NBER WORKING PAPER SERIES

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Julieta Caunedo
Namrata Kala
Haimeng Zhang

Working Paper 30788
http://www.nber.org/papers/w30788

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2022, Revised March 2026

We benefited from the discussion of an early version of this paper by Doug Gollin, and conversations with Johannes Boehm, Kevin Donovan, Joe Kaboski, Philip Kircher, Diego Restuccia, Todd Schoellman, Will Strange and Shouyong Shi, as well as seminar participants at Penn State, Syracuse University, Minneapolis and St. Louis FED, Cornell University, EIEF, SED, Y-RISE and BREAD annual meetings. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. O12, O13, O18, O47, R41

ABSTRACT

Rental markets are expanding access to mechanization for small-holder farmers in developing countries. However, gains from adoption depend on market structure and the spatial concentration of demand, which implies that understanding how mechanization is allocated during peak demand is key to understanding the returns to policies expanding access. We develop a model of equipment rental markets where demand varies by farm size and location, and supply varies by dispatch rule (first-come-first-served vs. profit-maximizing). An efficient allocation prioritizes large-scale demand, because the cost of moving equipment in space dilutes with scale; as well as small-scale demand in dense locations, because it maximizes machine-capacity utilization. Using novel transaction-level data and a new census of farmers from Karnataka, India, we calibrate the model and evaluate policy-relevant counterfactuals to expand access. Deregulating first-come-first-served rules to allow profit maximization raises aggregate surplus by 10% and reduces output costs from delays by 31% (about 2.8 p.p. in units of average productivity). All farmers experience gains, with large-holders benefiting relatively more. These effects are comparable in magnitude to a 20% increase in equipment supply, but save the cost of that increased capacity.

Julieta Caunedo
Cornell University
jdc364@cornell.edu

Haimeng Zhang
IESE Business School
hzhang@iese.edu

Namrata Kala
Massachusetts Institute of Technology
MIT Sloan School of Management
and CEPR
and also NBER
kala@mit.edu

1 Introduction

Agricultural production in many developing countries is characterized by low productivity as well as small-scale production (Adamopoulos and Restuccia, 2014). An important reason for this low productivity is the lack of technology embodied in capital (Chen, 2020), which accounts for up to 41% of productivity differentials between poor and rich countries (Caunedo and Keller, 2020). Recognizing the importance of timely access to mechanization, governments in several countries have spent significant resources in recent years to increase the overall supply of mechanization.[1] There are two key barriers to improving productivity through capital intensification: first, the presence of increasing returns to scale in land size and the potential gains from density; second, large fixed costs that limit investment in technology altogether. Rental markets for equipment overcome fixed costs of adoption (Bassi et al., 2022), but the gains from technology adoption depend on market and land structure, because of returns to agglomeration. Hence, the spatial concentration of demand interacts with the cost of adopting technology and the market structure to determine equilibrium returns to adoption. This interaction is fundamental to productivity in agriculture, but is often overlooked.

Earlier evidence on whether the expansion of mechanization rental markets is beneficial for aggregate productivity in agriculture finds mixed effects (Pingali, 2007; Daum and Birner, 2020). In this paper, we combine novel transaction-level data and a new census of farmers with a structural model. We study how the equilibrium interaction between allocation mechanisms (hereafter called dispatch systems) which determine *how* mechanization is allocated during peak demand along with the joint spatial productivity and size distribution of farms is key to understanding the returns to policies expanding access, and can account for heterogeneous results on returns to mechanization. These features of the market interact to produce patterns of mechanization access which have important implications for welfare, aggregate output as well as distributional implications such as whether smaller farmers or larger farmers get access when it is most valuable.

[1] For instance, since 2014, the Indian government has spent nearly a billion dollars subsidizing such access to mechanization at the Central level alone (Government of India, Ministry of Agriculture and Farmers Welfare, 2025), while state governments have similar programs. China's Agricultural Machinery Purchasing Subsidies (AMPS) similarly subsidized mechanization for smallholder farmers.

We propose and estimate a frictional model of search and matching in the allocation of mechanization rental. Such a model is the natural framework to study queuing, as well as sorting and rental rate dispersion, which are empirically relevant features of these markets. As in the labor search tradition, the main friction built into the model is that it takes time for an agent to find an equipment provider willing to provide services at a price that is acceptable for both parties.[2] Delays in provision are detrimental to agricultural productivity, where output is highly time-sensitive. At the same time, unused machine-service capacity is costly for providers, and servicing demand in spatially dense areas maximizes utilization. These features generate economies of density.

Formally, we model directed search with two sided heterogeneity: demand varies by hours requested, location, and the returns from service; while supply varies by the dispatch system for service provision. Providers set prices with commitment and agents build expectations about the queue lengths when deciding where to stand in line. Providers can accommodate multiple services per period and face service capacity constraints in terms of machine hours, our two main generalizations relative to Shi (2002). The first feature allows us to discuss compositional changes in serviced orders across demand hours as well as to optimize service provision in space. The second feature, paired with discreteness in hours demanded, speaks directly to the role of small-scale orders in maximizing capacity utilization within a period. Farmers understand that providers offering lower equipment rental rates are those where waiting times for service provision are longer, and they trade-off the probability of service, with the cost of service. Once they commit to a provider, they stand in line for a period.

We model providers' dispatch technologies following two prevalent allocation methods in the markets that we study: private profit-maximizing dispatchers ("market" *mkt* providers), and first-come-first-served dispatchers (*fcfs* providers). While the former ranks orders by profitability, the latter does not. First-come-first-served provision is often prevalent in markets subsidized by local governments, where there are concerns regarding small-holder access to subsidized services.[3] The main predictions of the model are that when small- and large-

[2] As highlighted by Lagos (2000) and Sattinger (2002), queuing models are powerful to micro-found a matching process between, in this case, farmers' orders and service providers.

[3] *fcfs* providers induce a matching technology that resembles an urn draw with multiple draws/vacancies per period. For *mkt* providers, the easiest way to characterize the matching technology is to work with queue lengths and its composition, since there is no closed-form counterpart.

scale farmers are equally distributed in space, small-scale farmers are more likely to be served by the *fcfs* providers than the *mkt* provider: travel costs imply that smaller orders are more costly to serve so profit-maximizing dispatchers would delay their service. But when serving large-scale orders leaves too much idle capacity, *mkt* providers have incentives to bring in small-scale orders and improve capacity utilization.

We can use our model economy to study the equilibrium implications of alternative market arrangements for aggregate productivity, aggregate surplus (our measure of welfare) and service finding rates to small-holder farmers. We do so consistently with the empirical distribution of demand for rental services that we observe in rental markets in Karnataka;a large, economically important state in India with over 60 million people and the third-highest GDP in India (Reserve Bank Of India, 2024). Bringing the model to the data requires augmenting our stylized theoretical framework by additional heterogeneity in equipment demand, spatial location and productivity distributions.

We combine primary data collection with a novel transaction-level database from custom-hiring centers (which are *fcfs* providers). Our primary data collection includes a Census covering over 40,000 farmers and their ownership and rental of agricultural equipment (*mkt* providers and renters), as well as a more detailed survey of about 5,500 farmers in these villages. We bring the model to the data in two steps. In the first step, we target the queue lengths for small-holder farmers, as observed in the transaction level data from custom hiring centers (henceforth referred to as hubs); the share of large scale farmers in each market, as inferred from the Census data; and the observed average profitability of hub providers. The main outcome of this calibration exercise are the endogenous queues by provider and farmer type (small and large), and the equilibrium rental prices per hour of equipment. In the second step, we bootstrap queues from the empirical joint distribution of service-hours demanded, productivity and plot location, as well as the service finding rates, and equilibrium output costs. The main outcome of this step are waiting times, productivity costs and welfare across providers and farmers of different types. We present the main results of the paper using a benchmark market (where we hold information on the largest number of transactions) and present heterogeneity across markets in the Online Appendix.

We conduct two policy-relevant counterfactuals. First, we ask how the current equilibrium, where *fcfs* and *mkt* providers coexist, compares to a deregulated market where *fcfs* use the same profit-maximizing dispatch technology which prioritizes larger farmers as *mkt* providers. Since provider profitability changes, we allow for endogenous entry and exit of providers to sustain a minimum profit margin of 10%, consistent with the baseline scenario. We find that average surplus in the market increases by 10% from deregulation, and that surplus gains are largest among farmers with higher machine-hours demand. Wait times and output costs decline for both small-holder and large-scale farmers, with the largest percentage decline in output costs for small-holder farmers. These output gains—the reduction in output lost to delays—amount to about 2.8 p.p. in units of average productivity. Thus, while output and surplus increase, the gains are unevenly distributed across farmer types.

Second, we ask what happens to allocations as we change the level of equipment services available in the market, a common policy used by governments in the form of equipment subsidies which increase overall supply of equipment (when capacity increases, the counterfactual is akin to a policy that lowers the cost of purchasing capital in increasing supply). We find that the cost of service drops with equipment supply and that the effect is asymmetric when we shrink or expand capacity around its baseline level. The same holds for service finding rates, our preferred measure of market access. Perhaps not very surprisingly, wait times for service drop with capacity, but the decay is non-linear, with largest cuts in wait times when capacity is relatively low. This non-linearity has direct implications for aggregate productivity, which depends on the output costs of delays and their distribution across farmers of different size, location and productivity. Aggregate productivity gains are also non-linear and largest when capacity is relatively low.

These counterfactuals generate several policy-relevant insights. Comparing the effects of changes in service capacity to those associated with market deregulation, we find that the cost of having *fcfs* providers accounts for 10% of aggregate surplus. The gains in output associated with market deregulation are comparable to those that obtained when aggregate service capacity increases by 20%. Since deregulation requires no additional service capacity build-up, this type of policy tool woudl likely be successful in improving productivity in a cost-effective manner.

Related Literature. Geography and land allocation are important drivers of productivity dispersion in agriculture (Adamopoulos and Restuccia, 2021; Bento and Restuccia, 2017). Rental markets for land could generate returns to technology adoption, but frictions in these markets are ubiquitous and an important margin for misallocation (Adamopoulos and Restuccia, 2021; Acampora et al., 2025); we show how rental markets for inputs could enable agglomeration even without land consolidation, with gains depending on the joint distribution of productivity and geography and on service dispatch systems.

Barriers to technology adoption in agriculture as a source of low productivity have received extensive attention (see Suri and Udry (2022) for a review). We contribute to the literature on mechanized practices (Caunedo and Keller, 2020; Caunedo and Kala, 2021) by focusing on rental markets, which can lower adoption costs (Yang et al., 2013; Manuelli and Seshadri, 2014; Yamauchi, 2016). However, frictions in these markets can impact returns to access.[4] Daum and Birner (2020) and Pingali (2007) document mixed evidence on mechanization in the 1970s–1980s and its delayed take-up in the developing world. Two questions arise: (a) what explains heterogeneity in outcomes; and (b) what is the best contracting model for service provision and how can it be supported. Our paper provides a theory and a quantifiable model along with novel data to make progress on these questions. We propose a tractable model that expands the seminal work of Shi (2002), along two relevant dimensions: multiple service provision within a period and service capacity constraints. Our quantitative model accommodates heterogeneity in land-size, productivity and geography, all relevant dimensions to assess outcomes. A novel feature of the theory is that service capacity constraints bring value to servicing small-scale orders, because they improve capacity utilization. This channel has been mostly overlooked in the literature, but we show it is important both for distributional and aggregate outcomes.

