Thick Tails and Thin Markets: Evidence from Indian Agriculture*

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Abstract

We study the consequences of land market frictions when agricultural productivity is subject to large and persistent shocks. Using data from rural India, the middle-income country with the largest agricultural workforce, we document that shocks to agricultural productivity are non-Gaussian: their distribution exhibits excess peakedness and thick tails. We incorporate these features into a dynamic model of land accumulation with non-convex adjustment costs, and discipline it using farm-level information on changes in landholdings over time. Removing land adjustment costs increases aggregate farm production by about 4.4%. The non-normality of productivity shocks accounts for about 60% of these gains.

Keywords: Agriculture, productivity, non-normality, investment, land market
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1 Introduction

Land market institutions, such as transaction taxes, statutory restrictions on sales, and tenancy regulations, are paramount in developing countries (Deininger et al., 2003). These institutions can create frictions that prevent land from being allocated toward its most productive uses, thereby reducing agricultural productivity (Deininger et al., 2003; Chen, 2017; Gottlieb and Grobovšek, 2019; Adamopoulos et al., 2022; Chen et al., 2022; Acampora et al., 2025; Bolhuis et al., 2026). In this paper, we study the agricultural productivity losses from these frictions.

We address this question using a model of heterogeneous farmers who are subject to productivity shocks, accumulate land *dynamically*, and face costs when adjusting their landholdings. As is standard in these models, time-varying productivity implies that current landholdings may no longer be optimal after a new productivity shock is realized, and adjustment costs give rise to dispersion in the marginal product of land. We model the adjustment cost as a *fixed* cost of participating in the land market, as in the canonical (S, s) model of lumpy investment (Khan and Thomas, 2008). As we discuss below, lumpiness is a prominent feature of landholding changes in rural India, the middle-income country with the largest agricultural workforce.

We use the latest ICRISAT panel to discipline the model. First, we show that changes in landholdings, comprising purchases and sales, as well as renting in and out, are highly concentrated at zero. We then provide novel evidence that the distribution of farm productivity shocks is *non-Gaussian*. Specifically, these shocks (i) are more peaked around zero than a normal distribution with the same variance, and (ii) exhibit thick tails. We use this evidence to estimate land adjustment costs their aggregate implications. Eliminating these costs increases aggregate farm output and productivity by 4.4% and 3.4%, respectively. This finding is consistent with a large literature quantifying the consequences of land market frictions in static frameworks (Adamopoulos et al., 2022; Chen et al., 2022, 2023; Bolhuis et al., 2026). Our dynamic framework also highlights previously unappreciated consequences of land market frictions. For example, without adjustment costs, the share of farms downsizing in response to negative productivity shocks increases by about 7 percentage points. Thus, land market frictions contribute to low average farm productivity by forcing low-productivity farms to operate at too large a scale.

Finally, we use our framework to quantify how departures from normality in farm productivity shocks affect the output gains from removing land market frictions. Specifically, we compare the output gains from eliminating land adjustment costs with those implied by a model in which productivity shocks are normally distributed with the same mean and variance. On the one hand, thick-tailed productivity shocks imply that the adjustment costs needed to rationalize the observed rate of inaction must be higher. On the other hand, excess peakedness around zero in the shock distribution reduces these costs. In our quantitative exercise, the effect of thick tails roughly offsets that of excess peakedness when adjustment costs are expressed relative to output per capita. We find that the output gains from eliminating land adjustment costs are about 60% smaller when productivity shocks are assumed to be Gaussian. Intuitively, under non-Gaussian shocks, farms are more likely to experience large positive or negative changes in productivity, which implies that land adjustments would be substantially larger in the absence of land market frictions. In this case, land adjustment costs are much more consequential for allocative efficiency.

Our paper makes three contributions: empirical, methodological, and quantitative. On the empirical front, we provide, to the best of our knowledge, the first evidence of non-normality in farm productivity shocks. This finding echoes recent evidence from developed countries on nonlinear dynamics and non-normality in firm-level productivity shocks (Fella et al., 2021; Ruiz-García, 2021; Jaimovich et al., 2025; Melcangi and Sarpietro, 2025) and household-level earnings (e.g., Arellano et al., 2017; De Nardi et al., 2020; Guvenen et al., 2021).

From a methodological perspective, we connect the literature on agricultural land markets in developing countries and on investment dynamics. This approach allows us to draw on frameworks developed to analyze lumpy capital investment (Caballero, 1999; Caballero and Engel, 1999; Cooper and Haltiwanger, 2006; Khan and Thomas, 2008; Asker et al., 2014). These models provide a natural way to rationalize the inaction observed in agricultural land markets in developing countries (Binswanger and Rosenzweig, 1986; Rosenzweig and Binswanger, 1993; Foster and Rosenzweig, 2011; Morten, 2019; Foster and Rosenzweig, 2022), while also providing an environment for analyzing the aggregate consequences of land market frictions from a dynamic perspective.

Finally, on the quantitative front, we provide new estimates of the gains from removing land market frictions using a structural model where land is a dynamically chosen input, exploiting information on changes in landholdings over time to discipline its parameters. We show that higher-order moments of the distribution of farm productivity shocks play a first-order role in determining the gains from removing land market frictions. This point is particularly relevant because existing quantitative models typically assume log-normally distributed farm productivity shocks (e.g., Adamopoulos and Restuccia, 2014). We show that failing to account for the thick tails of the farm productivity shock distribution can lead to downward-biased estimates of the severity of land market frictions.

The rest of the paper is organized as follows. In Section 2, we introduce a dynamic model of land investment and characterize the role of adjustment costs. In Section 3, we provide evidence on lumpy land adjustment and departures from normality in the distribution of farm productivity shocks. In Section 4, we estimate the model to match the observed productivity and investment dynamics and use it to quantify the aggregate losses from adjustment costs. In Section 5, we conclude.

2 A *dynamic* model of land accumulation

In this section, we adapt the canonical model of lumpy investment (Caballero and Engel, 1999; Cooper and Haltiwanger, 2006) to study land accumulation in the agricultural sector.

2.1 Environment

We consider a discrete-time, infinite-horizon economy. There is a fixed supply of land, $\overline{L}$, and the economy is inhabited by a unit mass of farms that differ in their idiosyncratic productivity, Z, which evolves according to a Markov process, $\Gamma(Z'|Z)$, where Z' denotes next period's productivity. This formulation allows for general, potentially non-Gaussian, transition dynamics for productivity, a key feature documented in Section 3.

