The Unproductive Wealth of Nations
The Case of Gold in India*

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Abstract

In high-income economies like the US, households allocate a large share of their savings to financial assets that fund productive investment. In contrast, household balance sheets in developing countries are dominated by non-financial and often unproductive assets such as gold. This paper quantifies the development costs of unproductive savings. We focus on the case of gold in India, where private gold holdings account for nearly one-fifth of aggregate assets. We develop an equilibrium model of households' portfolio choice and entrepreneurial investment in the presence of financial frictions. The model incorporates three main reasons for holding gold (social norms, hedging and returns, and liquidity) and matches key macro and micro moments of the Indian economy. We find that unproductive savings matter, but policies that narrowly focus on discouraging gold holdings will backfire. If idle gold could be utilized productively, output would increase by 13%. However, taxing gold leads to welfare losses and no output gains.

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1 Introduction

There are large differences across countries in the types of assets that households save and invest in. In rich countries like the US, households largely save in financial assets such as deposits, bonds, and pension funds, which are channeled into productive investments. In contrast, in developing countries like India, financial assets are mostly absent from household balance sheets. Instead, households often save in *unproductive* assets – assets that do not end up as capital in production – such as gold, foreign currency, idle real estate, and digital assets. At the same time, businesses in developing countries often lack capital and face severe credit constraints.

This paper asks whether it matters quantitatively that significant shares of household savings are in unproductive assets. We focus on the case of gold in India. Gold is the prototypical example of an unproductive asset; it mostly sits idle and the share of gold used in production is negligible. Importantly, gold can always be traded internationally for productive capital. Gold is also quantitatively important: its stock in India is around 60% of GDP, more than six times the size of aggregate bank deposits. Was Keynes (1913) right to believe that "India's love of the precious metals has ruined her development"?

To quantify the aggregate costs of (unproductive) gold savings, we build an equilibrium model of household business investment and portfolio choice. Households can save in gold and two productive assets: deposits and capital for their own business. Gold can thus directly crowd out productive investment; and aggregate savings are not equal to aggregate capital. The model incorporates three main motives for holding gold: (1) social norms, (2) hedging against aggregate income risk and financial returns, and (3) liquidity benefits. In line with the Indian data, there is only a small corporate sector and most output is produced by household businesses that face financial constraints. We calibrate the model using a combination of micro and macro moments and validate it using a rich set of untargeted moments, including household balance sheets across the wealth distribution, the firm size distribution and returns to capital as revealed by an RCT.

We establish two main results. First, unproductive savings matter. If idle gold could be utilized productively, output and welfare would increase by 13% and 10.7%, respectively. This is because bringing idle gold back into the financial system increases aggregate savings, relaxes borrowing constraints, and reduces existing misallocation. Second, discouraging gold demand backfires and policy should instead focus on addressing the root problem of financial frictions. Taxing gold leads to welfare losses and no output gains. Instead, gold demand would drop sharply if financial frictions were lowered.

A development accounting exercise.— To benchmark our main results and gain intuition, let us start with a simple thought experiment: how much would Indian output increase if India, as a small open economy, traded its existing stock of gold for capital goods from the rest of the world? Assuming a Cobb-Douglas aggregate production function (as is standard in the development accounting literature), aggregate output gains can be written as:

$$Y = ZK^{\alpha}N^{1-\alpha} \implies \frac{Y^{cf}}{Y} = \left(\frac{\text{Gold} + K}{K}\right)^{\alpha} \tag{1}$$

where Y denotes baseline aggregate output, and Y^{cf} aggregate output if the gold stock were to be fully traded for capital. With a capital-output ratio of 1.9,[1] a capital elasticity of $\frac{1}{3}$, and a gold-output ratio of 0.6, the "aggregate costs of gold" $\frac{Y^{cf}-Y}{Y}$ would be 10%, a sizable cost.

Our model captures two important aspects that are crucial for the quantitative results, but which the development accounting exercise misses. First, we model the drivers of household saving decisions, including demand for gold. Aggregate capital and gold in an economy are the result of saving decisions by households. Mechanically trading aggregate gold for capital goods ignores how households' portfolio choice and saving behavior endogenously respond to changes in the economy. Second, output costs depend on how capital is distributed across (household) businesses. The development accounting exercise implicitly assumes away any misallocation across businesses by assuming a representative firm. However, misallocation across businesses in India is well-documented, and endogenously responds to changes in the economic environment.

We consider three main motives for holding gold. The first motive is social norms around gold, including the special role of gold in Indian weddings, the dowry system, and wealth signaling. We model it as 'gold in the utility', so that households directly derive a flow utility from the stock of gold they hold, similar to a durable consumption good. The second motive is about gold as an investment good. Our model captures important aggregate risks to wage income and business profits, and gold can be used as a hedge against this risk since the gold price tends to depreciate in economic booms and appreciate in economic busts. Besides hedging, gold also has small positive conditionally expected returns in some states of the world, which makes it attractive to households with no access to lucrative investment opportunities. The third motive is liquidity: gold can be used to underwrite loans, capturing the quantitatively important role of "gold loans" in India.

[1] This measure of capital excludes housing and is based on national accounts data and detailed capital data from the Penn World Tables.

Alongside gold, there are two productive assets available to households: bank deposits that pay a safe interest rate, and investment in households' own business whose risky returns depend on their idiosyncratic productivity as well as aggregate productivity in the economy. Returns to and investment in productive assets are directly affected by three financial frictions that capture India's underdeveloped financial system. First, returns on bank deposits are low, given large spreads between deposit and borrowing rates as observed in the data. Second, we model standard collateral-based borrowing constraints that capture well-documented financial frictions even for larger businesses in India (Banerjee & Duflo, 2014). Borrowing constraints drive misallocation across businesses and explain heterogeneous returns to capital that can be particularly large for productive firms that are constrained. Third, there is no equity market in line with its small role on household balance sheets. Less productive households are thus deprived of access to lucrative business investments: absent a mature equity or debt market that allows them to supply capital to the most productive yet constrained entrepreneurs, they park their savings in gold (along with deposits).

We calibrate our model mostly to aggregate data; this includes data from Indian financial and national accounts, aggregate moments from household-level micro data (AIDIS: All India Debt and Investment Survey) including information on household borrowing, collateral use, and asset holdings; and microdata on household businesses for example to discipline parameters of the stochastic process on entrepreneurial productivity with data from a large panel of small- and medium-sized enterprises (IHDS: Indian Human Development Survey). For calibrating the aggregate risk, we rely on the gold price data from the central bank of India (RBI) while backing out the aggregate TFP series from a well-known dataset on the Indian corporate sector, CMIE (Centre for Monitoring Indian Economy) *aka* "Indian Compustat". We then validate the model using untargeted distributional moments, which are key for our investigation. This is to ensure that the model correctly captures the main features of household balance sheets across the wealth distribution and firm size distribution (from the Indian Economic Census). Finally, we also validate the (micro) returns to capital by replicating the RCT by De Mel et al. (2008) within our model, showing that the model accurately captures empirical returns to capital for small firms.

With the calibrated model in hand, we decompose the drivers of gold savings. We find that social norms account for 42.7%, financial returns and hedging for 47.3%, and liquidity motives for 10% of aggregate gold holdings. These contributions vary significantly across the wealth distribution. For poor households who – both in the data and our model – hold the highest shares of their assets in gold, the social norm channel dominates, explaining 80% of gold holdings. For wealthy households, return and hedging motives dominate.

We then quantify the importance of gold being unproductive. For this, we follow a thought experiment analogous to the development accounting exercise: what would happen if idle gold could instead be used productively? Suppose that banks could *monetize* a fraction of the gold that remains idle at any point in time and deposit it for households. In the limit case where all gold is monetized, we find large aggregate output gains of 13%, much larger than the 7% predicted by the naive development accounting exercise. Output gains are large because households increase their overall savings. The overall increase in savings also reduces capital misallocation because it particularly benefits the most productive households who end up being less constrained and thus expand capital investments the most. These output gains translate into similarly large welfare gains.[2]

Our second main result is more policy-focused: Given large aggregate costs of unproductive savings, it is tempting to discourage gold holdings. We show that this backfires and that policy should instead focus on the underlying frictions that cause households to hold more unproductive savings. Specifically, we quantify the output and welfare effects of taxing gold and redistributing proceeds lump-sum. We find that output does not increase and welfare decreases. Since gold enters utility, taxing gold hurts welfare, similarly to a consumption tax. Furthermore, the policy decreases the financial return to gold, thereby shrinking the investment opportunity set of households. This makes households poorer and decreases the overall level of aggregate savings. This negative wealth effect largely cancels out the policy's substitution effect from gold to productive capital. In contrast, if policy could directly relax financial frictions, the aggregate gold share would sharply decrease and output would increase.

Related literature.— This paper contributes to three strands of literature. First, this paper contributes to a classical literature on Macro Finance and Development. To our knowledge, this is the first paper to quantitatively revisit the question raised by Keynes (1913) a century ago, that has since resonated with policy makers in many developing countries: to what extent are unproductive savings responsible for low investment and output? What distinguishes our paper from earlier theoretical contributions such as (Acemoglu & Zilibotti, 1997; Greenwood & Jovanovic, 1990) is the quantitative nature of our inves-

[2]While it matters whether assets are unproductive, there are clearly practical limitations to making gold productive. In India, the 2015 *Gold Monetization Scheme* is one example policy that tried to utilize idle jewelry in the economy but ultimately failed to gain traction due to low take-up and size. While in part due to a lack of trust, differences can also be attributed to low offered returns and that deposited gold had to be melted, reducing demand.

tigation: we provide an estimate of the costs of unproductive savings in a model that can account for household balance sheets and the distribution of business returns in India.[3]

Second, this paper introduces household finance and portfolio choice into the Macro Development literature (e.g. Buera et al., 2011; 2021; 2023; Moll, 2014). We draw upon the theoretical Household Finance literature on asset allocation and portfolio choice with durables (e.g. Campbell & Viceira, 2002; Flavin & Yamashita, 2002; Piazzesi et al., 2007; Yogo, 2006) and comparative household finance (Badarinza et al., 2016), and contribute in three ways. First, we consider the aggregate implications for development when assets on household balance sheets differ not only in their risk-characteristics, but also in how productive they are. Second, we introduce gold as a new asset. Gold is quantitatively important in a development context and we realistically capture the main features that make it appealing to households: social norms, financial returns and hedging, and liquidity. Third, our combination of multiple assets including aggregate risk and a decreasing-returns-to-scale technology is novel.

Finally, we contribute to the Micro Development literature on household savings (e.g. Karlan et al., 2014; Schaner, 2018) and the returns on business investments in developing countries (e.g. De Mel et al., 2008). While we do not model any behavioral frictions in savings, our model can account for observed micro returns to household business capital and savings responses of households. Hence, our model can offer insights on aggregate implications of savings and financial frictions.

The rest of the paper is structured as follows. Section 2 introduces the data and establishes main stylized facts on unproductive savings and gold in particular. Section 3 introduces the model and Section 4 discusses the calibration and validation exercises. In Section 5, we quantify the aggregate costs of unproductive savings and consider the role of policy. Section 6 concludes.

2 Empirical evidence

The aim of this section is to give an overview of the importance of unproductive forms of savings on household balance sheets. The focus is on India and we start by describing the data that we use throughout.

[3]Strictly speaking, the above papers do not model "unproductive" savings. Instead, they limit the investigation to two productive technologies that differ in their returns, risk and fixed costs.

2.1 Data

The main data we draw on is the 2013 wave of the *All India Debt and Investment Survey* (AIDIS), which is a large-scale survey that provides representative information on household balance sheets across Indian households (NSSO, 2013). To compare India to a rich country, we also draw on the 2010 wave of the US *Survey of Consumer Finances*, SCF (2010) in short. To study how household balance sheets changed over time, we also draw on the 2019 AIDIS wave.

AIDIS is the oldest running survey on household wealth in developing countries, first conducted by the Reserve Bank of India (RBI) in 1951-52. Similar to the SCF, it contains detailed questions on all major categories of household wealth holdings. For the purposes of this paper, we group assets into six broad asset classes: (1) Residential real estate, (2) Vehicles, (3) Business assets, (4) Gold, (5) Deposits, and (6) Financials. Table 1 provides a detailed overview of what we include under each of the six asset classes for AIDIS and the SCF respectively. Importantly, we look at *net* assets, subtracting asset-specific debt when possible. One implication of focussing on these categories of net assets is that we ignore consumption-related debt such as credit card debt and student debt, which is important at the left tail in the US, but not sizable in India.

Common class	**In AIDIS**	**In SCF**
Residential real estate	Net equity in residential buildings; Residential urban and rural land	Net equity in primary residence of household and other residential real estate held by household
Vehicles	Transport equipment for household use	All (private) vehicles less corresponding debt
Business	Total of the following categories less all outstanding debt for business capital expenditure: Livestock and poultry; Agricultural machinery and implements; Non-farm business equipment; Transport equipment used mainly for farm or non-farm business; Non-residential buildings and land	Total value of business(es) in which the household has either an active or nonactive interest (net equity value of the household's interest); Net equity in nonresidential real estate
Gold	Bullion & ornaments	Other non-financial assets held by household (gold, silver, jewelry, antiques, art, etc.)
Deposits	Government deposits, NSC, KVP, saving bonds, post office deposits, other small savings schemes, etc.; Bank deposits; Deposits with non banking companies; Deposits with micro-finance institutions/self-help groups	All types of transactions accounts; Certificates of deposit
Financials	Shares & debentures; Annuity schemes; Fund shares; Insurance schemes; Receivables	Directly held stocks; Directly held pooled investment funds; All other financial assets

Table 1: Construction of common asset classes from AIDIS and SCF underlying data.

AIDIS has a large sample size with over 100k household observations for both the 2013 and 2019 waves, compared to the SCF with only roughly 6,500 households. The data quality of AIDIS is also generally considered to be high, but it does suffer from drawbacks.

Most importantly and as for the SCF, AIDIS is only a repeated cross-section, not a panel dataset, preventing us from zooming closer into within-household changes in wealth. Second, AIDIS does not have good information on household income nor does it have good information on costs and revenues for household businesses. For these reasons, we complement our analysis with detailed information on household businesses and household income using the India Human Development Survey (IHDS), a nationally representative panel with waves from 2005 and 2012 (Desai & Vanneman, 2005; 2012). Third, as is common for wealth surveys, AIDIS struggles to correctly capture the far right tail of the wealth distribution (Deaton, 2005).[4] As one data check, we compare the AIDIS-implied stock of aggregate bank deposits with the official RBI estimate based on bank-reporting; we find that AIDIS underestimates aggregate deposits by roughly 30%. While our model helps us to extrapolate for the far right tail, this only works well if the very wealthy do not behave systematically different.

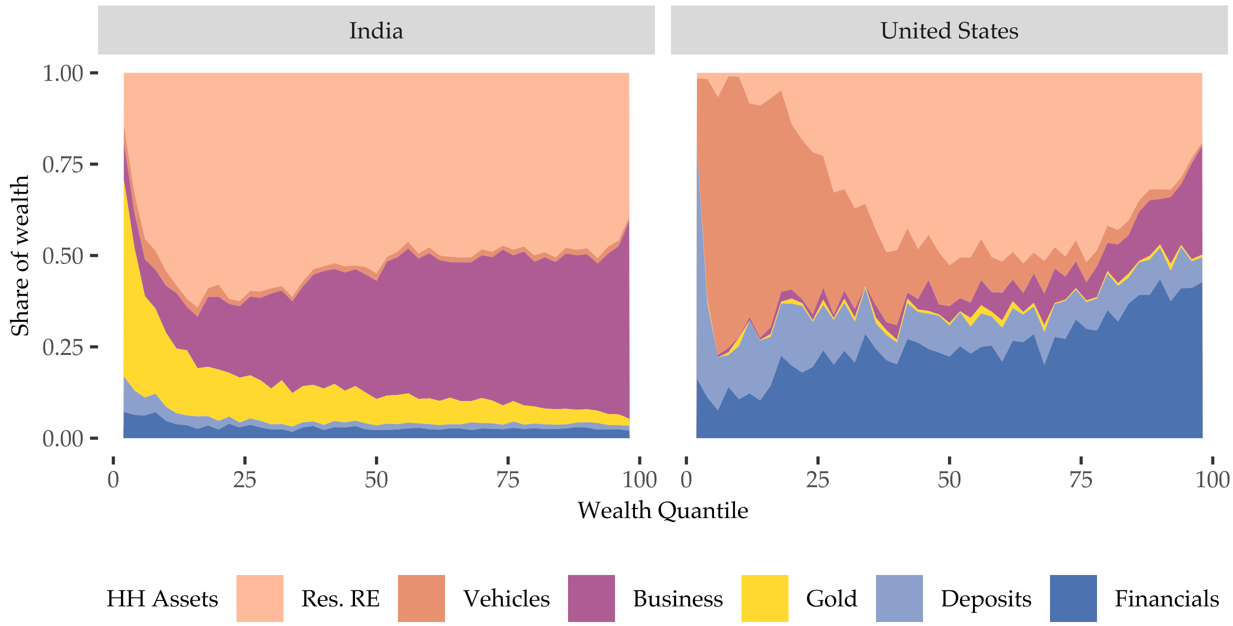
We closely follow Badarinza et al. (2019) for cleaning the AIDIS data to ensure comparability with previous research. Specifically, we restrict observations where the household head is at least 24 years of age, remove observations with no assets, negative values of urban land or negative values for company shares held, as well as households that have reported residential real estate or transport of value higher than their total real estate and transport ownerships. For SCF, we also remove records with negative real estate values and business holdings. These restrictions ensure that net asset shares are always positive. Appendix D provides further details on the data cleaning. These data cleaning steps have small effects on the overall sample; we only remove 2.6% and 2.4% of observations for the 2013 and 2019 waves respectively, and 5.5% for the SCF.

2.2 Main stylized facts

We start with a general overview of the household balance sheet distribution in Figure 1, comparing India to the US. Household balance sheets look remarkably different in India and the US in at least three important ways. First, deposits and financial assets play a small role in India, while they account for about 38% of total household assets in the US, with a split of 25% and 13% respectively. This difference is even stronger at the right tail; the wealthiest 10% in India hold less than 4% of their wealth in deposits and financial assets, while wealthy households in the US hold about half their wealth in them. Second,

[4]In contrast, the SCF is one of the few surveys that captures the far right tail by administering an additional list sample of wealthy households to deal with higher non-response rates among the wealthy Kennickell (n.d.).

Figure 1: Average household asset allocation by wealth quantile



Note: Data is based on the 2013 wave of AIDIS for India and the 2010 wave of the SCF for the US. Total wealth is the sum of net assets across the six asset classes (details in Table 1). "Res. RE" refers to residential real estate. Quantiles are computed independently for each country and the figure is smoothed by showing average shares within 50 equal-sized wealth bins. The figure restricts to (weakly) positive net assets and drops households with zero overall wealth, which affects less than 2% of observations in India and the US respectively. Since consumption is not part of assets, we do not include consumption loans in our measure of wealth.

while the importance of residential real estate (i.e. housing) is broadly comparable in the two countries, business wealth differs completely. Due to the importance of agriculture and much higher shares of self-employment, business wealth accounts for more than 30% of the aggregate household wealth in India. In contrast, business wealth in the US is mostly a feature of the right tail, in line with Bricker et al. (2014) and Smith et al. (2022). Third, and most importantly for this paper, gold plays a central role on household balance sheets in India, while it is almost entirely absent from household balance sheets in the US (<1%). The aggregate household wealth share in gold is 11% in India, making up around 40% of wealth at the left tail and then slowly decreasing over the wealth distribution.

In the Appendix, we provide further evidence. Figure A1 compares India and the US in terms of the level of wealth instead of the distribution, allowing us to compare similarly wealthy households in India and the US. The three main results above also hold conditional on the level of wealth; at every single level of wealth that can be compared, US households hold much less gold and business assets and much more financial assets. Of course, in this exercise we cannot compare the richest households in the US since they have no counterpart in India, and we cannot compare the poorest households in India because they have no counterpart in the US. Figure A3 looks at changes in the wealth distribution in India between 2013 and 2019. Patterns are very similar, but the biggest change between 2013 and 2019 has been an increasing importance of deposits at the left tail, and an overall bigger role for financial assets at the right tail. Throughout the paper, we use the 2013 AIDIS wave as main target for our model economy, but return to the change between 2013 and 2019 for when we discuss policy counterfactuals.

While Figure 1 gave an overview of the entire balance sheet of Indian households, our subsequent model abstracts from some features of the balance sheet which we think are either not key to our story or difficult to incorporate. Specifically, we abstract from residential real estate and vehicles, focusing only on the remaining four categories of household assets. Vehicles are small in India and given that they are durable consumption goods, we implicitly incorporate them as consumption goods in the model. Residential real estate, on the other hand, is large, but given the difficulty of disentangling productive and unproductive forms of real estate and the additional complications of modeling a housing and land market, we abstract from it in this paper. As for vehicles, we implicitly capture housing as a durable consumption good as part of consumption in the model, but we fully acknowledge its limitations. In the conclusion, we return to the issue of abstracting from housing and discuss how this might bias our main results.

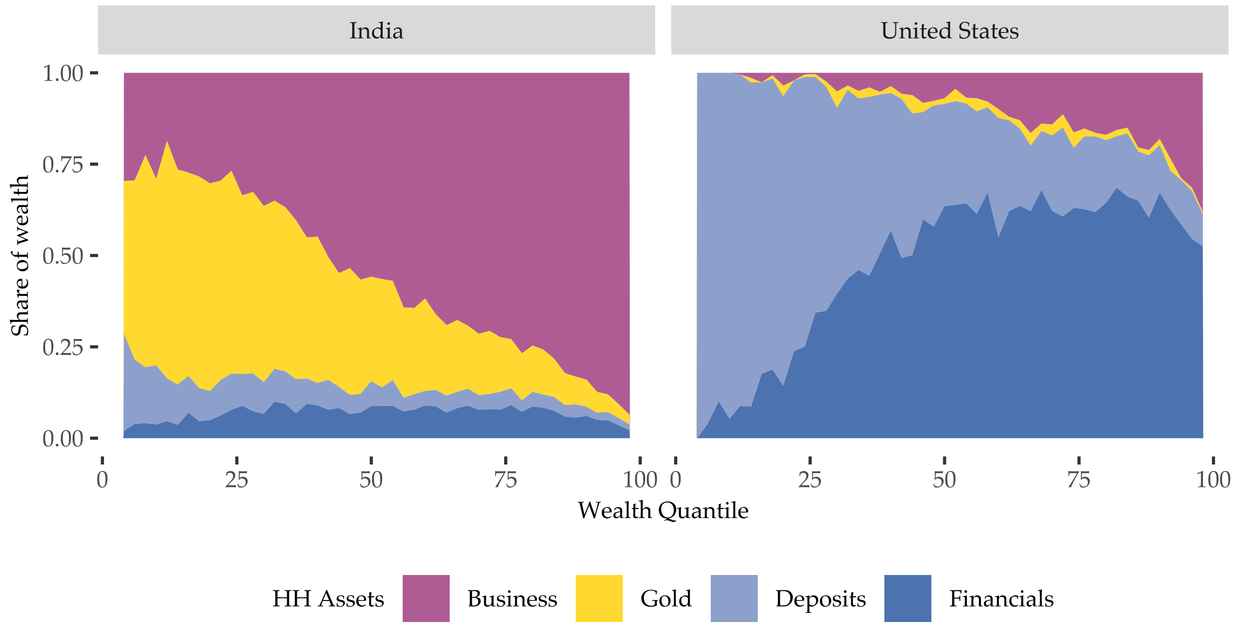
Figure 2 shows the main household balance sheet when abstracting from residential real estate and vehicles. The three stylized facts are now even clearer: (1) Deposits and financial assets are minor in India, while they are dominant in the US, (2) household business assets are dominant and increasing with wealth in India, and (3) gold makes up a sizable share of household wealth but is declining with wealth. For the remainder of the paper, Figure 2 serves as the main reference for the wealth distribution in India.

3 The Model

We proceed by quantifying the aggregate costs of unproductive savings within a model of household portfolio choice and entrepreneurial investment behavior. Households can save in productive and unproductive assets. For productive assets, we consider physical capital in household's own business, and bank deposits. We focus on gold as the unproductive asset given its importance in the Indian context and data availability.[5]

[5] As previously noted, we abstract from residential real estate and vehicles in this model, but capture durable consumption goods implicitly via consumption.