The notion that there might be scale economies associated with concentrating production in certain locations goes back to Marshall (1890). In agriculture, Holmes and Lee (2012) explore it in the context of crop choices of adjacent plots, where agglomeration economies rely on economies of scale in output. Duranton and Puga (2004) review the micro-foundations for agglomeration economies and classify them into three mechanisms: "sharing", "matching" and "learning". In our framework, the first two mechanisms are at play. Bassi et al. (2022) study the sharing mechanism, with an application to rental markets for door producers in urban Uganda, where they argue frictions are relatively limited. In contrast, we

[4] For instance, in recent work, Nottmeyer (2025) studies moral hazard and GPS tracking of tractors, and estimated output gains of 2% attributable to these frictions.

document substantial price dispersion in rental rates paired with unused service capacity, a common symptom of matching frictions. We study matching between providers and farmers across different dispatch systems, and how they affect rental prices, queueing behavior, and mechanization access.

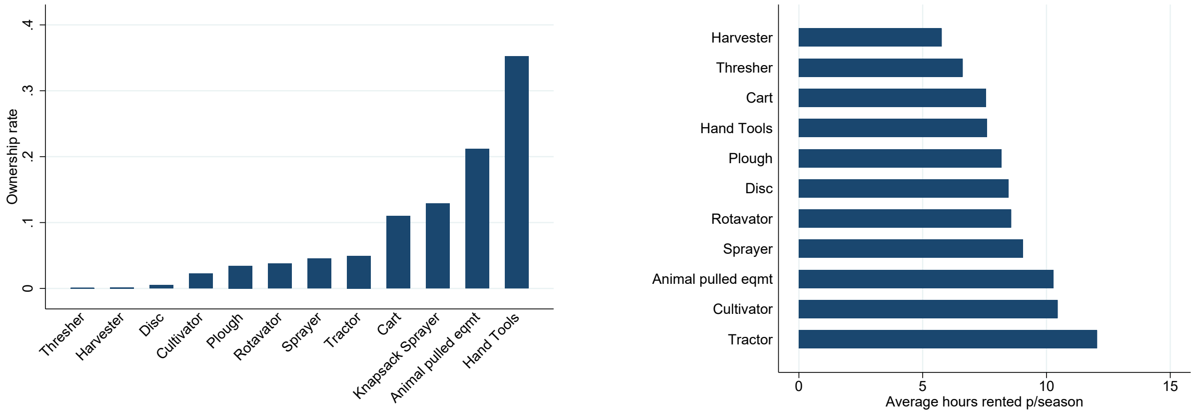
2 Agricultural equipment rental markets: an empirical exploration

We inform our theory by four characteristics of these markets that distinguish them from rental markets for other durable goods. First, equipment ownership is not cost effective because of the prevalence of small-holder farmers, and most of the service capacity is determined by equipment suppliers that specialize in equipment rentals. Second, demand is synchronous, leading to endogenous delays in service provision as a function of service capacity. These delays in land-preparation generate output costs for farmers (Paudel et al., 2019; Liu et al., 2023). Third, the joint distribution of travel time and service-hours requested determines access to equipment, because it determines the profitability of moving equipment in space to service an order. Fourth, we observe price dispersion in rental rates after controlling for observable household characteristics and market characteristics. Most importantly, service capacity often exceeds demand despite farmers facing delays. Both these features are consistent with frictional rental markets.

2.1 Data description

We combine four sources of data from agricultural rental markets in Karnataka, India. First, we use our own census of farming households covering 40,000 households across 150 villages, including information on equipment ownership and rental market engagement. This data allow us to characterize the universe of equipment supply and farmer demand in these markets. Second, we use transaction-level data from the universe of equipment rentals engaged through a large rental platform established via a public-private partnership during the Kharif

Figure 1: Ownership and rentals by implement.



Owned Rentals

The ownership rate is the share of farmers that report owning a given implement relative to the total population surveyed. Rental hours correspond to the average hours reported for the whole season. Source: Own survey of farmers.

season of 2018 (May-October).[5] Transactions include information on the number of hours requested, acreage, implement type, as well as farmer identifiers (such as their name, village, and phone number). Importantly, we observe queuing behavior for farmers of different characteristics. To obtain farmer characteristics we use farmer identifiers to match transactions with detailed survey data that we collected over 5500 farming households with information on rental market engagement, delays in service provision; as well as output and input expenses, crop choices and land ownership. This data allow us to report characteristics of the joint distribution of farm productivity, size and location.

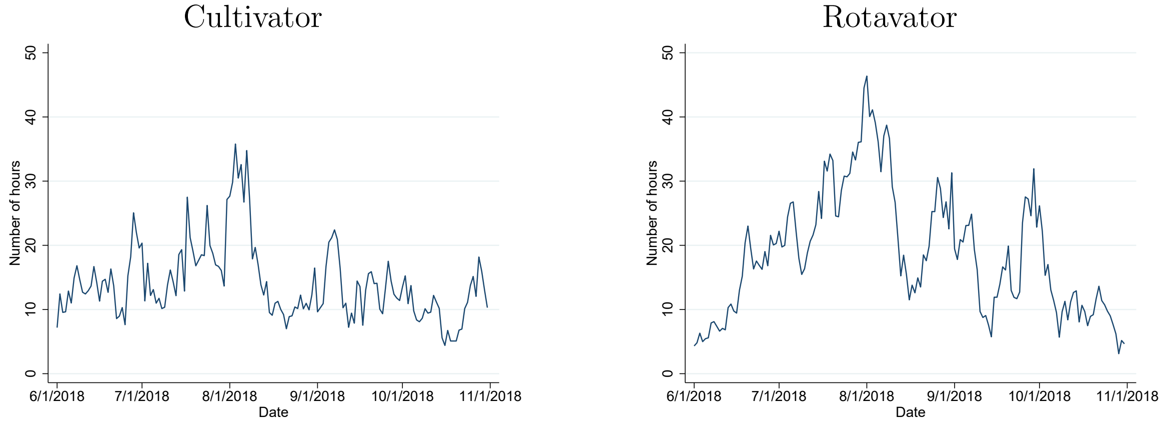
2.2 Equipment supply and demand

Rental markets are an important mechanism to access mechanization. In particular, less than 5% of the farmers report owning larger equipment such as tractors, rotavators or cultivators (see Figure 1).[6] We find the same ownership rates (less than 5%) for these types of equipment

[5]This platform was created in the context of a broader mechanization program subsidizing equipment purchases in the state of Karnataka since 2016, but transactions occurring outside of the platform are not recorded. Transactions in our sample cover the full range of farm sizes as well as the type of crops in our Census.

[6]Given land holdings, ownership of equipment is not cost-effective for most farmers. For instance, the rental price of a rotavator is between ₹750 and ₹1,000 per hour (including tractor, a driver and fuel) and the

Figure 2: Hours outstanding in the queue.



Notes: Average hours outstanding in the queue across hubs in Kharif 2018, overall (top panel) and by order size (bottom panel).

when analyzing census data (see Figure A1 in Appendix B).

Farmers rely on rental markets to access mechanization services. Since equipment ownership is low, equipment is mostly available through custom-hiring-centers or providers that travel to these locations seasonally. The average hours rented in a season per farmer is 12 hours for tractors, 10 hours for cultivators and 8 hours for Rotavators. With the exception of sprayers, which are used for plant protection, equipment rentals are mostly concentrated in implements related to the land-preparation stage. These include rotavators, ploughs and cultivators on the higher end, and animal pulled equipment (e.g. harrows) and disc which are typically cheaper to rent. Mechanization is most prevalent during land-preparation in our sample, a common first stage of mechanization in agriculture (Caunedo and Kala, 2021).

2.3 Queuing for service

Demand for equipment rental services vary by agricultural process, e.g. land preparation; and farm outcomes are sensitive to the timing of completion of such a process (we quantify the

average farmer demands about 6 hours of rotavator services in the season or between ₹4500 and ₹6000 in services. The purchase price of a new rotavator is over ₹110,000 which means that, even absent maintenance costs, the average farmer needs 19 years to amortize the investment. The rental rate for an inferior technology that serves a similar purpose, i.e. a harrow, is half of the rental rate of the rotavator (₹360) and the cost of purchase is about ₹50000.

Table 1: Delays as a Function of Land Area and Location Fixed Effects

	Delays (Sum of Average Delays Over the Season)			
Log(Area)	-0.215*	-0.144	-0.319**	-0.128
	(0.115)	(0.0926)	(0.145)	(0.108)
Observations	5,615	5,615	4,345	4,345
R-squared	0.002	0.182	0.003	0.252
Village Fixed Effects	No	Yes	No	Yes
Mean Delays	2.158	2.158	2.789	2.789

Estimated coefficients from a regression of reported delays in service provision and the log(area) owned. The first two columns include those that report zero delays whereas the last two columns only focus on those that report positive delays.

cost of these delays in later sections). The synchronous nature of many of these processes induces queuing in the market. Our transaction level data allows us to measure demand fluctuations measuring outstanding service hours for land preparation implements at a daily frequency, an empirical measure of the queue.

Figure 2 shows that queuing peaks by the end of July for rotavators and beginning of August for cultivators. At peak, the average provider faces 40 hours of demanded services in queue, which account for over 12 orders on average at a point in time.

2.4 Delays in rental services

We survey farmers on the most important issues in accessing equipment services. The most prevalent answer is "delays in provision", with 78% of farmers reporting it as an issue. This issue is more prevalent than lack of cash for example. Importantly, larger farmers, i.e. those cultivating at the 75th percentile of the land size distribution, are nearly 5 percentage points less likely to report delays as an issue. Columns (1) and (3) in Table 1 show that service delays are negatively associated with cultivated area.