Every period, farms produce output per hour of work, Y, by combining capital K and land L, both measured per hour of work, according to the following production function:

$$Y(Z, L, K) := ZK^{\alpha^K} L^{\alpha^L},$$

where $\alpha^K, \alpha^L \in (0, 1)$, $\alpha^K + \alpha^L \leq 1$, and the residual share $1 - \alpha^K - \alpha^L$ accrues to labor.

Capital is a *static* input: it is not subject to adjustment costs and can be rented each period at an exogenous rental rate $1 + r$. Land, by contrast, is a *dynamic* input. The stock of land held by a farm evolves according to the following law of motion:

$$L = L_{-1} + I \tag{1}$$

where L_{-1} is the stock of land inherited from the previous period, and I denotes net investment in land (expansions minus contractions) that occurred in the current period. Buying or selling land involves paying a fixed cost:

$$C(L, L_{-1}) := \lambda \mathbb{1}\left\{L \neq L_{-1}\right\},$$

where $\lambda > 0$ and $\mathbb{1}\{L \neq L_{-1}\}$ denotes the indicator function that takes the value one when landholdings change and zero otherwise. We interpret λ as the cost of participating in the land market, capturing various institutional barriers to adjusting landholdings (e.g., obtaining a land certificate to sell or rent out a parcel may involve high monetary costs). A fixed cost generates a region of *inaction* around the optimal land target in the absence of frictions: it is not worth it for the farm to adjust landholdings unless the benefit of doing so is large enough.

Two modeling choices deserve comment. First, the land adjustment cost is non-convex. We make this assumption because a convex adjustment cost does not give rise to inaction, which would not allow us to reproduce the evidence on the lumpiness of land adjustments in rural India documented in Section 3. Second, λ is independent of the size of the transaction. We make this assumption because it is the most parsimonious specification consistent with the documented lumpiness and leaves us with only a single parameter to estimate.

2.2 The farm's problem

The farm's problem can be decomposed into static and dynamic decisions. In every period, farms choose capital to maximize current profits, given their productivity and land stock:

$$\Pi(Z, L) := \max_K Y(Z, L, K) - (1 + r)K.$$

The optimal choice of capital is given by

$$K^*(Z, L) := \left(\frac{\alpha^K}{1 + r}\right)^{\frac{1}{1-\alpha^K}} Z^{\frac{1}{1-\alpha^K}} L^{\frac{\alpha^L}{1-\alpha^K}},$$

so that

$$\Pi(Z, L) = (1 - \alpha^K) \left(\frac{\alpha^K}{1 + r}\right)^{\frac{\alpha^K}{1-\alpha^K}} L^{\frac{\alpha^L}{1-\alpha^K}} Z^{\frac{1}{1-\alpha^K}}.$$

Note that Π is convex in Z through the endogenous response of capital to Z, which implies that productivity shocks have amplified effects on profits. This makes the higher moments of the distribution of productivity shocks important for the value of adjusting land.

The farm chooses land to solve the following recursive problem:

$$V(Z, L_{-1}) := \max_{L} \Pi(Z, L) - pI - C(L, L_{-1}) + \frac{1}{1+r} \sum_{Z'} V(Z', L)\Gamma(Z'|Z),$$

subject to Equation (1), where p is the equilibrium market price of a unit of land.

Definition 1. *A competitive equilibrium for this economy is a value function $V(Z, L_{-1})$, a policy function for land $L^*(Z, L_{-1})$, a price of land p, and a stationary distribution of farms across lands and productivity, $\psi(Z, L_{-1})$, such that:*

- *given p, the policy function $L^*(Z, L_{-1})$ solves the recursive problem of the farm and the value function $V(Z, L_{-1})$ attains its maximum;*
- *the distribution $\psi(Z, L_{-1})$ is stationary under the stochastic process for z and the land policy function $L^*(Z, L_{-1})$:*

$$\psi(Z', L) = \int_{L_{-1}} \sum_{Z} \Gamma(Z'|Z) \mathbb{1} \left\{ L^*(Z, L_{-1}) = L \right\} \psi(Z, L_{-1}) \, \mathrm{d}L_{-1};$$

- *the price p is determined by the land market-clearing condition:*

$$\int_{L_{-1}} \sum_{Z} L^*(Z, L_{-1}) \psi(Z, L_{-1}) \, \mathrm{d}L_{-1} = \overline{L}.$$

2.3 Optimal inaction

The optimality conditions for land choice reflect the discontinuity in the adjustment cost function at $I = 0$. For adjusting farms (i.e., when $L^*(Z, L_{-1}) \neq L_{-1}$), we have:

$$\begin{aligned}
&\Pi\Big(Z, L^*(Z, L_{-1})\Big) - \Pi(Z, L_{-1}) \\
&\quad + \frac{1}{1+r} \sum_{Z'} \Big[V\Big(Z', L^*(Z, L_{-1})\Big) - V(Z', L_{-1}) \Big] \Gamma(Z'|Z) \\
&\geq \lambda + p\Big(L^*(Z, L_{-1}) - L_{-1}\Big).
\end{aligned} \tag{2}$$

The left-hand side is the *net benefit of adjusting landholdings*, defined as the difference between the value of adjusting and the value of remaining inactive. The right-hand side is the total cost of adjustment. Adjustment occurs when the net benefit exceeds its cost, inducing either investment or disinvestment. Otherwise, the farm optimally keeps its landholdings unchanged.

Notice that equation (2) maps productivity dynamics into the probability of inaction. When the productivity process is concentrated on small changes, the net benefits of land adjustment are more likely to fall short of the cost. Greater mass on large productivity changes makes adjustment more likely. Thus, the dynamics of land accumulation are affected by the nature of the productivity process. In the following section, we provide evidence on both objects.

3 Thin markets and thick tails.

Here, we describe land and productivity dynamics in rural India. We establish two facts. First, agricultural land markets are thin: farms leave their landholdings unchanged in a large share of years, and when they do transact, they transact in large blocks. Second, the distribution of farm productivity shocks departs sharply from normality. It is more peaked around zero than a normal distribution with the same variance, and it has much thicker tails. In one sentence, and connecting back to the title: land markets are thin, and farm productivity shocks have thick tails.