Figure 2: Average household asset allocation by wealth quantile



Note: Data is based on the 2013 wave of AIDIS for India and the 2010 wave of the SCF for the US. Total wealth is the sum of net assets across four asset classes: Business assets, Gold, Deposits and Financials. This figure drops net residential real estate vehicles. Quantiles are computed independently for each country and the figure is smoothed by showing average shares within 50 equal-sized wealth bins. The figure restricts to (weakly) positive net assets and drops households with zero overall wealth, which affects less than 2% of observations in India and the US respectively. Since consumption is not part of assets, we do not include consumption loans in our measure of wealth.

To accurately capture why households invest in gold rather than in more productive assets, the model incorporates three main motives: (1) Social norms: households obtain direct utility from holding gold, in line with the cultural value of gold and the importance of gold in the dowry system; (2) Liquidity and collateral value: thanks to its liquidity, movability and divisibility, gold is widely used as collateral in India, to get loans which are easily accessible and with high loan to value ratio; and (3) Hedging and Return: households earn financial returns on gold in the form of capital gains from changes in the (global) gold price and the fact that gold depreciates little; more importantly, households can use gold as a hedge against risks to their income, given that the (global) gold price is observed to negatively covary with measures of factor income in India, such as wages and return on capital. Our model features aggregate risk due to changes in the exogenous global gold price and (exogenous) aggregate TFP. The latter captures, in a reduced form, business cycle risk from fluctuations in aggregate demand and exchange rate shocks. We model India as a small open economy that trades with the world and also accesses international financial markets for borrowing and lending. Importantly, in line with the data, India does not directly produce gold itself, so that it relies on imports of gold to satisfy domestic demand. We believe that this realistically captures the first-order policy concern of Indian policy makers that large imports of gold crowd out capital imports.

Demand for gold is also driven by the returns to alternative investment opportunities, namely capital and deposits. To accurately capture returns on capital, we consider a rich household production side similar to Moll (2014) and Buera et al. (2021) and in line with the importance of household businesses across the entire wealth distribution in India. Households differ in the productivity with which they run their business and they face idiosyncratic risk over their future productivity. Household businesses use both labor and capital. For labor, they can draw on family labor or, if they are productive enough, hire outside labor. For business capital, households can invest their own savings and also borrow capital from the financial market. However, in line with the ubiquity of collateral constraints in India, household businesses face standard financing constraints that limit their borrowing. One key novelty is that we do not only model collateral constraints in own capital but also allow households to collateralize (parts of) their gold, in line with the importance of gold loans in India. This introduces a potentially positive impact of gold, as it makes it easier for household businesses to borrow capital.[6] Finally, households can also choose to deposit parts of their wealth to diversify risk and to earn (safe) financial returns. A domestic financial intermediary collects all deposits and lends these to household businesses or the corporate sector. We model a separate corporate sector that demands both capital and labor to realistically account for the part of the Indian economy that is not captured by household businesses.

Model setup.— Our economy features three main actors: a corporate sector, a financial intermediary and a continuum of households of measure 1. There exist two goods in this economy: a consumption good (which can be freely converted to capital), and gold. The consumption good serves as numéraire and time is discrete. We denote the (exogenous) aggregate state of the economy by $\mathbf{\Omega} = \{P^g, Z, r^*\}$ where P^g denotes the global gold price, Z denotes aggregate TFP, and r^* the global interest rate. The endogenous domestic wage is denoted w. We start by describing households.

[6]This introduces a trade-off between the direct crowding-out of productive savings and the crowding-in from productive investments via the collateral channel. A similar trade-off is also key in Farhi and Tirole (2008), who consider it in a "short-run" setting of financial bubbles. The main difference is that we do not endogenize the price of gold and do not allow for a bubble, since we are interested in the long-run effects of holding unproductive assets.

3.1 Households

Preferences.— Households seek to maximise lifetime expected utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(c_t, g_{t+1} - \zeta g^{\ell}_{t+1})$$

where preferences for consumption c and gold g are described by:

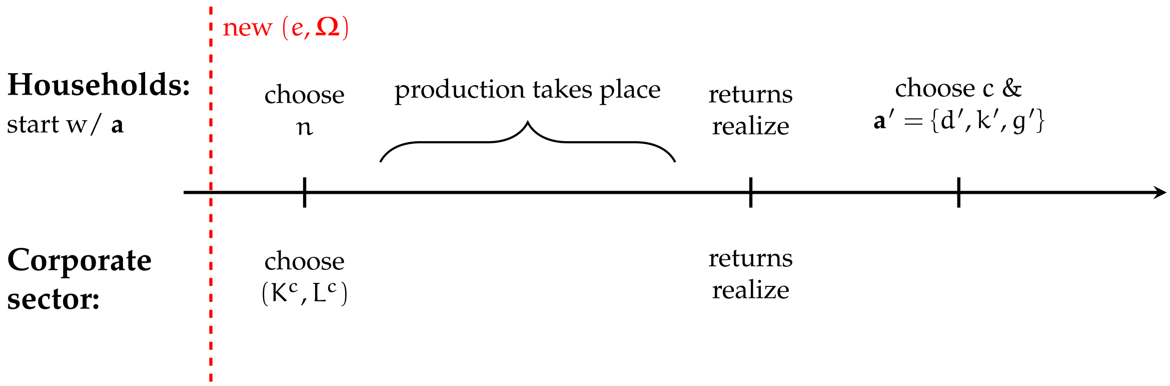
$$U(c,g) = \frac{1}{1-\gamma}\left[\left((1-\theta_g)^{\frac{1}{\varepsilon}} c^{\frac{\varepsilon-1}{\varepsilon}} + \theta_g^{\frac{1}{\varepsilon}} g^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}\right]^{1-\gamma} \tag{2}$$

This utility function combines standard inter-temporal CRRA preferences with standard intra-temporal CES preferences. We denote the coefficient of relative risk aversion by γ and the elasticity of substitution between services from holding gold and the consumption good by ε. For $\varepsilon \in (0,1)$, gold and the consumption good are complements, which will be the empirically relevant case. Complementarity pushes households towards balancing gold and consumption, and marginal utility of gold is increasing in consumption. Households derive a stream of utility from their gold holdings, adjusted for the part that is used as collateral. The total stock of gold that the household chooses at period t to carry over to the next period is denoted $g_{t+1} \geqslant 0$, and $g^{\ell}_{t+1} \leqslant g_{t+1}$ is the part of the stock that the household decides to use as collateral for gold loans. We allow for collateralized gold to not pay the same utility dividend as it goes to the custody of the financial intermediary, limiting its use. We model this by $(g_{t+1} - \zeta g^{\ell}_{t+1})$ where $\zeta \in (0,1)$ captures the utility penalty for collateralized gold. θ_g in the utility function is the key parameter that governs the strength of social norms for gold, capturing the cultural importance of gold beyond its return properties as an asset.[7]

Timing.— Figure 3 gives an overview of the main model timeline. Households enter a period with the wealth position **a**. Wealth is composed of three different assets that have been chosen in the previous period: physical capital k, deposits (or debt) d, and previous gold holdings g. After both the (exogenous) idiosyncratic business productivity e and the aggregate state of the economy $\mathbf{\Omega}$ are revealed at the start of the period, households choose how much labor n to hire for their business. After production, households earn

[7]This way of modeling gold in the utility has at least two different intellectual precursors. First, the same intra-temporal CES aggregator is used in the durable consumption literature to model preferences over (other) consumption and houses (Piazzesi & Schneider, 2016) or non-durable and durable consumption (Yogo, 2006). Second, it also resembles models of wealth in the utility and the spirit of capitalism (e.g., Bakshi and Chen (1996), Carroll (1998)), with the difference that in that literature it is the totality of wealth of a household that matters, not a specific item of it.

Figure 3: Main timeline of model



labor income, and returns on all components of their wealth – including their business – are realized. They then make choices on consumption c and new asset position $\mathbf{a}' = (d', k', g')$ that they carry forward to the next period.

The budget constraint.— Conditional on labor hiring n at the start of the period, households face the following budget constraint (in recursive notation):

$$c + \underbrace{d' + k' + P^g g'}_{\equiv a \text{ (savings)}} \leqslant \underbrace{x}_{\text{cash on hand}}$$
$$x = w + \overbrace{\left(1 + r^d\right) d\,\mathbf{1}_{\{d>0\}} + \left(1 + r^b\right) d\,\mathbf{1}_{\{d<0\}} + \underbrace{y(k, n, e, Z) - wn}_{\equiv \text{ HH business profit}} + (1 - \delta)k + P^g g}^{\equiv \text{ ex-post HH net worth } \tilde{a}} \tag{3}$$

Household's cash-on-hand (x) consists of labor earnings and today's value of the portfolio after realization of shocks, that is, the ex-post net worth $\tilde{a}$. Since each household is endowed with one unit of labor which they supply inelastically, labor earning at each period is equal to the wage rate w.[8] Ex-post net worth $\tilde{a}$ is composed of: (1) the ex-post value of the household business (which includes household business profit in addition to undepreciated capital $(1 - \delta)k$); (2) the ex-post value of gold holdings, which is the value of the stock of gold chosen yesterday, in today's prices; and (3) today's value of deposit or debt (depending on the sign of d), chosen yesterday.

We denote d as 'deposits' when $d \geqslant 0$, and as 'debt' when $d < 0$. Deposits chosen

[8] In terms of accounting, any payment of wages by household business to labor of its own members is accounted for as labor earning, separated from net business income (the gross operating surplus). For example, if $n^*_{it} = 1$ and the household's business only employs the labor of its own members, the wage payment w_t is referred to as labor earning of the household, netted out from their business income. The advantage is more clear notation when analyzing the optimal asset allocation between own capital, gold and deposits.

yesterday earn a rate of return r^d, and households have to pay the borrowing rate r^b for any debt. For ease of notation, we sometimes directly refer to the effective interest rate by $r(d)$. To capture realistic returns and costs of debt, we model standard wedges with respect to the international safe interest rate r^* such that: $r^d = r^* - \xi^d$ and $r^b = r^* + \xi^b$, where $\xi^d, \xi^b \geqslant 0$ are (exogenous) parameters indexing the efficiency with which India's financial system intermediates funds. Larger ξ^b captures higher screening costs and more intense moral hazard problems on the part of borrowers, whereas ξ^d reflects among others higher market power of banks.

Due to the imperfect nature of credit markets, households' borrowings are constrained by the size and composition of their wealth. In particular, they need collateral to borrow, which can be in the form of physical capital—as is standard in the macro-development literature, e.g., Moll (2014)—or gold, which is a novelty introduced in our model. We consider gold as a second form of collateral, because of the importance of *gold loans* in India, where they constitute a significant portion of the secured loan market (see Appendix E.1 for more context on gold loans in India). Specifically, we assume that:

$$d' \geqslant -\phi_k k' - \phi_g \left(P^g g^\ell\right), \qquad \phi_g, \phi_k \geqslant 0 \tag{4}$$

where (ϕ_k, ϕ_g) reflect the strength of financial markets, with lower ϕ corresponding to less developed financial markets. In particular, $\phi_k = \phi_g = 0$ implies no external borrowing is possible, and $\phi_g = \phi_k = 1$ corresponds to the case of perfect credit markets [9]. Note that thanks to liquidity, movability, and divisibility of gold, the loan-to-value ratio (LTV) of gold is significantly higher than business assets (i.e. $\phi_g >> \phi_k$). This is one aspect that can make gold a more attractive investment compared to business investment.

While deposits offer a risk-free saving vehicle, investment in both capital and gold is risky. Financial returns to gold are driven by changes in the global gold price, whereas return to household business are subject to both aggregate risk (aggregate TFP Z) and idiosyncratic risk (household's entrepreneurial productivity e). In particular, conditional on the hiring choice n, household's realized business profit is defined by total revenue of household's business less compensation of employees,

$$\pi(k, n, e, Z) = y(k, n, e, Z) - wn = eZ(k^{\alpha_h} n^{1-\alpha_h})^\eta - wn, \qquad \eta \in (0, 1) \tag{5}$$

[9]Following Buera et al. (2011), Buera and Shin (2013) and Buera et al. (2015), the term "perfect credit" here does not extend to consumption insurance and only applies to boundless borrowing business investment purposes.

with η denoting the span-of-control parameter. The attractiveness of investing in physical capital depends on both the idiosyncratic and aggregate productivity risk that household businesses face. We now describe the laws of motion for the idiosyncratic productivity and aggregate risk processes.

Idiosyncratic productivity process.— At the beginning of a period, households draw their new realization of productivity e. Productivity of individual households evolve independently from each other and from any aggregate risk. It follows a standard AR(1) process:

$$\log(e') = \mu_e + \rho_e \log(e) + u_e{}' \tag{6}$$

where $\rho_e \in (0,1)$ denotes the persistence of productivity, and innovations u_e are distributed iid over time according to $u_e \sim \mathcal{N}(0, \sigma_e^2)$.

Aggregate risk process.— Our economy features aggregate risk in terms of the (global) gold price P_t^g and aggregate TFP, Z_t. Indian households take the price of gold as given. $\log(Z)$ and $\log(P^g)$ jointly evolve according to a VAR(1) process. Specifically, denoting their logs by $\mathbf{X} \equiv [\log(Z), \log(P^g)]^\top$, the aggregate risks evolve according to

$$\mathbf{X}' = \begin{pmatrix} \rho_z & 0 \\ 0 & \rho_g \end{pmatrix} \mathbf{X} + \mathbf{U}'_{\mathbf{zg}} \qquad \text{with:} \qquad \mathbf{U}'_{\mathbf{zg}} = \begin{pmatrix} u'_z \\ u'_g \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_z^2 & \sigma_{zg} \\ \sigma_{zg} & \sigma_g^2 \end{pmatrix} \right) \tag{7}$$

where ρ_z and ρ_g denote the auto-correlation (persistence) parameters, and σ_z^2 and σ_g^2 are the variances of the innovation terms of the stochastic processes for $\log(Z)$ and $\log(P^g)$ respectively. σ_{zg} denotes the correlation between the two processes and is an important determinant of the hedging properties of gold against the aggregate fluctuations in return to capital and national income (a point we will further discuss in Section 3.2).

The household's problem.— Taking market prices as given, the optimal labor hiring, consumption, borrowing, and portfolio choice problem of a household who enters the period with the asset position $\mathbf{a} = (k, d, g)$, idiosyncratic productivity e, and aggregate state $\mathbf{\Omega} = (P^g, Z, r^*)$ can be stated as:

$$V(\mathbf{a}, e; \mathbf{\Omega}) = \max_{n,c,g^\ell,g',k',d'} U(c, g' - \zeta g^\ell) + \beta\, \mathbb{E}\left\{ V(\mathbf{a}', e'; \mathbf{\Omega}') \,|\, e, \mathbf{\Omega} \right\} \tag{8}$$

subject to the budget constraint (3), borrowing constraint (4), and laws of motion for household productivity and aggregate states (6), (7), and where $\mathbf{a}' = (d', k', g')$. Let's denote the corresponding policy functions by $q^n, q^c, q^{g\ell}, q^g, q^k, q^d$, all defined over the same domain as the value function V, such that, for example, optimal consumption is given by $c = q^c(\mathbf{a}, e; \mathbf{\Omega})$.

3.2 Optimal household choices: returns to capital and asset allocation

Before closing the model, we highlight a number of implications of household's optimal choices implied by the model.

Return on physical capital.— Returns to household capital investment in their business are given by the sum of business profits and undepreciated capital: $\pi(k, e; \mathbf{\Omega}) + (1-\delta)k$. The marginal rate of return on capital k, denoted by $R^k(k, e, \mathbf{\Omega})$, is then given by:

$$\frac{\partial}{\partial k}\pi(k, e; \mathbf{\Omega}) + 1 - \delta = \kappa_r \ (e\,Z)^{\frac{1}{1-\eta(1-\alpha_h)}} \ k^{\frac{-(1-\eta)}{1-\eta(1-\alpha_h)}} + (1-\delta), \tag{9}$$

where κ_r is a constant (see Appendix B for more details). One important implication of Equation (9) is that marginal returns to capital are decreasing in capital due to the decreasing-returns-to-scale (DRS) technology. Duflo and Banerjee (2011) provide a range of evidence in support of the DRS assumption for household businesses. However, a quantitatively important consequence of DRS is that a higher correlation between productivity and wealth in equilibrium pushes the most productive households to run larger businesses, which means they also have lower marginal rates of return on capital. This affects the weight of gold in their portfolio.

Optimal asset allocation and demand for gold.— Let's denote the stochastic discount factor (SDF) by

$$m'(\mathbf{a}', e'; \mathbf{\Omega}') = \beta \frac{\partial_c U\left(c', g'' - \zeta g^{\ell'}\right)}{\partial_c U\left(c, g' - \zeta g^{\ell}\right)} \quad ,$$

where $c' = q^c(\mathbf{a}', e'; \mathbf{\Omega}'), g'' = q^g(\mathbf{a}', e'; \mathbf{\Omega}')$, and $g^{\ell'} = q^{g\ell}(\mathbf{a}', e'; \mathbf{\Omega}')$. For the ease of notation, we simply refer to $m'(\mathbf{a}', e'; \mathbf{\Omega}')$ by m' in what follows. Proposition 1 characterizes the optimal level of investment in one's own business:

Proposition 1. *The optimal business investment*

a) for unconstrained households is given by

$$\mathbb{E}\left[m' R^k\left(k', e', \mathbf{\Omega}'\right) \mid (e, \mathbf{\Omega})\right] = \mathbb{E}\left[m' \ (1 + r(d)) \mid (e, \mathbf{\Omega})\right] = 1\,, \tag{10}$$

b) and for constrained households by

$$\mathbb{E}\left[m' R^k \left(k', e', \boldsymbol{\Omega}'\right) | (e, \boldsymbol{\Omega})\right] = \mathbb{E}\left[m' \, (1 + r(d)) \,|\, (e, \boldsymbol{\Omega})\right] + \frac{\mu \, (1 - \phi_k)}{\partial_c U(c, g' - \zeta g^{\ell})}. \quad (11)$$

Here, $R^k \left(k', e', \boldsymbol{\Omega}'\right)$ is the return to business investment ex-post realization of shocks tomorrow, $(1 + r(d))$ is the safe rate of return, and μ is the shadow cost of funds. Equation (10) states that unconstrained households invest in their business to the point where the SDF-discounted expected marginal return to the business investment—or the expected marginal return to business investment with respect to the equivalent martingale measure—(left-hand-side) is equal to the SDF-discounted opportunity cost of it (right-hand-side). Note that the opportunity cost is equal to $(1 + r^d)$ for the depositors and $(1 + r^b)$ for the debtors. The unconstrained households do not need to resort to their gold as collateral ($g^{\ell} = 0$).

Whereas for the unconstrained households the shadow cost of funds $\mu = 0$, it is positive for the constrained ones (i.e. households for whom $d' \leqslant -\phi_k k'$). For the latter, Equation (11) states that the SDF-discounted expected marginal return to business investment is strictly larger than the SDF-discounted opportunity cost of entrepreneurial investment, but the households are inhibited from larger investment in their businesses since they are hitting their collateral constraints (Equation (4)). The wedge between the expected marginal return to business investment and the opportunity cost is proportional to $\mu \times (1 - \phi_k)$; which is higher if the shadow cost of funds is higher, or if financial frictions are more severe (ϕ_k is lower).

Optimal gold investment.— Defining the financial rate of return on gold simply as the capital gain (or loss)

$$\widetilde{R}^g_t = \frac{P^g_t}{P^g_{t-1}}, \quad (12)$$

the following proposition characterizes the optimal level of investment in gold.

Proposition 2. *The optimal gold investment is pinned down by the Euler equation below:*

$$\underbrace{\beta \, \mathbb{E}\left[\partial_c U(c', g'' - \zeta g^{\ell'}) \, \widetilde{R}^{g'} \,|\, (e, \boldsymbol{\Omega})\right]}_{\textit{expected financial returns}} + \underbrace{\frac{1}{P^g} \partial_g U\left(c, g' - \zeta g^{\ell}\right)}_{\textit{gold utility dividend}} = \partial_c U\left(c, g' - \zeta g^{\ell}\right) . \quad (13)$$

where $\widetilde{R}^{g'} = \frac{P^g(\boldsymbol{\Omega}')}{P^g(\boldsymbol{\Omega})}$ is the ex-post realised return to gold. The left-hand-side is the *total return* on spending one more Rupee on buying gold, denominated in today's utility. The total return is composed of the expected discounted marginal utility of the financial return, and the utility dividend, i.e., the marginal utility of the additional 1 Rupee of gold. The right-hand-side is the opportunity cost of spending one more Rupee on gold at the expense of consumption.

Combining Equation (13) with Equation (10) and Equation (11), we obtain equations that (non-linearly) link the relative weights of gold and business assets in the portfolio, to the extent of financial frictions, productivity of business, preference for gold, and utility cost of gold as collateral:

Proposition 3. *Relative demand for gold is given by*

$$\mathbb{E}\left[m'\left(\widetilde{R^g}' - R^{k'}\right) \mid (e, \boldsymbol{\Omega})\right] + \frac{1}{P^g}\left(1 - \frac{\phi_k}{\phi_g}\,\zeta\,\mathbf{1}_{constrained}\right)\left(\frac{\theta_g}{1-\theta_g}\,\frac{c}{g' - \zeta g^{\ell}}\right)^{\frac{1}{\varepsilon}} = 0\,. \quad (14)$$

where $R^{k'}$ denotes $R^k\left(k', e', \boldsymbol{\Omega}'\right)$ and m' denotes $m'(\mathbf{a}', e'; \boldsymbol{\Omega}')$ to save on notation. Few comments are in order. First, Equation (14) expresses the no-arbitrage equation for gold and business investment (conditional on the household's state $(e, \boldsymbol{\Omega})$). It simply states that the SDF discounted return to gold in excess of return to capital should be zero. The first term on the left is the SDF-discounted financial return to gold in excess of return to business investment. The second term is the utility dividend to gold holding, denominated in today's marginal utility of consumption. Note again that for typical securities, not entering the household's utility, the no-arbitrage simply consists of the first term: SDF-discounted excess return is zero. Here, for the case of gold—or any other asset that produces utility for that matter—one should consider the total return. In other words, the household is willing to invest in gold even if the SDF-discounted financial return is lower than business investment, with the gap being given by the marginal utility premium of holding gold. Second, for the constrained households, their portfolios weigh more heavily towards capital the higher the utility penalty of gold as collateral (ζ) is, or the lower the liquidity of gold (ϕ_g) is—all else being equal. For them, any marginal unit of gold is valued both due to its usage as a liquid collateral for expanding business, and for the utility of it. Third, all else being equal, as the business gets larger and larger, the share of gold in household's portfolio increases. That is because marginal return on capital invested in own business is decreasing in scale (see Equation (9)); as businesses expand, it becomes increasingly difficult to run them as profitably as before, due to the span of control limits; hence households tend to weigh their portfolios more and more towards gold and financial assets the return on which is constant to scale. With a similar argument, less productive households tend to put a higher share of their assets in gold; since the opportunity cost of gold investment is lower for them.

Demand for gold, due to investment and social norms motives.— By rewriting Equation (14) for the unconstrained, one can get a clearer picture of how the hedging and return properties of gold affects the demand for gold (relative to consumption), compared with the case of a durable good without any investment properties (think refrigerator). This relation is given by the equation

$$\frac{P^g g'}{c} = \frac{\theta_g}{1-\theta_g} P^{g\,1-\varepsilon} \left(\underbrace{\mathbb{E}\left(R^{k'} - \widetilde{R^{g'}}\right)/R(d)}_{\text{opportunity cost}} + \underbrace{\mathrm{Cov}\left(R^{k'} - \widetilde{R^{g'}}, m'\right)}_{\text{hedging}} \right)^{-\varepsilon}, \tag{15}$$

where $R(d) = (1 + r(d))$ which is equal to $\left(1 + r^d\right)$, or $\left(1 + r^b\right)$, depending on whether the household is net depositor or debtor. The first part of the equation is the standard CES expenditure shares based on preferences, relative prices, and substitutability of gold with consumption. The big brackets capture the return and hedging properties of gold. In particular, note that gold has desirable hedging properties, if the covariance in the brackets is negative. In our context, this is indeed the case, which results from the strong negative correlation between aggregate productivity Z, and the international gold price P^g, itself resulting from $\sigma_{gz} < 0$ in the law of motion of aggregate state of the economy (Equation (7)). This increases the demand for gold, keeping the preference parameters and the expected opportunity cost constant. Note that if the purchased gold were assumed not to be tradable, i.e. the financial return were zero and there were no negative correlation of the financial return with the SDF, the Equation (15) would reduce to the standard CES demand equation.