Since equipment moves in space to service demand, it is possible that these delays are explained by the geographical location of plots, and the correlation between location and farm size. Columns (2) and (4) in Table 1 show that delays have an important spatial dimension: adding village fixed effects substantially attenuates the correlation between land-size and delays, and increases the r-squared by eight or nine times (depending on whether

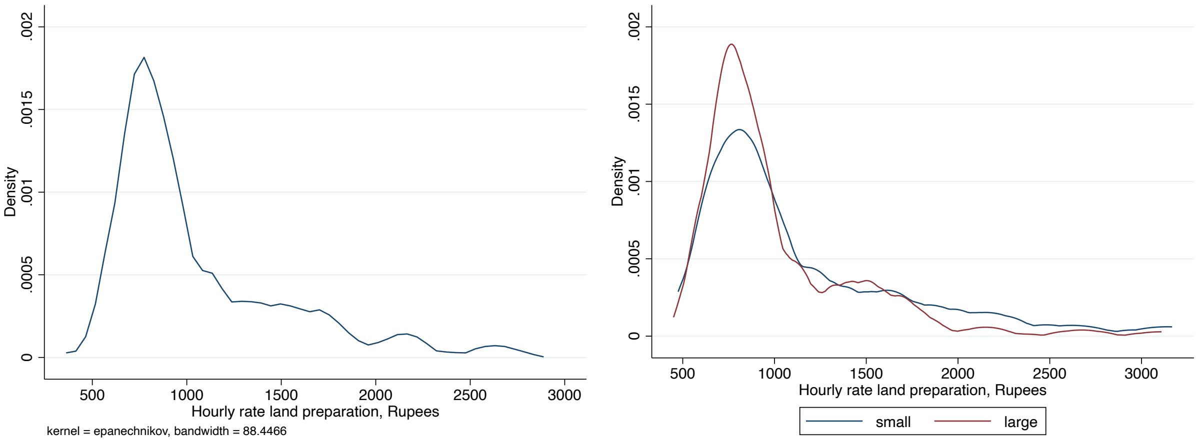


Figure 3: Rental rates

Notes: Hourly rental rates for equipment at land-preparation, including Cultivators and Rotavators. Panel (a) displays the residual rental rate dispersion after controlling for village fixed effects. Panel (b) presents these residuals for farmers with less than the average area cropped (small, < 3.3 acres); and for farmers with more than that area cropped (large, $>= 3.3$). Source: Own survey data.

only positive delays are considered, or all delays are included in the regression). That is, in the surroundings to a particular village, small and large farmers face similar delays. But the negative correlation between delays and size suggest that small farmers may also be located in less dense areas on average, so longer delays are a feature of remoteness rather than size.[7]

How long are these delays? and do they vary over the season? To investigate the nature of delays we rely on our transaction level dataset that includes higher frequency (daily) and more detailed data than survey information.

As demand fluctuates over the season in a somewhat predictable manner, it is expected that service supply adjusts accordingly. If supply expands proportionally to increased demand, delays could be constant. We define the service rates as the ratio of hours serviced within a day to the total number of hours outstanding. Service rates fluctuate during the season, and positively correlate with hours serviced suggesting incomplete adjustment in supply (see Online Appendix). At peak queue hours, service rates are 35% on average for rotavators, and 30% for cultivators. In other words, it takes 2.9 and 3.3 days on average to complete all hours outstanding in the queue, respectively.[8]

[7]The costs of remoteness and market access have been studied in the development context in a variety of settings including Atkin and Donaldson (2015).

[8]One reason to complement this data with our own survey is that we only observe delays for orders that are already in the queue, i.e. where the farmer has accepted to wait in line.

2.5 Frictional rental markets

Are delays a consequence of low service capacity, frictions in the rental market that prevent farmers and providers from contracting services when desired, or both? There are two features of the market that indicate the presence of frictions in this market.

To measure available supply, we start by building catchment areas of 10km around each piece of equipment either owned in the census data or in the inventory of the private-public enterprise.[9] We assume a six-week land-preparation season and that each piece of equipment serves three orders a day.[10] The latter is consistent with serviced orders per equipment per driver at peak utilization in our transactions dataset. We estimate that the number of available cultivators can serve up to 2016 orders per season, while average demand in these catchment areas is roughly 1190 orders, or half of the estimated supply. We estimate that the number of available rotavators can serve up to 1008 orders in the season while market demand is 450 orders. Hence, these estimates suggest that queuing may not be related to supply shortages unless farmers attempt to access equipment over a shorter time span than the one considered here.

We also observe price dispersion in rental rates within a 10km catchment area of each village. As part of our survey, we ask farmers how much they paid for land-preparation equipment rentals during the season prior to Kharif 2018. Figure 3 panel A shows the distribution of rental rates paid per hour, controlling for village fixed effects.[11] The interquartile range is 1.71 while the coefficient of variation is 0.67. Importantly, we find systematic disparities between farmers operating above and below the mean farm size in the sample, see Figure 3 panel B. Smaller farmers face more dispersion than their larger counterparts, consistently with queuing risk.

Burdett and Judd (1983) showed that price dispersion could arise in an environment with identical agents where consumers/farmers found it costly to search for providers. Price dispersion can also be related to informational asymmetries (Varian, 1980) or to consumer

[9]This 10km cutoff corresponds to maximum travel distance of the private-public platform from which we obtained transaction-level data, but results are robust to enlarging the catchment area to 20km radius.

[10]Our results are robust to assuming a plant preparation season of four weeks, and therefore lower equipment-order supply.

[11]Observed dispersion is similar even after we account for total area; and hourly rental rates are lower on average for farmers with larger areas.

preferences for certain providers over others (Rosenthal, 1980). The exchange of identical goods for heterogeneous prices is typically a sign of market frictions, our working hypothesis in this context.

3 A model of capital rental services in space

We build a model of capital rental services where farmers of different plot sizes and locations search for equipment providers with different technologies for service provision. Some providers prioritize high value requests whereas others simply use a first-come-first-serve dispatch system. The latter, simpler dispatch system, may service requests that would otherwise be rationed out from provision. Both these types of service provision are prevalent in agricultural equipment rental markets across the world.

Formally, we propose a two-sided heterogeneity directed-search model (Shi, 2002), where farmers request different service hours, and providers use alternative technologies for service provision. We further extend this framework along two dimensions: (a) providers can serve multiple orders within a period, enabling the study of optimal service routes and the role of travel time in assessing value across orders; and (b) providers face service-hours capacity constraints, enabling the study of congestion and equilibrium service delays.

3.1 Environment

Consider an economy populated by F farmers, heterogeneous in their service-hours demand and location; and H service providers (machines), heterogeneous in their dispatch technology and location. A market is a catchment area around any of these providers, and locations are exogenously given. A fraction $\mathfrak{s}$ of farmers are large-scale farmers and demand k_s hours, while the remaining $(1 - \mathfrak{s})$ fraction are small-scale farmers, and demand k_{s^-} hours. Hours demanded are determined by land holdings, and plots are either mechanized or not, bringing discreteness in demand.[12] A fraction $\mathfrak{h}$ of providers use a first-come-first-served (*fcfs*) dispatch technology, while the remaining fraction $1 - \mathfrak{h}$ has access to a selection technology

[12]The capital demand for a farmer is given exogenously. This is analogous to taking land holdings as given and model capital demand through a Leontief production technology.

that allows them to prioritize high value service requests (*mkt*).[13] For simplicity, we assume no depreciation or capital accumulation and no maintenance costs. Service providers have a machine-hours capacity constraint $\bar{k}$ per day.

Denote the ratio of farmers to service providers, $f = \frac{F}{H}$, and focus on the case where the market is large, i.e. $F, H \to \infty$ and neither side is infinitely larger than the other, $f \in (0, \infty)$. Providers post prices r_{ij} indexed by the scale of demand i and the type of provider j; and a selection rule (with commitment) $\chi_j \in [0, 1]$ simultaneously at the beginning of each period. A rule is a technology available only to *mkt* providers, and allows them to arrange orders in the queue. A provider prefers the large scale order if $\chi_j = 1$, prefers a small scale order if $\chi_j = 0$, and he is indifferent between them for $\chi_j \in (0, 1)$. When the *mkt* provider receives requests from a single farmer type, he randomly selects one farmer for service. The *fcfs* provider serves orders as they arrive in the queue.

The opportunity cost of moving equipment from a provider to the plot, entails the value of time for the equipment driver, i.e. his wage; as well as the value of the foregone services that could have been provided if the equipment would have not traveled, i.e. the shadow value of time given the providers' capacity constraint.

Farmers decide whether and which provider to approach (with commitment) generating queues for each available provider. Providers decide which orders to serve given their selection criteria and capacity constraint. Service provision takes place and farmers produce. Delays in provision occur in equilibrium inducing productivity costs for certain farmers. Given the large number of providers and farmers we focus on a symmetric mixed-strategy equilibrium where ex ante identical providers and farmers use the same strategy and farmers randomize over the set of preferable providers.

A type i-farmer's strategy is a vector of probabilities $P_i \equiv (p_{i,\text{fcfs}}, ...; p_{i\text{mkt}}, ...)$ where p_{ij} is the probability of applying to each type j-provider. Each farmer maximizes expected profits from farming trading off the probability of obtaining a rental service and the cost of such a service. There is no aggregate uncertainty in the economy and factor prices are time independent.

[13] Albeit h and H are assumed exogenous, both of them can be easily endogenized with a costly set up of providers and an associated free-entry condition.

3.2 Queue lengths as strategies.

A convenient object for analysis is the *queue length*, i.e., the expected number of farmers requesting a service from a given provider.[14] Let q_{ij} be the queue length of type i farmers that apply to a type j provider, where $i \in \{s, s^-\}$ and $j \in \{\text{fcfs}, \text{mkt}\}$. Then, $q_{sj} = \mathfrak{s}Fp_{sj}$ and $q_{s^-j} = (1-\mathfrak{s})Fp_{s^-j}$. The farmer type i is determined by its service-hours demanded and location.

Assumption 1. *Service-hours demanded satisfy $k_s > k_{s^-}$. The expected travel time to servicing small-holder farmers is weakly higher than that for large-scale farmers, $d_s \leq d_{s^-}$.*[15]

The probability of approaching different providers for a single farmer should add up to one, which leads to the following feasibility constraints

$$H\left(\mathfrak{h}q_{s,\text{fcfs}} + (1-\mathfrak{h})q_{s,\text{mkt}}\right) = F\mathfrak{s} \tag{1}$$

$$H\left(\mathfrak{h}q_{s^-,\text{fcfs}} + (1-\mathfrak{h})q_{s^-,\text{mkt}}\right) = F(1-\mathfrak{s}) \tag{2}$$

A farmer of scale i that requests service from provider j gets served with probability Δ_{ij}.[16] This probability depends on the provider's selection criteria, its capacity, machine-hours demanded k_i and the expected travel time for service d_i. Hence, Δ_{ij} is the sum of the probability of servicing $\bar{o}_i$ type i farmers, across all possible number of orders of type i being served, $\bar{o}_i$, i.e. $\phi_{ij}(\bar{o}_i)$; times the probability that a certain farmer of type i is chosen, $\tilde{\Delta}_{ij}(\bar{o}_i)$,

$$\Delta_{ij} = \sum_{\bar{o}_i} \phi_{ij}(\bar{o}_i)\tilde{\Delta}_{ij}(\bar{o}_i). \tag{3}$$

The probability of type i being served (weakly) declines in the queue length of type $i' \neq i$ farmers. For the *fcfs* provider the result is straightforward because service probabilities decline with the number of machine-hours in the queue, irrespective of their type. For the *mkt* provider with a selection criteria that favors type i' farmers, the decline in the probability

[14] When the number of providers and firms grow large, the probability of requesting a service to a given provider approaches zero and it is inconvenient to work with. Empirically, queues are observable to us.

[15] These features are born in the empirical evidence we discuss in Section 2.

[16] Section A in the Online Appendix contains a full derivation of these probabilities for the case where at most three orders are serviced within a period, the empirically relevant case.

of service for type $i \neq i'$ is strict as the number of type i' farmers in the queue increases. The service probability for type i' farmers is independent of the queue length of type $i \neq i'$ due to the selection criteria.

