigation of relative rank signaling," Tech. rep., National Bureau of Economic Research, Inc.

Esteban, J. and D. Ray (2011): "Linking conflict to inequality and polarization," *American Economic Review*, 101, 1345–1374.

Fershtman, C., K. M. Murphy, and Y. Weiss (1996): "Social status, education, and growth," *Journal of Political Economy*, 104, 108–132.

Frank, R. H. (1985): "The demand for unobservable and other nonpositional goods," *The American Economic Review*, 75, 101–116.

Galor, O. and Ö. Özak (2016): "The agricultural origins of time preference," *American Economic Review*, 106, 3064–3103.

Genicot, G. and D. Ray (2017): "Aspirations and inequality," *Econometrica*, 85, 489–519.

Goldin, C. (1994): "The U-shaped female labor force function in economic development and economic history," *National Bureau of Economic Research*.

Goody, J. (1971): "Class and marriage in Africa and Eurasia," *American Journal of Sociology*, 76, 585–603.

Hansen, G. D. (1985): "Indivisible labor and the business cycle," *Journal of Monetary Economics*, 16, 309–327.

Harris, I., T. J. Osborn, P. Jones, and D. Lister (2020): "Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset," *Scientific data*, 7, 109.

Heath, R. and S. Jayachandran (2017): "The causes and consequences of increased female education and labor force participation in developing countries," in *The Oxford Handbook of Women and the Economy*, Oxford University Press, 345–367.

Heise, S. and T. Porzio (2022): "Labor misallocation across firms and regions," Tech. rep., National Bureau of Economic Research.

Hnatkovska, V., A. Lahiri, and S. Paul (2012): "Castes and labor mobility," *American Economic Journal: Applied Economics*, 4, 274–307.

Ho, L., S. Jalota, and A. Karandikar (2023): "Bringing work home: Flexible work arrangements as gateway jobs for women in West Bengal," Tech. rep., Typescript.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019): "The allocation of talent and U.S. economic growth," *Econometrica*, 87, 1439–1474.

Jayachandran, S. (2006): "Selling labor low: Wage responses to productivity shocks in developing countries," *Journal of Political Economy*, 114, 538–575.

Judge, P. S. (2002): "Religion, caste, and communalism in Punjab," *Sociological Bulletin*, 51, 175–194.

Kim, S., M. Tertilt, and M. Yum (2024): "Status externalities in education and low birth rates in Korea," *American Economic Review*, 114, 1576–1611.

Klasen, S. (2019): "What explains uneven female labor force participation levels and trends in developing countries?" *The World Bank Research Observer*, 34, 161–197.

Luke, N. and K. Munshi (2011): "Women as agents of change: Female income and mobility in India," *Journal of Development Economics*, 94, 1–17.

Macchi, E. (2023): "Worth your weight: Experimental evidence on the benefits of obesity in low-income countries," *American Economic Review*, 113, 2287–2322.

Mayshar, J., O. Moav, and L. Pascali (2022): "The origin of the state: Land productivity or appropriability?" *Journal of Political Economy*, 130, 1091–1144.

Mitra, A. and D. Ray (2014): "Implications of an economic theory of conflict: Hindu-Muslim violence in India," *Journal of Political Economy*, 122, 719–765.

Munshi, K. (2019): "Caste and the Indian economy," *Journal of Economic Literature*, 57, 781–834.

Oh, S. (2023): "Does identity affect labor supply?" *American Economic Review*, 113, 2055–2083.

Oswald, F. (2019): "The effect of homeownership on the option value of regional migration," *Quantitative Economics*, 10, 1453–1493.

Ottaviano, G. I. and G. Peri (2012): "Rethinking the effect of immigration on wages," *Journal of the European Economic Association*, 10, 152–197.

Oxfam (2021): "Inequality Report 2021: India's Unequal Healthcare Story," Tech. rep.

Postlewaite, A. (1998): "The social basis of interdependent preferences," *European Economic Review*, 42, 779–800.

PROBE (1999): "Public report on basic education in India," Tech. rep.

Robinson, P. M. (1988): "Root-N-consistent semiparametric regression," *Econometrica*, 931–954.

Rogerson, R. (1988): "Indivisible labor, lotteries and equilibrium," *Journal of Monetary Economics*, 21, 3–16.

Shah, G., S. Thorat, S. Deshpande, and A. Bhaviskar (2006): *Untouchability in rural India*, Sage.

Srinivas, M. N. (1956): "A note on Sanskritization and Westernization," *The Far Eastern Quarterly*, 15, 481–496.

——— (1967): *Social Change in Modern India*, University of California Press.

——— (1977): "The changing position of Indian women," *Man*, 221–238.

Veblen, T. (1899): *The Theory of the Leisure Class: An Economic Study of Institutions.*

Weber, M. (1922): *Economy and Society*, University of California Press Berkeley [translated and reprinted 1978].

Weiss, Y. and C. Fershtman (1998): "Social status and economic performance: A survey," *European Economic Review*, 42, 801–820.

# Online Appendix

## A Variable Construction

**1. Population Density**: For the analyses with Indian (NSS, IHDS, DHS) data, we use population densities obtained from the 1951 population census, but keep track of the partitioning of districts that occurred over time. For example, if district A was divided into two districts, B and C at time $t$, then we measure all outcomes at the level of the contemporaneous district; i.e. based on the original district A boundaries up to $t$ and then, subsequently, separately for B and C. However, we continue to use 1951 population densities, which were based on district A boundaries, for B and C. Population densities will not be uniform even within a district and, hence, the values assigned to B and C will be measured with error. However, we always instrument for population density with potential crop yields in our analyses and these statistics are measured at the level of the contemporaneous district, which takes care of the measurement error. We use potential crop yields obtained from the FAO GAEZ database for 42 crops to predict population densities. These yields are provided at a resolution of 0.0174 degrees (1.943km. at the equator) and can be mapped to the Indian district.

For the analysis across regions at the country level (Figure 4a and Appendix Figure C2a) we use gridded population data from the year 2000, which are available at a resolution of 30 sec (1km. at the equator) from the NASA SEDAC Gridded Population of the World version 4. To predict population densities at the country level, we first compute population density statistics from the NASA SEDAC database at the district (second administrative unit) level. We then predict population densities at the district level using potential crop yields obtained from the FAO GAEZ database for the 42 crops. We finally take the population weighted average across all districts to construct a measure of (predicted) population density at the country level.

To construct population densities at the district level for the cross-regional analysis with DHS data, we start with the cluster-level statistics, which are also derived from the NASA SEDAC database. There are 25-30 households in each DHS cluster. We then average across all clusters to construct district-level population density statistics. We finally use potential crop yields obtained from the FAO GAEZ database to predict the population densities at the district level in Figure 4b and Appendix Figure C2b. The potential crop yields are used as statistical instruments in Appendix Table C10.

**2. Labor force participation**: The NSS labor force participation statistic is derived from the usual activity status of all working-age adults in the household. An individual is coded as participating in the labor force if they work in a household enterprise, are self-employed, work as a regular salaried or casual worker, had worked in the past but do not currently due to sickness or other reasons, and did not seek but are available for work. An individual is coded as not participating if they attend an educational institution, attend domestic duties only, or are otherwise unavailable for work. Individual responses are aggregated up to the district level.

The ILO UN STATS database provides estimates of labor force participation for the rural 15+ population in 2005, separately for men and women. This country-level statistic is used directly in Figure 4a and Appendix Figure C2a. The DHS provides information on employment and not labor force participation. The DHS survey elicits the following information for each respondent: whether they are currently employed;

i.e. worked in the past 7 days, worked in the past 12 months but are not currently employed, or were not employed in the past 12 months. We code an individual as working if they are currently employed or worked in the past 12 months. The individual responses are aggregated up to the district level to construct unemployment rates in Figure 4b and Appendix Figure C2b.

**3. Additional NSS variables**:

(a)Vegetarianism: If a household spent a positive amount in the preceding month on the consumption of chicken, pork, beef, goat, or eggs, then the vegetarianism variable is set to zero (one otherwise). We do not include fish in the list of non-vegetarian items because even Brahmins eat fish in coastal regions, where the bulk of this food product is consumed (Srinivas, 1967). The sample is restricted to rural Hindu households who did not have a religious ceremony in the 30 days preceding the survey.

(b) Teetotalism: If a household spent a positive amount in the preceding month on country liquor, foreign liquor, beer or toddy, then the teetotalism variable is set to zero (one otherwise). The sample is restricted to rural Hindu households who did not have a religious ceremony in the 30 days preceding the survey.