3.3 The Corporate Sector

We model the corporate sector as a representative firm that produces the single economy-wide consumption good with a constant-returns-to-scale production function:

$$Y^c(\boldsymbol{\Omega}) = Z\left(K^c\right)^{\alpha}\left(N^c\right)^{1-\alpha} \tag{16}$$

where K^c and N^c are, respectively, labor and capital used in the corporate sector, and α denotes the output elasticity with respect to capital. We assume that the corporate sector rents capital from the financial intermediaries at rate r^*, and the user-cost of capital is

$(r^* + \delta)$. The corporate sector also hires labor at wage rate w such that the corporate sector's full problem is:

$$\max_{\{K^c, N^c\}} Z\left(K^c\right)^{\alpha}\left(N^c\right)^{1-\alpha} - (r^* + \delta)K^c - wN^c \tag{17}$$

3.4 Financial Intermediaries

The intermediaries can borrow or lend funds on the international funds market at the global (fixed) rate r^*, and offer deposit and loan contracts to households at the rates r^d_t, r^b_t. Processing households' deposits is subject to a cost of ζ^d per Rupee, and monitoring of the loan to household businesses has a cost of ζ^b per Rupee. They also rent capital to the corporate sector at the rate r^*. Both households and the corporate sector have access to the technology to convert funds in units of numeraire to capital goods, and vice versa, 1-to-1.

Assets of the financial intermediaries hence consist of loans to households and the rest of the world, and capital lent to the corporate sector. Liabilities consist of deposits by domestic households, and borrowings from the rest of the world. Let's denote the distribution of households today over the joint asset positions and entrepreneurial productivity space $(\mathbf{a}, e)$ by $\Gamma(\mathbf{a}, e)$ and their marginal distribution over $\mathbf{a}$ by $\Gamma(\mathbf{a})$. Here, the asset position $\mathbf{a} = (k, d, g)$, and we use $d(\mathbf{a})$ to simply refer to the second component of $\mathbf{a}$, i.e. the position on debt/deposit. We also use $d^+(\mathbf{a})$, using the positive part notation, that is $d^+(\mathbf{a}) = \max\left(d(\mathbf{a}), 0\right))$ to capture deposits of the agent with the asset position $\mathbf{a}$; similarly, $d^-(\mathbf{a}) = \max\left(-d(\mathbf{a}), 0\right)$ is used to tease out the (absolute value) of debt. Using these, let's denote the aggregate deposits, aggregate debt, and aggregate net deposits by D^+, D^-, and D respectively, where

$$D^+ = \int_{(\mathbf{a},e)} d^+(\mathbf{a})\ d\Gamma(\mathbf{a}, e), \qquad D^- = \int_{(\mathbf{a},e)} -d^-(\mathbf{a})\ d\Gamma(\mathbf{a}, e)$$

and $D = D^+ + D^-$. These are all predetermined aggregates from today's perspective, they are decided yesterday. Hence, aggregate balance sheet of the financial intermediaries at the start of this period (ex-post realization of shocks), can be expressed as

$$D = D^+ + D^- = \int_{(\mathbf{a},e)} d(\mathbf{a})\ d\Gamma(\mathbf{a}) = B + K^c, \tag{18}$$

where B denotes the net foreign assets position (NFA) of the economy this period. When the aggregate demand by capital from the corporate sector exceeds the net domestic supply of funds by households $D < K^c$, financial intermediaries borrow internationally to meet the excess domestic demand for funds. And when $D > K^c$, they lend the excess supply of funds to the rest of the world.

The budget constraint for the financial intermediary is then written as:

$$r^d D^+ + \xi^d D^+ - \xi^b D^- \leqslant r^* K^c + r^* B - r^b D^-, \tag{19}$$

where the left-hand-side shows the expenditures, i.e., interest payment on household deposits and costs of processing deposits and monitoring loans; and the right-hand-side shows the income, consisted of interest payments received from the corporate sector, the rest of the world, and domestic loans. Free entry ensures zero profit in the equilibrium, which implies that $r^d_t = r^* - \xi^d$ and $r^b_t = r^* + \xi^b$ for all t.

3.5 Equilibrium

Our model features a standard open-economy version of a *Recursive Competitive Equilibrium with Aggregate Risk*. Define the distribution of households over $(\mathbf{a}, e)$ by Γ, the exogenous aggregate states by $\mathbf{\Omega} = \{P^g, Z, r^*\}$ and the law of motion of the distribution by: $\Gamma' = \mathcal{H}(\Gamma, \mathbf{\Omega}, \mathbf{\Omega}')$.

Then an equilibrium is given by $\mathcal{H}$, value function and optimal policies of households $\{V, q^n, q^c, q^{g\ell}, q^g, q^k, q^d\}$, capital and labor demand functions of the corporate sector, that is $\{K^c(\Gamma, \mathbf{\Omega})$ and $N^c(\Gamma, \mathbf{\Omega})\}$, net foreign asset position $B(\Gamma, \mathbf{\Omega})$ and price functions $r^d(\mathbf{\Omega}), r^b(\mathbf{\Omega}), w(\mathbf{\Omega})$, such that

1. Policy functions $\{q^n, q^c, q^{g\ell}, q^g, q^k, q^d\}$ solve the household problem 8, taking prices and laws of motions as given,

2. Free entry for the financial intermediary ensures zero profit such that $r^d(\mathbf{\Omega}) = r^* - \xi^d$ and $r^b(\mathbf{\Omega}) = r^* + \xi^b$.

3. The labor market clears such that

$$\int_{(\mathbf{a},e)} q^n(\mathbf{a}, e; \mathbf{\Omega})\, d\Gamma(\mathbf{a}, e) + N^c(\Gamma, \mathbf{\Omega}) = 1. \tag{20}$$

   And as long as $N^c > 0$ the equilibrium wage in the competitive labor market is pinned down by the marginal product of labor in the corporate sector such that:

$$w(\boldsymbol{\Omega}) = (1-\alpha)\left(\frac{\alpha}{r^* + \delta}\right)^{\frac{\alpha}{1-\alpha}} Z^{\frac{1}{1-\alpha}} \tag{21}$$

4. The capital market clears according to the Equation (18).

5. $\{K^c(\Gamma, \boldsymbol{\Omega}), N^c(\Gamma, \boldsymbol{\Omega})\}$ solve the corporate sector problem 17. Note that while the distribution Γ does not enter directly into the corporate problem, the scale of corporate sector is pinned down by the labor market clearing, so they implicitly depend on the Γ.

6. $\mathcal{H}$ is generated by the policy functions $\{q^g, q^k, q^d\}$ and the law of motion of the aggregate state, in the sense that given Γ over the current asset position and policies of households, their combined asset allocation policies corresponds to Γ' as given by the mapping $\mathcal{H}$.

7. The net foreign asset position evolves taking into account the net export and the net factor income of the economy. To define the evolution of net foreign asset position in this economy, let's start by specifying the key aggregate variables. Let's denote by C, the aggregate consumption of households, given by

$$C(\Gamma, \boldsymbol{\Omega}) = \int_{(\mathbf{a}, e)} q^c(\mathbf{a}, e; \boldsymbol{\Omega})\ d\Gamma(\mathbf{a}, e).$$

   Denote also by $\mathcal{G}(\Gamma)$ and $\mathcal{G}'(\Gamma, \boldsymbol{\Omega})$, respectively, the aggregate stock of gold that households bring in the period, and choose to invest in for the next period. Similarly, $K^h(\Gamma)$ and $K^{h'}(\Gamma, \boldsymbol{\Omega})$ denote the stock of capital with which households enter into the period, and their optimal investment in capital for the next period. Investment in the household businesses at this period is then defined as $I^h = K^{h'} - (1-\delta)K^h$:

$$I^h(\Gamma, \boldsymbol{\Omega}) = \int_{(\mathbf{a}, e)} \left(q^k(\mathbf{a}, e; \boldsymbol{\Omega}) - (1-\delta)k(\mathbf{a})\right)\ d\Gamma(\mathbf{a}, e).$$

   Finally, denote the investment for the corporate sector by $I^c(\Gamma', \boldsymbol{\Omega}')$ and aggregate output of the economy by $Y(\Gamma, \boldsymbol{\Omega})$, then the net export is given by:

$$NX = Y - C - (I^h + I^c) - P^g(\mathcal{G} - \mathcal{G}_{-1}) - \xi^d D^+ + \xi^b D^-$$

and the evolution of the net foreign asset by:

$$B'(\Gamma', \boldsymbol{\Omega}') = B'(\mathcal{H}(\Gamma, \boldsymbol{\Omega}, \boldsymbol{\Omega}'), \boldsymbol{\Omega}') = NX + (1 + r^*)B(\Gamma, \boldsymbol{\Omega}) \tag{22}$$

3.6 Solving the Model

The key to more tractably combining aggregate risk with heterogeneous agents in our economy is that the combination of the open-economy setup with constant-returns-to-scale production in the corporate sector ensures that prices are not endogenous functions of the entire distribution, as in Krusell and Smith (1998). This allows us to use global solution methods (instead of local approximations) to fully capture the portfolio choice and hedging motives of households without the need to predict prices using the entire distribution—an infinite dimensional object.

The downside of not having prices depend on the entire distribution of households is that we have to abstract from the interesting feedback loop of how household behavior affects prices. For example, we have to abstract from the general equilibrium mechanism whereby increases in Indian gold demand could additionally crowd out productive capital by either making imports or the cost of capital more expensive. However, note that the equilibrium market clearing in our setup still depends on the entire distribution of households; for example, both the employment share of the corporate sector and the net foreign asset position are functions of the aggregate state and the entire (time-varying) distribution of households.

4 Calibration & Validation

To quantify the aggregate costs of unproductive savings, we calibrate our model using a combination of micro data and aggregate moments. We then carefully validate our model using untargeted moments, including the entire distribution of household balance sheets shown in Figure 2 and replicating the RCT by De Mel et al. (2008) within our model.

4.1 Calibration

There are 22 structural parameters in total. A subset of parameters $\Theta^{ext} = \{r^*, \xi^d, \xi^b, \phi_g, \delta\}$ can be calibrated externally since they are policy parameters or other model parameters that can be directly mapped to data. We calibrate the remaining parameters internally in two steps. In the first internal calibration step, *aka* "direct calibration", we directly back out a set of parameters from observed data using equations from the model without the need for fully solving it, namely the first order conditions or the assumed laws of motions. Specifically, this relates to parameters of the production function, the micro-level productivity process, the parameters that govern aggregate risk and the loan to value (LTV) ratio for capital collateral, $\Theta^{\text{direct}} = \{\alpha_c, \eta, \rho_e, \sigma_e, \mu_e, \rho_z, \rho_g, \sigma_z^2, \sigma_{zg}, \sigma_g^2\}$. In the second internal calibration step, we find the remaining model parameters $\Theta^{\text{smm}} = \{\beta, \gamma, \varepsilon, \zeta, \theta_g, \alpha_h, \mu_e\}$ by minimizing the distance between a set of targeted empirical moments and their model counterparts, which requires fully solving the model. Table 2 provides an overview of all parameters $\Theta = \Theta^{\text{ext}} \cup \Theta^{\text{direct}} \cup \Theta^{\text{smm}}$ and how we calibrate them.

4.1.1 External calibration

The Θ^{ext} subset of parameters can be directly read from the data or policy announcements. This include the international interest rate r^* (which we set to 0.038), deposit and borrowing rate wedges ($\xi^d = 0.025$, $\xi^b = 0.08$ respectively), the depreciation rate δ (which we set to 7.5%), and the LTV ratio for gold collateral (which we read from policy announcements $\phi_g = 0.75$).

4.1.2 Direct calibration

Production function & firm productivity process.— We can directly back out the remaining parameters of the production function and productivity process by drawing on micro data for household businesses from the IHDS. Specifically, households' optimal labor decisions imply that:

$$(1 - \alpha_h)\eta = \frac{w_t \cdot n_{it}}{\text{Rev}_{it}} \tag{23}$$

which relates the return-to-scale parameter η to the observed labor share of household businesses (given the capital elasticityα_h). Based on the IHDS data using detailed information on household labor costs and revenue (net of intermediates), we use the median observed labor share to ensure results are not driven by outliers, which is 54%.[10] Together with $\alpha_h = 0.387$ estimated in the indirect estimation (see 4.1.3) we find that $\eta = 0.868$.

With η and α_h pinned down and with data on the revenue of household businesses, including their capital and labor inputs, we can back out their model-implied productivity: $x_{it} \equiv \log(Z_t) + \log(e_{it})$. In principle, we then simply estimate the AR(1) process using

[10] In Appendix C.1.1 we provide further details on measurement, including how we impute costs of household labor using local wages.

Table 2: Overview of parameter identification and estimation

Object	Description	Identification idea	Value	Details
Preferences:				
β	HH discount rate	SMM	0.87	Section 4.1.3
γ	IES	SMM	5.5	Section 4.1.3
ε	Elasticity of substitution g vs. c	SMM	0.68	Section 4.1.3
ζ	Utility cost of gold collateral	SMM	0.9	Section 4.1.3
θ_g	Preference share for gold	SMM	0.11	Section 4.1.3
Production:				
δ	Depreciation rate	Data	0.075	RBI
α_h	Capital share HH business	SMM	0.387	Section 4.1.3
α_C	Capital share corporate sector	Direct calibration	0.62	Section 4.1.2
η	Returns to scale	Direct calibration	0.868	Section 4.1.2
ρ_e	Autocorrelation e	Direct calibration	0.764	Section 4.1.2
σ_e	Std. dev. of e innovation	Direct calibration	0.666	Section 4.1.2
μ_e	Level of e	SMM	0.118	Section 4.1.3
Financing constraints & frictions:				
r^*	World interest rate	Data	0.038	RBI
ξ^d	Deposit rate wedge	Data	0.025	RBI
ξ^b	Borrowing rate wedge	Data	0.08	RBI
ϕ_k	Collateral constraint k	Direct calibration	0.69×0.40	Section 4.1.2
ϕ_g	Collateral constraint g	Data	0.75	RBI
Aggregate risk:				
ρ_z	Persistence of log Z_t	VAR direct estimate	0.63	Section 4.1.2
ρ_g	Persistence of log P_t^g	VAR direct estimate	0.81	Section 4.1.2
σ_z^2	Variance of u_t^z	VAR direct estimate	0.00046	Section 4.1.2
σ_{zg}	Covariance of u_t^z and u_t^g	VAR direct estimate	-0.00018	Section 4.1.2
σ_g^2	Variance of u_t^g	VAR direct estimate	0.0088	Section 4.1.2

Details:

measured productivity and controlling for time fixed effects μ_t to net out the effects of Z:

$$x_{it} = \mu_e + \mu_t + \rho_e x_{it-1} + u_{it} \ . \tag{24}$$

However, one main limitation of the IHDS panel data is that there are only two waves of data that are six years apart. We thus indirectly estimate the parameters of the AR(1) process using the Simulated Method of Moments (SMM). Specifically, we estimate in the data the auxiliary coefficients $\tilde{\mu}_e, \tilde{\rho}_e, \tilde{\sigma}_e$ based on Equation 24 and the two-year IHDS panel. We then simulate model-based data from an annual AR(1) process with true parameters μ_e, ρ_e, σ_e and estimate the true parameters by replicating the same auxiliary regression using only two waves that are six years apart and targeting the auxiliary coefficients. While the two-year panel prevents us from controlling for individual fixed effects, we do include a larger set of household-level controls to ensure our estimate of the persistence ρ_e is not driven by permanent differences across households that our model does not capture.[11]

Reassuringly, we can perfectly match the auxiliary coefficients. We find a value for the annual persistence parameter of $\rho_e = 0.76$, which is identified from within-household changes in (revenue) productivity. For the standard deviation of the productivity shock, we find a value of $\sigma_e = 0.67$. Both are in line with the existing literature. For example, Collard-Wexler et al. (2011) estimate AR(1) parameters on firm-level data for a set of 33 developing countries, finding pooled estimates of $\rho = 0.83$ and $\sigma = 0.6$. If anything, we estimate a lower persistence of productivity, which is likely due to our focus on household businesses and because we control for a larger set of fixed household characteristics. Indeed, without controlling for household characteristics, we find a higher value of $\rho_e = 0.82$, indicating that permanent differences across households could be an important confounder that is important to net out. For the variance of shocks, our estimate is slightly larger than the pooled estimate in Collard-Wexler et al. (2011), likely due to the bigger role of agricultural shocks in our sample. Appendix Table C.1 shows that our main estimates are robust to a variety of different specifications including different cutoffs for outliers and different sample selections.

Aggregate risk process & corporate sector production function.— Next, we estimate the parameters of the joint process for (Z_t, P_t^g) using standard VAR estimation tools. To measure the time series for Z_t, we draw on the CMIE Prowess database, which has information on all publicly listed firms in India, which we treat as a representative picture of the corporate sector in our model.[12] Specifically, we back out Z_t from Equation 16, using aggregate (real) value-added output, capital and labor payments together with a value for α_C, the capital output elasticity in the corporate sector. We compute α_C drawing on the model-based first-order condition of the corporate sector:

$$1 - \alpha_C = \frac{wL}{PY} \tag{25}$$

using the observed median labor share across all firm-year observations. We find that $\alpha_C = 0.62$, a relatively high value that reflects the low labor share in India's corporate sector. In the Appendix, we provide further details on the cleaning and estimation steps

[11]Specifically, we control for the education level of the household head, whether the household is urban or rural, their social group and caste, their state and district and the composition of the household. We provide further implementation details including how we deal with measurement error in Appendix C.1.2.

[12]While the number of firms in CMIE Prowess changed considerably over time, all we require for constructing Z is having a representative sample of the corporate sector at any point in time.

and show that our estimated Z-series is robust to different values of α_C. As a measure for P^g_t, we use the annual gold prices from the Reserve Bank of India database. With the series for (Z_t, P^g_t) in hand, we proceed to estimate the parameters of the aggregate risk process in Equation (7).

Denoting logarithms of the TFP and the gold price by $\mathbf{X}_t \equiv [\log(Z_t), \log(P^g_t)]^\top$, and the shock process by $\mathbf{U}^{zg}_t \equiv [u^z_t, u^g_t]^\top$, we estimate a VAR(1) process using the equation:

$$\mathbf{X}_{t+1} = \begin{pmatrix} \nu^z \\ \nu^g \end{pmatrix} + \begin{pmatrix} \mu_z \\ \mu_g \end{pmatrix} t + \begin{pmatrix} \rho_z & \rho_{zg} \\ \rho_{gz} & \rho_g \end{pmatrix} \mathbf{X}_t + \mathbf{U}^{\mathbf{zg}}_{\mathbf{t+1}}, \quad \mathbf{U}^{\mathbf{zg}}_{\mathbf{t}} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_z & \sigma_{zg} \\ \sigma_{zg} & \sigma^2_g \end{pmatrix} \right) \tag{26}$$

The trend estimates (μ_z, μ_g) are different, which makes a case against a balanced growth model. Hence, in line with our assumption of a stationary economy, we drop the trend parameters as well as the intercepts (ν^z, ν^g). Moreover, the estimates of ρ_{zg} and ρ_{gz} are not (statistically) significantly different from zero. Estimates for the main parameters of the process can be found in the bottom panel of Table 2. In solving the model, we discretize this VAR(1) process using the estimated parameters following the method (and codes of) Farmer and Toda (2017).

Collateral constraints.— We already discussed how we read the value of the gold LTV ϕ_g from the data. To pin down the LTV for business assets (ϕ_k), we draw on micro loan-level information in AIDIS. Intuitively, ϕ_k is identified from the ratio of household's loan size to collateral for the subset of households for whom the collateral constraint binds, which are households that are at the limit of their allowed loan size to collateral ratio. In the AIDIS data, households can have multiple loans at the same time but each loan is at most collateralized with either capital *or* gold, which allows us to separate them.[13] Another feature of the micro data that is important to capture is that most households that take out loans—even households that seem to be constrained—do not freely combine gold and capital loans. To capture this nuance, we rewrite the collateral constraints ϕ_k as the product of $\mathbb{P}(k - \text{loan}|\text{any loan})$, the probability that a constrained household takes out a k-loan, and $\tilde{\phi}_k$, the LTV ratio conditional on having taken out a loan on business capital.

We pin down $\mathbb{P}(k - \text{loan}|\text{any loan})$ by the share of constrained households that hold a loan collateralized by capital conditional on having any collateralized loan. We classify house-

[13] Among secured loans, roughly 75% of loans and loan volume are collateralized with either capital (57%) or gold (18%), with cash-flow based constraints being rare. . Importantly, only about 45% of loans in India are collateralized, with the remainder capturing a larger informal loan market. While we abstract from this, we note that unsecured loans are fine for our model as long as collateral constraints would not bind for them.

holds as being constrained if they are above the 80th percentiles for either the distribution of capital-backed loans over capital holdings. We find that $\mathbb{P}(k-\mathrm{loan}|\text{any loan}) = 69\%$.[14]

Next, we identify the collateral constraints $\tilde{\phi}_k$ by looking at borrowing limits in the data. Any constrained household would borrow $|d|$ up to what their LTV $\tilde{\phi}_k$ allows. In AIDIS, we observe both total asset values and loan sizes, which is critical for estimating *de facto* collateral constraints. While standard loan-level micro data would have total collateral value, it would not generally include total household assets. However, not all capital held by households is collateralizable, for example because some parts are hard to appraise, or because they lack proper documentation such as land titles. Taking total household assets as reported in AIDIS rather than only collateral values allow us to credibly capture these broader borrowing frictions in the Indian context.

$\tilde{\phi}_k$ is then identified from the maximally observed ratio of loan size $|d|$ to capital assets k among loans collateralized by capital: $\max_{i \in \text{k-loans}}\{(|d|/k')_i\}$. By loan size we mean the total size of all such loans held by a household. In practice, the maximum value is particularly susceptible to outliers, so we use the 95th percentile instead. Using this approach, we find that $\tilde{\phi}_k = 0.40$.[15] Our estimated value for $\tilde{\phi}_k$ implies that a loan taken out purely for investment purposes would need to be underwritten by at least 50% more own capital. Compared to the previous literature, we find a slightly higher, less binding collateral constraint; for example Buera et al. (2021) find $\phi = 0.15$ targeting aggregate data for India. Note that $\phi_k = 0.69 * 0.4 = 0.276$ is substantially lower than $\phi_g = 0.75$, which is in line with gold being easier to collateralize, to seize and to liquidate in case of default.

4.1.3 Indirect calibration: Simulated Method of Moments (SMM)

In the last step of the calibration, we set the remaining model parameters, that is $\Theta^{smm} = \{\beta, \gamma, \varepsilon, \zeta, \theta_g, \alpha_h, \mu_e\}$, to best match a set of empirical target moments. Specifically, let M^E denote a vector of empirical target moments and $M(\Theta)$ their counterparts in the simulated model economy. Θ^{smm} is pinned down by the parameter set that minimizes the

[14] Probabilities are very similar when using the 90th percentile as cutoff instead. See subsection C.3 of the Appendix for more details on the estimation steps.

[15] Values are relatively flat over most of the distribution but sharply increase at the right tail. At the 90th percentile, values are 0.27 and 1.68, respectively. The 95th percentile is thus a conservative choice as it leads to less binding collateral constraints.