3.1 Data

We make use of the latest ICRISAT panel (Townsend, 1994; Mazzocco and Saini, 2012; Morten, 2019; Pietrobon and Ruggieri, 2026). The data are derived from detailed survey interviews conducted between 2009 and 2014 in 18 villages in the Indian semi-arid tropics. Each village contributes 40 randomly selected households, 10 in each of four landholding-size groups: landless laborers, small farms, medium farms, and large farms. The classification is based on operational landholdings, defined as land owned plus land leased in, minus land leased out. We exclude landless laborers, since we study agricultural households (Singh et al., 1986; Benjamin, 1992). Hence, we refer to households as farms throughout the rest of the paper. The resulting panel contains 732 farms and 3215 farm-year observations, with 2551 farm-level observations on year-to-year changes. The survey also records information on the quantity and value of every input and output used in farm activities. Appendix A describes the variables used in the empirical analysis.

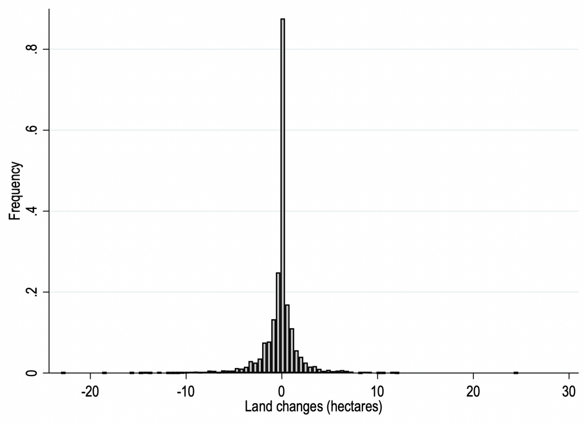
3.2 Evidence

Fact 1. Agricultural land markets are thin. Panel (a) in Figure 1 plots the histogram of changes in operational landholdings (measured in hectares) between two consecutive years. Panel (b) reports summary statistics for these changes.

Two features stand out. First, the distribution is concentrated at zero. Both the mode and the median of land adjustments are zero, and 17.73 percent of farm-years record no change at all. Moreover, about 31 percent of farm-year observations report changes in

Figure 1: Distribution of land adjustments

(a) Histogram of land changes



(b) Summary statistics

Description	Data
Median	0
Mode	0
Interquartile range	1.416
Inaction (no change) rate, %	17.73
Share within a "Beegah" ($\pm$ 0.25 ha), %	30.66
Share of obs. with negative adjustments, %	43.12
Spike rate: positive adjustment (+1 ha), %	17.48
Spike rate: negative adjustment (-1 ha), %	20.03

NOTES: Panel (a) plots the histogram of year-to-year changes in operational landholdings, in hectares. Panel (b) reports summary statistics for the same distribution. Both panels use the ICRISAT data.

landholdings no larger than a quarter of a hectare (commonly referred to as a "Beegah" in many Indian states). Second, conditional on adjusting, changes in landholdings are large. The interquartile range of land adjustment is 1.42 hectares, or 37 percent of the average holding of 3.82 hectares. In 37.5 percent of all farm-years, landholdings change by at least one hectare in absolute value. Thus, land adjustment is lumpy: it is characterized by inaction punctuated by occasional large adjustments, rather than by frequent marginal changes. This evidence is consistent with a large literature. Rosenzweig and Wolpin (1993) shows that land exhibits low turnover in rural India, in contrast to the much higher incidence of transactions in bullocks, a key productive asset used in agricultural operations such as tillage and sowing. Foster and Rosenzweig (2011) use data from a nationally representative household panel in India and find that only 3% of households bought or sold land between 1999 and 2008. Morten (2019) document that, in the ICRISAT data, landholdings remain unchanged for 57% of households between 1985 and 2001, and argue that this pattern is consistent with severe frictions in agricultural land markets.

Fact 2. Agricultural productivity shocks exhibit thick tails. We document that the distribution of log farm productivity shocks (i) is more peaked around zero than a normal distribution with the same variance, and (ii) exhibits thick tails.

We begin by constructing a measure of physical productivity across farms and years. In the spirit of Chen et al. (2023), we first compute the total factor productivity of farm i in year t, denoted by z_{it}, as

$$z_{it} := y_{it} - \alpha^K k_{it} - \alpha^L (\ell_{it} + q_{it}), \tag{3}$$

where y_{it}, k_{it}, ℓ_{it}, and q_{it}, denote the logs of physical output per hour of work, capital expenditure (including machinery and agricultural intermediates) per hour of work, landholdings per hour of work, and land quality—see Appendix A for additional details. The coefficients α^K and α^L correspond to the expenditure shares of capital and land, taken from Chen et al. (2023).

Because we are interested in shocks to individual farm productivity, we further refine this measure by removing variation in productivity that is attributable to village-level shocks, such as rainfall. Specifically, for every farm i in year t, $\widetilde{z}_{it}$, we estimate the residual from a regression of z_{it} on the full set of village-year fixed effects:

$$\widetilde{z}_{it} = z_{it} - \widehat{\mu}_{v(i)t},$$

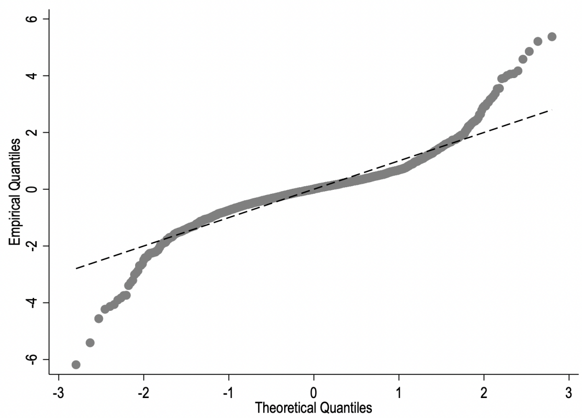
where $v(i)$ denotes the village to which farm i belongs. We define log farm productivity shocks, ϵ_{it}, as the year-to-year change in $\widetilde{z}_{it}$:

$$\epsilon_{it} := \Delta \widetilde{z}_{it} \tag{4}$$

Panel (a) in Figure 2 plots the empirical quantiles of ϵ_{it} against the corresponding quantiles of a Gaussian distribution with the same mean and standard deviation. The plot has the S-shape characteristic of a "leptokurtotic" distribution: relative to a Gaussian benchmark, it is flatter than the 45-degree line over the interior of the distribution and steeper in both tails. Panel (b) in Figure 2 quantifies both features.