3.3 Farmer's decisions.

We follow Burdett et al. (2001) and describe a farmer's decision as a function of the market price it would get for the rental service, r_{ij}, which in turn determines its expected "market" profit, U_i. Farmers take the value of the market profit as given when the number of agents in the economy is large, $F, H \to \infty$. Each farmer chooses a service provider to minimize costs given U_i and the production technology:

$$\min_j r_{ij} k_i$$

subject to

$$\pi_{ij}(z_{ij}, k_i, r_{ij}) \equiv \Delta_{ij} \left(z_{ij} k_i^{\alpha} - r_{ij} k_i \right) \geq U_i,$$

where π_{ij} are the expected profits of the farm when requesting service from provider j and $z_{ij} \equiv E(z(\Delta_{ij}))$ is the expected productivity in the farm, which is a function of expected service probability, through equilibrium delays.

Farm's productivity depends on the realization of a random shock determining the timing of agricultural activities. We summarize the optimal timing for agricultural activities by the "optimal" land preparation date, $\theta^{\star}$, and relate deviations from this optimal timing to productivity costs. The realization of the land preparation date is a random draw, θ, from a known distribution $G(\bar{\theta}(\Delta_{ij}))$ with mean $\bar{\theta}(\Delta_{ij})$ that depends on provider j's probability of service. If the realization of the preparation date differs from the optimal, the farmer faces a productivity cost proportional to the delay relative to the optimal date as follows,

$$z_{ij} \equiv E(z(\Delta_{ij})) = \bar{z}_i(1 - \eta(\bar{\theta}(\Delta_{ij}) - \theta^{\star}) I_{\theta^{\star} \leq \bar{\theta}(\Delta_{ij})}).$$

where η is the productivity cost per delayed service day in percentage points. The expected productivity is independent of the choice of provider whenever the expected wait time is relatively low, i.e. the probability of service is high.

Assumption 2. *Let* $\bar{\theta}(\Delta_{ij}) = -\ln(\Delta_{ij})$, *a strictly decreasing function of the probability of service.*

The expected productivity z_{ij} is a function of an exogenous component $\bar{z}_i$ and an endogenous component $1 - \frac{\partial z_{ij}}{\partial \Delta_{ij}} \frac{\Delta_{ij}}{z_{ij}}$ which depends on the elasticity of productivity to the probability of service. Under Assumption 2 this elasticity is constant and equal to η and hence, the surplus from transactions is independent of the probability of service.

A type i farmer requests a service from a type j firm with positive probability if the expected profits are weakly larger than U_i. The strict inequality cannot hold because then a type i farmer would apply to that provider with probability 1, yielding $q_{ij} \to \infty$ as the number of farmers grows large. Then, $\Delta_{ij} \to 0$ contradicting that $\pi_{ij}(z_{ij}, r_{ij}, k_i) > U_i$. The farmers' strategy is therefore

$$\begin{aligned} q_{ij} \in (0, \infty) \qquad &\text{if} \qquad \pi_i(z_{ij}, r_{ij}, k_i) = U_i, \\ q_{ij} = 0 \qquad &\text{if} \qquad \pi_i(z_{ij}, r_{ij}, k_i) < U_i. \end{aligned} \tag{4}$$

This expression summarizes the trade off between lower provision cost and higher farming profits; against a lower probability of service. Given the shape of the probability function (which enters into expected profits, π) there exists a unique queue $q(r_{ij}, U_i)$ that satisfies the problem of the farmer. The farmer decides his queuing strategy as a function of his capital demand, k_i, expected productivity z_{ij} and market prices r_{ij}.

3.4 Service provider's decisions.

A service provider j maximizes expected returns. The cost of servicing a farmer depends on its location relative to the provider. For a vector $\{U_i, k_i, d_i\}_{i=s,s^-}$, which providers take as given, they choose queue lengths by picking the cost of service of farmers of different scale r_{ij} and service strategy. The queue length is reset at the end of each period and therefore the service provision problem is static.[17] In making pricing and service strategy decisions, providers take capacity constraints as given.

[17] This feature allows us to handle the high dimensionality of the combinatorics problem when providers are allowed to prioritize certain farmer types.

Assumption 3. *Providers capacity satisfies*

$$o(k_{s^-} + d_{s^-}) <= \bar{k} \quad \text{and} \quad o(k_s + d_s) > \bar{k},$$

$$(o-1)(k_s + d_s) + k_{s^-} + d_{s^-} <= \bar{k},$$

$$(o-1)(k_{s^-} + d_{s^-}) + k_s + d_s <= \bar{k}.$$

Hence, if the provider serves only large-scale orders, it can serve $(o-1)$ orders, or it can instead combine those $(o-1)$ orders with one-small scale order. Service capacity is also enough to serve $o-1$ small scale orders and one large scale order. In either case, the provider serves up to o orders within a period. In computing service probabilities, we assume an empirically relevant upper bound for the number of orders per machine of $o = 3$.[18]

First-come-first-served (*fcfs*) provider. Consider the problem of a *fcfs* provider. His value is the expected return from servicing at most $o = 3$ orders within each period. Let $\bar{o}_i \leq o$ be the number of orders of type i being served within the period. The per period return $\tilde{V}$ from facing queue q_{fcfs} depends on the number of orders of each type being served, $\{\bar{o}_s, \bar{o}_{s^-}\}$ and the revenue per order type net of labor and transportation costs, $\{r_{i,\text{fcfs}}k_i - wk_i - wd_i\}$.[19] The value for a first-come-first-served provider is

$$V_{\text{fcfs}}(\bar{k}) = \max_{\{r_{i,\text{fcfs}}\}_{i=s,s^-}} \tilde{V}\left(\{\bar{o}_s, \bar{o}_{s^-}\}_{q_{\text{fcfs}}}, \{r_{i,\text{fcfs}}k_i - wk_i - wd_i\}_{i=s,s^-}\right), \tag{5}$$

subject to farmers' strategies, equation 4, and feasibility

$$\sum_{i \in q_{\text{fcfs}}} k_i + d_i \leq \bar{k}. \tag{6}$$

Hence, the cost of travel time includes the foregone services that could have been provided if the equipment was not traveling, as well as the opportunity cost of the driver, which commands a wage w per hour.

Market (*mkt*) provider. Consider now the problem of a *mkt* provider who, in addition

[18]This corresponds to the median number of daily orders serviced in our data.

[19]Optimal travel routes could potentially make these revenues non-separable across serviced orders. To keep the model tractable, we assume travel time associated with each order and relax this assumption in the quantitative exercise when allowing for optimal travel routes.

to choosing the cost of provision, $r_{i\text{mkt}}$, chooses a selection criteria χ. This choice in turn determines the type of orders being served and their quantity, given service capacity. The value of a *mkt* provider is

$$V_{\text{mkt}}(\bar{k}) = \max_{\chi, \{r_{i,\text{mkt}}\}_{i=s,s^-}} \tilde{V}\left(\{\bar{o}_s, \bar{o}_{s^-}\}_{(q_{\text{mkt}},\chi)}, \{r_{i,\text{mkt}} k_i - w k_i - w d_i\}_{i=s,s^-}\right), \tag{7}$$

subject to farmers' strategies, equation 4, and feasibility

$$\sum_{i \in q_{\text{mkt}}} k_i + d_i \leq \bar{k}. \tag{8}$$

The full description of the value of these providers, $\tilde{V}$, can be found in the Online Appendix.

Entry. Providers pay an entry cost I_j, so free entry assures that their expected profitability equals the entry cost,

$$I_j = V_j(\bar{k}). \tag{9}$$

4 Symmetric Equilibrium

Definition 1 (Equilibrium)**.** A symmetric equilibrium consists of farmers expected profits U_s, U_{s^-}, provider strategies r_{ij}, χ, and farmer strategies, q_{ij} for $i = \{s, s^-\}$ and $j = \{\text{fcfs}, \text{mkt}\}$, that satisfy:

1. given U_s, U_{s^-} and other providers' strategies, each type provider maximizes value, equations 5 and 7;

2. observing the providers' decisions, farmers choose who to queue with, equation 4;

3. the values U_s, U_{s^-}, through q_{ij}, are consistent with feasibility, equations 1 and 2; and

4. providers values $V_{\text{fcfs}}, V_{\text{mkt}}$ satisfy free-entry, equation 9.

Proposition 1. *In all symmetric equilibria where providers serve both types of farmers, the selection process is $\chi = 1$ and the per period profit of servicing farmers of type i is V_i^j. For*

$i = s, s^-$, the first term is the surplus from large-scale orders and the second from small-scale orders:

$$V_i^j = \gamma_{1i}^j(\tilde{z}_{sj}k_s^\alpha - wk_s - wd_s) + \gamma_{2i}^j(\tilde{z}_{s^-j}k_{s^-}^\alpha - wk_{s^-} - wd_{s^-}),$$

where $\gamma_{1,i}^j, \gamma_{2,i}^j$ are non-linear functions of the queue lengths and the elasticity of the service probabilities with respect to the length of the queue; and where $\tilde{z}_{ij} \equiv \bar{z}_i(1-\eta)$.

The expected per period value of servicing large-scale farmers is higher than for low-scale farmers, $V_s^j > V_{s^-}^j$. If the surplus from large-scale orders is sufficiently larger than from small-scale orders, the expected profit for large-scale farmers is greater than for small-holder farmers, $U_s > U_{s^-}$.[20]

A few characteristics are worth highlighting. First, differences in location and the cost of travel explain disparities in the incentives to serve farmers operating different scales. For two plots located at the same distance to the provider, the marginal cost of service is lower for large scale farmers. Second, small-scale farmers are useful in terms of capacity utilization (Assumption 3) and therefore, even providers that prioritize large-scale farmers have incentives to serve them. Third, the *fcfs* provider manages to attract some large-scale farmers by lowering their rental costs relative to the *mkt* provider. These lower costs for both large and small farmers compensate them for higher expected queues. Finally, the farmers' expected profit from equipment services depends on the return to his own demand for services and on the equilibrium rental rates. In equilibrium, farmers served by both providers are indifferent between them. Hence, the product between the probability of service and the cost of service equalizes across providers.

5 A quantitative assessment of the market for agricultural equipment rentals

In this section, we study the implications of alternative provider dispatch systems and the level of equipment supply given a dispatch system, on aggregate productivity and welfare. To ease the exposition, we discuss all our results focusing on a single market, *benchmark*

[20] The ratio of the surpluses $\frac{\tilde{z}k_s^\alpha - wk_s - wd_s}{\tilde{z}k_{s^-}^\alpha - wk_{s^-} - wd_{s^-}}$ must be larger than a constant that depends on the elasticity of the probability of service. See Section B in the Online Appendix for a detailed derivation.

market, and relegate results for other markets to the Online Appendix. For this market we hold information on service provision across three different implements and close to 1000 transactions for the 2018 agricultural season. We focus our analysis on rotavators, which account for slightly more than half of those transactions.

We proceed in two steps. First, we solve for the equilibrium market rental rates and queue lengths across providers and farmers of different production scale. Second, we simulate queues and service provision strategies across farmers.

In the first step, we take a stand on the heterogeneity in machine-hours demanded. We construct two groups of farmers following their average machine-hours transactions: those with requests of more than 3.5 machine-hours per order are denominated large-scale while those with requests of less than 3.5 machine-hours are denominated small-holder. Then, we solve for an equilibrium in which both types of farmers are served by both types of providers, as in the data. We call this equilibrium, *status quo*.