Table 3: Internally calibrated parameters: Model vs. Data

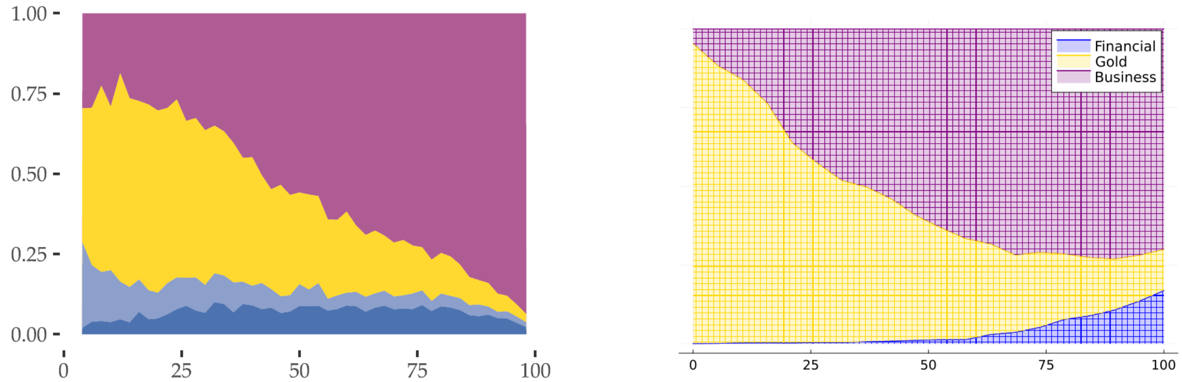
Parameter	Description	Value	Target moment	Data	Model
β	HH discount factor	0.87	Aggregate K/Y	1.86	1.85
γ	Relative Risk Aversion	5.5	Aggr. share of deposits	19%	18.9%
ε	CES b/w c & g'	0.68	Gold share 10th vs. 50th	1.821	1.833
θ_g	Preference share for gold	0.11	Agg. share of gold	28.8%	28.9%
ζ	Gold-collateral utility loss	0.9	HHs taking gold loan	3.5%	3.6%
α_h	Capital elasticity HH bus.	0.387	median k/y in HH sector	1.42	1.42
μ_e	Avg. entrepreneurial talent	0.118	GDP share of HH sector	85%	85.2%

distance between $M(\Theta)$ and M^E in relative norm-1 terms:

$$\min_{\Theta^{smm}} \sum_{m=1}^{S} \frac{|M_m(\Theta) - M_m^E|}{|M_m^E|}.$$

Table 3 provides an overview of our estimated parameters and the model fit. While parameters are jointly identified, in the following we discuss intuition for identification for each of the parameters. To pin down the discount factor, we target the aggregate capital to output ratio given its importance for the level of overall savings. For the relative risk aversion coefficient we target the aggregate share of deposits; deposits are the safe asset in the model, and higher relative risk aversion implies a higher weight of deposits in the portfolio. To pin down the elasticity of substitution between consumption and gold, we target the ratio of the gold share of assets in the 10th vs. 50th percentile of the wealth distribution. For the preference parameter for gold we target the aggregate share of gold. Higher θ_g implies a higher share of gold, keeping fixed the investment properties of gold. For the utility penalty of using gold as collateral, we target the percentage of households who take loans against their gold. To pin down the elasticity of capital for HH businesses, we target the median capital-to-output ratio of household businesses. Combined with the Equation (23), this also pins down the span of control parameter η. Finally, to pin down the intercept of the entrepreneurial productivity process, that is the mean level of entrepreneurial talent (compared to the corporate sector), we target the GDP share of the household sector. As shown in Table 3, our model accurately (though not perfectly) fits all targeted moments. Appendix C.4 provides more details, including a sensitivity matrix for the SMM-calibrated parameters with respect to the model moments.

Figure 4: Model Fit: Household Balance Sheet.



Note: Left: household balance sheet by wealth quantiles in the data. Right: household balance sheet by wealth quantiles in the model.

4.2 Validation

In this subsection, we carefully validate our model on a rich set of untargeted moments related to household savings and the production side, given that both dimensions are crucial for the main counterfactuals.

4.2.1 Validating household savings behavior

We start by validating our model on the household balance sheet. While our calibration targets a few moments for this distribution (e.g. the relative gold share at the 10th vs. 50th percentile), Figure 4 compares our model-implied household balance sheet over the entire wealth distribution and across all assets. We capture well the main savings patterns over the entire wealth distribution. Deposits/financials are small throughout, business assets are dominant and increase in wealth, and gold is sizable but declines in wealth. Currently, the model fails to correctly capture the extreme right tail in business assets and thus also erroneously predicts an increase in deposits at the right tail. As we shall see in the next subsection, this results from the fact that households in the top quantile, particularly the less productive ones, are still substantially investing in gold.

4.2.2 Validating the production side: Firm size distribution and returns to capital

To validate the production side of our economy, we consider two key validation exercises. First, we verify that our model can correctly capture the (household) firm size distribution by comparing our model predictions to the representative household business data from IHDS (wave 2005). The strong benefit of the IHDS data is that we can go beyond a simple measure of the number of workers and instead construct a continuous measure of labor demand n^* that closely follows the measurement in our model. Specifically, since each household is of size 1, n^* measures the share of (potential) household labor hours that is used for household businesses. We construct n^* in the data by the ratio of total labor hours worked in the household business over total *potential* labor hours of a given household. For the numerator, we add up all reported hours across all household members and across all household business activities, as well as adding in all hours worked by hired outside labor. As denominator, we construct the total potential hours of work across all household workers. Further details are provided in Appendix C.5.

Table 4 reports the corresponding validation results. Column 1 shows that we closely fit the average firm size of 0.724, i.e. the average household spends 72.4% of all household working hours on their own household businesses. This is lower than one in the data and the model because a sizable share of household labor is supplied to non-household businesses (the corporate sector in our model). Since we target the size of the corporate sector in our estimation, the fact that we closely fit the average based on the micro data shows that the micro and macro data broadly align. The remainder of the table then summarizes how we fit the entire distribution. Overall, the fit is good especially in the middle of the distribution, but our model overestimates the share of firms with very little labor ($n^* < 0.1$) and underestimates the share of large firms ($n^* > 1$). In the data, about 45% of households do not operate a household business ($n^* = 0$), while our model – because of the DRS technology – generates many very small firms, but no firms with $n^* = 0$. Similarly, at the very right tail, we generate too few large firms, but the large firms that we have are larger than in the IHDS data. This may actually not be a shortcoming because IHDS likely undersamples the very right tail of household businesses. In summary, we broadly fit the entire firm size distribution despite not having targeted it in the estimation.

Second, we validate the returns to capital as implied by our model. Given that the marginal returns to capital (MPKs) are crucial to our quantification exercise, we want to ensure that our model is in the right ballpark for empirical estimates of MPKs. For this, we draw on the influential RCT by De Mel et al. (2008), which gave out capital grants to micro-enterprises. We replicate the RCT within our model. We do so by carefully mimicking the selection rule in De Mel et al. (2008), focusing on household businesses without outside employees (i.e. $n^* \leqslant 1$) and a small initial capital stock. As we can show with the model, these selection criteria mean that returns to capital are much larger for this selected group of firms. Following De Mel et al. (2008), we then randomly form a control group and four different treatment arms in which we vary the grant amount and whether micro-

Table 4: Validating the firm-size distribution: Model vs. Data

	Mean	Mass in:	[0,0.1)	[0.1,0.25)	[0.25,0.5)	[0.5,1.0)	[1.0,2.0)	[2.0,∞)
Data	0.724		0.477	0.052	0.084	0.088	0.179	0.119
Model	0.766		0.575	0.118	0.087	0.096	0.053	0.071

Note: Table compares the firm size distribution in data and model based on labor demand n^*. For households who only use own workers, this can be interpreted as the share of household labor hours used on own businesses. In the data, n^* is measured from reported hours based on representative household-level data in IHDS, wave 2005. The first column reports the mean n^* across all households, while all subsequent columns report the total mass of households in different size bins for n^*.

enterprises receive cash or capital equipment. In line with the small scale of the program, we replicate the RCT in "partial equilibrium" in the sense that the share of households that receive the program is small, so that the program does not affect equilibrium allocations and prices. While the original RCT was conducted with micro-enterprises in Sri Lanka, not in India, we believe that the context of South Asia with a shared cultural history and a similar level of development makes this still comparable. We provide further details on the RCT and our implementation of the RCT in Appendix C.6. Here, we focus on the main results on the returns to capital. Specifically, we replicate the main reduced-form estimates of how different treatments affect firm profits as given by the following regression in De Mel et al. (2008):

$$\log(\pi_{it}) = \alpha + \beta_g T_{git} + \mu_i + \mu_t + \epsilon_{it} \tag{27}$$

where π_{it} are profits as defined in De Mel et al. (2008), β_g captures either the main pooled treatment effect (β_{pool}) in case we pool across all treatment arms, or separate treatment effects for each of the four treatment groups. μ_i & μ_t are individual and time fixed effects respectively. We report estimates at the annual frequency in line with our model.[16]

Table 5 reports results. For the main pooled treatment effect, the RCT results imply that a 100$ grant on average increases profits by about 15% (16.2% when using exact formula). Our model suggests very similar, but slightly lower effects of around 12%. These model estimates are comfortably within one standard deviation of the empirical estimates. Similarly, our model can also account well for the (noisily estimated) treatment-arm-specific effects, almost exactly hitting even the point estimate for the 200$ capital grant and 100$ cash grant. Overall, we believe this provides a strong validation for our model-implied returns to capital, which are driven by a combination of binding collateral constraints for

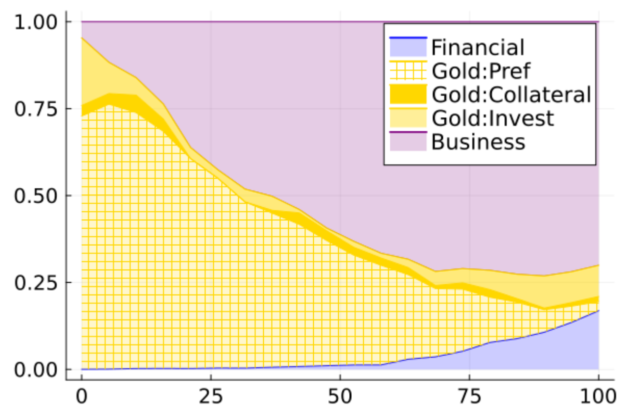
[16] The original results in De Mel et al. (2008) are at the quarterly frequency. Since our model is at the annual level, we re-estimate results in De Mel et al. (2008) by first aggregating at the annual level.

Table 5: Validating returns to capital using RCT by De Mel et al. (2008): Model vs. Data

	β_{pool}	β_{kap100}	β_{kap200}	$\beta_{cash100}$	$\beta_{cash200}$
Data	0.0015	0.010	0.290	0.113	0.299
	(0.0004, 0.0026)	(-0.214, 0.234)	(0.026, 0.553)	(-0.107, 0.334)	(-0.004, 0.602)
Model	0.0012	0.167	0.291	0.099	0.184

Note: This tables compares the main reduced-form results from the capital grant RCT by De Mel et al. (2008) with model-based results when replicating the same RCT within the model. "Data" shows the point estimate together with the 95% confidence band. Model estimates are without sampling uncertainty since we estimate on a large sample of firms. β_{pool} is the coefficient for the pooled regression using the level of transfers across all treatment arms. The other columns report separate treatment-group coefficients based on a single regression. "kap100" & "kap200" denote grants directly to capital of 100$ and 200$. "cash100" & "cash200" denote cash grants of 100$ and 200$.

Figure 5: Gold Demand Motives by Wealth



some households and high opportunity costs of holding capital in our model.

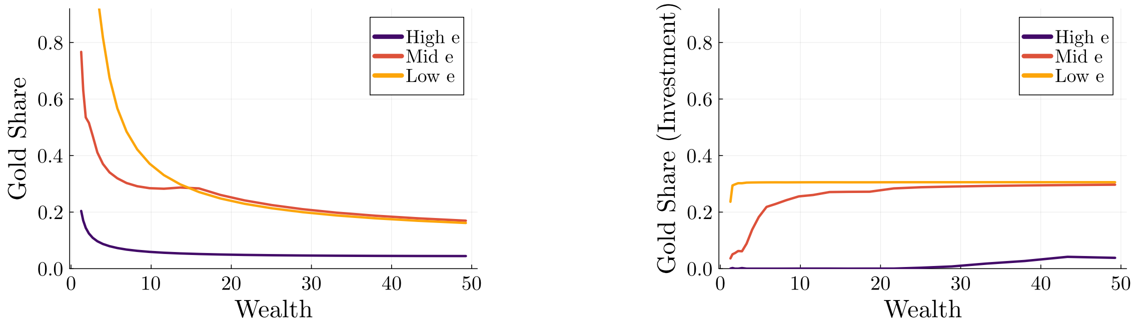
5 Main Results

In this section, we use our calibrated model to better understand the drivers of gold savings in India, answer our main research question, and study the role of policy.

5.1 Who holds how much gold and why?

We start our investigation by decomposing the demand for gold savings into different motives and discuss how the demand composition changes with wealth and productivity. This exercise not only sheds light on the relative importance of social norms versus financial reasons for holding gold, but also sets the stage for better understanding our main quantitative results.

Figure 6: Asset Share of Gold by Productivity



(a) All motives (b) Investment motive

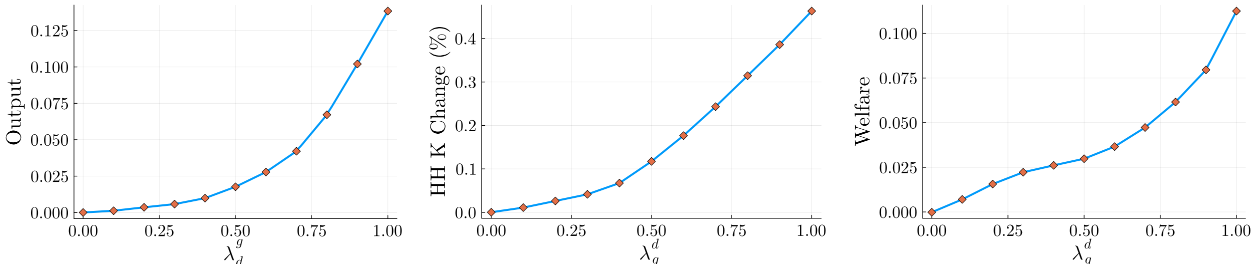
Note: The left panel shows the asset share of gold demanded for the baseline model, across the wealth distribution and for three different levels of productivity (the highest, medium, and lowest) with lighter shades corresponding to lower productivity. The right panel shows the same gold share for the counterfactual economy with investment and hedging motives only.

We decompose the demand drivers of gold using model counterfactuals in which we shut down one demand mechanism at a time and compare the resulting equilibrium to the baseline calibrated model. Specifically, we isolate the role of *social norms* by shutting off preferences for gold, setting $\theta_g = 0$ in Equation (2). For the *liquidity* value of gold, we shut down the collateral value of gold, setting $\phi_g = 0$ in Equation (4), which means households cannot take gold loans. Finally, we quantify the *investment and hedging* motive as a residual, shutting down both the cultural and the liquidity motives of holding gold.

Figure 5 shows results of this decomposition exercise over the entire wealth distribution. Note that we keep the relative savings share for business capital and financial assets fixed for this exercise and only decompose the gold share into its three motives, each denoted by a different gold-colored shading. In terms of the aggregate level of gold holdings, we find that social norms account for 42.7%, the liquidity motive for 10.0% and the investment motive for the remaining 47.3%. However, the relative importance of these motives varies considerably over the wealth distribution: the social norm motive is dominant across most of the distribution, except for the wealthiest households. For the richest (where most of the aggregate wealth is concentrated), the return and hedging motives clearly dominate, driving its higher contribution to aggregate gold holdings. Finally, the liquidity motive is more or less evenly distributed throughout the wealth distribution.

Next, we ask how the gold share of wealth differs with entrepreneurial productivity. Figure 6a plots optimal gold shares as a function of household wealth for different levels of productivity. Gold shares are decreasing in productivity, especially for low wealth households. The reason is that lower productivity means lower opportunity costs of saving

Figure 7: Aggregate Output and Welfare Costs of Gold Savings



(a) Change in output (%)   (b) Change in K^h (%)   (c) Change in welfare (%)

Note: All results are averaged over the aggregate states in stationary equilibrium. (a) shows the percentage change in output for various degrees of monetization. (b) shows the percentage change in average aggregate capital of household businesses. (c) shows the percentage change in average welfare, measured in util.

in gold rather than in productive capital, and returns to business capital are particularly high for low wealth households with high productivity. This is simply a function of the decreasing-returns-to-scale technology. Figure 6b shows the optimal gold share in an economy with only the investment motive. Investment demand for gold increases in wealth but is asymptotically constant. The reason is again tied to opportunity costs; as households grow wealthier, their returns to capital in their own business diminish and they search for alternative investments; given generally poor alternative investment opportunities in India, wealthy Indian households choose to invest sizably in gold.

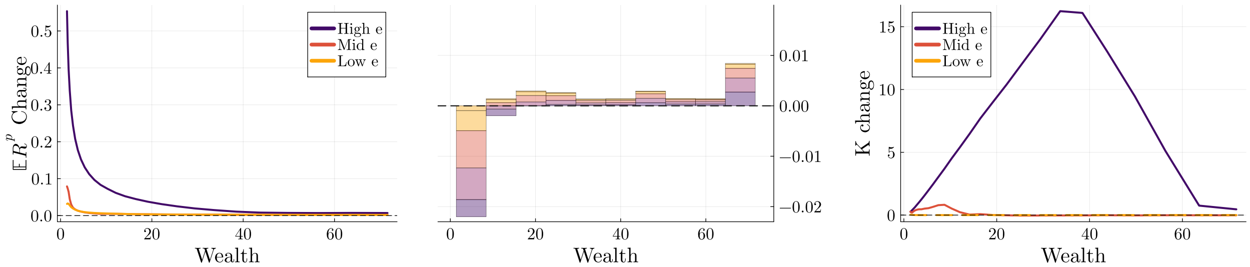
5.2 Costs of unproductive savings

To quantify the aggregate costs of unproductive gold savings, we follow a thought experiment analogous to the development accounting exercise: what would happen if idle gold could instead be used productively? Suppose that banks could *monetize* a fraction λ_g of gold that remains idle at any point in time by selling the idle gold internationally and investing the proceeds as they do for regular deposits. We treat this exercise as a headline quantitative benchmark, but return to its practical implementability when we discuss policy.

We model this counterfactual exercise as follows: at the end of each period, a fraction λ_g of each household's gold is traded for bank deposits earning interest. For a household who chooses the asset position $\mathbf{a}' = (d', k', g')$ today, tomorrow's cash-on-hand is given by

$$w' + R^f\left(d' + \lambda_g P^g g'\right) + P^{g\prime}(1-\lambda_g)g' + \pi(\mathbf{a}', e'; \boldsymbol{\Omega}') + (1-\delta)k'$$

Figure 8: Gold Monetization: Changes in Returns, Distribution, and Capital Allocation



(a) Change in return on wealth (b) Change in distribution (c) Change in capital level

Note: The left panel shows the change in the expected return to wealth of households with different entrepreneurial ability and wealth level. The middle panel shows the percentage change in histogram of the wealth distribution in the new economy compared to the baseline. The ten bins of the histogram, correspond to different buckets of wealth. And the colors within each bin, shows the productivity decomposition of the change in the population density of the bin. The right panel shows change in the capital of household businesses, in levels. Different colours correspond to (a selection of) different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange, and yellow represent the highest, the medium and the lowest productivity levels, respectively.

and the collateral constraint by $(d' + \lambda_g P^g g') \geqslant -\phi_k k' - \phi_g (P^g (1 - \lambda_g) g')$, which says that only non-deposited gold can be used as collateral. Given that a large share of household gold holdings sit idle in that they are gold coins and bars, or jewelry that is only worn for special occasions every few months, we assume that the fraction $(1 - \lambda_g)$ of the gold in their hand provides the same utility as before. We then simulate the stationary equilibrium of this economy, and compute the average output and welfare across aggregate states $\mathbf{\Omega}$. We measure welfare in a utilitarian manner according to:

$$\text{Welfare}(\Gamma, \mathbf{\Omega}) = \int_{(\mathbf{a}, e)} V(\mathbf{a}, e; \mathbf{\Omega}) \; d\Gamma(\mathbf{a}, e),$$

Figure 7a shows relative increases in average output for the counterfactual exercises as we increase the degree of gold monetization λ_g. Figure 7b and Figure 7c show the same change for aggregate capital of household businesses and welfare, respectively.

For the limit case of $\lambda_g = 1$, output gains are 13.5%, about 35% larger than what the naive development accounting exercise suggests. The large output gains stem from two forces: (1) an increase in the equilibrium level of savings and capital, and (2) a reduction in misallocation as additional capital rises more strongly for the most productive households. The key mechanism is that monetized gold offers households a superior asset: they can now earn deposit returns from holding gold. This raises overall incentives to save and additionally allows previously credit-constrained entrepreneurs—more productive and poorer entrepreneurs—to expand their business more rapidly.

Figure 8a depicts the sizable increase in the expected return to wealth, which drives increases in savings. As clearly visible, these positive changes in return are not uniformly distributed, but concentrated at the left tail and for the most productive, where annual returns increase by more than 50 percentage points, given that they were previously strongly credit-constrained. Figure 8b shows changes in the wealth distribution for different wealth bins, in levels; the left tail decreases as more households move into the upper rungs, with most gains at the far right. Figure 8c shows that increases in the level of wealth map to large increases in the level of productive capital, especially driven by the most productive entrepreneurs with intermediate levels of wealth who are still credit-constrained in the baseline economy. Thus, gold monetization induces a partial undoing of capital misallocation. Together, these three figures explain the large welfare increases from monetizing gold as shown in Figure 7c, with effects driven by the poor and most productive households.

5.3 The role of policy

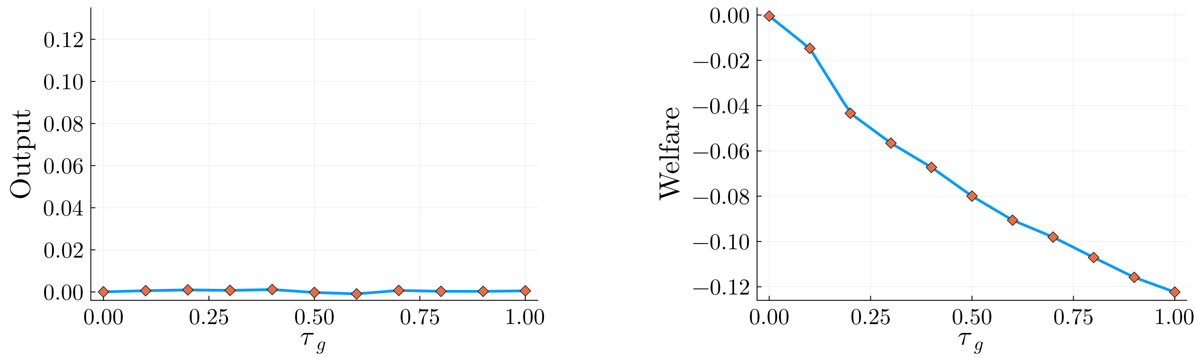
Given the large aggregate costs of unproductive savings, the question is whether policy can and should address the problem. India has a long and varied history of experimenting with different policies to address gold savings, with Appendix E providing a brief overview. One can distinguish four broad types of attempted policies: (1) the outright banning of gold and jewelry,[17] (2) price manipulation through duties and tariffs for discouraging gold holdings, (3) return-mimicking schemes (such as *Sovereign Gold Bonds*), and (4) deposit-based schemes (such as the *Gold Monetization Scheme*). In this subsection, we first look at the *Gold Monetization Scheme* to understand why real-world attempts to monetize gold can struggle to achieve sizable development effects. We then turn to the question of whether the government should simply tax gold instead.

5.3.1 The Gold Monetization Scheme

The *Gold Monetization Scheme* (GMS), initiated in 2015, is a real-world example of trying to monetize gold. It is also a policy that is widely regarded as having been ineffective due to low take-up and scale. There are at least three main features of the GMS program that distinguishes it from our theoretical monetization exercise and explain stark differences in

[17] Most prominently regulated by the Gold Control Act of 1968, which was abolished with the start of economic liberalization in the early 1990s.

Figure 9: Output and Welfare Effects of Taxing Gold with Lump-Sum Transfers



(a) Relative Change in Output

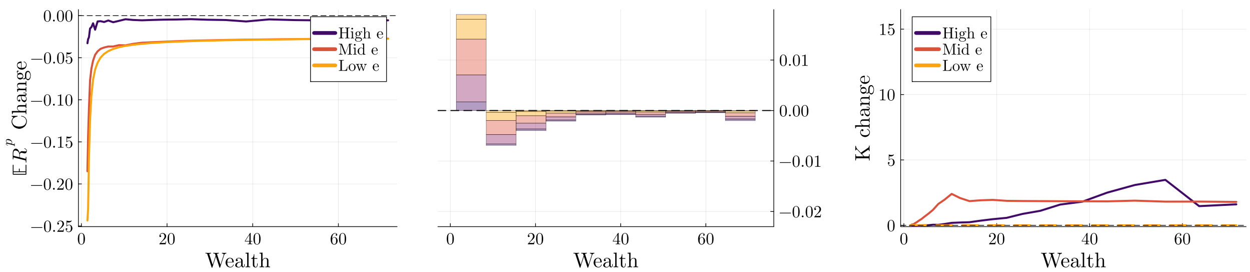
(b) Relative Change in Welfare

Note: The left panel shows the change in aggregate output in the gold tax counterfactual relative to the stationary equilibrium of the baseline economy. The right panel shows the relative change in welfare (in utils). For each τ_g, the output and welfare gains are computed after solving for the equilibrium lump-sum transfer T that balances the government budget intertemporally.

results. The first is simply a design choice. In our theoretical benchmark, we assumed that the monetized gold earns the same interest rate as deposits. In practice, GMS interest rates were set much lower than the already depressed deposit rate. For example, in 2019, the annual nominal rate of interest paid on 1-year GMS scheme was only 0.5%, while interest rates on saving accounts and term deposits were around 3.5% and 6.7% respectively (the annual inflation rate was around 3.7% over the same period).