Figure 2: Distribution of farms' productivity shocks

(a) Q–Q plot



(b) Summary statistics

	Prob($\epsilon_{it} \in \mathcal{S}$)		
$\mathcal{S}$	Data	$\mathcal{N}(0, \widehat{\sigma}^2)$	Ratio
$[-0.10, 0.10]$	0.154	0.089	1.730
$[-0.50, 0.50]$	0.633	0.452	1.400
$[-\widehat{\sigma}, \widehat{\sigma}]$	0.815	0.688	1.185
$\lvert\epsilon_{it}\rvert \geq 3\widehat{\sigma}$	0.019	0.003	6.333
Moment-based kurtosis	11.06	3	3.685
Quantile-based kurtosis	4.627	2.906	1.592

NOTES: Panel (a) plots the empirical quantiles of the log farm productivity shocks, ϵ_{it}, against the quantiles of a normal distribution with the same mean and variance; the dashed line is the 45-degree reference line. Panel (b) reports summary statistics for the same distribution. $\widehat{\sigma}$ denotes its standard deviation, equal to 0.839. The moment-based kurtosis refers to the Pearson measure of kurtosis. The quantile-based kurtosis refers to the Crow–Siddiqui measure of kurtosis.

Excess peakedness. Small productivity changes are far more common in the empirical distribution of log farm productivity shocks than under the Gaussian benchmark. The probability that $|\epsilon_{it}| \leq 0.10$ is 0.154 in the data against 0.089 under normality, a ratio of 1.73. Widening the window shrinks the gap monotonically: the ratio falls to 1.40 for $|\epsilon_{it}| \leq 0.50$ and to 1.19 for $|\epsilon_{it}| \leq \widehat{\sigma}$, where $\widehat{\sigma}$ denotes the standard deviation of log farm productivity shocks. Roughly one farm-year in six sees essentially no change in measured productivity.

Thick tails. Extreme changes are also far more common in the empirical distribution of log farm productivity shocks than under the Gaussian benchmark. The probability that $|\epsilon_{it}| > 3\widehat{\sigma}$ is 0.019 in the data against 0.003 under normality, a factor of 6.3. These are large events: $3\widehat{\sigma}$ corresponds to 2.52 log points, so a productivity change of this magnitude implies a change in measured productivity by a factor of more than twelve within a year. Nearly one farm-year in fifty experiences such an event.

Kurtosis. The distribution of ϵ_{it} is leptokurtotic. The moment-based kurtosis is 11.06, against 3 for the Gaussian benchmark, implying with an excess kurtosis of 8.06. Because moment-based kurtosis is sensitive to a few extreme observations, we also report the Crow-Siddiqui kurtosis, a quantile-based measure that is bounded by construction. It equals 4.63, against 2.91 for a normal distribution, a ratio of 1.59.

Measurement error. Because ϵ_{it} is the first difference of a regression residual, classical measurement error in output or inputs inflates its variance and induces negative autocorrelation. Neither works against our finding. In particular, classical measurement errors mechanically pull measured excess kurtosis toward zero.[1] Thus, in this case, our estimates provide a lower bound on the true departure from normality of the log productivity shock distribution. One remaining concern is the presence of non-Gaussian errors, such as coding or recall mistakes concentrated in the tails. We address this by recomputing every statistic on a sample of shocks constructed after trimming $\widetilde{z}_{it}$ at the 1st and 99th percentiles. Table 4 in Appendix B shows that results are robust: more than half of the excess kurtosis survives trimming, and the quantile-based kurtosis is quantitatively very similar.

Taking stocks. Farms adjust landholdings only occasionally, and when they do, they adjust by a large amount. At the same time, farms are much more likely to experience productivity changes close to zero than a normal distribution would imply, and also more likely to experience extreme positive or negative shocks. If we interpret changes in landholdings as responses to productivity shocks, where positive shocks induce farms to expand, and negative shocks induce them to contract, the observed

[1]If the true shock had excess kurtosis κ and variance σ^2, adding independent Gaussian noise of variance σ_e^2 would yield a measured excess kurtosis of $\kappa\sigma^4/(\sigma^2+\sigma_e^2)^2 < \kappa$.

inaction can be naturally rationalized by the presence of non-convex adjustment costs (Caballero and Engel, 1999; Khan and Thomas, 2008). At the same time, the observed thick tails of productivity shocks have ambiguous theoretical implications for the estimate for the adjustment costs. Holding the variance fixed, excess peakedness around zero raises the mass of shocks too small to justify a transaction, so a lower cost suffices to rationalize any given inaction rate. Thick tails raise the mass of shocks large enough to justify one, so a higher cost is required. Which force dominates is a quantitative question. Below, we use the evidence collected in this section to discipline our model and quantify the aggregate costs of land adjustment frictions.

4 Aggregate implications of land adjustment costs

4.1 Estimation strategy

We simulate the farm productivity process non-parametrically. We take the estimates of $\widetilde{z}_{it}$ from Section 3, partition them into 100 equally sized bins, and compute the transition probabilities across bins. Figure 3 in Appendix C reports the estimated process. This construction is deliberately nonparametric. It imposes no functional form on persistence, and no distributional assumption on innovations, so both the excess peakedness and the thick tails enter the model directly. Moreover, the estimated transition probabilities generate a kurtosis for the stationary distribution of productivity shocks of 8.19, close to the value of 11.06 found in the data (Table 2).

Then, we externally calibrate some of the parameters. In particular, we fix the yearly rental rate of capital r to 10 percent (Kamra and Ramakumar, 2019); we take capital and land shares from Chen et al. (2023), and set $\alpha^K = 0.18$ and $\alpha^L = 0.37$ accordingly; finally, we set the fixed supply of land $\overline{L}$ to average farm landholdings in the data (3.82 hectares). Table 5 in Appendix C summarizes the list of the model parameters, their values and source.

We are left with only one parameter to estimate, the adjustment cost λ. We estimate it by matching the fraction of farms that do not adjust their landholdings from one year to the next; i.e., the inaction rate. Notice that this is a dynamic moment, as it captures behavior over time.

We estimate the adjustment cost to be about 0.18% of the agricultural output per capita in the model, with a 95 percent confidence interval of [0.11%, 0.2%].[2] Recall that this cost is paid once per transaction and is independent of the size of the adjustment, so

[2]The standard error of λ is computed using the Delta method. That is, s.e.$[\widehat{\lambda}] = \widehat{\Omega}/J$, where J denotes the derivative of the model-implied inaction rate with respect to λ, while $\widehat{\Omega}$ is a bootstrapped estimate of the standard deviation of the empirical inaction rate.

it is most naturally compared to the fixed monetary and time costs of registering a transfer or lease.