(c) Expenditures and prices: For expenditures, we compute the amount spent in the last 30 days on rice, wheat, other cereals and their substitutes, pulses and their derivative products, milk and associated products, edible oils, meat and fish, vegetables, fruits, spices, tobacco, alcohol, fuel and light, clothing including footwear, education, medical services, entertainment, toiletries, transport, rent, and taxes. The NSS uses either a 7 day, 30 day, or yearly recall over different survey rounds and different consumption goods. We do an imputation to convert different reporting periods to a 30 day recall. For the price of meat and alcohol, we compute the consumption-weighted Paasche index, which is calculated as a weighted average of the price of different items, using the expenditure shares of the items as weights. The price for each item is calculated as its value divided by the quantity. For meat, we include goat meat/mutton, eggs, pork, beef/buffalo meat, other meat, and chicken. For alcohol, we include toddy, country liquor, beer, and foreign liquor.

(d) Wages: The daily wage is recorded for each individual over the past seven days. We take the average over all working days to construct the mean wage.

(e) Education: The NSS records each individual's education in the following categories: primary school completion, middle school completion, secondary school completion, and college graduate. In Appendix Table C6, we convert these categories into years of education, as follows: primary = 4 years, middle = 8 years, secondary = 12 years, and graduate = 16 years. For the structural estimation in Section 5, we define an individual as being educated if they have completed secondary schooling.

**4. Additional DHS variables**:

(a) Marriage and fertility: The district-level marriage rate is constructed as the fraction of women aged 15-49 who are married. The fertility rate is measured by the average number of children ever born and the average number of surviving children for women aged 40+.

(b) Decision-making and autonomy: The DHS survey asks who usually makes health care and expenditure decisions in the household. If the female respondent and her spouse both decide, then the variable is coded as one (zero otherwise). The survey also asks whether the repondent needs permission to visit her relatives. If the answer is negative, then the variable is coded as one (zero otherwise).

**5. Additional IHDS variables**:

(a) Decision-making and autonomy: The IHDS asks who in the family decides the following: how many children to have, what to cook on a daily basis, what items to buy, and the choice of treatment for sick children. If the female respondent has a say in a given decision, then the variable is coded as one (zero otherwise). The survey also asks whether the respondent needs permission to go out. If the answer is no, then the variable is coded as one (zero otherwise).

(b) Status signals: If a household spent a positive amount in the preceding month on the consumption of meat or eggs, then the vegetarianism variable is coded as zero (one otherwise). If the household spent a positive amount in the preceding month on intoxicants, including alcohol, *pan*, and tobacco, then the teetotalism variable is coded as zero (one otherwise). Note that the IHDS does not provide separate information on alcohol consumption.

**6. Rainfall:** The rainfall variable that we use for the instrumental variable analysis is constructed using the Climate Research Unit Time Series (CRU TS) gridded precipitation data (Harris et al., 2020), which is available at a resolution of $0.5° \times 0.5°$ each month over the 1901-2018 period. We first calculate total annual rainfall from the monthly data. We then use the spatial district maps to calculate average annual rainfall within each district in each year.

Table A1: DHS Countries and Sample Years

| Country | Sample years |
|---|---|
| *Sub-Saharan Africa* | |
| Angola | 2015 |
| Burkina Faso | 1999, 2003, 2010 |
| Benin | 1996, 2001, 2012 |
| Burundi | 2010, 2016 |
| Democratic Republic of Congo | 2007, 2013 |
| Cote d'Ivoire | 1998, 2012 |
| Cameroon | 2004, 2011 |
| Ethiopia | 2000, 2005, 2011, 2016 |
| Gabon | 2012 |
| Ghana | 1998, 2003, 2008, 2014 |
| Guinea | 1999, 2005, 2012 |
| Kenya | 2003, 2008, 2014 |
| Liberia | 2007, 2013 |
| Lesotho | 2004, 2009, 2014 |
| Mali | 1996, 2001, 2006, 2012 |
| Malawi | 2000, 2004, 2010, 2015 |
| Mozambique | 2011 |
| Nigeria | 2003, 2008, 2013 |
| Namibia | 2000, 2006, 2013 |
| Rwanda | 2005, 2010, 2014 |
| Sierra Leone | 2008, 2013 |
| Senegal | 2005, 2010, 2012, 2015, 2016 |
| Chad | 2014 |
| Tanzania | 1999, 2010, 2015 |
| Zambia | 2007, 2013 |
| Zimbabwe | 1999, 2005, 2010, 2015 |
| *South and South East Asia* | |
| Bangladesh | 2004, 2007, 2011, 2014 |
| India | 2015 |
| Cambodia | 2000, 2005, 2010, 2014 |
| Myanmar | 2016 |
| Nepal | 2001, 2006, 2011, 2016 |
| Philippines | 2003, 2008, 2017 |
| Pakistan | 2006 |

# B The Model

## B.1 Proof of Proposition 1

We begin with equation (4) in Section 2:

$$c_k = \frac{y_k}{1+Kw}.$$

where $K \equiv \frac{(y_H+y_L)^2}{y_H y_L}$ and $w \equiv \frac{N}{2v}$. Taking the average over $k = H, L$:

$$\overline{c} = \frac{\overline{y}}{1+Kw}.$$

Since $w$ is decreasing in $v$, it follows immediately that $\overline{c}$ is increasing in $v$. To derive the corresponding implications with respect to $\overline{y} = \frac{y_H+y_L}{2}$ and $\Delta y = \frac{y_H-y_L}{2}$, we rewrite $K$ as a function of $\overline{y}$, $\Delta y$:

$$K \equiv \frac{(y_H+y_L)^2}{y_H y_L} = \frac{4\overline{y}^2}{\overline{y}^2 - \Delta y^2}.$$

Differentiating $K$ with respect to $\Delta y$ and $\overline{y}$:

$$\frac{\partial K}{\partial \Delta y} = \frac{8\overline{y}^2 \Delta y}{(\overline{y}^2 - \Delta y^2)^2} > 0$$

$$\frac{\partial K}{\partial \overline{y}} = \frac{-8\overline{y}\Delta y^2}{(\overline{y}^2 - \Delta y^2)^2} < 0$$

Since $K$ is increasing in $\Delta y$, it follows immediately that $\overline{c}$ is decreasing in $\Delta y$. It is also straightforward to verify that $\overline{c}$ is increasing in $\overline{y}$ because $K$ is decreasing in $\overline{y}$ and $\overline{y}$ appears in the numerator of the $\overline{c}$ expression.

To compare the magnitude of the different partial effects, we derive the following expressions:

$$\frac{\partial \overline{c}}{\partial \overline{y}} = \frac{1}{1+Kw} - \frac{\overline{y}}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \overline{y}}$$

$$\frac{\partial c_L}{\partial \overline{y}} = \frac{1}{1+Kw} - \frac{\overline{y} - \Delta y}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \overline{y}}$$

$$\frac{\partial c_H}{\partial \overline{y}} = \frac{1}{1+Kw} - \frac{\overline{y} + \Delta y}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \overline{y}}$$

$$\frac{\partial \overline{c}}{\partial \Delta y} = \frac{-\overline{y}}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \Delta y}$$

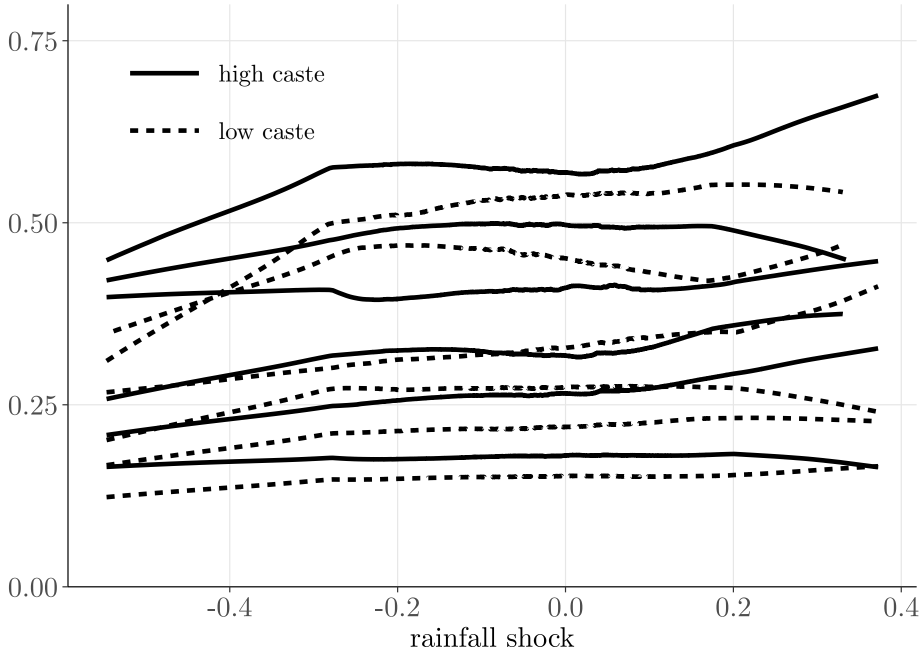
$$\frac{\partial c_L}{\partial \Delta y} = \frac{-(\overline{y} - \Delta y)}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \Delta y} - \frac{1}{1+Kw}$$

$$\frac{\partial c_H}{\partial \Delta y} = \frac{-(\overline{y} + \Delta y)}{(1+Kw)^2} \cdot w\frac{\partial K}{\partial \Delta y} + \frac{1}{1+Kw}$$