In the second step, we use equilibrium rental rates and queues to simulate 10,000 realizations of the queue $q^{\star}$, with equilibrium composition $(q_s^{\star}, q_{s^-}^{\star})$. The sample paths for queues are drawn from the joint empirical distribution of productivity, machine-hours and geographical location. Hence, while farmers sort based on their scales and rental rates, the simulation exercise allows for realizations of the queue that display additional heterogeneity in space, productivity and hours requested across farmers.[21]

For each simulated queue realization, we compute the expected delay in service provision and the associated output costs for farmers. The simulation directly provides a measure of waiting time conditional on an order being within the first three positions in the queue. To obtain the unconditional waiting time—i.e., the expected wait upon joining the queue—we adjust this conditional measure by the number of orders per discretized machine hour in the queue. We refer to this adjusted measure as the wait time. A wait time of one day indicates that no delay occurs. Since providers can only price (on the margin) based on scale and not on distance traveled, the distribution of delays is a function of the geographical distribution of demand. In addition, there is variation in productivity across farmers within

[21]Solving the pricing and sorting equilibrium with this level of heterogeneity makes the combinatorial problem expand substantially and becomes computational challenging. A general problem with this heterogeneity would imply heterogeneity in rental rates that we do not observe in the data.

size categories, which in turn feeds into the aggregate output costs of different equilibrium dispatch strategies.

We also compute provider's profitability under alternative dispatch systems. Our benchmark results follow a "hub and spoke" pattern, i.e. the equipment must return to the CHC between two consecutive orders; we then also allow providers to optimize service provision in space, i.e. they solve a "traveling salesman problem". The value of an order for these providers depends on the density of orders around them, and the size of the order relative to its service capacity.[22]

Finally, we compute the surplus associated with different dispatch system, which allow us to assess overall welfare.

5.1 Calibration

There are eleven parameters to calibrate, as shown in Table 2. We calibrate eight of these parameters directly from data while the remaining two are calibrated internally by solving the model. Consistently with the evidence in Section 2 we use data for the Kharif season (May to October) in year 2018. We should also calibrate the optimal planting date, $\theta^\star$ and a mapping between the probability of service and the realization of the service date, $\theta(\Delta_{ij})$. First, we assume enough service capacity such that on expectation, farmers face no productivity losses from using mechanized services, i.e. $E(z(\Delta_{ij})) = \bar{z}$.[23] Second, we assume $\theta(\Delta_{ij}) \equiv -\ln(\Delta_{ij})$, so the elasticity of farm productivity to the probability of service is constant and equal to productivity cost of delays η, see Online Appendix.

There are five parameters that are common across markets: the providers' discount factor β, their opportunity cost of moving equipment in space w, the productivity cost of delays η, the curvature of the farming profit function α and the maximum service capacity for each machine $\bar{k}$. We set the discount factor to $\beta = 0.999$ with an implied daily discount rate of 0.1%. The opportunity cost of travel time equals the hourly wage for drivers from

[22] As we explain in the Online Appendix, this is a high dimensional problem, and the number of possible combinations of orders to be served within a period grows exponentially with the number of orders in the queue and their dimensions of heterogeneity.

[23] This is analogous to a farmer's outside option that is large enough so that farmers participate in the mechanization market only if on expectation, they face no productivity costs. An example of this outside option is hired/family labor.

Table 2: Parameterization

Parameter	Description	Value	Source/Moment
Measured directly in the data *common across hubs*			
α	Curvature of the profits function	0.6	Survey data
β	Discount factor	0.999	Interest rate
w	Travel/op. cost (INR/hr)	75	Platform data
η	Productivity loss/day	3.4%	ICRISAT sample
$\bar{k}$	Hub-capacity (hours)	11	Platform data, peak
hub specific		method/value	
h	Share of fcfs providers	0.17	Census data
μ	Log-normal location parameter of productivity	8.85	Survey data
σ	Log-normal scale parameter of productivity	2.56	Survey data
ρ	Correlation order size and productivity	0.16	Survey + Platform data
k_i, d_i	Joint-distribution of order size and travel time	B-splines	Platform data
Calibrated using the model (hub-specific)			
s	Share of large farmers	0.35	Census data
f	No. of farmers/No. of equipment	4.6	Small-scale queue, fcfs

Notes: Benchmark model parameterization. Productivity is measured as output per acre. Hub-capacity corresponds to the hours serviced per machine within a day at the peak of service demand, i.e. the maximum number of hours outstanding in the queue during the season.

our transaction data, at $w =$₹75. The curvature of the profit function is set to $\alpha = 0.6$, as estimated from our own survey data on farm profitability and the structural relationship, i.e. $\pi_i = (1 - \alpha)y_i$. We set α to the average ratio of profits to value added reported by farming households. To discipline the productivity costs of delays, $\eta = 3.4\%$, we use high frequency (daily) data on farm profitability and planting decisions from ICRISAT, see Appendix A for a detailed explanation. The maximum service capacity for each machine is set to $\bar{k} = 11$ hours, consistently with the assumptions of the theoretical model, which allows each machine to serve up to three small orders or up to two large orders.

The remaining 6 parameters and joint-distribution of order sizes and travel time are market specific. These parameters include the share of fcfs providers in the market, h, the mean and dispersion of the productivity distribution, μ, σ, the correlation between order size and productivity, ρ, the share of large farmers, s, and the number of farmers per unit of equipment, f. The first 4 parameters and the joint-distribution of order size and travel time are estimated without solving the model. We use our census to compute equipment

Table 3: Moments

	Share of large scale s		Queue q_{s-fcfs}		Queue *untargeted* q_{sfcfs}/q_{s-fcfs}	
	data	model	data	model	data	model
benchmark	0.35	0.35	2.5	2.5	0.8	0.9

Notes: Calibration moments, data and model counterparts, Columns (2-5); untargeted queue length for large-scale farmers relative to small-holder farmers, Columns (6-7).

ownership and combining it with hub's implement inventories we compute the share of first-come-first-serve providers (machines) relative to the total supply of equipment in each market h. To characterize the productivity of farmers requesting different machine-hours we use the subsample of transactions that overlaps with the survey data (approximately, 1,300 observations) and compute the underlying correlation between farm productivity, measured as output per acre, and machine-hours requested. For our benchmark market, this correlation is positive at 0.16.[24]

We assume that the distribution of productivity is log-normal, $\ln(\bar{z}) \sim N(\mu, \sigma)$ and fit the empirical distribution of value-added per acre for survey farmers in the catchment area of each hub via maximum likelihood. The estimated mean in the benchmark market is 8.85 and its variance is 2.56.[25] Finally, we fit the joint distribution of machine-hours demanded and travel time to services from our transactions dataset via B-splines, see Online Appendix for a graphical representation.[26] On the travel dimension, the distribution is typically bimodal, with orders bunching at less than 10-minutes travel time and 30-minutes travel time from the hub.

The last two parameters are calibrated jointly and in equilibrium. The ratio of providers to farmers minimizes the distance between the model predicted queue of small-holder farmers at the *fcfs* provider and the data. This requires a ratio of 4.6 farmers per provider in our benchmark market to obtain a queue of 2.5 orders on average, see Table 3. We also pick the

[24]Their correlation ranges from -0.16 to 0.16, see Online Appendix.

[25]Productivity distributions vary across markets with estimates of average productivity from 7.42 to 9.83 log points, and a log-variance ranging from 1.0 to 2.9, these are available on request.

[26]We could have alternatively calibrated a joint distribution of productivity, machine-hours requested and travel time. We favor our approach, which lowers the computational burden on equilibrium allocations.

Table 4: Baseline Equilibrium

	FCFS			**Market**		
	Small-scale	**Large-scale**	**Total**	**Small-scale**	**Large-scale**	**Total**
Queue length	2.50	2.34	4.84	3.06	1.45	4.51
Rental rates (INR)	132	90	–	137	94	–
Service probability	37.9%	38.4%	–	44.0%	57.3%	–
Service finding rates	20.7%	19.7%	–	29.5%	18.2%	–

Notes: Equilibrium queues, prices and probabilities of service, benchmark market.

share of large-scale requests that is closest to its empirical counterpart while generating an equilibrium allocation that displays service request from both types of farmers to both types of providers (as in the data). For our benchmark market, the share of large-scale orders is 35% in the model and in the data.

For completeness, we report the (untargeted) ratio of queue lengths of large-scale and small-holder farmers. This ratio is slightly higher in the model than in the data (0.8 in the data vs. 0.9 in the model). Thus, the model predicts that large-scale farmers should be more strongly sorted into *fcfs* providers than observed in the data.[27]

5.2 Equilibrium

We solve for the rental rates and queue lengths when both types of farmers have access to both types of providers.

We present rental rates in INR, and their magnitudes should be interpreted relative to the cost of labor per service hour ($w =$ INR75). These rental rates are consistent with a minimum profit margin of 10% per hour across both types of providers.[28] We find that rental rates for both types of farmers are lower for the *fcfs* provider than for the *mkt* provider, see Table 4.[29] . These lower rental rates compensate for longer queues with *fcfs*. Queue composition varies across providers, with *mkt* providers serving relatively more small-holder farmers, and

[27]Outcomes for all other markets can be found in the Online Appendix.

[28]Profit margins depend on the composition of demand because larger orders entail lower marginal costs (by distributing travel costs across more hours).

[29]See Online Appendix for these statistics across all hubs

fewer large ones than their *fcfs* counterparts. Since farmers are indifferent across providers, service probabilities compensate for the differential rental rates and relative queues. Service probabilities are smaller with *fcfs* than *mkt* providers irrespective of farmer size; and more similar across heterogeneous farmers queueing with *fcfs* providers. Service probabilities are the highest for large farmers queueing with *mkt* providers, which is partially explained by the composition of their queues (with a larger share of small-scale orders). The combination between service probabilities and queues determines service finding rates, a common measure of the probability of a match in search models. The ratio between the number of serviced orders per period and the number of farms searching for a service is $\frac{q_{ij}\Delta_{ij}H}{F} = \frac{q_{ij}\Delta_{ij}}{f}$, following Barnichon and Figura (2015). Despite service probabilities being the highest among large farmers that queue with *mkt* providers, service finding rates are the lowest. The reason is that only a small number of farmers queue with those providers.[30]

5.2.1 Farmer allocation by size and travel time

Despite rental rates being determined by order size and sorting, the simulated equilibrium characterizes allocations by order size, land-size and service travel time, as we show in Appendix Figure A2. The average land size served by a *mkt* provider is 3.04 acres, compared with 3.32 acres for a *fcfs* provider. This difference is a consequence of the disparities in the queue composition discussed before. Since land-size and order size are positively correlated but not perfectly, it turns out that large farmers are more strongly selected into *fcfs* providers along the order size dimension than along farm sizes (the average order size served by a *mkt* provider is 2.44 hours , whereas the average order size served by a *fcfs* provider is 2.94 hours).

For this hub, the sorting of farms along the spatial dimension is similar between *fcfs* and *mkt* providers. Over the course of a service day, *mkt* providers travel an average of 1.02 hours, while *fcfs* providers travel slightly less at 1.01 hours. This differential travel time reflects mostly differences in the queue composition across size, and its correlation with farm locations, e.g. large farmers are sorting into *fcfs* and those farmers are closer to the hub.