Table 1 compares several untargeted empirical moments with their model counterparts. Despite being parsimonious, the model replicates two salient features of the data, such as the share of observations with negative adjustment (0.4084 in the model against 0.4312 in the data) and the serial correlation of adjustment rates is (-0.3857 against -0.3405). The latter is notable: negative serial correlation in adjustment is the signature of lumpy adjustment, since a farm that jumps to its target has no reason to move the following year again.[3]

Table 1: Adjustment dynamics (untargeted) - Model vs. Data.

Moments	Data	Model
Share of obs. with negative adjustments	0.4312	0.4084
Serial correlation of adjustment rates	-0.3405	-0.3857
Dispersion of adjustment rate (IQR)	1.4164	1.9216
Spike rate of adjustment ($\pm$ 1 ha)	0.3752	0.4964
Land size GINI	0.5219	0.7200

NOTES: This table reports selected untargeted moments of land adjustment dynamics and their model counterparts. IQR stands for interquartile range.

4.2 Counterfactual exercise

To assess the aggregate consequences of land market frictions, we compare the baseline economy with a counterfactual one with no adjustment costs; i.e., in which $\lambda = 0$. Because the land supply is fixed, this counterfactual exercise measures the gains from reallocating a given stock of land across farms. It does not measure gains from land accumulation or from converting land to other uses.

In the frictionless benchmark, the optimality condition shown in Equation (2) collapses to an equation in which the marginal value of an additional unit of land, $\partial\Pi(Z, L)/\partial L$, equals the marginal cost of acquiring it, p, net of the discounted marginal value of selling the land in the future, $p/(1 + r)$:

$$\frac{\partial\Pi(Z, L)}{\partial L} = p - \frac{1}{1 + r}p$$

Land is durable and resaleable, so the relevant cost is the purchase price net of its

[3] The model slightly overstates the size of adjustments. The interquartile range of adjustment is 1.92 He. in the model against 1.42 in the data, the spike rate is 0.4964 against 0.3752, and the land size Gini is 0.7200 against 0.5219. The source is the pure fixed cost. Because the cost does not scale with the size of the transaction, a farm that pays it jumps all the way to its frictionless target, so conditional adjustments are too large, and the stationary size distribution is too dispersed.

discounted resale value. Table 2 compares outcomes across the two economies.

Land adjustment dynamics. The inaction rate of adjustment falls from 17.73 to 2.98.[4] The share of farm-years with negative adjustments rises from 0.4084 to 0.4810, an increase of 7.3 percentage points, while the spike rate falls from 0.4964 to 0.4131. These two numbers together describe how the friction operates. Farms hit by negative productivity shocks are forced to maintain their scale of operation despite low productivity. Removing the friction enables roughly one farm in fourteen to reduce its landholdings. Second, the friction does not merely reduce the volume of reallocation; it concentrates it. Without the fixed cost, farms adjust far more often, but by a lesser amount, so large transactions become relatively less common. Thin markets and lumpy transactions are two sides of the same friction.

Misallocation. In our model, the adjustment cost is the only source of misallocation, so the standard deviation of the (log) marginal product of land falls from 0.3774 to zero when we set $\lambda = 0$. At the same time, land inequality rises, with the GINI coefficient going from 0.7200 to 0.7932. In particular, in the baseline, farms underreact to both positive and negative productivity shocks, which compresses the farm size distribution. This effect is consistent with Adamopoulos and Restuccia (2014), who argue that distortionary policies may account for the low dispersion in farm size observed in developing countries.

Output and productivity. Aggregate agricultural output is 4.36 percent higher without adjustment costs, while agricultural productivity (TFP) increases by 3.44 percent.[5] These numbers are substantial, both in absolute and relative terms. For instance, Chen (2017) find that eliminating untitled land in Malawi would only change the aggregate agricultural output by 1%. Gottlieb and Grobovšek (2019) find that removing the communal land tenure system in Ethiopia would generate an increase in agricultural output of 2.6%. The output gains from removing land market frictions arise from a reduction in cross-sectional misallocation and from allowing farms to freely adjust their landholdings in response to productivity shocks, expanding after positive shocks and contracting after negative shocks. Output also becomes more dispersed after removing land market frictions.

[4] It is not exactly zero only because of the discreteness of the process used to simulate farm productivity.

[5] Capital deepening accounts for the remaining difference.

Table 2: Implications of removing adjustment costs

	Baseline (1)	Counterfactual (2)
Price of land, p	1	1.1869
landholding GINI	0.7200	0.7932
Adjustment inaction rate	0.1773	0.0298
Spike rate of adjustment ($\pm$ 1 ha)	0.4964	0.4131
Share of obs. with of negative adjustments	0.4084	0.4810
S.d.(log MPL)	0.3774	0
Aggregate agricultural output	1	1.0436
S.d.(log agricultural output)	2.0973	2.2870
Agricultural TFP	1	1.0344

NOTES: This table reports selected model outcomes for baseline (column 1) and counterfactual (column 2) economies. The price of land, aggregate output, and TFP are reported relative to the value in the baseline economy. MPL denotes the marginal product of land, and s.d.(x) denotes the standard deviation of x. Aggregate agricultural output refers to aggregate production minus adjustment costs expenditure.

4.3 The role of non-normality in agricultural productivity

What role does non-normality in agricultural productivity play in explaining the aggregate gains from removing land market frictions? To answer this question, refer to our baseline environment as the *non-Gaussian economy*, and consider an alternative economy in which log farm productivity follows an AR(1) process,

$$\widetilde{z}_{it} = \rho \widetilde{z}_{it-1} + \varepsilon_{it}, \tag{5}$$

where ε_{it} is normally distribute with the same mean and variance as ϵ_{it}, as defined in Equation (4). Call this *Gaussian economy*. We re-estimate λ in the Gaussian economy using the same strategy and the same target, and conduct the same counterfactual exercise.[6]

Table 3 reports the results. Output gains from removing land adjustment costs are 1.79 percent in the Gaussian economy against 4.36 percent in the non-Gaussian economy, a difference of 2.57 percentage points. Non-normality thus accounts for 59 percent of the estimated gains. For TFP, the pattern is similar: gains are 1.27 percent against 3.44 percent, a difference of 2.17 percentage points, or 63 percent. In the Gaussian economy, the tails of the log productivity shock distribution are thin, so there are few large productivity changes and few large adjustments waiting to happen; removing land adjustment costs unlocks very little. Under the empirical distribution, extreme shocks are six times more common, so the frictionless economy features far more reallocation and the same friction is far more costly in terms of foregone output.

[6] Details of the estimation are in Appendix D.