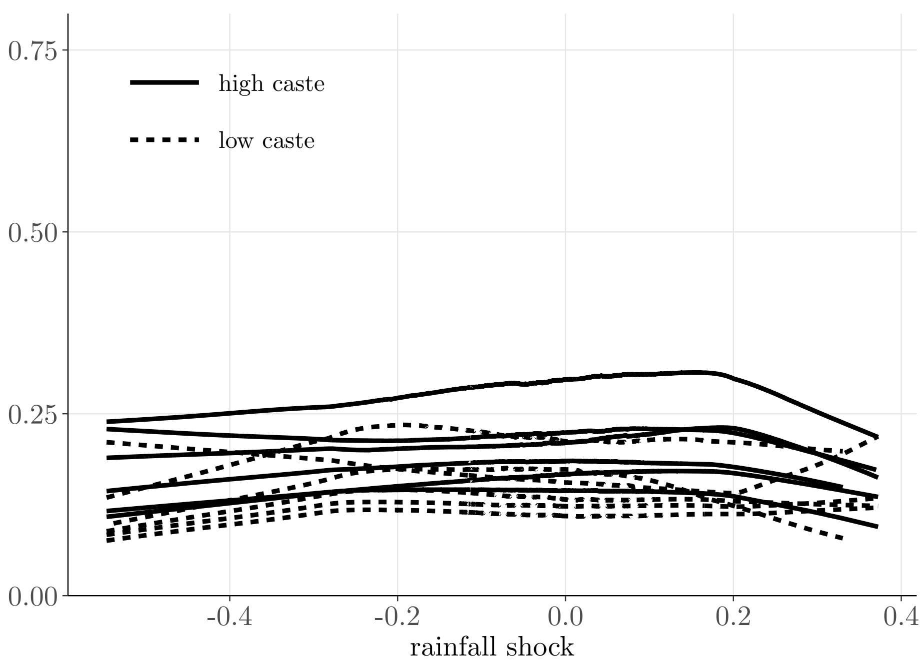
If we assume that $\frac{\Delta y}{(1+Kw)^2} \approx 0$, then it follows that:

$$\frac{\partial \overline{c}}{\partial \overline{y}} = \frac{\partial c_L}{\partial \overline{y}} = \frac{\partial c_H}{\partial \overline{y}}, \quad \left|\frac{\partial c_L}{\partial \Delta y}\right| > \left|\frac{\partial \overline{c}}{\partial \Delta y}\right| > \left|\frac{\partial c_H}{\partial \Delta y}\right|$$

Figure B1: Wages against rainfall shocks, by caste-gender-occupation




(a) Male




(b) Female

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
Rainfall shocks are measured as the difference between contemporaneous rainfall and mean rainfall in the district.
District and NSS round fixed effects are partialled out prior to nonparametric estimation using the Robinson (1988) procedure.

Table B1: Wages against rainfall shocks, allowing for caste interactions

| Dep. var. | mean wage | |
|---|---|---|
| Sample: | male | female |
| | (1) | (2) |
| Rainfall shock | 0.044** | -0.008 |
| | (0.017) | (0.023) |
| Low caste dummy | -0.071*** | -0.043*** |
| | (0.003) | (0.003) |
| Low caste dummy × Rainfall shock | -0.063*** | -0.014 |
| | (0.018) | (0.022) |
| Dep. var. mean | 0.230 | 0.138 |
| Observations | 5680 | 5680 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
Rainfall shocks are measured as the difference between contemporaneous rainfall and mean rainfall in the district.
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B2: First stage regression

| Dep. variable | $\overline{y}$ | $\Delta y$ |
|---|---|---|
| | (1) | (2) |
| $\overline{y}_{IV}$ | 1.079*** | 0.252** |
| | (0.073) | (0.114) |
| $\Delta y_{IV}$ | 0.022 | 0.783*** |
| | (0.052) | (0.074) |
| $F$-statistic excluded instruments | 126.36 | 86.62 |
| | [0.000] | [0.000] |
| Observations | 2828 | 2828 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B3: Female labor force non-participation within districts over time ("thick" rounds only)

| Dep. variable | FLFNP | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.256*** | 0.212** | 0.336*** | 0.579*** | 0.530*** | 0.928*** |
| | (0.081) | (0.084) | (0.102) | (0.173) | (0.174) | (0.258) |
| caste-gap in potential income | -0.080 | 0.000 | -0.208*** | -0.347** | -0.126 | -0.693*** |
| | (0.052) | (0.054) | (0.067) | (0.155) | (0.160) | (0.222) |
| Kleibergen-Paap LM statistic | – | – | – | 63.53 | 63.53 | 63.53 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 50.24 | 50.24 | 50.24 |
| Dep. var. mean | 0.657 | 0.691 | 0.589 | 0.657 | 0.691 | 0.589 |
| Observations | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 |

*Source:* NSS ("thick" rounds) and CRU TS precipitation data
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B4: Female labor force non-participation within districts over time (national-level population shares)

| Dep. variable | FLFNP | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.246*** | 0.167*** | 0.355*** | 0.775*** | 0.816*** | 1.043*** |
| | (0.059) | (0.061) | (0.076) | (0.156) | (0.176) | (0.215) |
| caste-gap in potential income | -0.101*** | -0.005 | -0.229*** | -0.212** | -0.057 | -0.558*** |
| | (0.038) | (0.041) | (0.050) | (0.105) | (0.106) | (0.153) |
| Kleibergen-Paap LM statistic | – | – | – | 96.20 | 96.20 | 96.20 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 96.98 | 96.98 | 96.98 |
| Dep. var. mean | 0.651 | 0.686 | 0.586 | 0.651 | 0.686 | 0.586 |
| Observations | 2903 | 2903 | 2903 | 2903 | 2903 | 2903 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
The instruments are constructed using national-level population shares.
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B5: Female labor force non-participation within districts over time (dependent variable measured by signaling cost)

| Dep. variable | FLFNP × wage | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.714*** | 0.802*** | 0.523*** | 0.473*** | 0.575*** | 0.380*** |
| | (0.056) | (0.070) | (0.046) | (0.079) | (0.102) | (0.057) |
| caste-gap in potential income | -0.032 | 0.286*** | -0.332*** | -0.024 | 0.152 | -0.232*** |
| | (0.033) | (0.046) | (0.030) | (0.069) | (0.121) | (0.052) |
| Kleibergen-Paap LM statistic | – | – | – | 98.60 | 98.60 | 89.86 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 94.71 | 94.71 | 99.01 |
| Dep. var. mean | 0.086 | 0.101 | 0.060 | 0.086 | 0.101 | 0.060 |
| Observations | 2489 | 2489 | 2489 | 2489 | 2489 | 2489 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
The dependent variable is constructed as the product of FLFNP and the relevant wage: mean female wage for the specification with all castes and high (low) caste female wage for the specification with high (low) castes.
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B6: Female labor force non-participation within districts over time (population density interacted with time period effects)