The second and third reason are more directly linked to the practical difficulties of monetization and highlight why the large theoretical gains from monetization that we quantified in the previous section are likely hard to achieve in practice. Most importantly, the GMS program required that physical gold deposited would have to be melted and deformed to make into a uniform good that could be traded. This was a significant disincentive for families to deposit their jewelry and other personal forms of gold. The last related reason is about low take-up that could be driven by a combination of transaction costs and lack of trust and information. For example, according to a (representative) survey of "Household Gold Consumption" in 2023, 58% responded positively to the question: *"Whatever idle gold you possess in the form of jewelry, bars or coins, would you be interested if the Government safeguards (deposits) your gold without any charges and provides return on them?"* However, actual take-up of the program was less than 1%.

Figure 10: Gold Taxation: Change in Returns, Distribution, and Capital Allocation



(a) Change in return on wealth (b) Change in distribution (c) Change in capital level

Note: The left panel shows the change in the expected return to wealth of households with different entrepreneurial ability and wealth level. The middle panel shows the percentage change in the wealth distribution, which is discretized in deciles for readability. Colors within each bin show changes by productivity. The right panel shows the level change in capital of household businesses. Colours correspond to (a selection of) different entrepreneurial ability levels (e) with lighter shades corresponding to lower productivity.

5.3.2 Taxing gold

Given large aggregate costs from gold being unproductive, it is tempting to simply tax the holding of gold. In this subsection, we show that this backfires because taxing gold is ineffective at increasing the productive stock of capital in the economy while substantially hurting welfare.

Specifically, we consider an exercise in which the government levies a fixed tax rate τ_g on any gold holdings and redistributes the tax revenue lump-sum to households via a common per capita transfer T. Households then face the budget constraint:

$$c + d' + k' + (\mathbf{1} + \boldsymbol{\tau}_{\mathbf{g}})P^g g' \leqslant w + R^f d + y(k, n, e, Z) - wn + (1 - \delta)k + P^g g + \mathbf{T}. \quad (28)$$

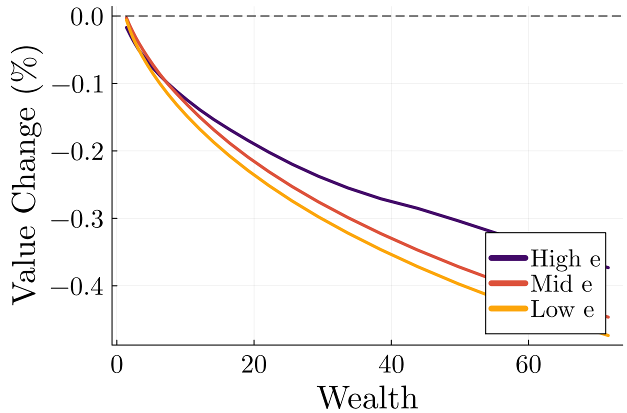
Given a constant tax rate and lump-sum transfer that do not depend on the aggregate state, the government budget is assumed to balance intertemporally, meaning, the following equation should hold in the stationary distribution of the economy,

$$\mathbb{E}\left[\sum_{t=0}^{\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_s^*}\right)\tau_g P_t^g G_{t+1}\right] = \mathbb{E}\left[\sum_{t=0}^{\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_s^*}\right)T\right]. \quad (29)$$

Technically, we solve for the transfer rate that balances the government budget according to Equation (29) for a fixed tax rate τ_g.

Figure 9a and Figure 9b show the aggregate effects for output and welfare as we vary

Figure 11: Gold-Taxation: Relative change in households' value functions



Note: This figure shows the percentage change in the value function of households compared to the baseline economy. Different colours correspond to (a selection of) different entrepreneurial ability levels (e): lighter shades correspond to lower productivity.

the tax rate τ_g. Output effects are close to zero while welfare strongly decreases with the tax rate. The main reason is that the substitution effect of shifting households away from gold towards productive investments is almost entirely canceled out by the negative effect of the tax policy on the level of wealth. To see this more clearly, let us focus on the case of $\tau_g = 0.3$. In this case, gold demand falls sharply, by more than 80%, however, the increase in productive capital is much lower: the total capital stock only increases by about 1% while the capital stock of the entrepreneurial sector increases by 4%. Figure 10a shows how the gold tax has a negative effect on the expected return to wealth as it lowers the financial return to gold, which now equals

$$\widetilde{R_t^g} = \frac{P_t^g}{(1+\tau_g)P_{t-1}^g}. \tag{30}$$

Figure 10b displays the overall effect on the wealth distribution which—contrary to the gold monetization case—shifts to the left: households are on average poorer in a world in which gold is taxed. A comparison of Figure 10c with Figure 8c shows that, in contrast to gold monetization, the change in business investment induced by the taxation policy does not align with the credit-constraints of households; in the former, the most productive credit-constrained entrepreneurs expand their business most, while in the gold taxation case, it is mostly mediocre and richer entrepreneurs who expand most. Therefore, contrary to the gold monetization case, misallocation slightly worsens.

Finally, gold taxation is welfare-decreasing. According to Figure 9b, welfare decreases by more than 6% relative to the baseline (for the case of $\tau_g = 0.3$). The major driver of this decrease is that households are on average poorer in the gold-taxation economy. However, households at the same level of wealth and productivity are also worse-off compared to the baseline economy. Figure 11 shows that welfare of the poorest households is only slightly affected by the gold tax, as the higher price of gold is compensated by the lump-sum transfers. However, the relative loss in welfare increases in wealth and is most pronounced for the least talented wealthy people for whom the investment opportunity set is shrunk while lump-sum transfers are negligible for them.

6 Concluding Thoughts

Savings in unproductive assets—assets that do not directly enter as capital in production—are widespread in developing countries. By looking at the case of gold in India, this paper shows that the aggregate consequences of unproductive assets can be sizable. Using a novel structural model that we carefully calibrate and validate on macro and micro data, we show that output and welfare could rise by more than 10% if gold was productive instead. However, we also show that real-world policies to address the issue of unproductive savings can struggle to actually make unproductive assets productive and that seemingly well-intended policies like taxing unproductive assets can strongly backfire. These quantitative insights are novel and we hope they spawn more research at the intersection of Macro Development and Household Finance in the future.

We end this paper with two further insights that are crucial for policy. First, it is important to note that one fundamental reason for the strong demand for gold in India are rampant financial frictions that weaken the functioning of the financial system and depress returns on productive investments. In Appendix F.3, we show that in a counterfactual economy without financial frictions, the aggregate portfolio share of gold would fall by 40%, partly explaining much lower gold shares in countries with better functioning financial systems. Policy makers interested in reducing unproductive savings should thus consider solving underlying financial market frictions.

At last, we want to emphasize the power of social preferences in shaping economic outcomes. Throughout this paper, we took preferences for gold as given. However, there is strong evidence that at least part of the preferences for gold are related to inefficient status signaling.[18] As a thought experiment, in Appendix F.4 we thus consider a coun-

[18]For example, according to the "Household Survey of Gold Consumption" conducted by IGPC-PRICE, 59% of Indians agree or strongly agree with the statement "I believe that possessing gold is a symbol of

terfactual in which households' preferences would instead partly shift to signaling their business capital rather than gold. We find that even small changes in these social norms could have sizable effects on productive investments and aggregate output. We believe that research on the malleability of social preferences and their macroeconomic effects are another interesting direction for future work.

success." 18% agree or strongly agree with the statement "I buy gold because I want to show others that I am rich."

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A Further details on data & empirics

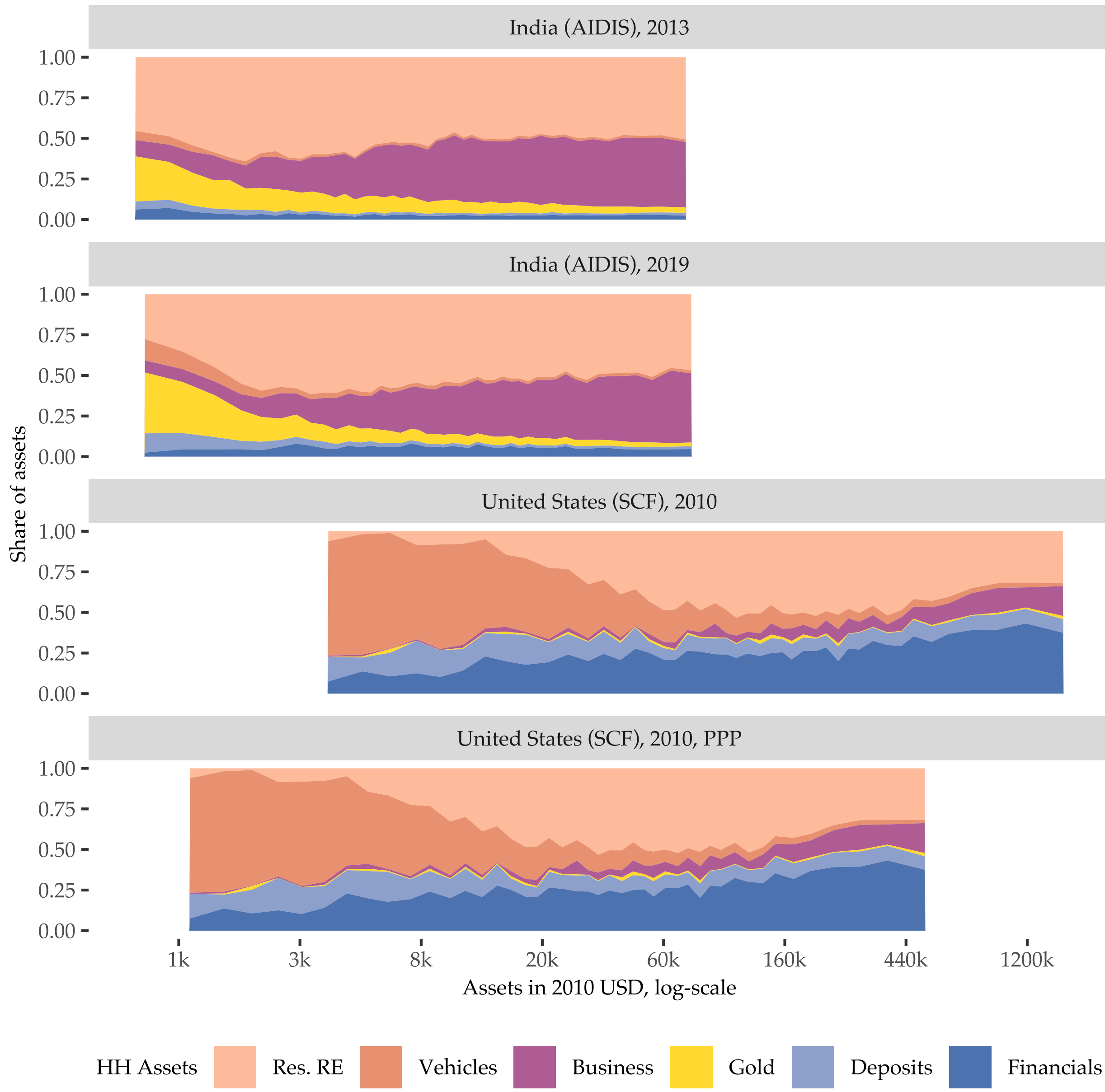


Figure A1: Average household asset allocation by wealth percentile in India and the US.

Note: This figure is based on 2013 and 2019 waves of AIDIS and 2010 wave of SCF. The definition of wealth is as in Figure 1. Additionally, we exclude the poorest and richest households by removing the bottom and the top 6 percentiles, i.e., 3+3 bins out of 50 bins (see the note for Figure 1).

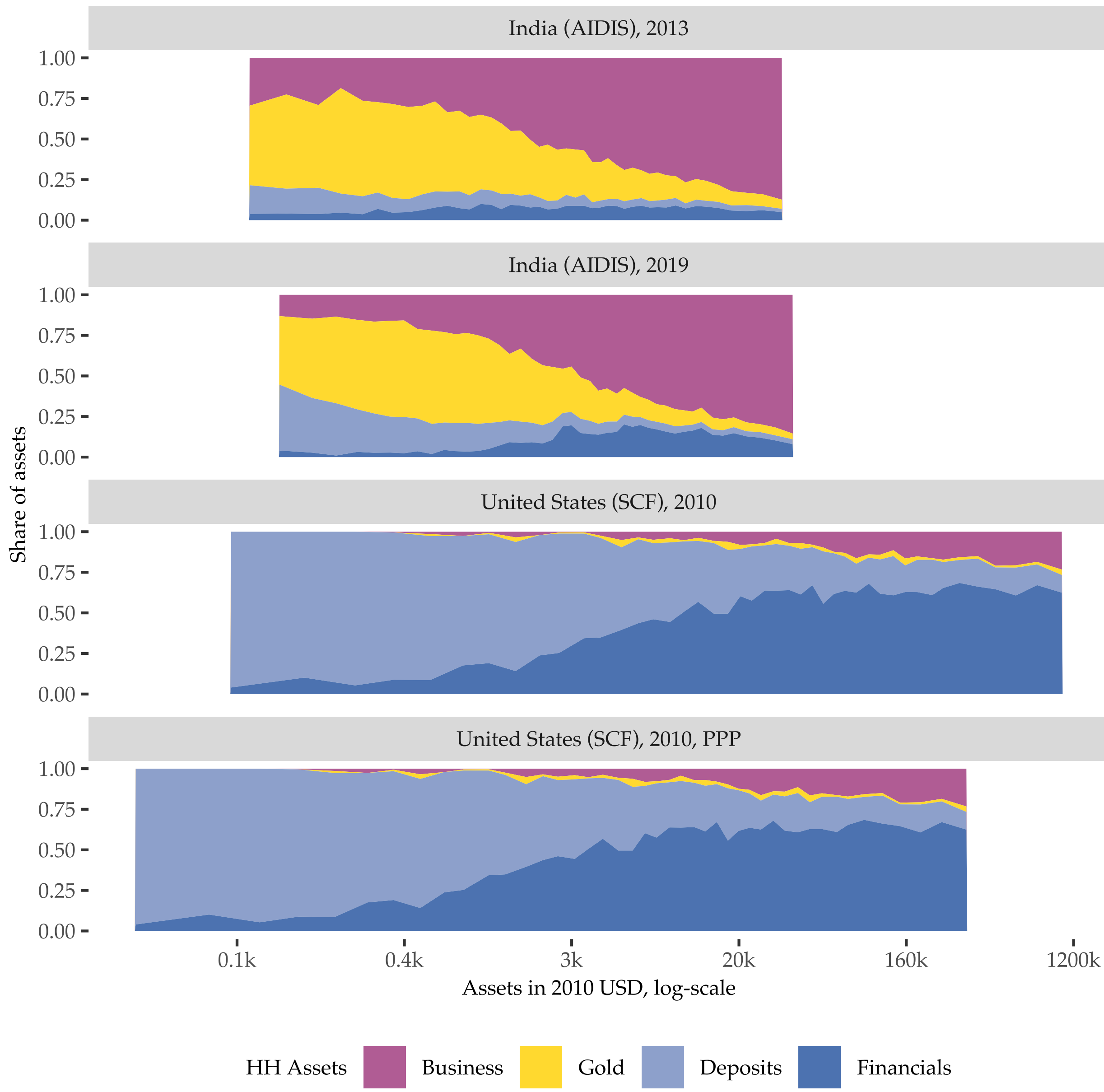


Figure A2: Average household asset allocation by wealth percentile in India and the US.

Note: This figure is based on 2013 and 2019 waves of AIDIS and 2010 wave of SCF. The definition of wealth is as in Figure 2. Additionally, we exclude the poorest and richest households by removing the bottom and the top 6 percentiles, i.e., 3+3 bins out of 50 bins (see the note for Figure 1).

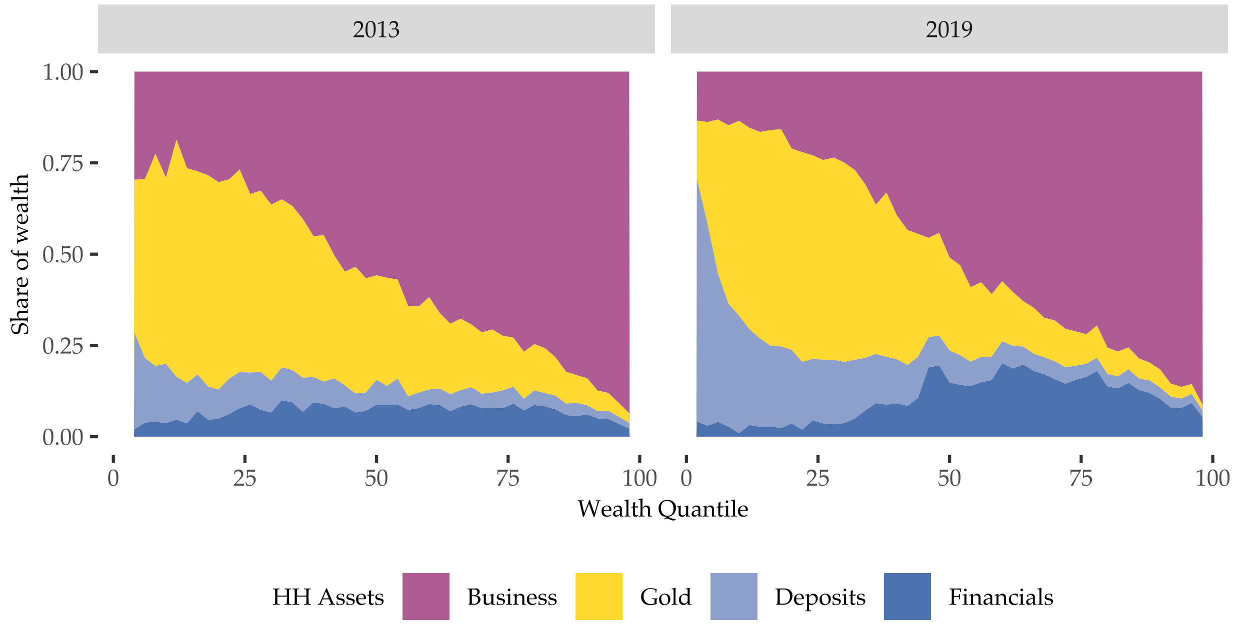


Figure A3: Average household asset allocation by wealth percentile in India: 2013 and 2019

Note: This figure is based on 2013 and 2019 waves of AIDIS. The definition of wealth is as in Figure 2.

B Further model details

B.1 Household business decisions

'Household business profit,' defined in Equation (5) is revenue less compensation of employees. 'Return on physical capital' is household business profit plus the value of undepreciated capital. Therefore, a natural place to start investigating the return on capital is the hiring policy $n(\mathbf{a}, e; \mathbf{\Omega})$ of the household whose value function is represented by Equation (8). Optimal hiring is one that maximizes household's profit, ex-post realization of idiosyncratic and aggregate productivity (e, Z):

$$\pi(k|\mathbf{a}, e; \mathbf{\Omega}) = \max_{n} \left\{ eZ \left(k^{\alpha} n^{1-\alpha} \right)^{\eta} - wn - (r^f + \delta)k \right\} \tag{31}$$

where $(r^f + \delta)$ denotes the user-cost of capital. Hiring policy, and ex-post profit function are then given by

$$n^* = n(\mathbf{a}, e; \mathbf{\Omega}) = \left(\eta \,(1-\alpha)\, Z\, e\, k^{\alpha\eta}\; w^{-1} \right)^{\frac{1}{1-\eta(1-\alpha)}}, \tag{32}$$

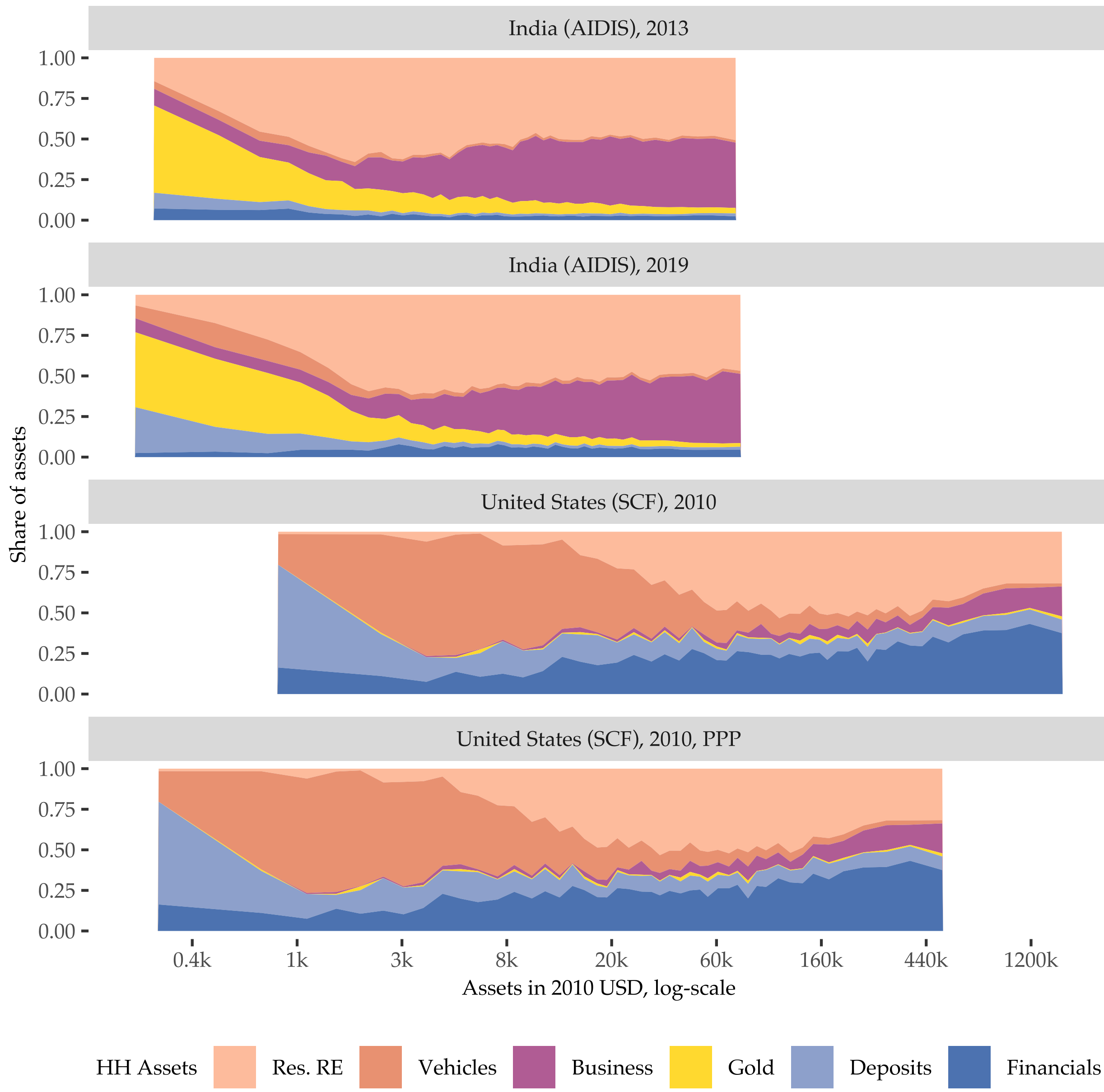


Figure A4: Average household asset allocation by wealth percentile in India and the US.