Table 3: Non-normality of productivity shocks and aggregate gains

	Non-Gaussian economy (1)	Gaussian economy (2)	Differences (3)
ΔY	4.36%	1.79%	2.57 p.p. (58.94%)
ΔTFP	3.44%	1.27%	2.17 p.p. (63.08%)

NOTES: ΔY and ΔTFP denote agricultural output and TFP percent changes from removing adjustment costs. Column (1) refers to the economy with non-Gaussian shocks. Column (2) refers to the economy in which farm productivity follows the Gaussian AR(1) process described in Equation (5). In column (3), we report the difference between column (1) and column (2) in percentage points and percent (in parentheses).

Higher-order moments of the distribution of farm productivity shocks play a first-order role in model-based inference about the gains from removing land market frictions. This result has a direct implication for the existing literature, which typically assumes log-normally distributed farm productivity shocks (e.g., Adamopoulos and Restuccia, 2014). Failing to account for the thick tails of the shock distribution might lead to downward-biased estimates of the severity of land market frictions.

5 Conclusions

Adjusting landholdings in developing countries is costly. Several institutions can make access to and participation in the land market expensive, generating dispersion in the marginal product of land and substantial inaction. The under-reaction of landholdings to productivity shocks contributes to low aggregate farm productivity. In rural India, the middle-income economy with the world's largest agricultural sector, removing these costs increases aggregate agricultural output and productivity by 4.4% and 3.4%, respectively. Frictions distort not only who holds land at a point in time, but also how quickly land moves when circumstances change. This dynamic margin is what makes agricultural land markets thin.

We find that the distribution of productivity shocks plays an important role in determining the costs of land market frictions. Specifically, after documenting that log farm productivity shocks are non-Gaussian (i.e., they exhibit excess peakedness and thicker tails than a normal distribution), we show that their non-Gaussianity accounts for about 60% of the output gains achievable from removing land adjustment costs.

Two features of our framework bound our estimates of the costs of land market frictions. First, land supply is fixed, so we measure the gains from reallocating existing agricultural land across farms, not from expanding agricultural land. Second, we do not consider labor reallocation. Allowing either margin to operate would likely raise the productivity gains we find. We leave both extensions for future research.

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Appendix (not intended for publication)

A Data

We use information from the "Village Dynamics Studies in South Asia" (VDSA) project by ICRISAT, a widely used panel data set (Townsend (1994), Mazzocco and Saini (2012), Morten (2019), and Pietrobon and Ruggieri (2026), among many others). The data is collected through different modules (general endowment, cultivation schedule, rainfall schedule, among others) containing questions on different topics generally asked to the household head. Questions asked only to the household head generally refer to information about the whole household.

Most modules are collected at a monthly frequency (e.g., the employment schedule) while others only come at a yearly frequency (for instance, the general endowment schedule, and the questions in the cultivation schedule that refer to agricultural output). We aggregate individual-level data to the household level and monthly-level data to the yearly level. Given that we drop landless laborers from our sample (see Section 3), we end up with a yearly household-level panel data, containing information on agricultural production for farms in 18 villages in the Indian semi-arid tropics.

General endowment schedule. This schedule provides annual, individual-level data on various characteristics of household members, including age, sex, education, and primary and secondary occupations. Additionally, it offers farm-level details on landholdings, such as ownership status, total and irrigable areas, and various soil characteristics. The schedule also contains yearly farm-level data on capital goods.

The general endowment schedule provides detailed information on each farm's landholdings annually, with the plot as the unit of observation. This includes data on ownership status—whether owned, leased, shared, or mortgaged—and identifies the household members associated with each plot. It also details both total and irrigable areas, proximity to the house, irrigation sources and their distances. Additionally, the schedule provides information on plot attributes such as soil type (e.g., red, shallow black, medium black, deep black), fertility (an ordered scale from 0 to 4), slope (an ordered categorical variable indicating the degree of the plot's slope), soil degradation (a categorical variable indicating whether the plot is subject to soil degradation and specifying its type), and average soil depth in centimeters. The schedule also notes the presence of bunds, number of trees, if the plot is owned or leased, potential sale revenue, actual rent paid or received, and an imputed rental value for owned plots. We utilize the detailed information on plot attributes to construct measures of average soil depth, slope, fertility, and degree of degradation, which we use to construct a measure of land quality used in the estimation of farm physical productivity (see Equation (3)). Specifically, following De Giorgi et al. (2026), we construct this measure based on plot-level indices of agricultural suitability, which are estimated from a comprehensive regression of plot rental values on land characteristics, while controlling for village-level permanent unobserved heterogeneity and year fixed effects. The idea behind this approach is that the rental value of a plot reflects valuable information about its suitability for agricultural production; i.e., its "quality." Specifically, we run the following regression:

$$\begin{aligned}\log\left(\text{rental}_{pit}\right) &= f\left(\text{type}_{pit}, \text{fertility}_{pit}, \text{slope}_{pit}, \text{degradation}_{pit}, \text{depth}_{pit}; \boldsymbol{\varrho}\right) \\ &\quad + \varphi_v + \varphi_t + \epsilon_{pit},\end{aligned}$$

where rental_{pit} represents the self-reported rental value of plot p cultivated by farm i in year t; "type" denotes a categorical variable reflecting the plot's soil type; "fertility" is an ordered categorical variable measuring the plot's fertility on a scale from 0 to 4; "slope" is an ordered categorical variable indicating the degree of the plot's slope; "soil degradation" is a categorical variable indicating whether the plot is subject to soil degradation and specifies its type; "depth" refers to the average depth of the plot measured in centimeters; f is a function that represents linear and higher-order terms for the included variables, along with multiple interaction terms between those variables; $\boldsymbol{\varrho}$ is a parameter vector; φ_v are village fixed effects; and φ_t are year fixed effects. We use the predicted values of this regression, $\widehat{\log\left(\text{rental}_{pit}\right)}$, as plot-level indices of agricultural suitability. The intuition is that these predicted values contain information about the extent to which the interactions of multiple soil characteristics, village-level permanent unobserved factors, and year-level aggregate shocks influence the suitability of a plot for agricultural production. To generate a farm-year level land quality index, we average these suitability indices as follows:

$$Q_{it} := \frac{\sum_{p \in P_{it}} \left(\widehat{\log\left(\text{rental}_{pit}\right)} \times L_{pit} \right)}{\sum_{p \in P_{it}} L_{pit}},$$

where L_{pit} denotes the area of plot p cultivated by farm i in year t, and P_{it} is an index set for the set of plots cultivated by farm i in year t. In Equation (3), $q_{it} := \log Q_{it}$.