| Dep. variable | FLFNP | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.264*** | 0.194*** | 0.368*** | 0.930*** | 0.941*** | 1.114*** |
| | (0.058) | (0.061) | (0.076) | (0.156) | (0.172) | (0.210) |
| caste-gap in potential income | -0.104*** | -0.024 | -0.223*** | -0.278** | -0.159 | -0.560*** |
| | (0.036) | (0.039) | (0.049) | (0.109) | (0.111) | (0.159) |
| Kleibergen-Paap LM statistic | – | – | – | 101.76 | 101.76 | 101.76 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 96.84 | 96.84 | 96.84 |
| Dep. var. mean | 0.649 | 0.684 | 0.583 | 0.649 | 0.684 | 0.583 |
| Observations | 2840 | 2840 | 2840 | 2840 | 2840 | 2840 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
Predicted population density interacted with time period effects is included in the estimating equation.
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table B7: Female labor force non-participation within districts over time (accounting for income from land)

| Dep. variable | FLFNP | | | | | |
|---|---|---|---|---|---|---|
| Regression: | OLS | | | IV | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| mean potential income | 0.240*** | 0.170*** | 0.348*** | 0.893*** | 0.874*** | 1.061*** |
| | (0.059) | (0.059) | (0.075) | (0.160) | (0.176) | (0.198) |
| caste gap in potential income | -0.093** | -0.015 | -0.211*** | -0.265** | -0.108 | -0.572*** |
| | (0.038) | (0.039) | (0.048) | (0.125) | (0.129) | (0.181) |
| Kleibergen-Paap LM statistic | – | – | – | 85.35 | 85.35 | 85.35 |
| Kleibergen-Paap Wald F-statistic | – | – | – | 84.17 | 84.17 | 84.17 |
| Dep. var. mean | 0.648 | 0.683 | 0.582 | 0.648 | 0.683 | 0.582 |
| Observations | 2828 | 2828 | 2828 | 2828 | 2828 | 2828 |

*Source:* NSS ("thick" and "thin" rounds) and CRU TS precipitation data
Caste-specific land incomes are included in the estimating equation.
District and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

# C Cross-Sectional Evidence

**Robinson Procedure**

Consider the following semi-parametric estimating equation:

$$y_j = f(Z_j) + X_j\beta + \epsilon_j$$

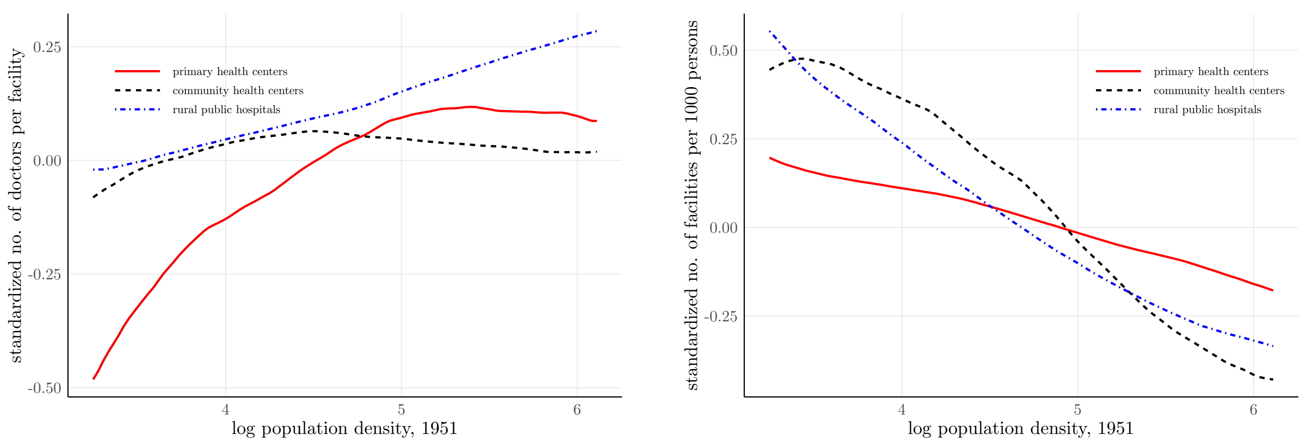
where $y_j$ is an outcome, such as FLFNP in district $j$, $Z_j$ is population density, $X_j$ is a vector of covariates, such as state fixed effects, that need to be partialled out prior to nonparametric estimation of the $y_j - Z_j$ association and $\epsilon_j$ is a mean-zero disturbance term. The Robinson Robinson (1988) procedure is implemented as follows:

**Step 1**. Separately regress $y_j$ and each element of the $X_j$ vector nonparametrically on $Z_j$.

**Step 2**. Regress the residuals from the first equation, $\hat{\xi}_y$, on the residuals from the other equations, $\hat{\xi}_X$, using a linear specification without a constant term to estimate $\hat{\beta}$.

**Step 3**. Nonparametrically regress $y_j - (X_j - \overline{X})\hat{\beta}$ on $Z_j$, where $\overline{X}$ is the sample mean of each element in the vector of covariates.

Figure C1: Size and Supply of medical facilities (rural India)




(a) Size of medical facilities

(b) Medical facilities per capita

*Source:* 2011 population census, Village Directory (Asher et al., 2021) and 1951 population census
Population density in 1951, measured in logs, is predicted by FAO GAEZ potential crop yields.
Number of doctors per facility is top-coded at 30.
All variables are standardized by subtracting the mean and dividing by the standard deviation.
State fixed effects are partialled out prior to nonparametric estimation using the Robinson (1988) procedure.

Table C1: Health services and facility size (IHDS)

| Dep. var.: | procedures (1) | tests (2) | equipment (3) |
|---|---|---|---|
| *Panel A: Primary health centers* | | | |
| facility size | 0.534*** | 0.587*** | 0.990*** |
| | (0.097) | (0.205) | (0.169) |
| Dep. var. mean | 16.090 | 13.202 | 18.282 |
| Observations | 535 | 535 | 535 |
| *Panel B: Community health centers* | | | |
| facility size | 0.319*** | 0.459*** | 0.243** |
| | (0.087) | (0.162) | (0.097) |
| Dep. var. mean | 19.696 | 17.574 | 24.549 |
| Observations | 204 | 204 | 204 |
| *Panel C: Rural public hospitals* | | | |
| facility size | 1.305*** | 1.418*** | 1.691*** |
| | (0.080) | (0.115) | (0.111) |
| Dep. var. mean | 16.137 | 13.425 | 18.594 |
| Observations | 160 | 160 | 160 |

*Source:* IHDS Medical Facility Survey, 2011
Health facility size is measured by the number of doctors in place (top-coded at 30).
Procedures include child immunizations, contraceptive services, prenatal care, incision of abscesses and boils, saline IV, setting broken bones, treating gynaecological conditions, treating STDs/STIs, DOTS for tuberculosis, eye exams, treating diarrhea, changing a wound dressing, stitching wounds, treating malaria, treating minor illnesses like fever, rabies injections, childbirth, abortion, blood transfusion, cataract surgery, abdominal surgery, and heart surgery.
Tests include pregnancy, blood pressure, blood sugar, haemoglobin, white blood cell count, HIV/AIDS, cholesterol, urine culture, stool, chlorine level in water, malaria, cerebral malaria, TB, and pap smear.
Equipment includes stethoscope, thermometer, vaginal speculum, sonograph/ultrasound, x-ray machine, blood pressure gauge, oxygen, otoscope for ear exam, ophthalmoscope for eye exam, delivery kit, forceps, partograph for tracking delivery, IV stand, laryngoscope for throat, catheter (urethal), microscope, centrifuge, refrigerator, cold chest, ECG monitor, ambulance, wheelchair, stretcher on a trolley, computer, internet connection, landline telephone, and mobile phone communicating with patients.
The dependent variable is the number of procedures, tests, equipment (based on the IHDS list provided above) in the facility.