[30] The Online Appendix presents relative probabilities of service and queue lengths across farm sizes and providers for all markets in our dataset.

Table 5: Travel Time by Delivery Route and Dispatch System

Delivery route	Hub and Spoke		Traveling Salesman	
Dispatch system	**FCFS**	**Market**	**FCFS**	**Market**
Mean travel time (hr)	1.01	1.02	0.72	0.70
as % of total service time	12.3%	13.4%	8.8%	9.4%

Notes: Travel times across dispatchers and delivery routes.

5.2.2 Effectiveness in service delivery

Travel times are an important dimension in our problem, because they directly affect the ability of providers to service farmers by affecting machine capacity utilization. They also affect farmers directly through delays in service provision.

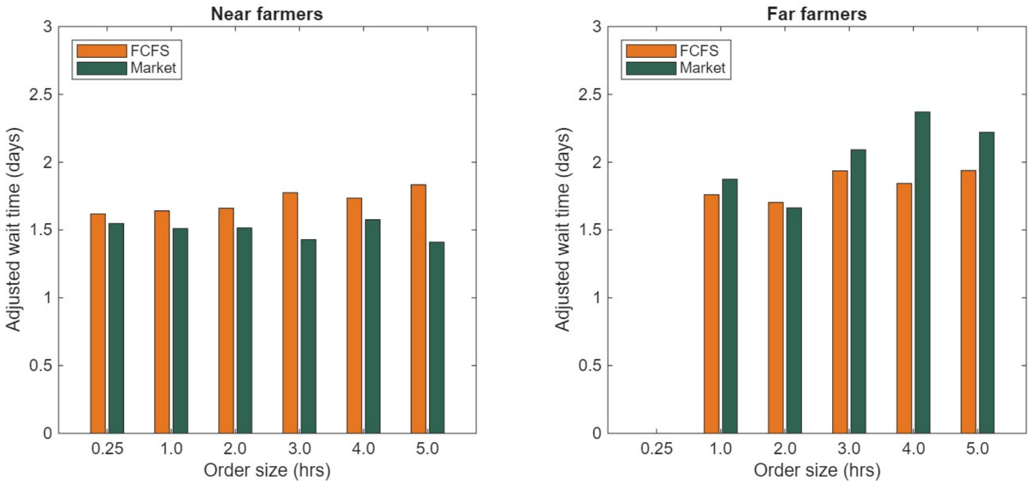
Travel time across providers. Table 5 shows that market providers spent slightly more time traveling in units of service hours (1.1 percentage points more), which is a reflection of the spatial sorting of demand. Since providers use different dispatch technologies, the scope for improving allocations by optimizing service delivery routes within a day differs across providers. We compare equilibrium travel times to those associated with providers that solve a traveling salesman problem within each day. The ability to optimize travel lowers travel time to both providers by 3.3 percentage points for *fcfs* providers and by 4 percentage points among *mkt* providers. Travel time (as % of service time) is 13.4% for the *mkt* provider and it declines to 9.4% once optimizing routes. The reason for the slightly larger gains among market providers is the above mentioned sorting of higher travel-time farmers to the market providers. Absent sorting, the gains would be largest for *fcfs* providers.[31]

This result already points out to the joint sorting along space and service hours dimension in determining the impact of alternative dispatch technologies.

Wait time across farmers. Figure 4 compares waiting times across different dispatch system and demand characteristics using our bootstrapped samples. On average, the median wait time faced by farmers queueing with *fcfs* providers is 1.66 days, longer than the 1.52 days observed for those queuing with *mkt* providers. Wait times are largest among large

[31] This result highlights the importance of evaluating allocations in an equilibrium model. The Online Appendix reports these statistics for all additional markets.

Figure 4: Wait time by travel time and order size.



Note: "Near farmers" are located within 20 minutes of travel from the CHC; "far farmers" are located further than 20 minutes of travel from the CHC.

orders within 20 minutes from the hub of *fcfs* providers. Among farmers farther away from the hub, wait times are largest among small-holder farmers queueing with *mkt* providers. These results suggest that longer delays facing small-holder farmers may be related to their spatial distribution rather than purely their size.

Implications for productivity. Delays in service provision induce productivity costs for farmers, parameterized by η (the productivity cost per day of delay). We report these costs in output terms—as a share of value added per acre or per farmer—which we refer to as output costs.

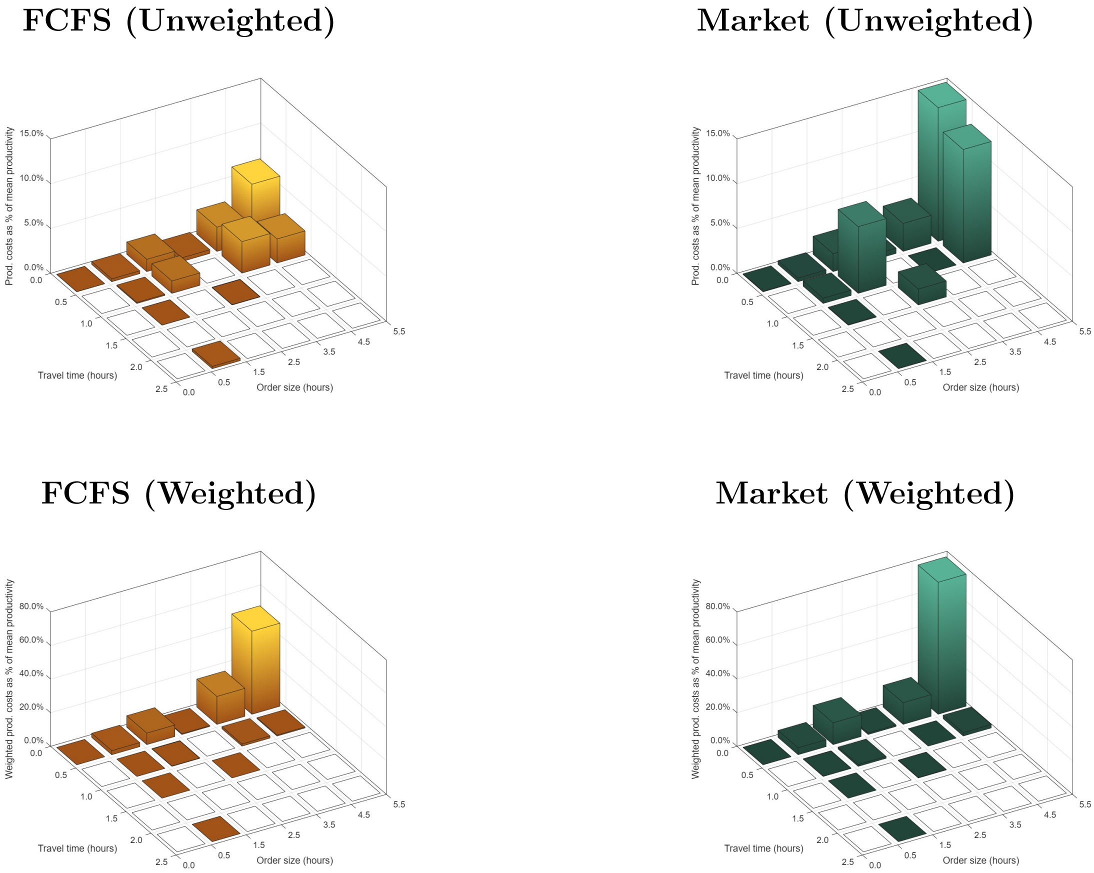
We construct a measure of output costs per farmer across providers as follows:

$$\text{output costs}_i = \frac{z_i}{\bar{z}} k_i^{\alpha} \eta \times \text{days of delay} \times \text{land size},$$

where z_i is the per-acre productivity of the farmer, $\bar{z}$ is the mean per-acre productivity of the hub.[32] Since the sorting of farmers is determined by travel time and requested machine-hours (i.e., bins), we define the average output costs for bin b and provider j as $\overline{\text{output costs}}_{bj} = \frac{1}{N_{bj}} \sum_{i \in (b,j)} \text{output costs}_{ij}$, where N_{bj} denotes the number of farmers in bin–provider cell (b, j). We then aggregate across providers using the equilibrium queue composition, adjusted

[32] This normalization allows us to more easily compare surpluses across markets, which we show in the Online Appendix

Figure 5: Output costs (weighted and unweighted) by travel time and order size



Notes: The top panels present output costs as % of per-acre mean productivity in the market for each travel-hour-order-size combination. The bottom panels weigh costs by the allocation of farmers to providers.

by the share of providers from each dispatch system, $\tilde{q}_{bj} = q_{bj} h_j$ for h_j the share of dispatch system j:

$$\overline{\text{output costs}}_b = \sum_j \frac{\tilde{q}_{bj}}{\sum_j \tilde{q}_{bj}} \overline{\text{output costs}}_{bj}.$$

The top two panels of Figure 5 show the expected output costs for a farmer in a given bin. A few patterns arise. Average output costs are particularly high for large farmers queueing with market providers, even when located in areas with low travel times. The patterns of farmer sorting are such that output costs are smaller for those queueing with the *fcfs* providers, and the costs are particularly large for larger orders which are unlikely to get served given others in the queue. In other words, for the current calibration, savings in travel times that dissipate among larger scale orders are relatively small compared to the cost of holding idle capacity by serving those large orders. The bottom two panels of Figure 5 show effective output costs given farmer's sorting across providers. Interestingly, the expected output costs for farmers with order sizes in the median (3.5 hours) are highest when queueing with *fcfs* providers, even if nearby. The expected output costs are also concentrated in large farmers queueing with *mkt* providers. Farmers with smaller orders face higher expected output costs with *mkt* providers, in part because the pattern of sorting is such that they are more likely to queue with them.

While these results highlight heterogeneity, it is also interesting to study the equilibrium implications for aggregate productivity. Aggregate output costs weight the average output costs per bin by the distribution of farmers across bins, ω_b, which is constructed using the equilibrium queue lengths and census data on farmers,[33]

$$\text{aggregate output costs} = \sum_b \omega_b \, \bar{\text{output costs}}_b.$$

The measure of aggregate output costs is therefore normalized by market size and analogous to a geometric average of the output costs across relevant dimensions of heterogeneity in the data.

Aggregate output costs The aggregate output costs induced by the allocations in the baseline equilibrium is 9% of average productivity per acre in the market, see Table 6. These are sizable and concentrated among the largest farmers in the sample. Output costs across providers are 8.6% for those queuing with *fcfs* providers and 9.1% for those queuing with the *mkt* providers. These output costs are an equilibrium outcome from farmer sorting across providers and endogenous delays. We can compare these output costs to those obtained when optimizing travel time across providers. We find that aggregate output costs fall to 8.6%, with an average output cost for *fcfs* of 8.3% and for *mkt* providers of 8.7%. These gains from optimizing service within a period across space are relatively modest. The reason is that the equilibrium order sorting does not change much.

[33] The total weight of small farmers relative to large farmers matches the ratio of their respective equilibrium queue lengths. Within each farmer type, the relative weights across bins follow the empirical distribution observed in the census data.