Finally, we leverage the farm equipment section of the general endowment schedule to construct a measure of farm capital. Each year, the household head is asked to report the names and values of all farm equipment items owned by the farm, including plows, sprayers, dusters, electric motors, diesel pumps, bullock carts, tractors, trucks, threshers, pipelines, rice mills, and flour mills, among others. We aggregate these data at the farm-year level to construct a measure of the value of farm capital goods for each farm and year.

Cultivation schedule. The cultivation schedule is divided into two main sections: inputs and outputs. We begin with an overview of the input section. This section collects detailed monthly data on the inputs used by each farm for every operation conducted on each cultivated plot. Specifically, interviewers ask the household head to report all operations carried out on each cultivated plot in each month. For each operation, they collect information on the quantities and costs of the inputs used. Thus, the unit of observation in this section is the operation conducted on each plot by each farm in each month.

One important variable obtained from the input section of the cultivation schedule is farm labor, which we use to estimate the regression in Equation (3). This section records the total labor hours devoted to each farming operation. To construct total labor supplied by a household to its farm, we aggregate the labor hours contributed by family members across operations and plots at the farm-year level.

The output section collects information on crop production at the plot-season level. Specifically, interviewers collect information from household heads on the quantity (in kilos) and value of each crop harvested during the agricultural seasons: Rabi, Kharif, annual, perennial, and summer. We use these data to construct total annual output per farm, which enters the estimation of Equation (3). Specifically, we aggregate output across crops, cultivated plots, and seasons at the farm-year level.

B Empirical Evidence

Table 4 reports selected summary statistics for farm's productivity shocks, ϵ_{it}, computed after trimming $\widetilde{z}_{it}$ at the 1st and 99th percentiles.

Table 4: Summary statistics of farms' productivity shocks - 1% trimming

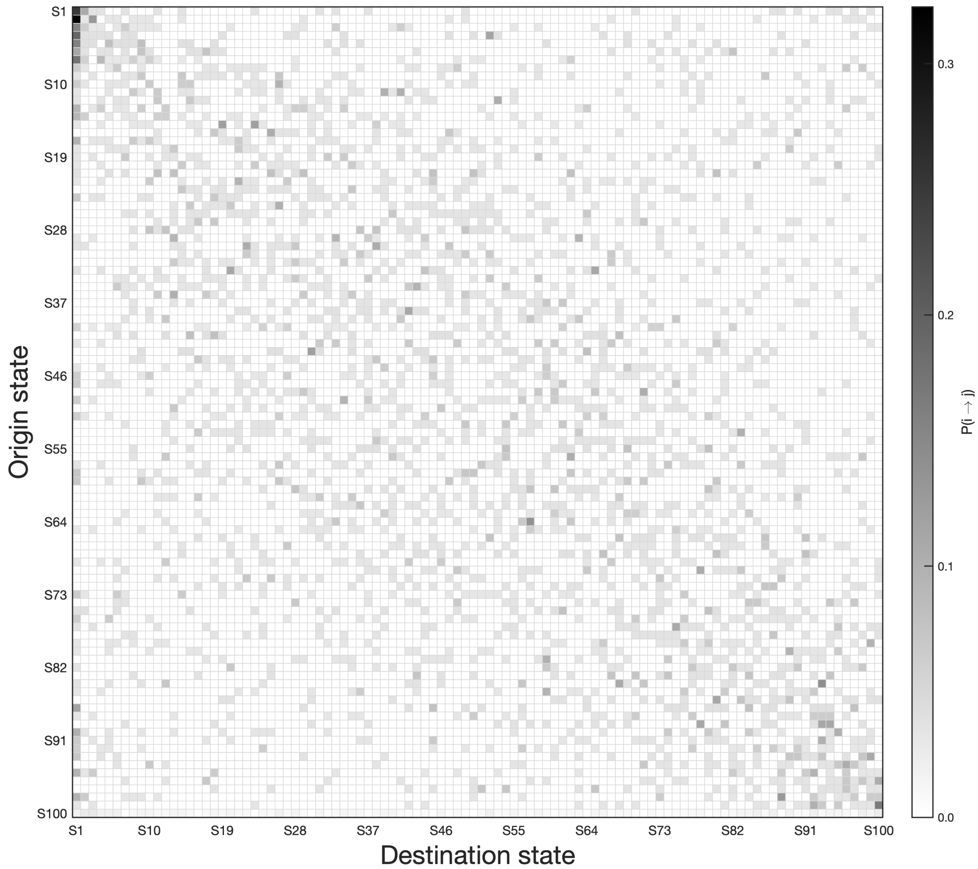
	Prob($\epsilon_{it} \in \mathcal{S}$)		
$\mathcal{S}$	Data	$\mathcal{N}(0, \widehat{\sigma}^2)$	Ratio
$[-0.10, 0.10]$	0.158	0.110	1.436
$[-0.50, 0.50]$	0.650	0.538	1.208
$[-\widehat{\sigma}, \widehat{\sigma}]$	0.786	0.703	1.118
$(-\infty, -3\widehat{\sigma}] \cup [+3\widehat{\sigma}, \infty)$	0.017	0.002	8.350
Moment-based Kurtosis	7.301	3	2.434
Quantile-based Kurtosis	4.362	2.906	1.501

NOTES: This table reports summary statistics for the distribution of log farm productivity shocks, ϵ_{it}, computed after trimming $\widetilde{z}_{it}$ at the 1st and 99th percentiles. $\widehat{\sigma}$ denotes its standard deviation, equal to 0.709. The moment-based kurtosis refers to the Pearson measure of kurtosis. The quantile-based kurtosis refers to the Crow-Siddiqui measure of kurtosis.

C *Non-Gaussian* Economy

Figure 3 reports the empirical transition probabilities for farm productivity.

Figure 3: Empirical transition probabilities of farm productivity



NOTES: This figure shows the empirical transition matrix for the estimates of $\widetilde{z}_{it}$ from Section 3. We partition the distribution of $\widetilde{z}_{it}$ into 100 equally sized bins and compute the transition probabilities across bins. Each dot represents a transition from one percentile bin to another, with darker dots indicating higher transition probabilities.

Table 5 summarizes the list of the model parameters under non-Gaussian productivity shocks, their values, and their source. We estimate a value for λ of 0.18% of the agricultural output per capita, with a 95% confidence interval ranging from 0.11% to 0.24%.