Table C2: Rural labor force non-participation, NSS "thick" rounds (Indian districts, NSS))

| Dep. variable | rural labor force non-participation | | | | | |
|---|---|---|---|---|---|---|
| Gender: | female | | | male | | |
| Caste group: | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Population density | 0.135*** | 0.144*** | 0.101*** | 0.001 | -0.001 | 0.001 |
| | (0.030) | (0.033) | (0.027) | (0.004) | (0.004) | (0.008) |
| Population density × time trend | -0.004*** | -0.004*** | -0.002*** | 0.000** | 0.000 | 0.000* |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| Kleibergen-Paap Wald F-statistic | 26.62 | 28.78 | 26.95 | 26.58 | 28.70 | 26.97 |
| Dep. var. mean | 0.664 | 0.697 | 0.598 | 0.082 | 0.089 | 0.070 |
| Observations | 2080 | 2073 | 2060 | 2082 | 2074 | 2059 |

*Source:* NSS ("thick" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table C3: Rural labor force non-participation, Muslims and other religions (Indian districts, NSS)

| Dep. variable | rural labor force non-participation | | | |
|---|---|---|---|---|
| Religion | Muslims | | other religions | |
| Gender | female | male | female | male |
| | (1) | (2) | (3) | (4) |
| Population density | 0.087*** | 0.015* | 0.130*** | -0.015 |
| | (0.022) | (0.009) | (0.047) | (0.015) |
| Population density × time trend | -0.003*** | 0.000 | -0.003 | 0.001 |
| | (0.001) | (0.000) | (0.002) | (0.001) |
| Kleibergen-Paap Wald F-statistic | 10.79 | 10.86 | 13.41 | 12.48 |
| Dep. var. mean | 0.761 | 0.077 | 0.629 | 0.085 |
| Observations | 2622 | 2625 | 1782 | 1765 |

*Source:* NSS ("thick" and "thin" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table C4: FLFNP and population density association, conditional on potential income

| Dep. var. | FLFNP<br>(1) | MLFNP<br>(2) |
|---|---|---|
| Population density | 0.125*** | 0.011*** |
| | (0.018) | (0.003) |
| Population density × time trend | -0.004*** | -0.000* |
| | (0.001) | (0.000) |
| $\overline{y}$ | 0.799*** | 0.122*** |
| | (0.176) | (0.032) |
| $\Delta y$ | -0.459*** | 0.023 |
| | (0.133) | (0.027) |
| Kleibergen-Paap LM statistic | 112.47 | 112.47 |
| Kleibergen-Paap Wald F-statistic | 193.16 | 193.16 |
| Dep. var mean | 0.648 | 0.083 |
| Observations | 2981 | 2981 |

*Source:* NSS ("thick" and "thin" rounds) and 1951 population census
MLFNP denotes male labor force non-participation, $\overline{y}$ denotes mean potential income and $\Delta y$ denotes the caste-gap in potential income.
$\overline{y}$ and $\Delta y$ are instrumented using rainfall shocks.
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table C5: Rural expenditures and prices (Indian districts, NSS)

| Dependent var. | log total expenditures<br>(1) | log food expenditures<br>(2) | log meat price<br>(3) | log alcohol price<br>(4) |
|---|---|---|---|---|
| Population density | 0.085*** | 0.043** | -0.249* | -0.046 |
| | (0.031) | (0.021) | (0.131) | (0.081) |
| Population density × time trend | -0.001 | -0.001 | 0.005 | 0.003 |
| | (0.001) | (0.001) | (0.007) | (0.004) |
| Kleibergen-Paap Wald F-statistic | 12.23 | 25.33 | 27.21 | 22.40 |
| Dep. var. mean | 6.818 | 6.367 | 1.966 | 0.814 |
| Observations | 1765 | 2083 | 2057 | 1968 |

*Source:* NSS ("thick" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table C6: Rural female wages and education (Indian districts, NSS)

| Dep. variable | mean log wage | | | mean log years of education | | |
|---|---|---|---|---|---|---|
| Caste group | all | high | low | all | high | low |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Population density | 0.123** | 0.089 | 0.140** | 0.463*** | 0.375*** | 0.358*** |
| | (0.062) | (0.083) | (0.065) | (0.078) | (0.076) | (0.107) |
| Population density × time trend | -0.003 | -0.001 | -0.005* | -0.012*** | -0.011*** | -0.002 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) |
| Kleibergen-Paap F-statistic | 14.86 | 10.37 | 8.34 | 21.50 | 20.10 | 6.50 |
| Dep. var. mean | 2.303 | 2.380 | 2.202 | 0.960 | 1.146 | 0.428 |
| Observations | 3206 | 2893 | 2908 | 3408 | 3381 | 3109 |

*Source:* NSS ("thick" and "thin" rounds) and 1951 population census
Population density in 1951, measured in logs, is instrumented using FAO GAEZ potential crop yields.
Time trend is measured as the year minus 1987 and, hence, the population density coefficient corresponds to the association in 1987.
State and NSS round fixed effects are included in the estimating equation.
Standard errors are clustered at the level of 1981 district boundaries.

Table C7: Rural demographic characteristics and gender norms (Indian districts, DHS)

| | status signal | demographic characteristics | | | gender norms | | |
|---|---|---|---|---|---|---|---|
| Dep. variable | female unemployment | marriage rate | children ever born | children alive | health decisions | expenditure decisions | can visit relatives |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Population density | 0.049** | -0.009 | -0.039 | -0.042 | 0.009 | 0.002 | 0.008 |
| | (0.022) | (0.008) | (0.031) | (0.028) | (0.016) | (0.018) | (0.016) |
| Kleibergen-Paap F-statistic | 7.08 | 4.55 | 4.69 | 4.69 | 7.08 | 7.08 | 7.08 |
| Dep. var. mean | 0.631 | 0.782 | 1.186 | 1.092 | 0.738 | 0.719 | 0.729 |
| Observations | 512 | 598 | 590 | 590 | 512 | 512 | 512 |

*Source:* 2015 DHS and 1951 population census
Marriage rates and fertility rates, measured by the number of children ever born and children alive, are measured in logs at the district level in Columns 2-4.
Gender norms are measured at the district level by the fraction of women who have a say with regard to household decisions about health and expenditures, and who can visit their relatives without permission, in Columns 5-7.
Population density in 1951, measured in logs, is instrumented by FAO GAEZ potential crop yields.
State fixed effects are included in the estimating equation.

Table C8: Rural gender norms (Indian districts, IHDS)

| Dep. variable | how many children (1) | whom children marry (2) | what to cook (3) | what to buy (4) | treatment of sick children (5) | does not need permission to go out (6) |
|---|---|---|---|---|---|---|
| Population density | 0.039 | 0.000 | 0.028 | 0.026* | 0.019 | 0.040 |
| | (0.025) | (0.016) | (0.038) | (0.016) | (0.025) | (0.026) |
| Kleibergen-Paap Wald F-statistic | 7.20 | 7.20 | 7.20 | 7.20 | 7.20 | 7.20 |
| Dep. var. mean | 0.197 | 0.111 | 0.688 | 0.106 | 0.259 | 0.201 |
| Observations | 237 | 237 | 237 | 237 | 237 | 237 |

*Source:* IHDS and 1951 population census
Gender norms are measured by the fraction of women who report having a say in household decisions and not needing permission to go out.
Population density in 1951, measured in logs, is instrumented by FAO GAEZ potential crop yields.
State fixed effects are included in the estimating equation.

Table C9: Rural status signaling (Indian districts, IHDS)

| Dep. var.: | FLFNP (1) | vegetarianism (2) | teetotalism (3) |
|---|---|---|---|
| Population density | 0.064** | 0.037 | 0.050** |
| | (0.030) | (0.040) | (0.021) |
| Kleibergen-Paap Wald F-statistic | 7.20 | 7.20 | 7.20 |
| Dep. var. mean | 0.679 | 0.687 | 0.306 |
| Observations | 237 | 237 | 237 |

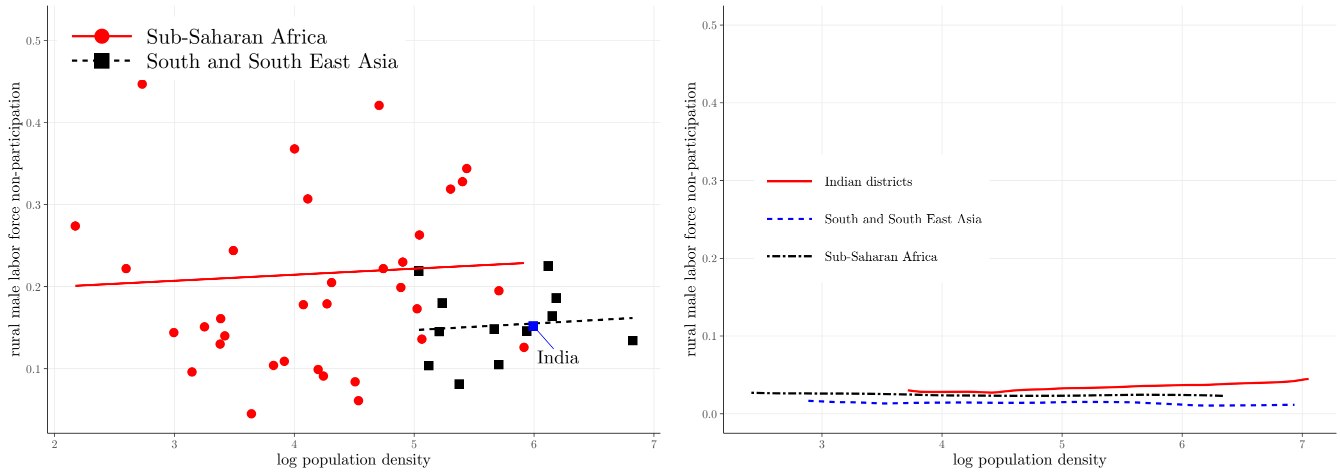
*Source:* IHDS and 1951 population census
Population density in 1951, measured in logs, is instrumented by FAO GAEZ potential crop yields.
State fixed effects are included in the estimating equation.