Table 6: Baseline Equilibrium: Aggregate Surplus and Output Costs

Group	FCFS			Market			Weighted	
	surplus	**output costs**	**Share of farmers**	**surplus**	**output costs**	**Share of farmers**	**surplus**	**output costs**
All farmers	**1.74**	**8.6%**	**100%**	**3.31**	**9.1%**	**100%**	**3.05**	**9.0%**
0-0.5hrs	-0.16	0.0%	4%	0.00	0.3%	5%	-0.02	0.3%
0.5-1.5hrs	-0.24	0.7%	27%	-0.09	0.8%	35%	-0.11	0.8%
1.5-2.5hrs	0.28	2.8%	17%	2.41	6.1%	22%	2.11	5.6%
2.5-3.5hrs	-0.93	1.2%	4%	-0.05	2.5%	5%	-0.18	2.3%
3.5-4.5hrs	1.36	7.9%	22%	4.00	13.0%	14%	3.35	11.7%
>4.5hrs	5.68	23.2%	27%	12.42	30.1%	18%	10.75	28.4%

Note: Weighted surplus and output costs are calculated as weighted averages of the mean values under each dispatch system, using weights equal to queue lengths adjusted by the shares of the two dispatch systems.

5.2.3 Welfare

Equilibrium allocations have heterogeneous costs and benefits for farmers of different size, location and productivity due to their sorting across dispatchers. They also affect providers differentially given farmers' sorting. To assess welfare, we construct a measure of aggregate surplus in the economy.

We start by defining the surplus per farmer across providers

$$\text{surplus}_i = \Big(\frac{z_i}{\bar{z}} k_i^{\alpha}(1 - \eta\text{days delay}) - \frac{w}{\bar{z}}(k_i + d_i)\Big) \times \text{land size.}$$

Since the sorting of farmers follows travel time and machine-hours requested (bins), we can define $\bar{\text{surplus}}_{bj} = \sum_i \text{surplus}_{ij}/\#\text{farmers p/bin-provider}$ as the average surplus for a bin b and provider j. One can then aggregate across providers following the equilibrium queue composition adjusted by the share of providers across dispatch systems, $\bar{\text{surplus}}_b = \sum_j \frac{\tilde{q}_{bj}}{\sum_j \tilde{q}_{bj}} \bar{\text{surplus}}_{bj}$, where $\tilde{q}_{bj} = q_{bj} * h_j$, h_j is the share of providers in dispatch system j.

Finally, the total surplus weighs the average surplus per bin by the distribution of farmers across bins, ω_b, following information from the equilibrium queue length and our census of farmers,

$$\text{aggregate surplus}_1 = \sum_b \omega_b \text{surplus}_b.$$

With these definitions at hand we can evaluate the surplus across different providers and across the distribution of order sizes. Table 6 shows that the aggregate surplus is 90% higher among those queueing with *mkt* providers relative to *fcfs* ones (3.31 vs. 1.74 in units of per-acre mean productivity). The levels of the surplus are normalized to average productivity in the market, with aggregate surplus (unconditional of providers) being 3.05 times the average productivity per farm in the market.

These surpluses are unevenly distributed among farmers. The highest surpluses accrue to those that demand higher machine-hours, particularly if queuing with *mkt* providers, where their surplus is more than twice as large as if they queue with *fcfs* providers (e.g., 12.42 vs. 5.68 for the largest orders in Table 6). The reason for these relatively larger surpluses is the savings associated with travel times. Interestingly, the relative surplus of *mkt* vs. *fcfs* providers is the highest among small-holder farmers. The reason is that small-scale orders improve machine utilization if they can be shuffled in the queue to accommodate larger orders too. Given the constraints in dispatch technology, only *mkt* providers can reshuffle these orders.

When we aggregate across providers and only focus on heterogeneity by order size, the largest surplus is also accrued to the largest farmers, and it is possible to sustain negative surpluses for small farmers, i.e. service costs exceed the benefits to those farmers.

6 The supply of technology: implications for aggregate productivity and welfare

In this section we take the calibrated economy and characterize how allocations and aggregate outcomes change across alternative counterfactual economies. First, we implement a deregulation of the market that allows *fcfs* providers to have access to a technology to prioritize the most profitable orders. We study this change allowing providers entry and exit so that equilibrium profitability resembles that of the baseline economy with two dispatch

Table 7: Comparison of Outcomes: Baseline vs Deregulation

	Aggregate Surplus		**Mean Wait Time (Days)**		**Ag. Output Costs per Acre**		**Ag. Output Costs per Farmer**	
Group	**Baseline**	**Dereg.**	**Baseline**	**Dereg.**	**Baseline**	**Dereg.**	**Baseline**	**Dereg.**
All farmers	**3.05**	**3.35**	**1.59**	**1.37**	**1**	**0.69**	**1**	**0.68**
small-scale	0.62	0.65	1.55	1.34	1	0.64	1	0.63
large-scale	7.45	8.23	1.67	1.42	1	0.70	1	0.69

Note: Entry and/or exit are allowed in the deregulation case.

systems. Second, we study counterfactual scenarios where we change the supply of equipment above and below its current levels, when the market arrangement follows that of the deregulated economy.

6.1 Market deregulation: from *fcfs* to *mkt* providers

One of the findings in Section 5.2.2 is that given a common distribution of demand, the benefits to *fcfs* providers from optimizing equipment in space would always be weakly higher than those of *mkt* providers. The reason is that the *mkt* provider can always choose to mimic the *fcfs* if that behavior is profit maximizing. Equilibrium farmer sorting may however imply that *fcfs* spend less time traveling (as % of service time) when they are more likely to attract nearby farmers than their *mkt* counterparts. This sorting in turn depends on the correlation between farmer sizes and space. Thus, sorting and provider incentives interact to determine the scope for gains in prioritizing high marginal return orders.

A market deregulation in our context amounts to allowing *fcfs* providers to adopt the same prioritization technology as *mkt* providers at no cost—i.e., to prioritize high marginal return orders (larger orders with lower travel time). Equivalently, setting $h = 0$ mimics this allocation since all providers use the *mkt* dispatch technology. *fcfs* providers are at least as well off with the technology (they can always choose not to prioritize), but endogenous farmer sorting and pricing require analyzing this counterfactual in equilibrium.

Table 7 shows that average surplus increases by 10.0% relative to the baseline equilibrium (from 3.05 to 3.35 in units of average productivity in the market). These gains are prevalent across all farmer sizes, but are largest among farmers with higher machine hours demand.

Surplus gains are explained by declines in output costs associated with lower wait times. The average wait time declines by 14.0% from 1.59 to 1.37 days (Table 7). This decline in wait times contributes to the surplus gains, which are mostly driven by the gains among the most productive farmers. The table also reports aggregate output costs per acre and per farmer (normalized to the baseline). The deregulation generates a decline in aggregate output costs of about 31% (to 0.69 of baseline output costs). The current market arrangement implies aggregate output costs of 9 p.p. in units of average productivity (Table 6); these output gains from deregulation—the reduction in output lost to delays—amount to about 2.8 p.p. Output costs decline for both small-holder and large-scale farmers, with the largest percentage decline for small-holder farmers (normalized output costs per farmer fall from 1 to 0.63 for small-holder and 1 to 0.69 for large-scale). A deregulation of the market benefits small-holder farmers disproportionally more, while gains in welfare are mostly driven by servicing large-holder farmers. The reason is that providers benefit from the deregulation by serving relatively more large orders.

6.2 Alternative relative supply of equipment

An extensive literature in agricultural economies has studied the effect of government subsidies for equipment, a commonly used policy tool to increase access to mechanization. Two conclusions arise: (a) equipment subsidies are regressive because they benefit relatively wealthier farmers; (b) the impact of these subsidies in mechanization is widely heterogeneous, with only a handful of successful cases (see review in Pingali (2007)).

Our results suggest a different interpretation of the heterogeneity in the effectiveness of subsidies. First, small-holder farmers can benefit from shifts in the market structure, even though large-scale farmers may benefit relatively more both in terms of surplus and output costs. Since the magnitude of these gains depends on equilibrium farmer sorting and endogenous delays in provision, which are in turn a function of pricing and dispatching, we study shifts in the relative supply of equipment of various magnitude. We construct equilibria where machine capacity shrinks by half or 80% of our baseline scenario, and others where machine capacity increases by 20 or 50% relative to our baseline.

Table 8 shows a variety of outcomes across equilibria. Service finding rates increase with

Table 8: Comparison Across Supply of Machine-Hours, H

	H_{ps}	H relative to H_{ps}			
	1	50%	80%	120%	150%
A. Service finding rates					
Average farm	**22%**	**8%**	**16%**	**28%**	**35%**
small-scale	10%	2%	6%	13%	17%
large-scale	13%	6%	10%	15%	19%
B. Rental rates (INR)					
small-scale	138	160	150	123	107
large-scale	95	102	99	90	84
C. Wait time (days)					
All farmers	**1.59**	**3.19**	**1.99**	**1.33**	**1.07**
small-scale	1.57	3.14	1.96	1.30	1.04
large-scale	1.64	3.27	2.04	1.38	1.10
D. Relative output costs per farmer					
All farmers	**1**	**3.57**	**1.63**	**0.59**	**0.15**
small-scale	1	3.81	1.70	0.53	0.07
large-scale	1	3.52	1.62	0.60	0.16
E. Relative surplus per farmer					
All farmers	**1**	**0.93**	**0.98**	**1.01**	**1.02**
small-scale	1	0.89	0.97	1.02	1.04
large-scale	1	0.93	0.98	1.01	1.02
F. Normalized output costs per farmer					
All farmers	**0.10**	**0.34**	**0.16**	**0.06**	**0.01**
small-scale	0.03	0.10	0.04	0.01	0.00
large-scale	0.22	0.78	0.36	0.13	0.04
G. Normalized surplus per farmer					
All farmers	**3.32**	**3.07**	**3.26**	**3.36**	**3.40**
small-scale	0.64	0.57	0.62	0.65	0.67
large-scale	8.15	7.59	8.01	8.24	8.34

Note: Column H_{ps} corresponds to the post-subsidy supply of machine-hours in the short run. The post-subsidy level is estimated as the equipment supply absent CHC's machine hours, as measured by the Census data. Service finding rates are computed as described in the text.

machine supply and respond asymmetrically to increases versus decreases in supply. Service finding rates for small-scale requests respond more to movements in equipment supply than service finding rates for large-scale orders (even though the levels are always higher for large-scale orders). Not surprisingly, rental rates are decreasing in capacity, with an elasticity of 0.3 for small-holder farmers and 0.14 for large-holder farmers, when we are reducing capacity from the baseline. When we increase capacity, the rental elasticity is much larger, doubling for small-holder farmers and raising to 3% for larger-holder farmers. In other words, a 1% increase in capacity generates a 0.6% decrease in the rental rate of capital for small-holder farmers, and a decrease of 3.2% for large-holder farmers .