Table 5: Parameter values and sources - *Non-Gaussian* economy

Description	Value	Source/target
Externally calibrated parameters		
Interest rate, r	0.10	Kamra and Ramakumar (2019)
Capital share, α^K	0.18	Chen et al. (2023)
Land share, α^L	0.37	Chen et al. (2023)
Land supply (ha), $\overline{L}$	3.82	Data
Estimated parameters		
Adjustment cost, λ		
(% of aggregate output)	0.18% [0.11%, 0.24%]	Inaction rate $= 0.1773$

NOTES: This table summarizes the values of the model parameters, indicating whether each is externally calibrated or estimated, and the source used to pin down its value. The 95% confidence interval for the adjustment cost λ (in brackets) is computed using the Delta method.

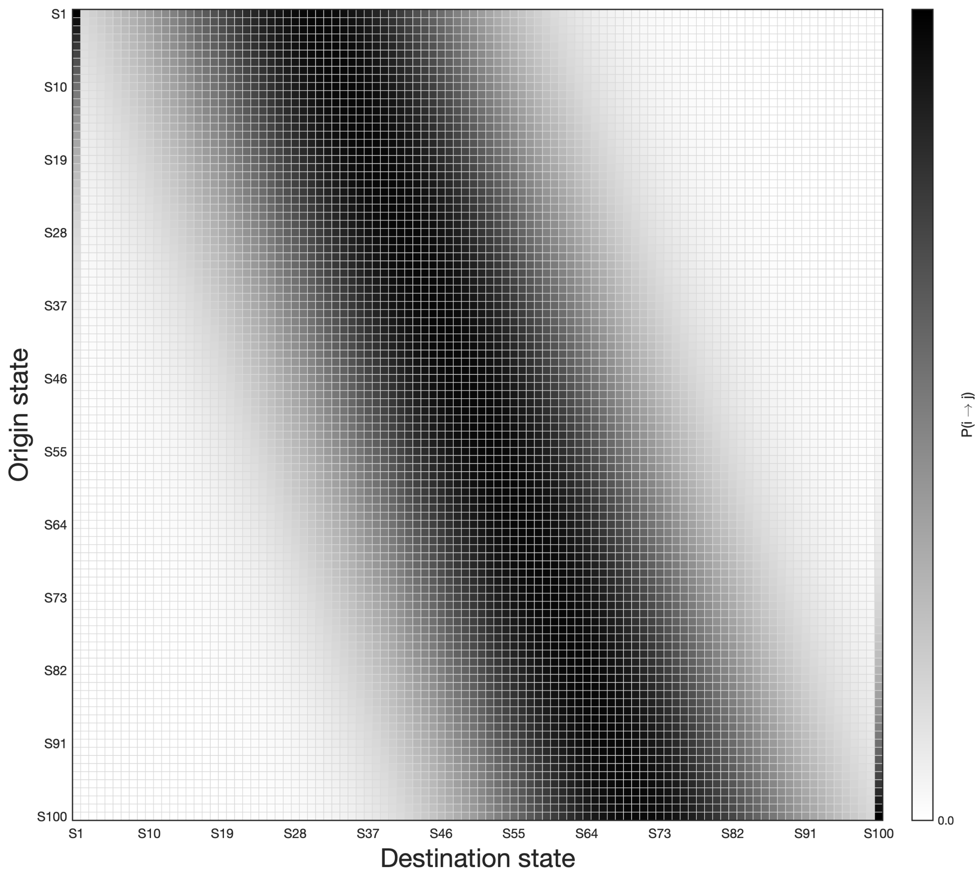
D *Gaussian* Economy

We begin by estimating the following autoregressive process for $\widetilde{z}_{it}$:

$$\widetilde{z}_{it} = \rho \widetilde{z}_{it-1} + \varepsilon_{it}$$

where $\rho \in (-1, 1)$ and $\varepsilon_{it} \sim \mathcal{N}(0, \sigma^2)$. We obtain OLS estimates of ρ of 0.404 (s.e.=0.018) ans select $\sigma = 0.767$, such that the standard deviation of the Gaussian shocks, s.d.$[\Delta \widetilde{z}_{it}] = \frac{2\sigma}{1-\rho^2}$, equals the standard deviation of the non-Gaussian shocks (0.839, see Table 2 in the main text). We then discretize this process following Tauchen (1986), and obtain the transition matrix reported in Figure 4

Figure 4: AR(1) transition probabilities of farm productivity



NOTES: This figure shows the transition matrix obtained by discretizing the estimated AR(1) process for $\widetilde{z}_{it}$ following Tauchen (1986). Each dot represents a transition from one percentile bin to another, with darker dots indicating higher transition probabilities.

Table 6 summarizes the list of the model parameters under Gaussian productivity shocks, their values, and their sources. We estimate a value for λ of 0.30% of the agricultural output per capita, with a 95% confidence interval ranging from 0.21% to 0.39%.

Table 7 compares selected outcomes between baseline (with adjustment costs) and

Table 6: Parameter values and sources - *Gaussian* economy

Description	Value	Source/target
Externally calibrated parameters		
Interest rate, r	0.10	Kamra and Ramakumar (2019)
Capital share, α^K	0.18	Chen et al. (2023)
Land share, α^L	0.37	Chen et al. (2023)
Land supply (ha), $\overline{L}$	3.82	Data
Estimated parameters		
Adjustment cost, λ		
(% of aggregate output)	0.30% [0.21%, 0.39%]	Inaction rate = 0.1773

NOTES: This table summarizes the values of the model parameters, indicating whether each is externally calibrated or estimated, and the source used to pin down its value. The 95% confidence interval for the adjustment cost λ (in brackets) is computed using the Delta method.

counterfactual (without adjustment costs) in the *Gaussian* economy.

Table 7: Implications of removing adjustment costs - *Gaussian* economy

	Baseline (1)	Counterfactual (2)
Price of land, p	1	1.0854
landholding GINI	0.7667	0.7990
Adjustment inaction rate	0.1773	0.0224
Spike rate of adjustment ($\pm$ 1 ha)	0.5243	0.4938
Share of obs. with of negative adjustments	0.4127	0.4890
S.d.(log MPL)	0.1487	0
Aggregate agricultural output	1	1.0179
S.d.(log agricultural output)	1.990	1.8569
Agricultural TFP	1	1.0127

NOTES: This table reports selected model outcomes for baseline (column 1) and counterfactual (column 2) economies. The price of land, aggregate output, and TFP are reported relative to the value in the baseline economy. MPL denotes the marginal product of land, and s.d.(x) denotes the standard deviation of x. Aggregate agricultural output refers to aggregate production minus adjustment costs expenditure.