Table C10: Rural labor force non-participation across regions (district data, DHS)

| Dep. variable | rural unemployment | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Gender | female | | | | male | | | |
| Region | Africa | Asia | | | Africa | Asia | | |
| Sub-region: | All (1) | all (2) | only India (3) | excluding India (4) | all (5) | all (6) | only India (7) | excluding India (8) |
| Population density | -0.012 | 0.042*** | 0.028*** | 0.038*** | -0.000 | 0.001 | 0.003 | -0.001 |
| | (0.008) | (0.005) | (0.009) | (0.005) | (0.002) | (0.001) | (0.002) | (0.001) |
| Kleibergen-Paap Wald F-statistic | 22.02 | 17.55 | 10.73 | 21.48 | 22.41 | 17.60 | 10.73 | 21.58 |
| Dep. var. mean | 0.342 | 0.377 | 0.658 | 0.304 | 0.026 | 0.018 | 0.037 | 0.013 |
| Observations | 5943 | 2801 | 579 | 2222 | 6328 | 2740 | 579 | 2161 |

*Source:* DHS and NASA SEDAC
Labor force non-participation is measured by unemployment with DHS data.
Population density in 2000, measured in logs, is instrumented by FAO GAEZ potential crop yields.
First administrative unit (state) fixed effects and survey year effects are included in the estimating equation.

Figure C2: Rural male labor force non-participation across regions (country data, ILO; district data, DHS)




(a) Country data

(b) District data

*Source:* ILO UN STATS, DHS, and NASA SEDAC
Labor force non-participation is measured by unemployment in panel (b) with DHS data.
Population density in 2000, measured in logs, is predicted by FAO GAEZ potential crop yields.
For DHS, first administrative unit (state) fixed effects and survey year effects are partialled out prior to nonparametric estimation using the Robinson (1988) procedure.

# D Structural Estimation and Policy Simulations

**Solving for status signals**: Household $i$ belonging to caste group $k$ chooses $c_{i,sk}$, $c_{i,uk}$, taking potential income $y_{i,k}$ as given, to maximize:

$$\log(y_{i,k} - c_{i,sk} - c_{i,uk}) + \frac{\mathbb{C}_k}{\mathbb{C}_k + \mathbb{C}_{-k}} \cdot \frac{N_k + N_{-k}}{N_k} \cdot v \tag{D.1}$$

where $c_{i,k} = \left(c_{i,sk}^{\phi} + c_{i,uk}^{\phi}\right)^{1/\phi}$ and $\mathbb{C}_k = \sum_i c_{i,k}$.

Making the symmetry assumption as usual, the first-order conditions are derived as

$$\frac{1}{y_k - c_{sk} - c_{uk}} = \frac{c_{-k}N_{-k}}{(c_k N_k + c_{-k}N_{-k})^2} \cdot \frac{N_k + N_{-k}}{N_k} \cdot v \cdot \left(c_{sk}^{\phi} + c_{uk}^{\phi}\right)^{1/\phi - 1} \cdot c_{sk}^{\phi-1} \tag{D.2}$$

$$\frac{1}{y_k - c_{sk} - c_{uk}} = \frac{c_{-k}N_{-k}}{(c_k N_k + c_{-k}N_{-k})^2} \cdot \frac{N_k + N_{-k}}{N_k} \cdot v \cdot \left(c_{sk}^{\phi} + c_{uk}^{\phi}\right)^{1/\phi - 1} \cdot c_{uk}^{\phi-1} \tag{D.3}$$

By inspection of (D.2) and (D.3),

$$c_{sk} = c_{uk}. \tag{D.4}$$

Since $c_{sk} = c_{uk}$, one of the first-order conditions above is redundant, say equation (D.3). We thus substitute $c_{sk} = c_{uk}$ in equation (D.2) and replace $c_k$, $c_{-k}$ with $c_{sk}$, $c_{-sk}$ in the status function to obtain:

$$\frac{1}{y_k - 2c_{sk}} = \frac{c_{-sk}N_{-k}}{(c_{sk}N_k + c_{-sk}N_{-k})^2} \cdot \frac{N_k + N_{-k}}{N_k} \cdot \frac{v}{2} \tag{D.5}$$

The corresponding equation for the $-k$ group is obtained by reversing the $k$ and $-k$ subscripts:

$$\frac{1}{y_{-k} - 2c_{-sk}} = \frac{c_{sk}N_k}{(c_{sk}N_k + c_{-sk}N_{-k})^2} \cdot \frac{N_k + N_{-k}}{N_{-k}} \cdot \frac{v}{2} \tag{D.6}$$

Dividing equation (D.5) by equation (D.6), we derive an expression for $c_{-sk}$ as a function of $c_{sk}$:

$$c_{-sk} = \frac{c_{sk} y_{-k} N_k^2}{B(c_{sk})} \tag{D.7}$$

where $B(c_{sk}) \equiv y_k N_{-k}^2 + 2c_{sk}(N_k^2 - N_{-k}^2)$. Without loss of generality, let $N_k > N_{-k}$, which implies that $B'(c_{sk}) > 0$. Substituting the expression for $c_{-sk}$ from (D.7) in (D.5), and rearranging terms, we arrive at an equation that can be used to solve for $c_{sk}$:

$$\frac{c_{sk} \left[B(c_{sk}) + y_{-k} N_k N_{-k}\right]^2}{B(c_{sk}) y_{-k} N_{-k}} = (y_k - 2c_{sk}) \cdot \frac{N_k + N_{-k}}{N_k} \cdot \frac{v}{2} \tag{D.8}$$

Since $N_k$ is assumed to be greater than $N_{-k}$, the $k$ group corresponds to the majority $H$ caste and $-k$ corresponds to the minority $L$ caste in equations (D.5)-(D.8). While $N_H$, $N_L$ are not observed, we do know their ratio $f \equiv N_H/N_L$. We thus rewrite the preceding equation in terms of $f$:

$$\frac{c_{sH} \left[B(c_{sH}) + y_L f\right]^2}{B(c_{sH}) y_L} = (y_H - 2c_{sH}) \cdot \frac{f+1}{f} \cdot \frac{v/N_L}{2} \tag{D.9}$$

where $B(c_{sH}) \equiv y_H + 2c_{sH}(f^2 - 1)$ and $B'(c_{sH}) > 0$. We will thus estimate $\tilde{v} \equiv v/N_L$, but this has no bearing on the analysis.

The left hand side of the preceding equation is zero at $c_{sH} = 0$ and positive at $c_{sH} = y_H/2$. The right hand side is positive at $c_{sH} = 0$, zero at $c_{sH} = y_H/2$, and monotonically decreasing in $c_{sH}$. It follows that there will be a unique solution for $c_{sH} \in (0, y_H/2)$ if the left hand side is monotonically increasing in $c_{sH}$. Differentiating the left hand side with respect to $c_{sH}$, we obtain:

$$\frac{[B(c_{sH}) + y_L f]}{[B(c_{sH})]^2 y_L} \left\{ [B(c_{sH}) + y_L f]\, y_H + 2c_{sH} B(c_{sH}) B'(c_{sH}) \right\} > 0$$

Once we have solved for $c_{sH}$, we derive $c_{sL}$ from equation (D.7), which can be rewritten as $c_{sL} = \frac{c_{sH} y_L f^2}{B(c_{sH})}$. Since skilled and unskilled signaling costs are equal within a group from equation (D.4), we can finally derive $c_{uH}$, $c_{uL}$.