Note: This is an alternative to Figure A1. Here, instead of cutting bottom 6 percentiles, we require at least 100 USD in wealth as described by the corresponding wealth measure. For the right tail, we still drop top 6 percentiles.

and

$$\pi(\mathbf{a}, e; \mathbf{\Omega}) = \kappa_n \; (e\, Z)^{\frac{1}{1-\eta\,(1-\alpha)}} \;\; w^{\frac{-\eta\,(1-\alpha)}{1-\eta\,(1-\alpha)}} \; k^{\frac{\alpha\,\eta}{1-\eta\,(1-\alpha)}} - (r^f + \delta)\, k, \tag{33}$$

where $\kappa_n = \kappa_n(\eta, \alpha) = (1 - \eta\,(1-\alpha))\, [\eta\,(1-\alpha)]^{\frac{\eta\,(1-\alpha)}{1-\eta(1-\alpha)}} > 0$ is a positive constant.

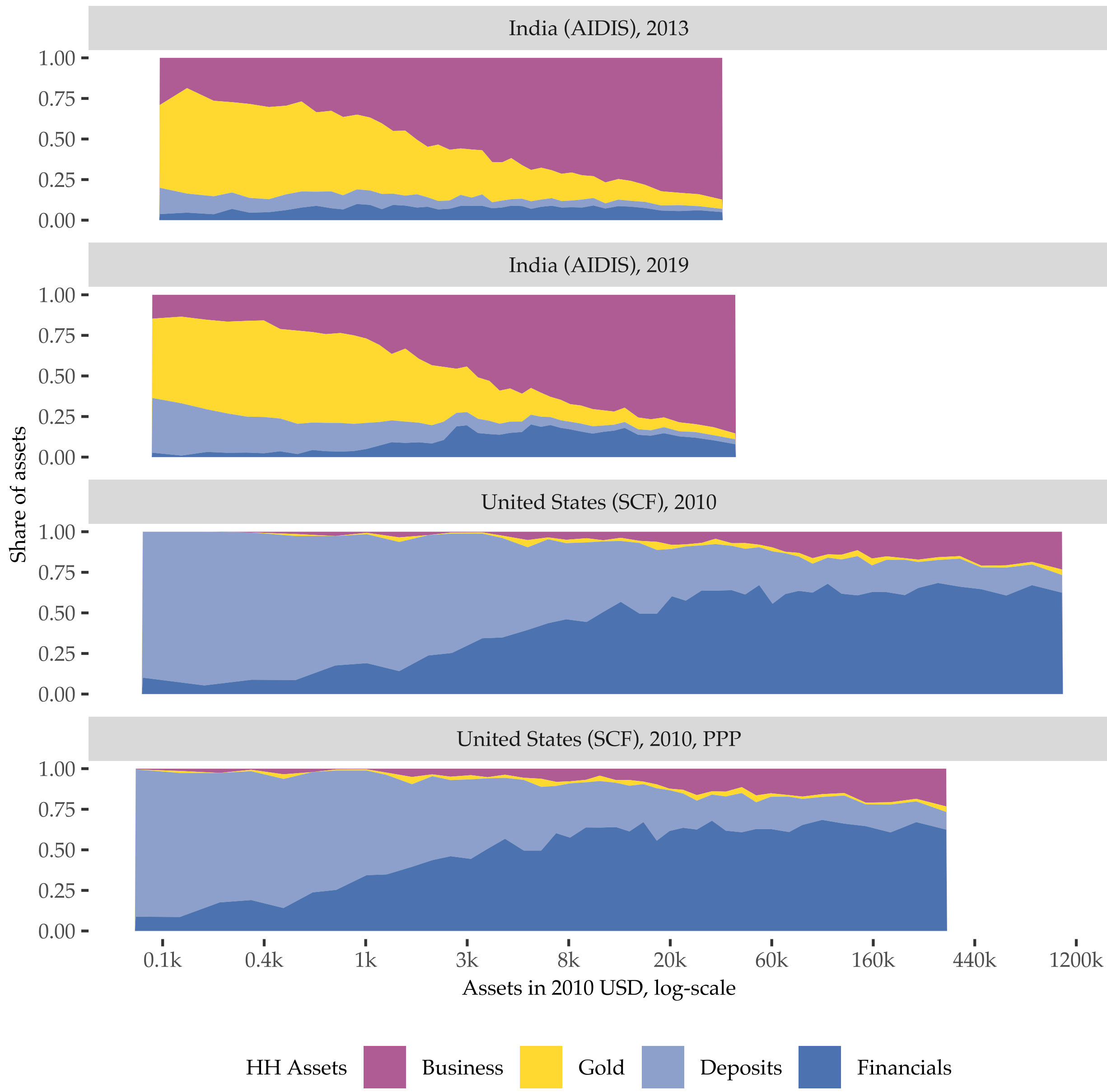


Figure A5: Average household asset allocation by wealth percentile in India and the US.

Note: This is an alternative to Figure A2. Here, instead of cutting bottom 6 percentiles, we require at least 100 USD in wealth as described by the corresponding wealth measure. For the right tail, we still drop top 6 percentiles.

As return on physical capital k is given by

$$y(k, n(\mathbf{a}, e; \mathbf{\Omega}), e, Z) - w\, n(\mathbf{a}, e; \mathbf{\Omega}) + (1 - \delta)k = \pi(\mathbf{a}, e; \mathbf{\Omega}) + (1 + r^f)k,$$

the business profit amounts to the excess return on capital investment, i.e., return in excess of the risk-free rate. Finally, the marginal rate of return on capital of size k in household business, denoted by $R^k(k)$, is given by

$$\begin{aligned} R^k\left(k, e, \boldsymbol{\Omega}\right) &= \frac{\partial}{\partial k}\pi(k, e;\, \boldsymbol{\Omega}) + 1 - \delta \\ &= \alpha_h \eta \left(\frac{\eta\left(1-\alpha_h\right)}{w}\right)^{\frac{\eta\left(1-\alpha_h\right)}{1-\eta\left(1-\alpha_h\right)}} \left(e\, Z\right)^{\frac{1}{1-\eta\left(1-\alpha_h\right)}}\; k^{\frac{-(1-\eta)}{1-\eta\left(1-\alpha_h\right)}} + (1-\delta) \end{aligned} \tag{34}$$

B.2 Algorithm

Taking r^*, the safe interest rate on the financial markets as given, the equilibrium wage rate is pinned down by the Equation (21):

$$w(\boldsymbol{\Omega}) = (1-\alpha)\left(\frac{\alpha}{r^* + \delta}\right)^{\frac{\alpha}{1-\alpha}} Z(\boldsymbol{\Omega})^{\frac{1}{1-\alpha}}$$

- For the household entering the period with the asset position $\mathbf{a}(d, k, g)$ and idiosyncratic and aggregate states being revealed as $(e, \boldsymbol{\Omega})$ let's denote the ex-post net-worth as:

$$\begin{aligned} \widetilde{a}(\mathbf{a}, e, \boldsymbol{\Omega}) &= (1+r^f)d + y\left(k, n, e, Z(\boldsymbol{\Omega})\right) - wn + (1-\delta)k + P^g(\boldsymbol{\Omega})g \\ &= (1+r^f)(d+k) + \pi(\mathbf{a}, e;\, \boldsymbol{\Omega}) + P^g(\boldsymbol{\Omega})g \end{aligned}$$

  and the cash-on-hand by

$$x(\mathbf{a}, e, \boldsymbol{\Omega}) = w(\boldsymbol{\Omega}) + (1+r^f)(d+k) + \pi(\mathbf{a}, e;\, \boldsymbol{\Omega}) + P^g(\boldsymbol{\Omega})g$$

  where the household business profit is given by the Equation (33):

$$\pi(\mathbf{a}, e;\, \boldsymbol{\Omega}) = \kappa\, \left(e\, Z\right)^{\frac{1}{1-\eta\,(1-\alpha)}}\; w^{\frac{-\eta\,(1-\alpha)}{1-\eta\,(1-\alpha)}}\; k^{\frac{\alpha\,\eta}{1-\eta\,(1-\alpha)}} - \left(r^f + \delta\right) k,$$

  and $\kappa = \kappa(\eta, \alpha) = \left(1 - \eta\,(1-\alpha)\right)\left[\eta\,(1-\alpha)\right]^{\frac{\eta\,(1-\alpha)}{1-\eta(1-\alpha)}}$ is a constant. Note that this expression for profit, already assumes the optimal labor choice, so we will drop the hiring policy n as an explicit choice variable of households in the rest of this section.

- For solving the model, one can reduce dimensionality of the problem by rewriting the value function in terms of the cash-on-hand variable:

$$V(x, e, \boldsymbol{\Omega}) = \max_{c, g', k', d'} U(c, g') + \beta\, \mathbb{E}\left\{V(x'(g', k', d', e'; \boldsymbol{\Omega}'), e';\, \boldsymbol{\Omega}') \,|\, e, \boldsymbol{\Omega}\right\} \tag{35}$$

subject to

$$
\begin{aligned}
c + P^g(\boldsymbol{\Omega})g' + d' + k' &\leqslant x, \\
g' \geqslant 0, \quad k' &\geqslant 0, \\
d' \geqslant -\phi_k\, k' - \phi_g\,(P^g\, g')&.
\end{aligned}
$$

C Further estimation & validation details

C.1 Production function and productivity process estimation details

C.1.1 Data details

To estimate the household production function parameters (α_h, η) and the productivity process for household businesses, we draw on the IHDS data.

The IHDS data separately reports input costs and revenues for farm and non-farm businesses. For farm businesses, the IHDS separately captures information on livestock-related and crop-related businesses, which we aggregate. For non-farm businesses, the IHDS asks separately for up to three different businesses a household may run simultaneously, which we also aggregate whenever possible. Throughout, we closely follow the data cleaning procedure for the IHDS in Bolhuis et al. (forthcoming).

Measuring labor input & labor costs.— The IHDS separately reports labor input and labor costs for farm and non-farm businesses. For both farm and non-farm businesses, we measure labor costs as the sum of salary expenses and imputed household labor costs. We start with non-farm businesses. For non-farm businesses, salary expenses capture reported costs of any hired workers for up to three household non-farm businesses, which we sum together. The reported data only asks about total labor costs, not hours or workdays. In contrast, for the labor input of household members, the IHDS reports average work days and average hours per work day on the non-farm business for each household member. We first compute total hours worked for each household member and then aggregate across household members using adult-equivalence scales (0.5 for a child, 0.8 for women) following the Indian Cost of Cultivation Surveys.

For farm businesses, the data reports salary expenses and hours worked for hired workers, giving us a measure of total quantity and costs for hired farm labor. For family labor, we proceed as for non-farm businesses, aggregating up all hours worked by each household member and weighing their relative efficiency using adult equivalence scales. To derive total costs of household labor for farm and non-farm businesses, we use the own-farm price of hired labor when available and otherwise use median state-level hourly farm wages.

Our final labor input and labor cost measures have two drawbacks. First, we use farm-level wages to impute non-farm wages, since we cannot directly compute an hourly non-farm wage from the IHDS household data. This may underestimate imputed household-level wages for non-farm work if non-farm wages are higher than farm wages. Second, the data unfortunately does not measure household labor hours on animal husbandry, which means we also likely underestimate total household hours.

Measuring revenue.— Through the lens of the model, we need to construct total (value-added) revenue across all household businesses y. IHDS separately reports revenue for farm and non-farm businesses. For non-farm businesses, the questionnaire reports *net income* after subtracting intermediate expenditures ("other expenditures") and labor costs. We thus construct (value-added) non-farm business revenue as *net income* plus adding back labor costs. For farm business revenue we proceed analogously: we draw on *net income* which takes out spending on a comprehensive list of intermediate inputs such as seeds, manure, pesticides, irrigation and other costs. Since *net income* for farm businesses also subtracts labor costs as well as different capital expenditures, we make sure to add them back. Note that we do not add back imputed household labor costs for revenues as they are also not subtracted in *net income*.

Measuring capital & land.— Our measure of the total capital stock includes both capital and land. Importantly and as stated in the main text, the IHDS only asked about capital and land for farm businesses and unfortunately not for non-farm businesses. We closely follow Bolhuis et al. (forthcoming) in constructing the stock for both. We start with land.

We measure total land cultivated as the sum of own land cultivated and land rented-in in wave I. In wave II, we calculate total land cultivated (own land + rented-in - rented-out) by season and then take the maximum value of the three. Similarly, total land rented-in and rented-out are taken as the maximum over all three seasons reported. To compute the total *value* of land, which we need to aggregate capital and land, we first compute the median rental value for an acre of land reported in the IHDS in wave 1. We then divide this by our model-implied interest rate r^* to get to the total value of land, assuming that there is no depreciation of land. We enforce the same value across both waves to ensure that we measure quantities of "capital + land" and do not factor in price appreciation.

For capital, we again follow Bolhuis et al. (forthcoming) to aggregate (net) capital rentals and different capital items that farm businesses own. The stock of capital items is calculated as the value of electric pumps, diesel pumps, bullock carts, tractors, threshers, and draft animals owned by the farm. We impute the value of machinery using 1997-98 prices reported in table 24 of Singh (2006). Electric and diesel pumps are priced at Rs. 18,000, bullock carts at Rs. 10,000, tractors at Rs. 250,000, and threshers at Rs. 25,000. For draft animals, we first take the average value of the minimum and maximum reported price for draft animals in the village database of the respective wave of IHDS, and then use the median of this value. A measure of capital items owned is then constructed as the total value of all machinery and draft animals owned by the farm.

IHDS also reports expenditure on renting capital as well as income made from renting out capital from the farm. We convert these rental values to capital stock values using our model implied (world) interest rate and capital depreciation. That is, we assume the data reports the rental costs for renting capital K^R as $R \times K^R$ where $R = r^* + \delta$. Bolhuis et al. (forthcoming) instead use the median nominal interest rate paid by households on loans from banks. We deviate from this because we believe bank loans do not correctly capture the depreciation costs priced into capital rentals. Correspondingly, our measure of R (11.5%) is higher than what Bolhuis et al. (forthcoming) use (8.5%).

Total capital stock employed on the farm is calculated as capital owned plus capital rented in minus any capital rented out. To this value we follow Bolhuis et al. (forthcoming) by adding a minimum amount of capital to every household equal to 10 percent of the median capital-to-land ratio multiplied by HH-specific operated land to account for basic tools used on the farm not usually reported in the data.

Measuring productivity.— We measure (revenue) productivity for all businesses for which we can construct revenue and inputs (labor and capital). Importantly, given that capital is only reported for farm businesses, this means we cannot construct productivity for non-farm businesses. For our productivity measure, we enforce the production function and structure of our model, which implies that log productivity x_{it} is given by:

$$x_{it} = \log(y_{it}) - \alpha\eta\log(k_{it}) - (1-\alpha)\eta\log(n_{it})$$

C.1.2 Productivity process estimation details

Details on estimating sample.— Given a measure of a households' business productivity x_{it}, the IHDS data gives us a two-wave panel with waves for 2005 and 2011. We restrict to businesses that we can observe in both waves and we drop the bottom and top 1%

of businesses based on their initial productivity in 2005 and based on their changes in productivity between 2005 and 2011 to reduce the influence of outliers and measurement error. However, we replicate the same sample selection in our indirect inference, which ensures that this does not bias our results. For the baseline sample this gives 9,206 businesses (each observed twice). As one robustness estimation, we also consider only those household businesses for which the household did not split over time, which reduces the sample slightly to 7,767 businesses.

Details on the baseline estimation.— In the data, we estimate an auxiliary AR(1) regression in which observations are 6 years apart:

$$x_{i,2011} = \tilde{\mu}_e + \tilde{\rho}_e x_{i,2005} + \mu_i + \tilde{e}_{i,2011} \tag{36}$$

where μ_i captures a set of household fixed characteristics that control for permanent differences across household businesses, and $(\tilde{\mu}_e, \tilde{\rho}_e, \tilde{\sigma}_e)$ are the auxiliary coefficients of interest (with $\tilde{\sigma}_e$ denoting the standard deviation of $\tilde{e}_{i,2011}$). To estimate the true annual AR(1) parameters we then use the Simulated Method of Moments (SMM) by targeting the estimated coefficients of the auxiliary regression $(\tilde{\mu}_e, \tilde{\rho}_e, \tilde{\sigma}_e)$. To construct the same auxiliary regression based on the model-based AR(1) process, we start from an initial sample of business productivities $\mathbb{X}_0$, simulate an annual AR(1) process forward for six years for this sample and then estimate the auxiliary AR(1) on the panel that includes the initial and last year only. For the baseline estimation, we take the initial sample $\mathbb{X}_0$ directly from the data. To ensure that model-based estimates do not additionally face sampling uncertainty, we duplicate the initial sample many times, as is best practice for SMM. As controls, we use fixed effects for state and district, social group and caste, whether a household is urban or rural, the education level of the household head, and the number of men and women in the household.

Results and robustness.— Table C.1 reports parameter estimates for different specifications. We focus on the estimates for ρ_e & σ_e, but for completeness also report the estimates for μ_e.[19] The baseline estimates give $\rho_e = 0.764$ and $\sigma_e = 0.666$, which are fairly robust to alternative specifications. Among the different specifications, running the auxiliary regression without controls (column 2) leads to the most changes, producing higher estimates of persistence ($\rho_e = 0.816$) because permanent differences across households get wrongfully attributed to the persistence in idiosyncratic productivity. Other specifications produce very similar results than the baseline estimation, showing that the baseline estimates are

[19]Note that μ_e is harder to interpret since the level is arbitrary and also captures aggregate shocks over time, which is why we do not use μ_e in the subsequent model calibration.

Table C.1: SMM estimates of $(\rho_e, \sigma_e, \mu_e)$ for different specifications

	Baseline	No controls	Drop 2.5%	Drop 5%	Initial	Non-split
ρ_e	0.764	0.816	0.771	0.777	0.759	0.768
σ_e	0.666	0.655	0.644	0.632	0.677	0.661
μ_e	0.211	0.166	0.209	0.208	0.215	0.211
Specification differences						
Controls?	Yes	No	Yes	Yes	Yes	Yes
Outliers 2005?	1%	1%	2.5%	5%	1%	1%
Outliers 2005 vs. 2011?	1%	1%	2.5%	5%	1%	1%
Initial sample?	Data	Data	Data	Data	LN	Data
Exclude split HHs?	No	No	No	No	No	Yes

Notes: "Controls?" indicates whether the auxiliary regression controls for fixed household-level characteristics. "Outliers 2005?" indicates the percentage of observations that are dropped at the top and the bottom based on the 2005 productivity distribution. "Outliers 2005 vs. 2011?" is similar but refers to observations dropped based on changes in productivity between 2005 and 2011. Any dropping of outliers is implemented exactly the same in the SMM loop with simulated data. "Initial sample?" refers to whether the simulated data starts from the 2005 data sample or from a simulated log-normal distribution (LN) with the same mean and variance as the 2005 data. "Exclude split HHs" denotes whether households that split between 2005 and 2011 are excluded or not.

pretty robust. For example, dropping a higher share of outliers (columns 3-4) only has small effects on the estimates, which is reassuring. Outliers could theoretically play a role either because of measurement error or because the true distribution of errors is more or less heavily tailed than the log-normal distribution we assume. To gauge the importance of the latter effect and to further validate our modeling choice, Figure C1 compares the distribution of errors from the auxiliary regression in the data and model-based simulated data. Both line up well, which we interpret as indicating that our assumption of log-normal errors is reasonable.

Similarly, starting instead not from the initial sample but from a log-normal distribution produces almost indistinguishable estimates (column 5). Similarly, focusing only on non-split households (which reduces the sample quite a bit) also has no meaningful effect on the estimated coefficients (column 6). In summary, we believe this provides strong evidence that our main estimates for the persistence and volatility of the productivity process are robust.

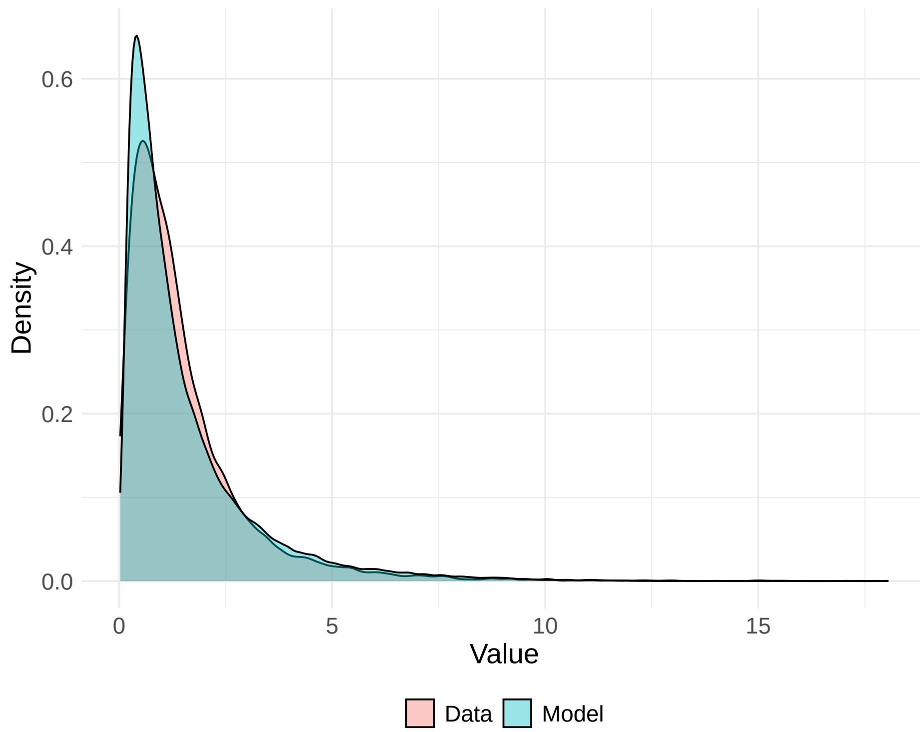


Figure C1: Error distribution model vs. data for auxiliary regression

Note: Plots the distribution of errors of the auxiliary regression (data vs. model-based simulated data) for the baseline productivity process estimation.

C.2 Details on Z-estimation in corporate sector

In this subsection, we provide further details on how we estimate the Z-process using the CMIE's Prowess database on publicly listed firms and other large firms – the Indian equivalent to Compustat. Drawing on the CRS production function in the corporate sector, we need to construct measures of (real) value added output Y, capital K and labor L, together with an estimate of α_C, the capital output elasticity in the corporate sector to back out Z:

$$Z = \frac{Y}{K^{\alpha_C} L^{1-\alpha_C}}$$

We start out with labor, or more precisely of the wage bill wL, for which we draw on a measure of the total costs of labor that include direct labor compensation (i.e. wages) but also bonuses and other forms of employee compensation. Since CMIE Prowess reports different measures of the labor wage bill, we make sure to always use the maximum reported wage bill within a firm-year observation. Specifically, we take the maximum among the following three measures of payroll expenses: "Compensation to employees", "Salaries and bonuses", and "Salaries".

Next, we compute value added output Y as total sales minus total intermediates. Since we do not have a direct measure of the costs of goods sold (COGS), which is commonly used as a measure of total intermediates, we indirectly infer total intermediates using the accounting identity whereby costs of intermediates are given by the difference between sales (we use "net sales"), PBDITA (profits before capital costs) and wL. At last, we use the measure of "capital employed" to measure capital K. To ensure that all variables are in real terms ($P = 1$), we deflate all three variables by the aggregate CPI.

We are then still left with a measure of the wage bill wL rather than a direct measure of labor L. To separate the two, we look at the wage bill per worker at the firm-year level. To allow for firms to use a different composition of worker skills (and thus different average wages per worker), we infer changes in wages from within-firm changes in the wage bill per worker. Specifically:

$$\Delta w = \Delta_i \frac{wL}{N} \tag{37}$$

as long as the ratio $\frac{L}{N}$ is constant in expectation at the firm-level. We then estimate wage changes over time by taking the median-observed change in the wage bill per worker at the firm level. We normalize the initial level of the wage w to one, without loss of generality. The corresponding wage series is plotted in Figure ??. Wages per worker almost triple over the 30 year window that we look at, with a particularly rapid rise in the late 1990s, coinciding with the Indian growth miracle.