Wait times are also declining in machine supply, and the decline is also non-linear, with higher savings in wait time at relatively low levels of service capacity. This is consistent with congestion eventually tapering off. The non-linear effect on wait times has direct implications for output costs: shrinking service capacity by 50% from the baseline more than triples aggregate output costs (Table 8); conversely, increasing capacity by 50% reduces output costs to 15% of baseline. The degree of market congestion is therefore a key determinant of the implications of policy for agricultural productivity.

Finally, despite the substantial effects on output costs and waiting time, surplus (welfare) changes by a smaller magnitude. Halving service capacity induces a decline in surplus of 7%. The reason for these smaller effects (relative to output) is twofold. First, output costs are paid by farmers that contribute little to aggregate welfare, given the population distribution across sizes and productivity. Second, increased output costs from low capacity are compensated by higher rental rates (and therefore profits) for service providers. In other words, while the distributional consequences of alternative supply levels are large, the aggregate welfare effects of those are more muted.

If we compare the effects of changes in service capacity to those associated with market deregulation, see Table 7, one concludes that the cost of having *fcfs* providers accounts for 30% of aggregate output, which is comparable to reducing service capacity by 20% to the baseline level (Table 8). In other words, deregulating the market without changing service capacity achieves an equivalent allocation to increasing service capacity by 20%.

7 Conclusion

Rental markets hold considerable promise in expanding mechanization access and increasing productivity in the farming sector. However, which market structures expand to increase access to such services - for instance, those prioritizing larger farmers, or not - have important implications for welfare and equity, and therefore determine the returns to such markets. This paper provides an equilibrium framework to assess the implications of disparities in joint spatial and productivity distribution of demand for alternative market arrangements, evaluating two commonly used structures.

We show that returns to these rental markets depend on spatial density, i.e. the proximity of suppliers to farmers, the overall supply capacity, and the ability to optimize traveling equipment time. We show that gains in service capacity improvements are non-linear, with the largest gains in welfare and aggregate output being realized when initial service capacity is low. We show that when increases in service capacity are not feasible, market segmentation, with providers that exploit a *fcfs* dispatch technology can improve allocations particularly among small-holder farmers.

A key takeaway from our exercise is that endogenous sorting in space and across size is fundamental to assess the returns and equity implications of different arrangements. While we take the location of service providers as given, a natural step forward would be to study the properties of the endogenous location choices of providers in space, as in Oberfield et al. (2020). Furthermore, understanding how other agricultural markets such as land rental markets impact the spatial distribution of farms by size would allow estimating the returns to these different market arrangements under different levels of land rental market activity.

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A Costs of delays

Simple correlations between farm productivity and service delays cannot recover the cost of delays if ex-ante productivity is correlated with the timing of farmers' engagement in the rental market. To overcome this hurdle we exploit high-frequency (daily) data from ICRISAT and estimate the whole profile of profitability for farmers preparing their land at different dates during the agricultural season, using plots of comparable characteristics to those in our sample.

We define an optimal planting time as the date that maximizes the profits per acre in a given village year. Then, we define the cost of the delay as the difference in average value added per acre or profit per acre (depending on the variable of interest) as we move away from the optimal planting date.

Formally, we estimate

$$Y_{i,year} = \beta_0 + \beta_1^{+}(\text{Planting Date-Optimal})_{>0} + \beta_1^{-}(\text{Planting Date-Optimal})_{\leq 0} + \alpha X_{i,year} + \epsilon_{i,year}$$

where X are controls for plot characteristics, farmer, village and time fixed effects. Standard errors are clustered at the village level.

Our estimates for the costs in value added per acre are reported in Table A1. They indicate that within a 5-day window, each additional day away from the profit maximizing date entails a cost of 3.4% in terms of value added per acre. In the 5-day window, for farmers that plant too early relative to the optimal date, moving *closer* to the optimal date by one day increases value added per acre by INR 391 per acre. Conversely, for farmers that plant too late relative to the optimal date, moving *away* from the optimal date by one day reduces value added per acre by INR 215 per acre. Therefore, moving closer to optimal date increases returns. This result is robust to enlarging the window around the optimal planting date, with an estimate cost of delay in the planting date of 8.5% per day.

As a robustness check, we also estimate the cost of deviation with sowing time estimated at the weekly rather than daily level. These estimates are reported in Table A2. They indicate a cost of delay of between 5.6% to 11.5% for an additional week's delay in terms of value added per acre, or between 0.8% and 1.6% per day of delay (depending on whether we restrict delay to be within 5 or 3 weeks of optimal sowing time, respectively).

These estimates are also consistent with agronomic estimates that estimate yield losses from deviating from the optimal planting time in other contexts - for instance, Liu et al. (2023) estimate yield losses of about 13% for a 10-day deviation from the optimal sowing time for winter wheat in China, or about 1.3% per day.[34]

Table A1: Costs of Delays Relative to Optimal Planting Time, Value Added per Acre

	Cost per day, value added per acre				
	Whole Sample	5-day around optimal		10-day around optimal	
		Before	After	Before	After
β_1	-41.97	391.1**	-215.7	1,166***	-931.1***
	(26.33)	(140.2)	(146.9)	(338.7)	(298.5)
Observations	6,034	1,461	1,882	1,010	1,221
R-squared	0.408	0.625	0.584	0.706	0.659
Mean of Value Added per acre	10228	11425	10694	11921	10998

Notes: The optimal date is a village-year measure, and is the sowing date that maximized mean value added per acre in the village in a given year. Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

Table A2: Costs of Delays Relative to Optimal Planting Time by Week, Value Added per Acre

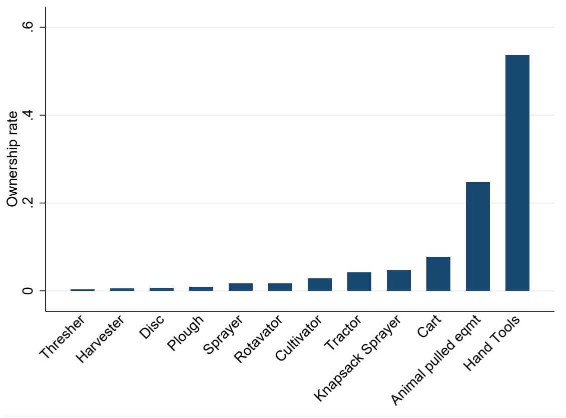
	Cost per Week, value added per acre				
	Whole Sample	5 weeks around optimal		3 weeks around optimal	
		Before	After	Before	After
β_1	-164.5	-115.7	-665.7**	171.3	-1,313**
	(146.6)	(301.8)	(275.9)	(292.7)	(470.4)
Observations	6,034	2,799	4,049	2,333	3,416
R-squared	0.405	0.518	0.432	0.535	0.453
Mean of Value Added per acre	10228	11810	9926	11344	10155

Notes: The optimal date is a village-year measure, and is the week of sowing that maximized mean value added per acre in the village in a given year. Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

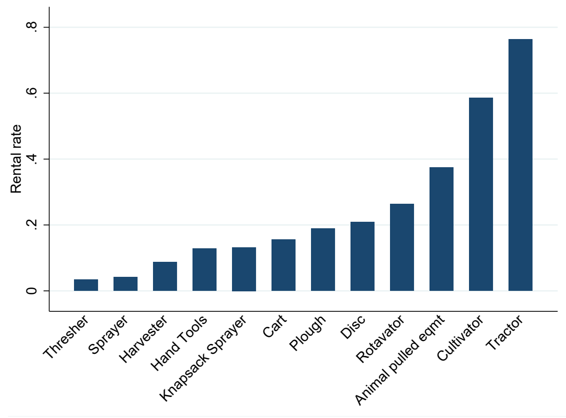
B Additional Tables and Figures

[34]ICRISAT's sample sizes after controlling for crops are too small to reliably estimate the effects on yields. The point estimates for yield costs in crops such as pea are 5.3% over a five day window of the optimal planting date.

Figure A1: Ownership and rentals by implement.



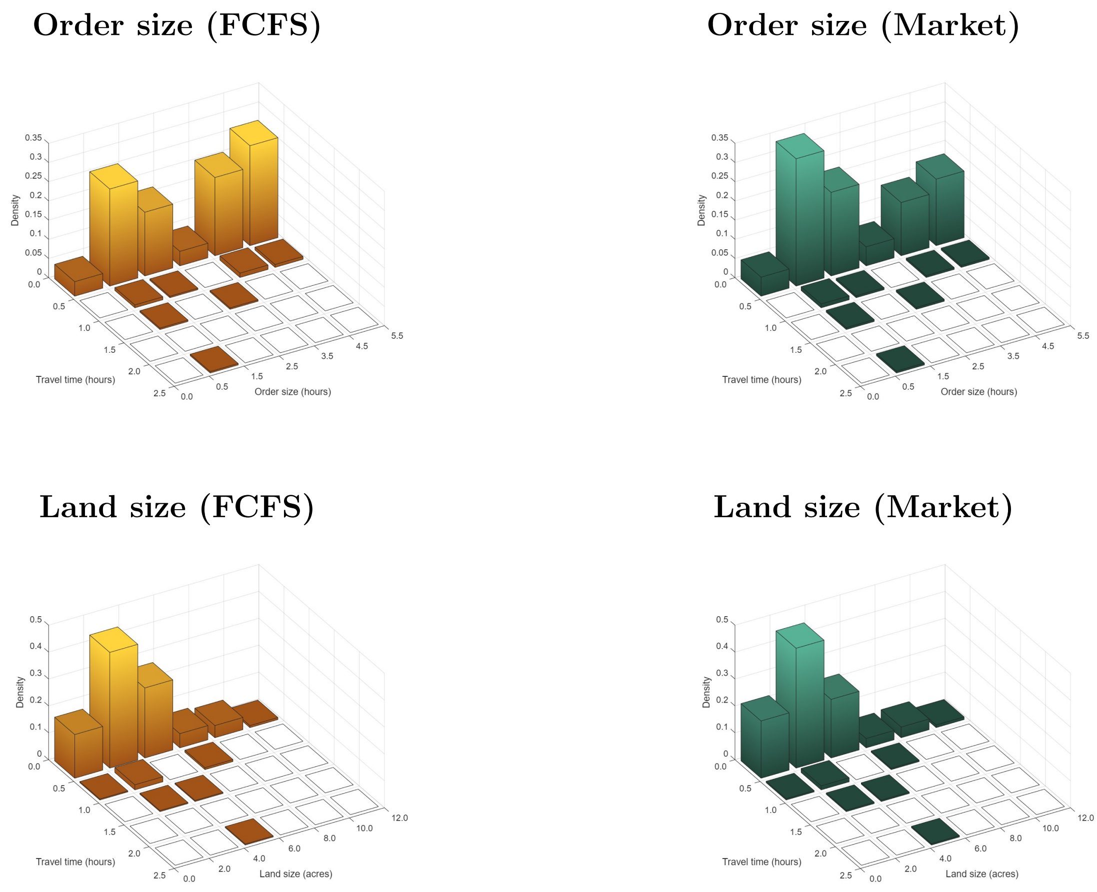
Owned



Rentals

Notes: The ownership (rental) rate is the share of farmers that report to own a given implement relative to the total population surveyed. Sources: Own census of farmers

Figure A2: Distributions over travel time vs. (top) order size and (bottom) land size.



Notes: Distribution of orders across hours requested (order size) and land size across providers. Benchmark equilibrium.