**Solving for wages**: There are eight different wages $w_{skg}, w_{ukg}, g = \{m, f\}, k = \{H, L\}$, which are determined by the following equations:

$$w_{skg} = \frac{\partial Y}{\partial E_{skg}} = \frac{\partial Y}{\partial E} \times \frac{\partial E}{\partial E_g} \times \frac{\partial E_g}{\partial E_{kg}} \times \frac{\partial E_{kg}}{\partial E_{skg}},$$
$$w_{ukg} = \frac{\partial Y}{\partial E_{skg}} = \frac{\partial Y}{\partial E} \times \frac{\partial E}{\partial E_g} \times \frac{\partial E_g}{\partial E_{kg}} \times \frac{\partial E_{kg}}{\partial E_{ukg}}.$$

Solving the partial derivatives:

$$w_{skg} = A\theta_g \theta_{kg} \theta_{skg} E^{1-\rho} E_g^{\rho-\rho_g} E_{kg}^{\rho_g - \rho_{kg}} E_{skg}^{\rho_{kg}-1} \tag{D.10}$$
$$w_{ukg} = A\theta_g \theta_{kg} \theta_{ukg} E^{1-\rho} E_g^{\rho-\rho_g} E_{kg}^{\rho_g - \rho_{kg}} E_{ukg}^{\rho_{kg}-1} \tag{D.11}$$

$E$, $E_g$, $E_{kg}$, $E_{skg}$, $E_{ukg}$ can be expressed as functions of $\xi_{kg}$, $\tau_{sk}$, $\tau_{uk}$ from the aggregate production function specified in Section 5.

**Estimation**: The source of exogenous variation in the structural model is (predicted) population density. In each survey round, we construct a log population density grid with 20 intervals, such that each grid interval contains an equal number of districts. Population density in a given interval and time period determines total factor productivity, $A$, and the value of status, $v$, or, equivalently, $\tilde{v}$ which, in turn, allow us to solve for wages, education, and FLFNP (for a given set of parameters). To estimate the parameters, we solve the following problem:

$$\min_{\boldsymbol{\Theta}} \boldsymbol{e}(\boldsymbol{\Theta})'\boldsymbol{e}(\boldsymbol{\Theta}) \tag{D.12}$$

where $\boldsymbol{e}(\boldsymbol{\Theta})$ is an error vector, computed as the percentage difference between the data moments and the model moments, and $\boldsymbol{\Theta}$ is the set of structural parameters.

We assume the following functional form for $A$ and $\widetilde{v}$

$$A(p) = \alpha_{A_1} p^{\alpha_{A_2}}$$
$$\widetilde{v}(p) = \alpha_{\widetilde{v}_1} p^{\alpha_{\widetilde{v}_2}}$$

where $p$ is the (predicted) log population density in a given interval.

Table D1 lists the parameters to be estimated. There are 37 parameters, which we divide in two groups: Group 1 parameters are associated with the cost of education, the signaling cost multiplier, and the status function. Group 2 parameters are associated with the aggregate production function. Given the large set of parameters and the objective

Table D1: Parameters to estimate

| Group 1 | | Group 2 | |
|---|---|---|---|
| Social status | $\alpha_{\widetilde{v}_1}, \alpha_{\widetilde{v}_2}$ | Total factor productivity | $\alpha_{A_1}, \alpha_{A_2}$ |
| Cost of education, linear term | $\beta_{1,Lf}, \beta_{1,Hf}, \beta_{1,Lm}, \beta_{1,Hm}$ | Gender, productivity | $\theta_f, \theta_m$ |
| Cost of education, quadratic term | $\beta_{2,Lf}, \beta_{2,Hf}, \beta_{2,Lm}, \beta_{2,Hm}$ | Gender, elasticity of substitution | $\rho$ |
| Signaling cost multiplier | $\eta_{sL}, \eta_{sH}, \eta_{uL}, \eta_{uH}$ | Caste-gender productivity | $\theta_{Lf}, \theta_{Lm}, \theta_{Hf}, \theta_{Hm}$ |
| | | Caste-gender elasticity of substitution | $\rho_f, \rho_m$ |
| | | Skill-caste-gender productivity | $\theta_{sLf}, \theta_{sLm}, \theta_{sHf}, \theta_{sHm}$, $\theta_{uLf}, \theta_{uLm}, \theta_{uHf}, \theta_{uHm}$ |
| | | Skill-caste-gender elasticity of substitution | $\rho_{Lf}, \rho_{Lm}, \rho_{Hf}, \rho_{Hm}$ |

to find the global minimum, the estimation proceeds in the following steps in each NSS round:

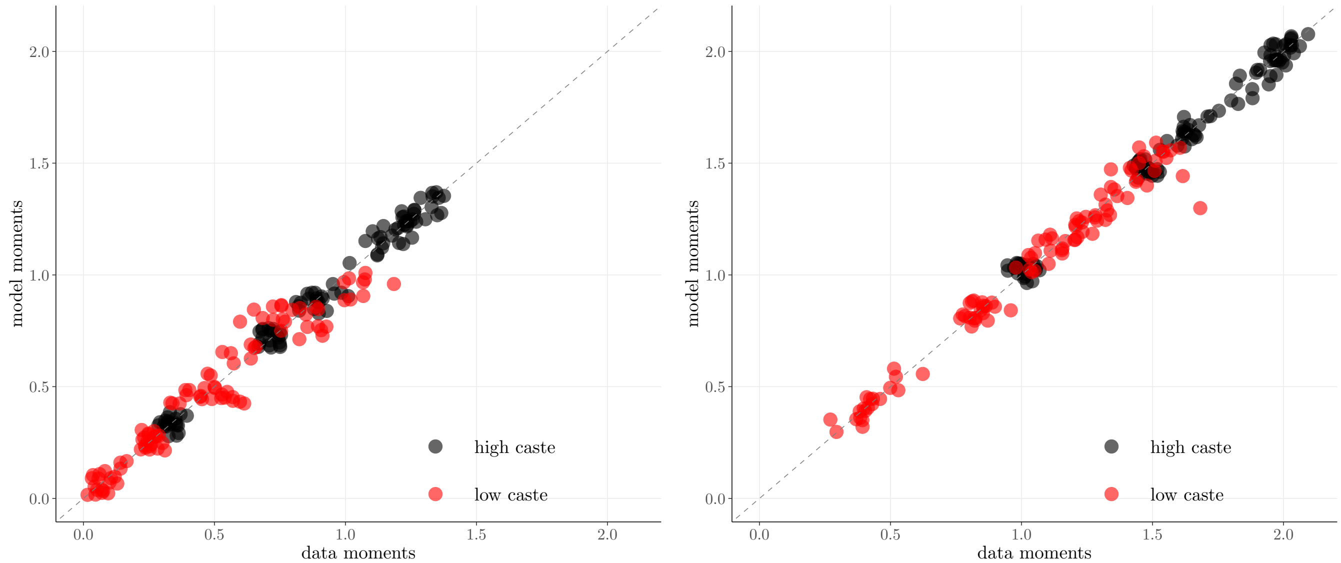
**Step 1** Taking wages as given, solve for $\tau_{sk}, \tau_{uk}, \xi_{kg}$ in each population density interval for a given set of Group 1 parameter values. Estimate the Group 1 parameters by performing a search over all parameter values to find the combination that minimizes the error between data moments and model moments across all population density intervals.

**Step 2** Taking education and FLFNP as given, solve for $w_{skg}$, $w_{ukg}$ in each population density interval for a given set of Group 2 parameter values. Estimate the Group 2 parameters by performing a search over all parameter values to find the combination that minimizes the error between data moments and model moments across all population density intervals.

**Step 3** Use the iterative algorithm described in Section 5 to solve all the endogenous variables simultaneously in each population density interval. Use the values obtained in Step 1 and Step 2 as the initial set of parameters when solving the model and then implement a search procedure to find the set of parameters that minimizes the distance between the data and model moments with respect to FLFNP, education, and wages.

For **Step 1** and **Step 2** we first deploy Particle Swarm Optimization (PSO) with 5,000 particles over 500 iterations to conduct a global search of the parameter space. We then use the resulting parameter values as the starting point for a local search using the Nelder-Mead simplex algorithm. For **Step 3** we use PSO with 2,500 particles over 250 iterations, where the algorithm incorporates adaptive inertia weights that decrease over iterations.