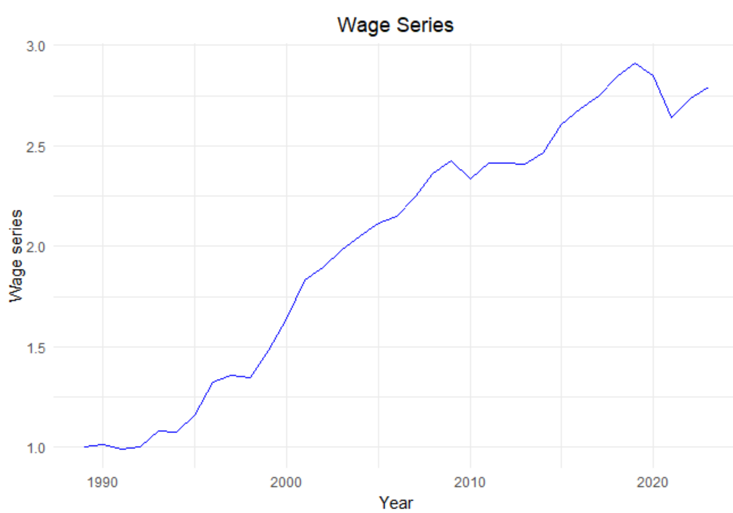


Figure C2: Wage series over time in the corporate sector.

At last, we infer α_C using the first-order condition of the corporate sector, specifically:

$$1 - \alpha_C = \frac{wL}{Y}$$

We draw on the median observed labor share across firms which gives $\alpha_C = 0.62$.

The corresponding Z-series is shown in Figure ??. After an initial blip around 1990, productivity growth in the corporate sector was strong between 1994 and 2005, again coinciding with the Indian growth miracle. Since then, productivity declined in the wake of the Global Financial Crisis, but has been recovering more recently since 2013.

Figure C3: Z series in corporate sector inferred from CMIE Prowess database

C.3 Details on calibration of collateral constraints

In this subsection, we outline the exact procedure used to obtain collateral constraints $\tilde{\phi}_k$ and $\tilde{\phi}_g$, as well as probabilities $\mathbb{P}(k - \mathrm{loan}|\text{any loan})$ and $\mathbb{P}(g - \mathrm{loan}|\text{any loan})$. The steps are as follows:

1. Create a sub-sample of the cleaned sample (see Appendix D) in which there are only such households that have at least one loan and whose oldest loan is issued in 2010 or later. The purpose of the issuance year restriction is that, ideally, we want to measure constraints at the moment of borrowing. Using 2010 is a compromise choice: it is arguably not too far from 2013 when they survey is conducted, and at the same time allows to consider most of households with debt. Around 16% of debtors have a loan originated prior to 2010, and are not considered further.

2. In the sub-sample, calculate collateral to debt ratios: 1) total debt backed with business assets by business assets, 2) total gold backed loans by gold holdings. For 1), we consider loans to be backed by business assets if they have one of the following collateral types (called "type of security" in the survey schedule): first charge on

immovable property, mortgage of immovable property, agricultural commodities, movable property other than bullion, ornaments, shares, agricultural commodities etc. Since such debt also includes mortgage debt, we subtract from this sum any debt that falls under these types and at the same time has "purpose of loan" specified as "for housing". For business assets, the definition is as in Table 1 but without subtracting debt.

3. To deal with cases of very small denominator, which inflates the right tail of the distribution of ratios, we use a filter that requires debt-holding households to have respective collateral assets larger than the 15th percentile in the distribution of all households holding any such assets (but not necessarily indebted). For example, for business assets, we take the cleaned dataset, select observations with strictly positive business assets, and in this distribution of business assets, take the 15th percentile. We record these two thresholds, which, coincidentally, are both equal to 5k Indian rupees.

4. Further split the sub-sample obtained in step 1 to two sub-samples. First is obtained by requiring business assets strictly above the threshold obtained in the previous step and strictly positive business-backed debt. Second is obtained by requiring gold assets strictly above the threshold obtained in the previous step and strictly positive stock of gold loans. For the sub-sample of business debtors, we further introduce the following condition: value of non-residential buildings and land are at least half of for-business mortgages, calculated as the stock of mortgages of the household less any mortgages taken out for housing. This filter is motivated by the data themselves. There are cases when mortgage is recorded on the balance sheet with a purpose other than "for housing", yet non-residential real estate assets are very small or zero. This may be partially driven by cases when the value of non-residential real estate is for some reason lost or strongly diminished some time after taking a loan; we allow for up to 50% loss of value and consider other cases to be driven instead by incorrect specification of the purpose of the loan, i.e., that these loans are in fact for housing but are not recorded as such in the survey.

5. Determine the values of the ratios that are close to constraining. For this, in the two-sub-samples, we take 80th percentile of the respective ratios.

6. Construct a combined sub-sample of constrained borrowers by taking a union of the observations in the two sub-samples satisfying (independently) the condition described in the previous step.

7. In this combined sub-sample, determine $\mathbb{P}(k-\mathrm{loan}|\text{any loan})$ and $\mathbb{P}(g-\mathrm{loan}|\text{any loan})$ by looking at the shares of the sample with positive stock of the respective debt types.

8. Finally, obtain collateral constraints $\tilde{\phi}_k$ and $\tilde{\phi}_g$ as 95th percentile values of the respective ratios in the respective sub-samples. These are the same sub-samples from which 80th percentiles are drawn three steps before. The distributions up to 95th percentile are plotted in Figure C4.

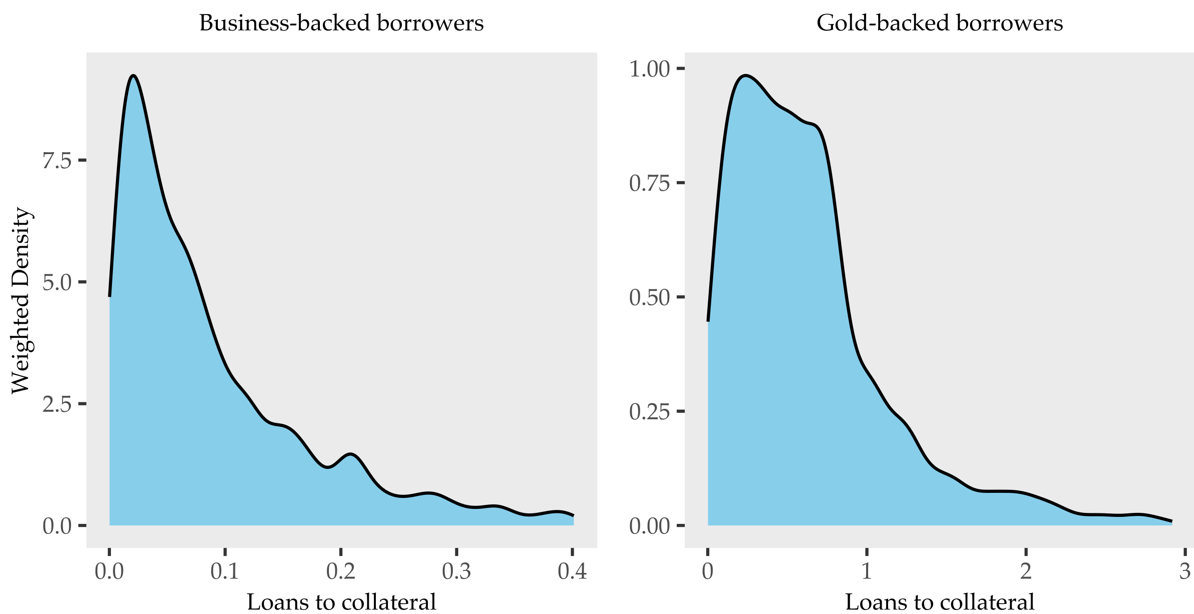


Figure C4: Probability distribution: ratio of the total value of business- and gold-backed loans to reported stock of collateral

Note: This figure is based on 2013 wave of AIDIS. The distributions are those from which the collateral constraints are estimated (see subsection C.3). The maximum value of the ratio in the plots is the 95th percentile, i.e., the collateral constraint. The unit of observation is still the household. Hence, to measure debt we sum up all the loans secured with the respective asset. As described in subsection C.3, only households with at least one loan and all debt issued no earlier than 2010 are considered for the construction of the collateral constraints.

C.4 Details on the indirect calibration

C.5 Details on measuring firm size distribution in data

In this part of the Appendix, we provide a few further details on how we measure labor demand n^* in the IHDS data. As described in the main text, we construct n^* as the ratio of total hours worked on the household's businesses (including outside labor) divided by total *potential* hours of household labor.

IHDS reports labor hours on farm and non-farm household businesses for each household member. We aggregate up these hours by household member and then aggregate across household members within a household using standard equivalence scales as weights to ensure we down weigh work of children. One main caveat for this step is that the IHDS data does not measure hours of work for animal husbandry. This means we likely underestimate total hours of work by household members, which we take into account when measuring *potential* hours of work.

For the numerator of total hours worked, we also add in all hours worked by hired outside labor. Hired hours of work are well reported for farm businesses (apart from animal husbandry), but are not reported for non-farm household businesses. Instead, IHDS then reports paid salary to outside workers, which we convert to hours worked by using an estimate of wage per hour based on reported farm-level expenses. We believe this gives a reasonable estimate of quality-adjusted hours of work that is even household- and region-specific.

For the denominator of measuring total *potential* hours of household labor, we proceed as follows. IHDS reports for all household members whether they work outside the household businesses or not. For those who report to not work outside the household businesses, we take their total reported household labor hours as their total potential hours. An alternative would be to use an estimate of total possible yearly hours (e.g. 52 weeks at 50 hours per week), but we decided against this because this measure ignores underemployment and lower hours for child labor, which would mean we would systematically bias n^* downward. For those workers who report to also work outside the household business, we would ideally like to construct their total hours worked and use this as a measure of total potential hours. Unfortunately, this is not systematically reported. Instead, we thus use as total potential hours in these cases the assumption of 50 weeks at 40 hours per week, which also accounts for systematic underemployment of workers throughout the year.

C.6 Details on replicating capital-grant RCT in model

In this part of the Appendix, we provide further details on the capital-grant RCT by De Mel et al. (2008) and how we implement it within our model. We divide this discussion into four crucial parts: Selection, Experiment, Measurement, and Results.

Selection

De Mel et al. (2008) randomly select microenterprises based on an employment and capital threshold. Specifically, they first pre-select areas with a high share of self-employed workers based on the census. They then enumerate everyone in the area, interviewing only those that run a business without any paid employees. At last, of those interviewed, they drop firms with more than \$1,000 USD in capital (excluding land and buildings). We try to implement the same selection rule within our model. To only capture micro-enterprises without paid employees, we restrict to firms with $n^* \in [n_{low}, 1.0]$. The upper bound rules out employer firms that hire workers from outside the own household. The lower bound n_{low}, instead, ensures that we focus on actual micro-enterprises rather than households who are primarily wage workers. We choose the cutoff n_{low} such that we replicate the share of households who report that they do not run a household business in the IHDS data, which is 45.7% (see Appendix C.5 for details). While our model cannot deliver an exact $n^* = 0$, our model does generate a large share of businesses with a very small n^*. We find that $n_{low} = 0.055$, which means we only classify a household as a household business if the household uses more than 5.5% of their time allocation on any household business activities.

For the capital threshold, one important limitation is that our model does not distinguish different types of physical capital within a firm, which means we cannot enforce the same \$1,000 USD threshold for a subset of the capital. Instead, we enforce the same threshold as De Mel et al. (2008) in terms of the percentage of firms that get dropped. This means we drop the 6.22% of selected firms with the highest capital. As in De Mel et al. (2008), these dropped high-capital firms are more likely to be firms with low returns to capital. Through the lens of the model, the reason is that they are either wealthy households with relatively low productivity or households that invested in their business but saw a negative ex post realization of their business productivity e (and thus chose a relatively low n^*).

With these selection criteria in hand, we draw a large number of micro-entrepreneurs which we randomly allocate into treatment and control group, as in the main paper. The large number ensures that sampling uncertainty is not an issue for us. Importantly, we also shut down uncertainty from variation in aggregate states by running the RCT many different times from different aggregate starting points and we subsequently control for different paths of aggregate states in the estimation.

Experiment

The experiment gave out four different treatment types, which we mimic in our model-based replication. Treatment arms 1 and 2 gave out capital grants of \$100 and \$200 dollars each, while Treatment arms 3 & 4 respectively gave out the same amounts in cash instead.

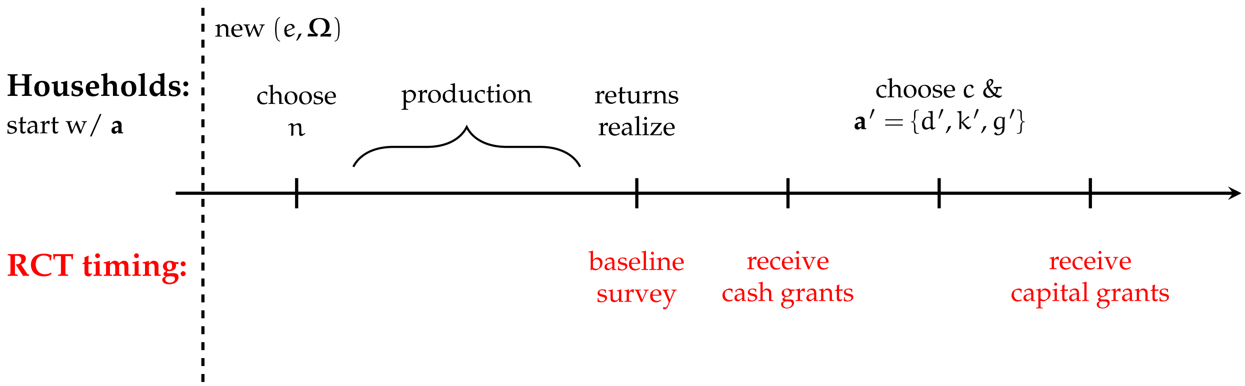


Figure C5: Timeline of RCT within the model

Figure C5 shows how we think about the timing of the experiment within our model. Cash grants in our model are treated as additional cash-in-hand at the end of a period before making future consumption and savings choices. Capital grants are instead handed out *after* households made their savings choices for tomorrow and simply add to the households' choice of capital. This is to replicate that capital grants were unanticipated and micro-entrepreneurs had to directly buy the capital. An alternative modeling choice would have been to allow households to still choose capital, deposits, and gold while already knowing they would receive an additional capital bonus after.

In De Mel et al. (2008), for funding reasons, half the grants were given out immediately after the baseline survey, while the other half were randomly given out only after the third survey wave (approximately 6 months later). Since our model period is 1 year, we cannot implement this staggered roll-out and simply assume everyone received the treatment after the baseline survey. Since we can more flexibly control for the state of the aggregate economy and there are no general equilibrium effects of the program, we do not see how this would bias our results.

Measurement

De Mel et al. (2008) follow the treatment and control group of selected micro-entrepreneurs for 2 years, or 8 waves after the baseline survey at the quarter frequency. Given that our model time period is annual, we aggregate the data in De Mel et al. (2008) at the yearly level and show results at this frequency, in line with our model. The main outcome variable in De Mel et al. (2008) is the *monthly* profits of the firm measured as total business income after paying out all expenses including wages to employees, but not including income paid to the household. Our corresponding measure of profits is:

$$12 \times \hat{\pi}^{RCT} \equiv \begin{cases} y(e, \Omega, k, n^*) & \text{if } n^* \leqslant 1 \\ y(e, \Omega, k, n^*) - w(n^* - 1) & \text{if } n^* > 1 \end{cases}$$

Importantly, we follow De Mel et al. (2008) in not subtracting capital depreciation. Note that this definition still incorporates paid employees, because selected firms may over time hire workers even if they did not have any paid employees at baseline.

Results

De Mel et al. (2008) consider three main sets of regression results:

1. Basic reduced-form treatment effects:

$$Y_{i,t} = \alpha + \sum_g \beta_g T_{g,i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

   where Y is the outcome of interest and (λ_t, λ_i) are fixed effects for time and individual firms. Results are reported for the two main outcomes in levels and logs:

$$(k, \log(k), \hat{\pi}^{RCT}, \log(\hat{\pi}^{RCT}))$$

2. Pooled reduced-form treatment effects:

$$\hat{\pi}^{RCT}_{i,t} = \alpha + \beta \text{Treatment amount (in \$)}_{i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

3. Returns to capital regression (IV):

$$\hat{\pi}^{RCT}_{i,t} = \alpha + \beta k_{i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

   where $k_{i,t}$ is instrumented using the treatment amount T_i.

In the main text, we focus on the reduced-form results (both pooled and non-pooled) on measured profits. We abstract from the results on capital because – as previously noted – our model-based measure of capital is not consistent with how De Mel et al. (2008)

measure capital. De Mel et al. (2008) measure capital either net of land and buildings or inclusive of both. Instead, our model and underlying data measures capital inclusive of buildings but exclusive of land. This means that our model-based estimates on the effects of the treatment on the capital stock will by construction be different from De Mel et al. (2008), which then also affects the IV-based returns to capital.

Reassuringly, if we run the reduced form regressions on capital using the two different measures of capital in De Mel et al. (2008) and compare it to our estimates, we find that our estimates exactly fall in between the two estimates, exactly as one would expect. Similarly for the IV estimates, our model estimate falls in between the estimates for each of the different capital stocks. We take this as another validation of our main estimates, but do not report this in the main paper, because one cannot quantitatively compare these different estimates.

At last, we note that in addition to De Mel et al. (2008), we run the above regressions for many different aggregate states and then add aggregate state fixed effects to ensure results are robust to starting in different aggregate states. We have also tried a version where we run separate regressions for each sequence of aggregate states and then average across treatment effects afterwards; results are almost identical.

Pseudo-code

Consider a large set of initial (aggregate) states $(\Omega_0, \Gamma_0)_\tau$ with $\tau \in \mathcal{T}$.

For each state $\tau \in \mathcal{T}$:

1. **Selection at t=0**, start from $(\Omega_0, \Gamma_0)_\tau$ and randomly draw $2 \times N$ firms (indexed by i) among firms with $n_0^* \in [n_{low}, 1.0]$ and $k_0 <= \bar{k}$.

2. **Roll-out**:

   (a) Measure baseline profits $\hat{\pi}_{i,0}^{RCT}$, capital $k_{i,0}$, revenues $y_{i,0}$ and save in dataframe

   (b) Randomly divide N firms in control group (C), N firms in treatment group (T)

   (c) Among treated firms, divide into 4 groups $g \in \{kap100, kap200, cash1, cash2\}$:

   - Capital grant \$100: kap100
   - Capital grant \$200: kap200
   - Cash grant \$100: cash100
   - Cash grant \$200: cash200

(d) Hand out cash grant after returns at $t = 0$ but before decisions (c_0, k_1, g_1, d_1) are made; hand out capital grant after decisions are made, but before (e_1, Ω_1) are revealed.

3. **Tracking:** Follow simulated firms in T & C over 2 years, save their decisions:

$$(\hat{\pi}_1^{RCT}, \hat{\pi}_2^{RCT}, k_1, k_2, y_1, y_2)$$

4. **Results:** Following De Mel et al. (2008), run three types of regressions

   - Basic treatment effects:

$$Y_{i,t} = \alpha + \sum_g \beta_g T_{g,i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

   where Y is the outcome of interest and (λ_t, λ_i) are fixed effects for time and individual firms. Results are reported for the two main outcomes in levels and logs:

$$(k, \log(k), \hat{\pi}^{RCT}, \log(\hat{\pi}^{RCT}))$$

   - Pooled treatment effects:

$$\hat{\pi}_{i,t}^{RCT} = \alpha + \beta \text{Treatment amount (in \$)}_{i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

   - Returns to capital regression (IV):

$$\hat{\pi}_{i,t}^{RCT} = \alpha + \beta k_{i,t} + \lambda_t + \lambda_i + \varepsilon_{i,t}$$

   where $k_{i,t}$ is instrumented using the treatment amount T_i.

In addition to De Mel et al. (2008), we run the above regressions for many different aggregate states and then add aggregate state fixed effects to ensure results are robust to starting in different aggregate states.

D Data cleaning

This section covers data cleaning procedure for household balance sheet data. The filters are developed such that the parts of assets are all positive and sum up to one. We also follow Badarinza et al. (2019) in limiting the sample to household heads that are at least

24 years old. We apply the same set of filters to both waves of AIDIS (Tables D.1 an D.3) and, where applicable, extend them to SCF (Table D.2).

Table D.1: AIDIS 2013 cleaning procedure

No	Cleaning step	Obs.	Share	Removed	Notes
Sample before any filters		110,800	100.00%		
1	Household head at least 24 years of age	2,269	2.05%	−2,269	Foll. BBR
2	Transport for HH needs not larger than total transport	10	0.01%	−10	Our filter
3	Residential buildings no larger than total buildings	4	0.00%	−4	Our filter
4	Residential urban land no larger than total land	14	0.01%	−14	Our filter
5	Residential rural land no larger than total land	14	0.01%	−14	Our filter
6	Urban land value not negative	1	0.00%	−1	Our filter
7	Value of stockholdings not negative	11	0.01%	−11	Our filter
8	Total assets strictly positive	1,096	0.99%	−584	Our filter
Sample after cleaning		107,893	97.38%	−2,907	

Details: "Obs." are counts of observations that do not satisfy the filter in the sample before any filters, and "Share" are corresponding fractions. For summary rows (before and after cleaning), this column contains observations present and their share of the original sample. "Removed" is the number of observations removed at each step; as some filters overlap, this number may be smaller than "Obs." BBR is Badarinza et al. (2019).

To avoid negative denominator when calculating asset shares for constructing asset decompositions, e.g. for Figures 1 and 2, we require that those asset classes from which debt is subtracted are non-negative. In particular, for AIDIS, we require that net equity in residential real estate and business is at least zero, affecting 1931 and 1543 negative records, i.e., around 1.8% and 1.4% of the clean sample, respectively. For SCF, 275 observations with negative residential real estate equity (4.4%), 54 observations with negative vehicles equity (<1%) and zero observations with negative business equity are likewise replaced with zeroes. Once the replacements are made, total wealth measures are recalculated to ensure that the parts of assets sum up to one.

Table D.2: SCF 2010 cleaning procedure

No	Cleaning step	Obs.	Share	Removed	Notes
Sample before any filters		6,482	100.00%		
1	Household head at least 24 years of age	188	0.16%	−188	Foll. AIDIS procedure
2	Total value of primary residence not negative	3	0.00%	−3	Our filter
3	Net equity in non-residential RE not negative	15	0.01%	−15	Our filter
4	Business equity not negative	4	0.00%	−4	Our filter
5	Total assets strictly positive	160	0.14%	−144	Our filter
Sample after cleaning		6,128	94.54%	−354	

Details: See the notes for Table D.1.

Table D.3: AIDIS 2019 cleaning procedure

No	Cleaning step	Obs.	Share	Removed	Notes
Sample before any filters		116,461	100.00%		
1	Household head at least 24 years of age	2,591	2.22%	−2,591	Foll. BBR
2	Transport for HH needs not larger than total transport	0	0.00%	0	Our filter
3	Residential buildings no larger than total buildings	0	0.00%	0	Our filter
4	Residential urban land no larger than total land	0	0.00%	0	Our filter
5	Residential rural land no larger than total land	0	0.00%	0	Our filter
6	Urban land value not negative	0	0.00%	0	Our filter
7	Value of stockholdings not negative	4	0.00%	−4	Our filter
8	Total assets strictly positive	492	0.42%	−251	Our filter
Sample after cleaning		113,615	97.56%	−2,846	

Details: See the notes for Table D.1.

E Gold policies in India

Since the 1960s, India's gold policy has undergone shifts, though its overarching objective has remained consistent: to reduce pressure on current account stemming from gold imports and mobilize idle stock held by households and temples. The Gold Control Act of 1968 marked the beginning of a restrictive era, banning production and sale of jewelry above 14 carats, ownership of bars and coins, and imposing a ban on gold imports that lasted until the 1990s Reddy (2002) and Reserve Bank of India (2012). The 1990s brought liberalization, but quantitative restrictions remained important in the government's toolkit (Soundararajan et al., 2014).

There have been several forms of quantitative restrictions. These include outright bans, such as the 1962–1990 import ban, elevated import duties, and more recent measures like the 80:20 rule introduced in 2013, which required importers to set aside 20% of imports for re-exports (Chilkoti, 2014). Such interventions have been able to affect official flow of gold into India, but have had a side affect of activating unofficial channels. For example, following a series of import duty hikes, smuggling activity surged in 2013 with seizures nearly doubling compared to the previous year (2013b). The demand for gold in India is widely considered price inelastic due to strong traditions, and it persisted through any "stick" measures. As one analyst put it, "whatever the methodology, the impact will be the same" (Singh & Bang, 2013).