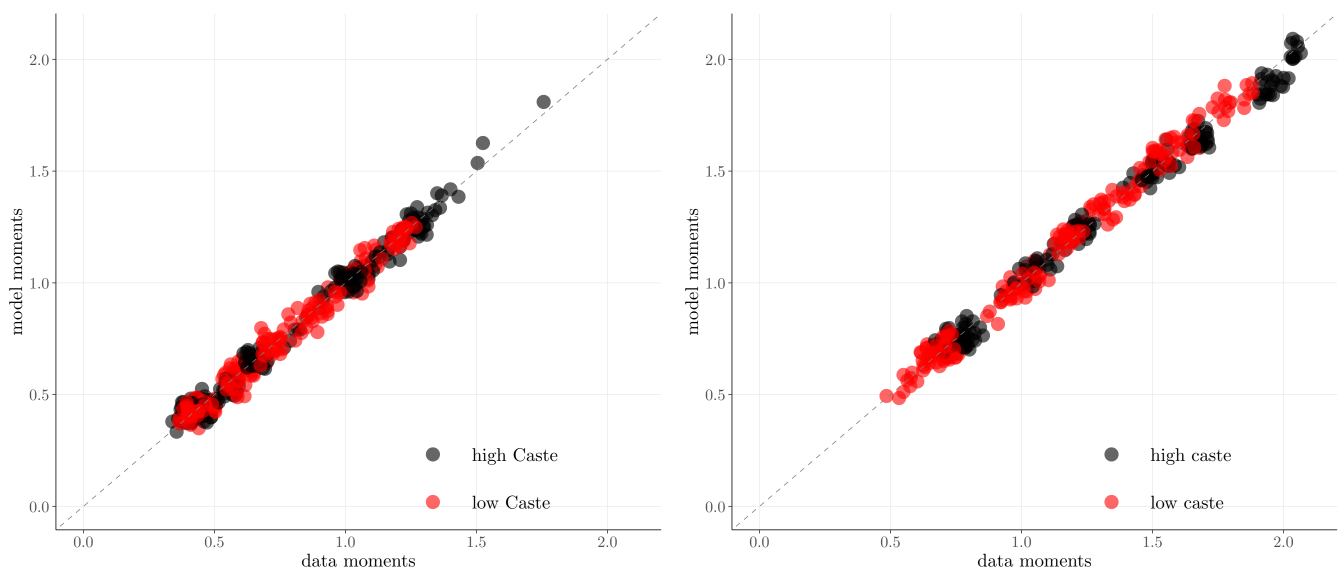
Figure D1: Comparing model and data moments for education, separately by gender and caste




(a) Female (b) Male

*Source:* NSS "thick rounds" and 1951 population census are used to estimate the structural model.
To be consistent with Figure 5b, the data and model moments are divided by mean education (at the caste-gender-time period level).

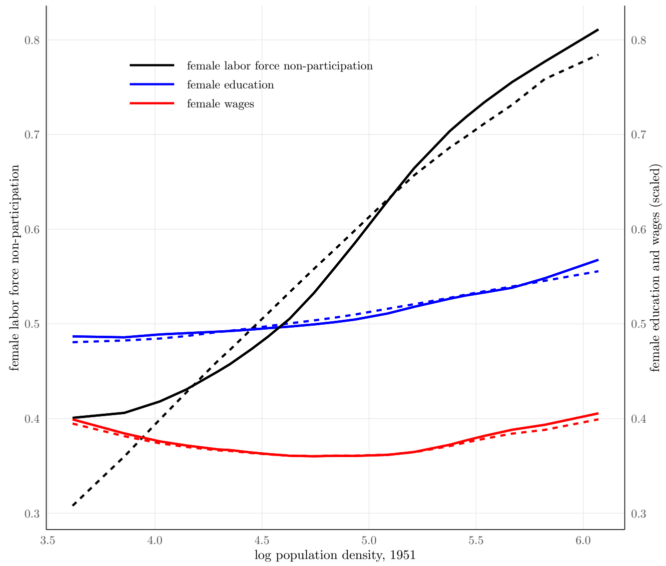
Figure D2: Comparing model and data moments for wages, separately by gender and caste



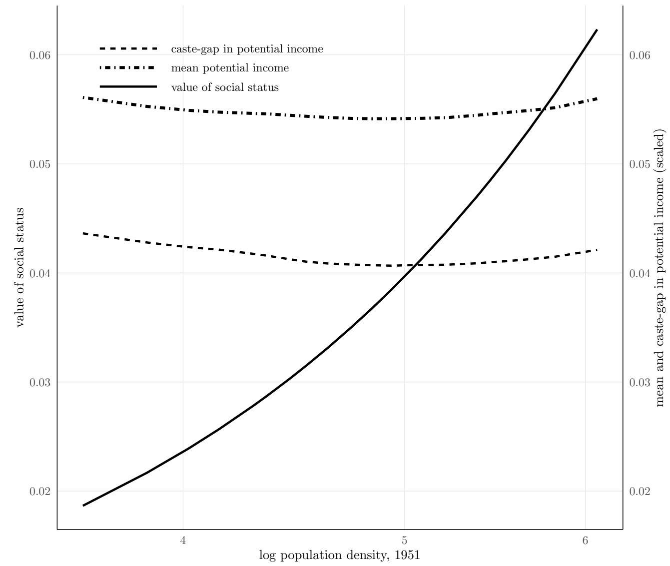

(a) Female (b) Male

*Source:* NSS "thick rounds" and 1951 population census are used to estimate the structural model.
To be consistent with Figure 5b, the data and model moments are divided by the mean wage (at the caste-gender-time period level).

Figure D3: Model fit and status factors in the cross-section (1987)



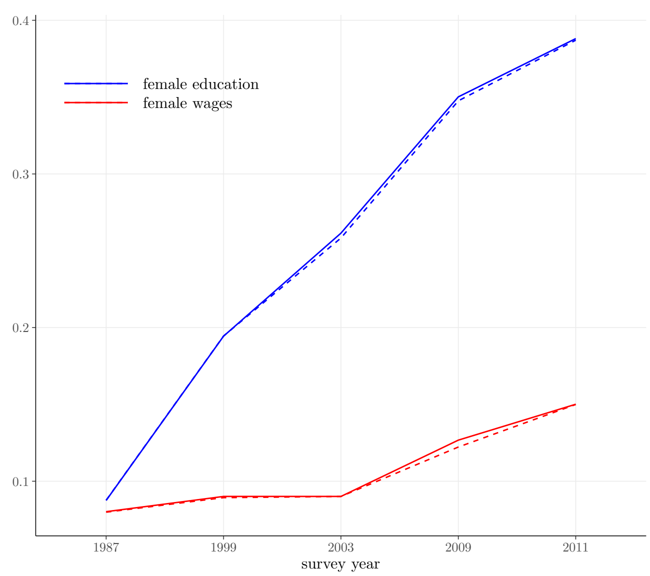

(a) FLFNP, female education, and female wages



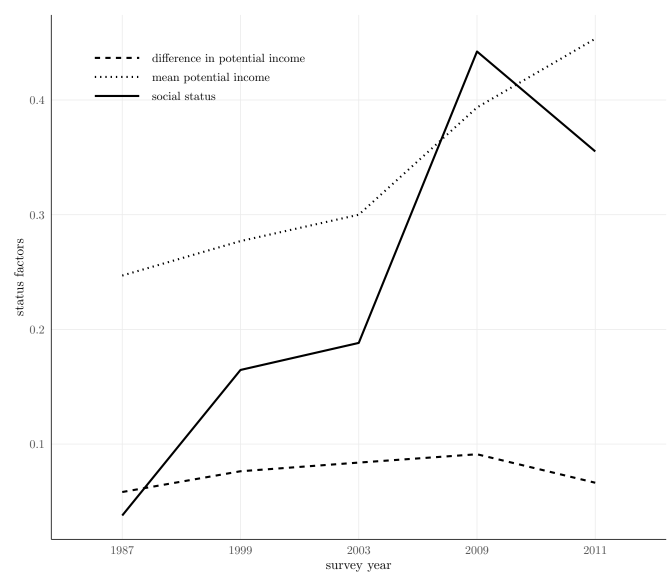

(b) Status factors

*Note:* NSS "thick" rounds and 1951 population census are used to estimate the structural model.
Solid lines denote the data and dashed lines denote model predictions in Figure D3a.
The value of social status is measured by $\tilde{v} \equiv v/N_L$ in Figure D3b.

Figure D4: Female education, female wages, and status factors over time




(a) Female education and female wages




(b) Status factors

*Note:* NSS "thick" rounds and 1951 population census are used to estimate the structural model.
Solid lines denote the data and dashed lines denote the model predictions in Figure D4a.
The value of social status is measured by $\tilde{v} \equiv v/N_L$ in Figure D4b, where $v$ is the value of social status and $N_L$ is the number of low caste households in the village.