To mobilize existing gold, the government introduced two types of schemes: deposit-based schemes and return-mimicking schemes. The former allowed households to deposit physical gold with banks, which was then melted down and reused. Households would get tax-free interest in return, and the principal at maturity. Particularly, the most recent Gold Monetization Scheme (GMS), introduced in 2015, aimed at bringing the mobilized gold to jewelers, who account for a sizable fraction of gold imports (International Monetary Fund. Asia and Pacific Dept [IMF], 2016; Kaminska & Keohane, 2015). Uptake was minimal due to limited awareness, logistical difficulties, and cultural attachment to jewelry (Parkin, 2019), which can be worn and used as a status symbol in addition to its financial value. The scheme was mostly discontinued in 2025 (Ministry of Finance, Government of India, 2025).

The most notable return-mimicking scheme is the 2015's Sovereign Gold Bonds (SGB), introduced together with the GMS. For SGBs, the government issues gold-denominated bonds, effectively borrowing at the gold price (International Monetary Fund. Asia and Pacific Dept [IMF], 2016). As the policy did not require the government to back up all holdings, import demand was reduced. At the same time, it exposed the government to excessive increases in gold price, which materialized during the post-Covid years and led the government to stop offering new SGBs (Mittal, 2025).

Deposit policies are estimated to have mobilized around 100t of gold since the 1960s (Reddy, 2002; World Gold Council [WGC], 2023), and the SGB scheme around 146t since 2015 (Reserve Bank of India [RBI], n.d.). The latter policy has been relatively more successful, yet both make up only a small fraction of the total gold stock in India, estimated by various sources at 20kt-25kt or more in recent years (Parkin, 2019; Sanderson & Parkin, 2020).

E.1 Gold loans

In contrast, lending against gold has become the most widespread gold-related financial activity in India. Small operations by pawnbrokers and moneylenders have been present for centuries, particularly in rural areas of southern Indian states (Chilkoti, 2013a; Reserve Bank of India, 2012). In these regions, access to banking has been limited and gold has been used as a liquid store of wealth. In the last decades, there has been a trend toward formalization of the sector, with specialized non-banking financial companies (NBFC) rapidly gaining market shares alongside traditional banks (2012; Venugopal, 2025).

Conventionally, households have pledged gold when facing bad financial conditions, e.g. due to crop failures and medical emergencies. As of 2013, average loan size of gold loans is around Rs50-80k ($900-1400) at banks and less at NBFCs, with interest rates ranging between 12% to 30% and gold loans have had minimal default rates historically (Chilkoti, 2013a; Reserve Bank of India, 2012). In very recent years, elevated gold prices and economic slowdown have further boosted demand (Venugopal, 2025), leading to higher default rates and tighter regulations by the RBI (Reserve Bank of India [RBI], 2025). World Gold Council (WGC, 2023) reports 2.9-3.4kt of golden jewelry (bars are not accepted) being used as collateral in India. The sector has attracted interest beyond India, as evidenced by Bain Capital's acquisition of a significant stake in Manappuram Finance, one of the largest NBFC lenders (Reuters, 2025).

Newer instruments like gold ETFs and digital gold apps have also emerged. ETFs, first launched in 2007, gained traction during Covid-19 and saw record inflows in 2025 (Schipani & Alim, 2025; WGC, 2023). Digital apps backed by major tech firms offer small-scale investment options, but holdings per user are generally under $100 (Sanderson & Parkin, 2020). Overall adoption of digital holding solutions remains modest, with ETFs and other digital formats comprising less than 1% of India's total gold stock (WGC, 2023).

In sum, gold lending stands out as the most impactful gold-related financial product. Monetization schemes have faltered, and while digital products are growing quickly, their scale remains limited. Still, their expansion offers a modestly hopeful path toward integrating India's deep gold tradition into a more productive financial system.

Figure F1: Gold Price and Aggregate TFP in the Simulated Economy

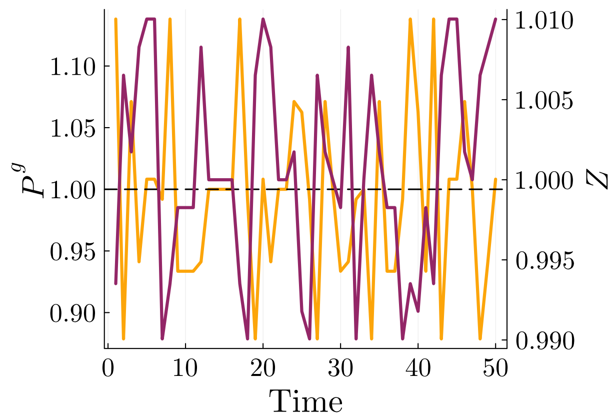


Figure F2: Gold Demand Motives by Wealth

Note: This figure shows a sample trajectory of the aggregate TFP Z, and the gold price P^g

F Further results details

F.1 The stationary equilibrium of the model

F.2 Taxing gold to subsidize capital

Assuming a constant tax rate of τ_g on gold, the household budget constraint for the case with a capital subsidy is given by:

$$c + d' + (\mathbf{1} - \boldsymbol{\tau}_\mathbf{k})k' + (\mathbf{1} + \boldsymbol{\tau}_\mathbf{g})P^g g' \leqslant w + R^f d + y(k, n, e, Z) - wn + (1 - \delta)k + P^g g \quad (38)$$

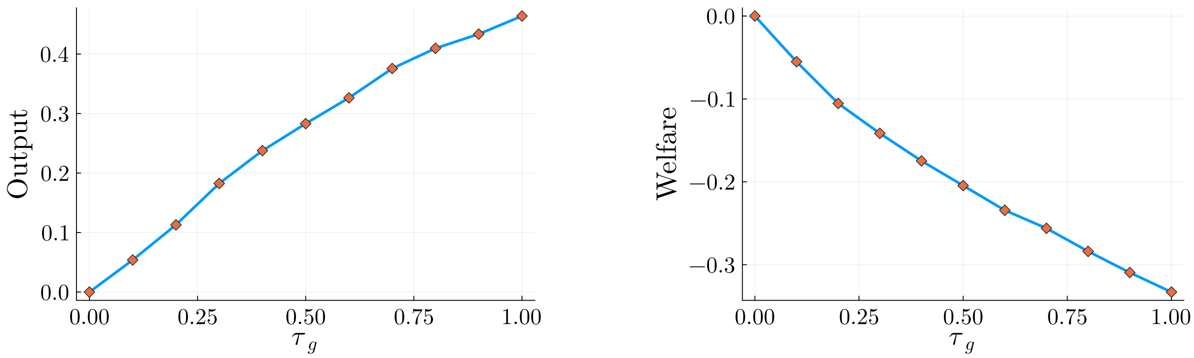
Note that the tax rate on gold and the subsidy rate on capital are both assumed to be constant and not contingent upon the aggregate state. Hence, the government budget is also assumed to balance intertemporally, meaning, in the stationary distribution of the economy,

$$\mathbb{E}\left[\sum_{t=0}^{\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_s^f}\right)\tau_g P_t^g G_{t+1}\right] = \mathbb{E}\left[\sum_{t=0}^{\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_s^f}\right)\tau_k K_{t+1}\right]$$

should hold.

Figures F3a and F3b show, respectively, the output and welfare effects of taxing gold and subsidizing capital. Although output gain is large, welfare nevertheless falls. To better understand the results, let us focus on the case of $\tau_g = 0.3$, which leads to 18.5% increase

Figure F3: Output and Welfare Effects of Taxing Gold and Subsidizing Capital

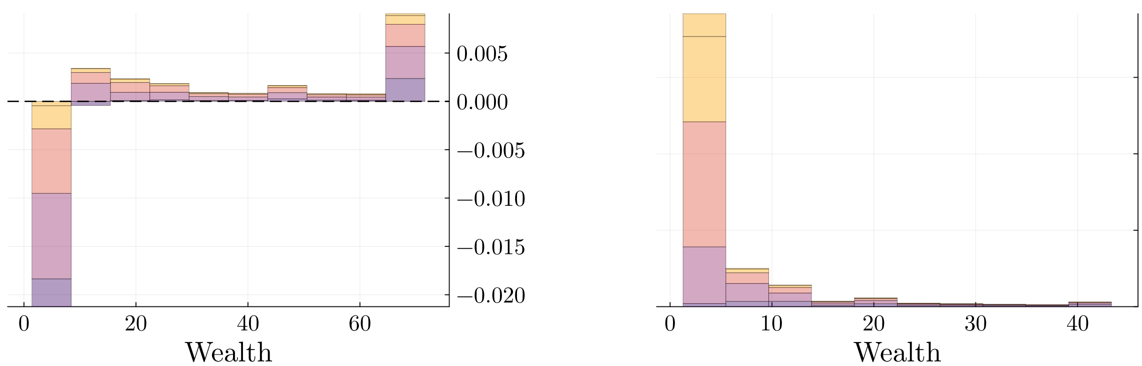


(a) Relative Change in Output

(b) Relative Change in Welfare

Note: The left panel shows the relative change in aggregate output in the tax-gold-subsidize-capital counterfactual, relative to the stationary equilibrium of the baseline. The right panel shows the relative change in welfare. For each τ_g, the output and welfare gains are computed after solving for the equilibrium capital subsidy rate τ_k that makes the government budget intertemporally balanced.

Figure F4: Distributional Effects of Taxing Gold and Subsidizing Capital



(a) Change in Distribution

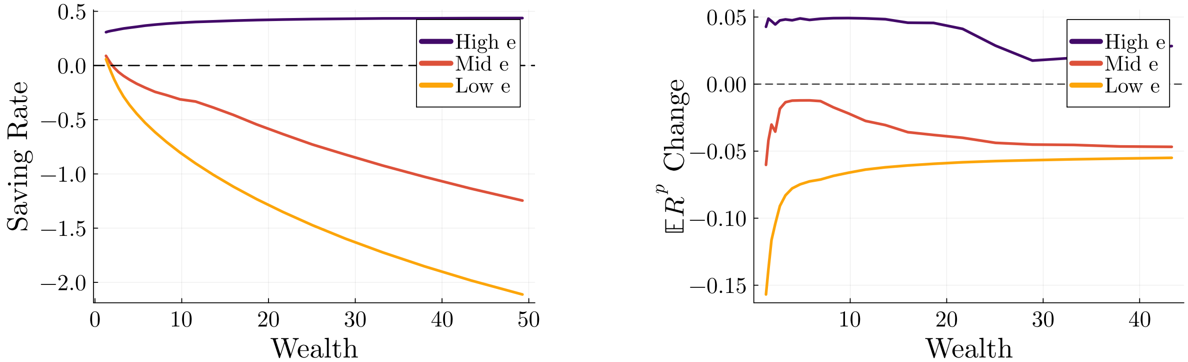
(b) Baseline Distribution (Histogram)

Note: The left panel shows the change in the stationary equilibrium distribution of assets, in the tax-gold and subsidize-capital counterfactual. The right panel shows the average wealth distribution (by productivity) in the baseline economy. Different colours correspond to different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange and yellow, respectively represent the highest, the medium and the lowest productivity levels.

in output compared to the baseline (but close to 14% decrease in welfare). Stock of capital in the household business sector increases by approximately 80%.

The corresponding change in the distribution is depicted in Figure F4a, while Figure F4b shows the baseline wealth distribution (averaged over the aggregate states in the station-

Figure F5: Saving Rates and Return Gains of Taxing Gold and Subsidizing Capital



(a) Saving Rates in Baseline

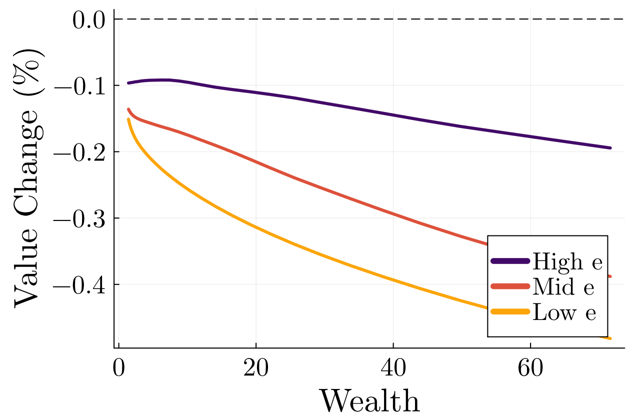
(b) Change to Return to Wealth (pp)

Note: The left panel shows the saving rates in the stationary equilibrium of the baseline economy. The right panel shows the change in return to wealth, by productivity and assets. Different colours correspond to different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange and yellow, respectively represent the highest, the medium and the lowest productivity levels.

ary equilibrium). Although there is a significant reduction in the number of households in the lowest asset bracket, the main driver of the increase in aggregate wealth are asset gains by the rich and productive households. The reason is that in the counterfactual economy the return to capital increases strongly for highly productive households who already have the highest saving rates. Highly productive households are thus the main winners of this policy and their wealth holdings increase strongly. This can be seen in Figures F5a and F5b, that show the average saving rates of households at the baseline equilibrium (left), and change (measured in percentage point) in the return to wealth of households at different levels of wealth and productivity, in the counterfactual economy relative to the baseline.

Note that changes in returns to wealth in Figure F5b are a combination of asset compositions and changes in the relative return to assets for households at different levels of productivity and wealth. For example, for most of the households to the very left of the distribution, there is a larger reduction in returns to wealth; this results from the fact that those households are the ones who tend to have a higher share of gold in their assets through the social-norm channel, and high taxes on gold means that the financial return to gold decreases significantly in the counterfactual economy (see Equation (30)). On the other hand, return to capital investment would increase more for households with higher idiosyncratic productivity and households with lower levels of capital. The latter results

Figure F6: Gold-Taxation and capital subsidy: Relative change in households' value functions



<u>Note</u>: This figure shows the percentage change in the value function of households compared to the baseine economy. Different colours correspond to (a selection of) different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange, and yellow represent the highest, the medium and the lowest productivity levels, respectively.

from the span of control forces: with decreasing returns to scale, when the entrepreneur's ability is spanned over a larger firm, each additional unit of (subsidized) capital receives a lower portion of it, and its marginal product will increase by less. This is formalized in the following proposition:

Proposition 4. *With a subsidy on capital goods as in Equation (38), the increase in the marginal rate of return on capital (Equation (9)) is larger for entrepreneurs with*

1. *higher productivity;*
2. *or lower capital, provided that the technology has decreasing returns to scale ($\eta < 1$).*

Finally, Figure F6 shows the relative loss in the value function in the new economy. Households are much worse-off compared to the case where gold tax revenue is transferred lump sum. Most evidently for the poorest households whose gold holding is now taxed without any (partial)compensation in the form of transfers.

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F.3 The effects of financial frictions

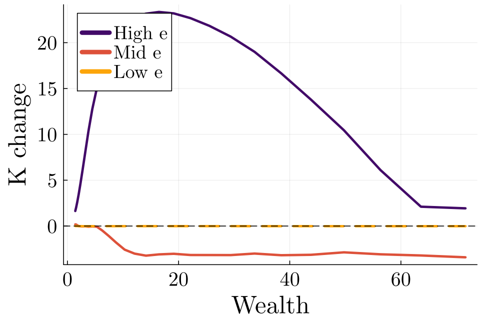
There are two main sources of financial frictions in the model: collateral constraints and the interest rate wedge, in particular the low interest rates on deposits. Whereas our first counterfactual exercise studied how the demand for unproductive and mostly idle gold interacts and exacerbates existing financial frictions, we can also look at the reverse direction: how existing financial frictions affect the portfolio choice and, in particular, gold demand of households at different levels of wealth and entrepreneurial talent. In particular, we now consider the case where $\phi_k = 1$ in Equation (4) which reflects the collateral constraint of households:

$$d' \geqslant -\phi_k \, k' - \phi_g \left(P^g \, g'\right), \qquad \phi_g, \phi_k \geqslant 0.$$

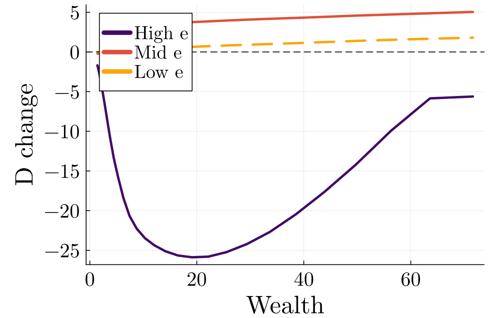
This means that any household can borrow up to the full value of their business investment, thus a significant relaxation of the borrowing constraints. Moreover, we assume that the banking system becomes more efficient in processing funds, in the sense that it can offer higher deposit rates to households, at the same level as the international interest rate, $r^d = r^*$.

The new equilibrium shows a huge increase in output and capital and a significant decline in the share of portfolio allocated to gold. Output increases by close to 66%, a number not too different from the huge loss of output from misallocation, as documented by Hsieh and Klenow (2009). The average share of gold in the portfolio falls from around 28% to below 17%. Note that the relative demand for gold declines as there is a reallocation of savings towards the productive assets, but it is far from vanishing; gold is still desirable, either because of the social norms or for hedging and return purposes.

Figure F7: Financial reforms: Changes in the household business assets and deposits



(a) Change in the Business Assets



(b) Change in the Deposits/Debt

Note: The left panel shows the level change in business assets, across the wealth and productivity. The right panel shows the level change in debt or deposits. Different colours correspond to (a selection of) different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange, and yellow represent the highest, the medium and the lowest productivity levels, respectively.

There is interesting heterogeneity in the way portfolios of households at different levels of wealth or productivity are affected by the improvements in the financial system. For the least productive entrepreneurs, only the deposit rate margin matters not the collateral margin on capital, as they run almost no business in the baseline equilibrium. They have a small reallocation from gold to deposits: the increase in the deposit rate means higher opportunity cost of holding gold, thus less gold in the portfolio. In contrast, for the most productive entrepreneurs, only the collateral margin matters, not the increase in the deposit rate. They now borrow much more to fund the more rapid expansion of their business. Finally, for the mediocre entrepreneurs, both margins matter depending on their wealth levels. The poorest mediocre entrepreneurs take advantage of looser collateral constraint to borrow more and increase business assets. Mediocre entrepreneurs at any higher wealth level, reallocate from both business assets and gold toward deposits; as higher deposit rate implies higher opportunity costs of investing in both business assets, and gold.

F.4 Signaling through gold versus the spirit of capitalism

Thus far, we have interpreted gold in utility as any other durable consumption good, such as housing or cars: gold provides some stream of services that the households value because of the cultural or societal norms, the way houses provide a stream of sheltering services and cars a stream of transportation services. In this last exercise, we look more closely into what constitutes this social-norm preference.

Evidence from the "Household Survey of Gold Consumption," conducted by IGPC-PRICE, suggests that Indian households consider wealth signaling to be a major aspect of “social” or “cultural” value of gold. In particular, 59% of the respondents (by population weights) agreed or strongly agreed with the statement “I believe that possessing gold is a symbol of success.” And 18% agreed or strongly agreed with the statement “I buy gold because I want to show others that I am rich.” This suggests that an alternative way to interpret the appearance of gold in utility is to consider it as a symbol of status. In other words, the intra-temporal utility of Equation (2) can be rewritten as

$$U(c,s) = \frac{1}{1-\gamma}\left[\left((1-\theta_g)^{\frac{1}{\varepsilon}} c^{\frac{\varepsilon-1}{\varepsilon}} + \theta_g^{\frac{1}{\varepsilon}} s^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}\right]^{1-\gamma}$$

where s denotes the status of the household, and the social norms govern the technology that produces the status, where in India the level of the gold holding determines the status of households:

$$s = g'. \tag{39}$$

This way of modeling gold is also reminiscent of models of wealth in utility and spirit of capitalism (e.g., Bakshi and Chen (1996), Carroll (1998) and Calvet and Sodini (2014)), with the difference that in that literature it is the totality of wealth of a household (either in level, relative to the average wealth, or in terms of household’s perception) that matters, not a specific item of it. In our final counterfactual exercise, we ask how the economy changes if the social norms also value productive capital. In other words, what if the status production technology of Equation (39) becomes

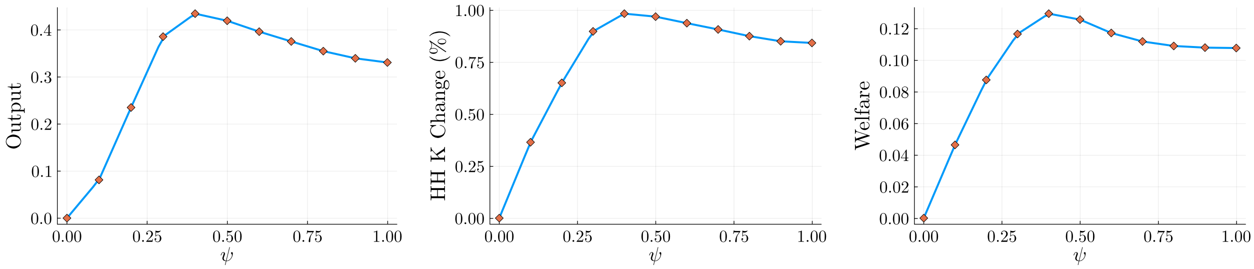
$$s^{cf} = \psi k' + (1-\psi) g',$$

with $\psi > 0$ denoting the weight of business assets in the social perception of status.

Figure F8a and Figure F8b show that the relative increase in output and household business assets from this exercise are massive. Even if social status tilts towards business assets only by 20%, there will be a staggering 60% increase in the average equilibrium level of entrepreneurial investment and 24% increase in the average equilibrium level of output. Moreover, share of gold in the portfolio falls by approximately 30% to 19.6 percentage points.

Figure F9a, Figure F9b and Figure F9c show how the return to wealth, the wealth distri-

Figure F8: Social norms: Aggregate Output, Household Business and Welfare

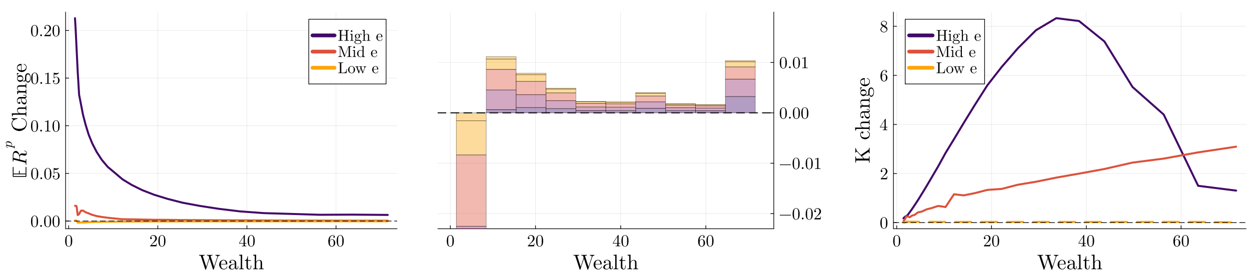


(a) Change in output (%) (b) Change in K^h (%) (c) Change in welfare (%)

Note: The left panel shows percentage change in output (averaged over the aggregate states in stationary equilibrium) for various wights of business assets in status technology. The middle panel shows the percentage change in average aggregate capital of household business. The right panel shows the percentage change in average welfare, measured in util.

bution, and the size of entrepreneurial businesses change in this new economy. Overall, forces that bring about a large increase in output in this case are similar to those we discussed for the monetization exercise. However, there are differences between the two: in the social norm exercise, accumulation of capital is more pronounced, while there is less improvement in misallocation of capital. When capital enters the social status, even lower type entrepreneurs will be tempted to run their businesses at levels that exceed productive efficiency of their businesses. On the other hand, when both capital and gold are socially appreciated, saving becomes more attractive, and saving rates out of income increase for almost every household; as a result, the wealth distribution shifts to the right even more than the case of monetization.

Figure F9: Social norms: Changes in Returns, Distribution, and Capital Allocation



(a) Change in return on wealth (b) Change in distribution (c) Change in capital level

Note: The left panel shows the change in the expected return to wealth of households with different entrepreneurial ability and wealth level. The middle panel shows the percentage change in histogram of the wealth distribution in the new economy compared to the baseline. The ten bins of the histogram, correspond to different buckets of wealth. And the colors within each bin, shows the productivity decomposition of the change in the population density of the bin. The right panel shows change in the capital of household businesses, in levels. Different colours correspond to (a selection of) different entrepreneurial ability levels (e): lighter shades correspond to lower productivity, darker shades to higher productivity. Specifically, the deep violet, the red-orange, and yellow represent the highest, the medium and the lowest productivity levels, respectively.